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*Asia-Pacific Network for Sustainable Forest Management
and Rehabilitation*

COMPLETION REPORT

Adaptation of Asia-Pacific Forests to Climate
Change-Phase II

(January 1st, 2016 – December 31st, 2018)

Faculty of Forestry
University of British Columbia

BASIC INFORMATION

Project Title(ID)	Adaptation of Asia-Pacific Forests to Climate Change-Phase II		
Supervisory Agency	Canadian Forest Service		
Executing Agency	Faculty of Forestry, University of British Columbia		
Implementing Agency	Faculty of Forestry, University of British Columbia		
Date of Project Agreement: 18/06/2015			
Duration of implementation: [01/01/2016], 36 months			
Total project budget(in USD)	\$ 899,200	APFNet disbursed Grant(in USD)	\$499,200
APFNet assured Grant (in USD)	\$ 499,200	Actual cost from APFNet(in USD)	\$499,200
Disbursement Status		Date of disbursement	Amount(in USD)
Initial disbursement		1/16	\$38,065
Second disbursement for year 1		10/16	\$172,401
Second disbursement		5/17	\$166,400
Third disbursement		6/18	\$122,334
Balance to be disbursed non			
Reporting Status		Schedule ¹ implementation	Project progress status ²
First reporting (7/16 – 12/16)		On track	Satisfactory
Mid-term Progress Report (1/16-7/17)		On track	Satisfactory
Semi-annual progress report (7/17-12/17)		On track	Satisfactory

¹ Schedule ¹implementation status could be on track/behind/ahead of schedule

² Project progress status could be ranked as satisfactory, dissatisfactory, moderately satisfactory, moderately dissatisfactory

Executive Summary

The Asia–Pacific region is particularly vulnerable to climate change given its large population, high biodiversity, and large number of forest-dependent communities. Climate change has already affected many forest ecosystems in the region through widespread increases in drought-related mortality, placing many tree species and associated ecosystem types at risk. As climate regimes continue to change, species adapted to historic climate patterns will be subject to increasing abiotic (e.g., temperature and moisture) and biotic (pests and diseases) stress. Mismatches between historic and future conditions may severely compromise the resilience of forest ecosystems and jeopardize the critical ecosystem services they provide. With the unrelenting progression of climate change, policy makers, statutory decision makers and forest managers are under increasing pressure to consider new approaches and adaptive strategies to establish and maintain healthy and resilient forest ecosystems. The development of effective adaptation strategies to reduce the negative impacts of climate change on forest resources requires the application of models that include detailed representations of plant-climate relationships. However, the limited availability of high-quality climate data represents a critical barrier to the construction and application of such models. Moreover, there is also a lack of capacity among policy makers and forest managers in the region to use the tools and models that are essential to develop adaptive strategies required to achieve resource management objectives. To address these issues, the “Adaptation of Asia-Pacific Forests to Climate Change phase II” was implemented during the period January 1st, 2016 to December 31st, 2018 with a focus on tropical and sub-tropical species and forest ecosystems in the region. The overall goal was to build upon the successfully completed outputs of phase I and continue to substantially improve the capacity of policy makers and forest managers in selected economies to develop robust adaptation strategies to improve the health, productivity and resilience of forest ecosystems in the context of changing climates.

Specific objectives of the project include:

- 1) Improve and expand the essential tools developed in the previous phase of the project, including climate, niche- and process-based models, to further facilitate and promote related research and applications in more locations throughout the Asia-Pacific;
- 2) Continue to build a strong scientific basis and provide adaptive management options to enhance the target economies’ capacity for decision making regarding adaptation to climate change;

- 3) Expand the network built in phase one and continue capacity building through workshops, communication and policy notes to further enhance information sharing and technology transfer.

All of the research and associated activities have been completed including the following key outputs and achievements.

Substantial improvements have been made to an updated version of ClimateAP, which can generate scale-free high-resolution climate model for a large number of climate variables for historical and future periods. The improved ClimateAP (v2.12) can generate monthly climate data for each year from 2011 to 2100 instead of only three normal periods (2020s, 2050s and 2070s). The newly added time series functions for historical and future periods allow users to obtain climate data for multiple years and multiple locations in a single run. At the same time, we have also extended the years of coverage for the base period from 1901-2012 to 1901-2017. An R version of ClimateAP for Chinese Taipei, *clim.regression*, has been developed that can better utilize locally available climate data. ClimateAP is user-friendly and does not require GIS or other sophisticated computing skills. The scale-free feature of ClimateAP enables it to generate climate data for exact locations representing a significant advantage over other existing models. This improvement makes it an essential tool to help facilitate climate change studies from local applications to regional scales.

Climate niche models were built for 10 important forest tree species and economic specific forest ecosystems using a state-of-the-art, multiple-forest, machine-learning modeling algorithm and consensus projection approach, to enhance the accuracy of models and to deal with uncertainty in future climates. The suitable climate areas for the majority of the eight modelled tree species in China are projected to contract to some extent particularly large reductions for conifer species in the north including the two larch species. The consensus projections for the forest ecosystems (ecotypes) in China demonstrated a general trend of a northward shift in distribution. However, some ecotypes are projected to expand substantially, including the “multiple ripens grain fields and deciduous orchards” in Mideast China, and the “multiple ripens grain fields and evergreen orchards and subtropical economic plantations” in the south. In Malaysia, the consensus projections predicted a dramatic expansion of the “Inland forest” ecotype under climate change while the “Hill Dipterocarp Forest” is projected to contract to a small fraction of its original size. These model projections provide a solid scientific basis for assessing the impact of climate change, identifying most vulnerable species and ecosystems, and for developing adaptive strategies including assisted migration for the major forest tree species and ecosystem in the region.

The calibration and application of the FORECAST Climate model in a series of pilot sites facilitated detailed evaluations of alternative climate change scenarios and management options on a range of regionally important forest types. These included

Teak/bamboo plantation forests in Myanmar, *Acacia mangium* plantations throughout Malaysia and mangrove forests (*Rhizophora apiculata*) in coastal Malaysia. The output from the completed modelling work provided valuable insight in terms of how each of the target ecosystem types might respond to a changing climate with respect to forest health and productivity. Several training workshops were held to build capacity among local forest managers to use the models as decision-support tools to help understand the potential implications of climate change and to help achieve management objectives.

Google-Maps-based, economy-specific web platforms (climateap.net) have been developed for each of the five pilot economies. This economy-specific platform allows users to access the scale-free climate data in an interactive context simply by clicking on the Google map. The interface allows users to visualize the spatial projections of major climate variables and climate niche for a species and/or a forest ecotype. It can also be used by researchers to conduct studies and by the public to visualize the impact of climate change on individual tree species and a forest ecotype for education purposes thus facilitating data access and spatial visualization of model outputs.

This project has significantly contributed to advance science, technology, and capacity building related to climate change adaptation of Asia-Pacific forests. Moreover, it has enhanced regional management capacity and policy development through its publications in peer review journals, reports, handbooks as well as organization/ participation of conferences, hands on trainings and seminars. Three hands-on training events were organized and two associated training manuals were produced and distributed to build capacity of our local partners and other interested parties in the Asia-Pacific region. Team members participated in and/or helped to organize 11 international conferences and various seminars to communicate with scientists, stakeholders and policy makers across Asia-Pacific and to facilitate information sharing and knowledge transfer. Six peer-reviewed papers have been published and at least five new papers are either under review or in preparation for publication. Publishing peer-reviewed papers not only helps to share and promote the project outcomes, tools and models but also helps to demonstrate the scientific credibility of the project outcomes, tools and models.

The project has addressed the general lack of tools and models required to help increase our understanding of the potential impacts of climate change on species and forest ecosystem in the partner economies in particular and throughout the Asia-Pacific region in general. In addition, it has helped to consolidate extensive scientific knowledge on tree species, ecosystems, and current and future climate impacts in the Asia-Pacific region. It has also helped to increase scientific capacity through the development of cutting-edge models and tools for exploring national

and local predicted climate change scenarios, forest adaptation strategies, and ecosystem dynamics. This work will help to ensure continued social, economic, and environmental benefits into the future, through the maintenance of forestry dependent industry, jobs, and communities, and continued gains from the ecosystem and cultural services provided by forest ecosystems. Lastly, there is a continuing need to maintain and further developed the modelling tools to meet the increasing demand of research and applications in forest adaptation to climate change in the region.

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1. BACKGROUND AND INTRODUCTION

1.1 Project context

The impact of climate change on the health and services provided by forest ecosystems is a major concern in the Asia-Pacific region. Shifting climate patterns have led to increased drought-related mortality throughout the region (e.g. Allen et al., 2010; Zhao and Running, 2010) and increasing deviations between past and future climate regimes are placing many species and associated ecosystem types at risk. As climate regimes continue to change, species that have adapted to historic climate patterns will be subject to increasing abiotic (e.g., temperature and moisture) and biotic (pests and diseases) stress. Mismatches between historic (reflected in species adaptations to climate) and future conditions may severely compromise the resilience of forest ecosystems and jeopardize the critical ecosystem services they provide. Southeast Asia is particularly vulnerable to climate change in that the health of human communities and forest ecosystems are often closely linked. Forests in many parts of this region have been degraded due to over-harvesting for fuel wood and timber production and due to declines in soil productivity associated with swidden agricultural practices. Despite these risks, little progress has been made towards developing robust regional forest management strategies to tackle such challenges.

During the initial phase of this project, we refined and tested a suite of scientifically credible modelling tools designed to help regional forest managers develop and evaluate the potential impacts of climate change on forest ecosystems within the Asia-Pacific region. Specifically, a regional climate model called ClimateAP was created to address fundamental data gaps and to facilitate the development and application of detailed climate niche models for five major tree species across large, complex landscapes. ClimateAP, using dynamic local downscaling technology, generates high accuracy, scale-free climate data, explaining over 97% of the total variation in temperature and about 90% in precipitation observed by weather stations over the entire region. This model can be used by anyone interested in climate change or climate-related studies and applications in this region.

The climate niche models apply a novel composite modeling approach that integrates multiple Random Forest models to model the climate niche of each species at a high accuracy (error rate < 10%). These models are then used to generate consensus projections of the geographic distribution of the climate niche of each species in multiple future climate scenarios. These projections are sufficiently robust to serve as the scientific basis for policy makers and practitioners developing adaptive strategies for forests and forest-dependent communities.

In addition, case studies, including the application of a range of process-based forest management models, have been conducted at three pilot sites. The key results and

management recommendations from this work have been summarized and presented in the form of multiple research papers, project reports, management notes and at a regional APFNet workshop held in Kunming in July 2014.

We have also developed web-based tools including a map-based version of Climate-AP (<http://climateap.net>). It provides interactive access to scale-free climate data for historical years and future periods. It also allows spatial visualization of climate maps and spatial projections of climate niches generated from outputs of ecological models for Chinese fir, Chinese pine, Masson pine and bluegum for three future periods. In addition, we have developed a project website (<http://asiapacific.forestry.ubc.ca>) that serves as a gateway to the project including research objectives, organization, research team members, events, etc. These web-based tools facilitate scientists, stakeholders, policy makers, and curious citizens easy access to access the most up-to-date information and knowledge on climate change for anywhere in the Asia-Pacific region.

The regional focus of the initial phase of the project was on temperate and subtropical ecosystems. To further advance the capability of forest managers to protect and promote forest resources throughout the Asia-Pacific region, the tools should to be extended (e.g., from individual species to entire ecosystems) and applied to a broader range of ecosystems, including tropical regions and associated communities. In addition, more work is required to make these tools and their byproducts more widely available and more accessible for use by local practitioners through continued training and technology transfer. Together, these represent the main objectives of the second phase of this project.

With the unrelenting progression of climate change, policy makers, statutory decision makers and forest managers are under increasing pressure to consider new approaches and adaptive strategies to establish and maintain healthy and resilient forest ecosystems. The development of effective adaptation strategies to reduce the negative impacts of climate change on forest resources requires the application of models that include detailed representations of plant-climate relationships. However, the availability of high quality climate data represents a critical barrier that limits the construction and application of such models. The development of ClimateAP during the initial phase of this project provided an essential resource that will serve as a foundation for future research. Building on the advances of other climate models (WorldClim, ANUSPLIN, PRISM, ClimateWNA, etc.), ClimateAP, developed at the University of British Columbia (UBC), provides an essential resource for future modelling endeavors. Its defining features include the projection of scale-free (or high-resolution) data, the inclusion of a broad range of useful climate variables and indices derived from thousands of climate stations, the option to select from multiple climate change scenarios developed from world-class GCMs and widely accepted emissions scenarios, and a web-based, user-friendly interface to ensure data accessibility. In the second phase of the project, we propose to improve the

usefulness of ClimateAP by making its outputs available at a national scale and adding annual time series projections into the model.

One of the most straightforward and accessible approaches to the development of adaptive management strategies has been the application of climate niche models. This method is based on the idea that climate regimes, defined using complex statistical analyses of regional climate data, represent a fundamental limiting factor to the distribution of tree species and ecosystem types. The approach was pioneered in western North America by Hamann and Wang (2006) and Rehfeldt et al. (2006), but these original studies were limited in the range of future climate projections included in the analyses. Wang et al. (2012) at UBC generated consensus projections for British Columbian ecosystem types and species based on 20 climate-change scenarios. These projections have been used in developing provincial guidelines for tree species selection and seed transfer in forest resources management. In the first phase of the project, we were able to capitalize on the high-resolution climate maps generated by ClimateAP and existing maps of species distributions to construct bioclimatic envelopes (climate niches) for five key tree species in the Asia-Pacific region (Wang et al. 2016). Such information allows managers to evaluate the climate conditions for which species have been successful in the past and make predictions about where they will likely be successful in the future under changing climate regimes. In the second phase of the project, we propose to extend the climate niche models to include 10 new key species in these regions. We will also upscale the analysis to cover entire ecosystems in the selected economies to determine whether existing ecosystem classification schemes will remain robust under changing climate conditions. This is particularly important, as it will allow us to associate a large number of individual tree species (not limited to the original 10 species) with the ecosystem classification schemes and to make predictions for all of these species. This will make the method more applicable to subtropical and tropical regions, where a large number of species coexist in the same ecosystem. Furthermore, for the countries without inventory data on individual species, the analysis of existing ecosystem classification schemes can serve as an effective alternative.

In parallel with climate niche models, process-based models also play an important role in evaluating the impacts of climate change on forest productivity, water balance, and carbon storage. FORECAST Climate (Seely et al. 2014), an extension of the hybrid forest growth model FORECAST (Kimmins et al. 1999), was created in phase one of the project through the dynamic linkage of FORECAST with the stand-level hydrology model ForWaDy (Seely et al. 1997). This linked model is capable of demonstrating the impacts of climate change on forest growth dynamics. TACA is a mechanistic species distribution model (Nitshke and Innes 2008) that facilitates an analysis of the response of trees to climate-driven phenological and biophysical variables. It assesses the probability of a species being able to regenerate, grow and survive under a range of climatic and edaphic conditions. FORECAST Climate and TACA models were employed in pilot sites in temperate and north

sub-tropical regions to evaluate the long-term impacts of alternative climate change scenarios on forest growth and development. Results from the models were subsequently utilized in a tradeoff analysis associated with alternative forest management practices. In the second phase of the project, we propose to expand the application of these models to include additional forest types, particularly in tropical ecosystems of Southeast Asia, at a larger scale, and to improve the accessibility of tools, byproducts and results.

Successful management strategies and practices must be robust in the context of changing conditions associated with climate change and effective in terms of protecting key ecosystem services for the region and local communities. Scientifically credible decision-support tools built from climate/ecosystem models will provide an essential resource to help policy makers design policies that will aid local decision makers, and help forest managers understand the potential long-term costs and benefits of management choices on forest health and ecosystem services. The experience gained from working with local partners to calibrate and help facilitate the transfer of technologies has laid an effective foundation for the expanded application of these decision-support tools into tropical regions in Southeast Asia. This phase of the project will expand the application range of the decision-support tools established during the previous phase and will enhance the capacity of local forestry communities to use the tools to help them achieve their resource management objectives.

Target Area

In contrast to phase one, which focused mainly on temperate regions, phase two focused on Southeast Asian economies, particularly in sub-tropical and tropical regions (Figure 1). Southeast Asia has been identified as one of the most vulnerable regions to climate change, where adaptive strategies are urgently needed. Five economies were selected: Chinese Taipei and Malaysia to represent well-developed economies while Laos and Myanmar to represent less developed economies of the Asia-Pacific region. In addition, China has been a key focus of this project, as afforestation and reforestation are prevalent and offer a good opportunity to implement forest adaptation by selecting suitable tree species. However, Laos was dropped later in the second year of the project duration because of the administrative challenges to implement the project. To compensate for this loss opportunity, the project further included the mangrove forest in Malaysia.



Figure 1. Map of project partner sites: China, Chinese Taipei, Malaysia and Myanmar

1.2 Project goal(s) and objectives

The overall goal of this project is to build upon the successfully completed outputs of phase one and continue to substantially improve the capacity of policy makers and forest managers in selected economies to develop robust adaptation strategies to improve the health and productivity of forest ecosystems and their resilience to climate change.

Specific objectives of the project include:

- 1) Improve and expand the essential tools developed in the previous phase of the project, including climate, niche and process-based models, to further facilitate and promote related research and applications in more locations throughout the Asia-Pacific;
- 2) Continue to build a strong scientific basis and provide adaptive management options to enhance the target economies' capacity for decision making regarding adaptation to climate change;
- 3) Expand the network built in phase one and continue capacity building through workshops, communication and policy notes to further enhance information sharing and technology transfer.

1.3 Project expected outputs and outcomes

Output 1: ClimateAP with future annual climate projections

We have developed ClimateAP to successfully generate climate data for the use of all models in Phase I. However, the limits imposed by projecting future climates for only three periods have become an issue, as modelers and users expect to project the future on an annual basis to reflect annual fluctuations and extremes. This limitation will be overcome in this phase of the project by adding annual projections into the model. In particular, the expanded version of ClimateAP will allow for annual time series projections to be generated for any location in the region in a single run. With this development, ClimateAP now can generate high-resolution climate data for historical years (1901-2017) and future years (2011-2100) in addition to the three future periods (2011-2040, 2041-2070 and 2071-2100) already included in the model. It will serve as an essential tool to facilitate and promote climate change studies in the region.

Output 2: Assessments of the impact of climate change on forest ecosystems, key species and vegetation types

Ecological models, including climatic niche models and process-based models, will be extended to include more species and entire ecosystems in more economies. Future projections for ecosystems will be particularly important as they may serve as a reference for all species associated with those ecosystems. Meanwhile, we will take advantage of our modeling expertise to improve the current classifications of the existing ecosystems. These projections will provide assessments of the impact of climate change on forest ecosystems and key species in terms of the shifts in geographic distribution of suitable climate niches, species selection and vulnerability to abiotic and biotic stresses. Species, ecosystems and vegetation types to be projected are as follows:

China: two larch (*Larix gmelinii* and *L. olgensis*) species, Scots pine (*Pinus sylvestris*), Yunnan Pine (*Pinus yunnanensis*), black locust (*Robinia pseudoacacia*), Chinese cork oak (*Quercus variabilis*), aspen (*Populus tremula*), moso bamboo (*Phyllostachys edulis*) and entire ecosystems.

Chinese Taipei: *Cyclobalanopsis longinux* (syn. *Quercus longinux*), *Lithocarpus megalophyllus* and entire ecosystems.

Lao, Malaysia and Myanmar: Vegetation types.

Output 3: Evaluations of adaptive forest ecosystem management strategies through model integration, development of indicators and trade-off analysis

One of the ultimate objectives of this project is to facilitate policy discussions through scientifically credible evaluation of existing data and information. It aims to help policy makers and practitioners understand the complex systems they are dealing with, as well as provide opportunities for addressing policy and data gaps to formulate alternative adaptive forest management strategies. We will achieve this objective by developing indicators from the results of the integration of process-based (FORECAST/FORECAST Climate) and niche-based models, as well as input from local partners, to conduct trade-off analyses at representative pilot areas in Southeast Asia (Myanmar and Malaysia). With this framework, Teak plantation (*Tenctona grandis*) productivity will be forecasted under various future climatic scenario and management alternatives (with or without bamboo competition, water balance and nutrient) using process based model (FORESCAST Climate) climatic data derived from ClimateAP, field data collection and local input. Similarly, in Malaysia, how productivity of *Acacia mangium* plantation and *Rhizophora apiculata* mangrove plantation will be modeled under different future climate scenario and various management alternative. Note that, because of administrative challenges, Lao as a pilot site was dropped, instead, Rhizophora mangrove plantation, Matang valley in Malaysia was added later in the project.

Output 4: A web platform for data access and visualization for specific economies

A Google Maps based web tool has been developed (climateap.net) to provide a platform for data access and spatial visualization of model outputs. It facilitates and promotes the outreach of project outcomes to users. Due to the large area and the large number of economies in the region, it will be very difficult to interpret these maps if all outputs of the project are piled up on the same map. It is also difficult to visualize local variations on a large map due to limits in color spreads. Economy-specific maps using the same platform will be developed in this project to make the spatial visualization and data access more effective and more user-friendly.

Output 5: Networking and capacity building

A comprehensive network, involving scientists, policymakers, decision-makers, practitioners and other stakeholders, will be extended and the capacity of stakeholders will be enhanced through a suite of approaches designed to address the needs of different types of stakeholders. In particular, the capacity of government officials and local forest managers will be enhanced in the area of policy making and policy implementation related to forestry adaption to climate change by conducting hands on training and workshops and sharing models and tools developed in the project through participation in the conferences and publication of training manuals. Furthermore, to enhance networking and capacity building, young visiting scholars mostly from Chinese Universities will be engaged in various activities

related to the project and climate adaptation of forest in China and Asia-Pacific through workshops, teachings and researches.

2. PROJECT IMPLEMENTATION

2.1 Project schedule and implementation arrangements

For effective and efficient implementation of the project activities, annual work plan with key milestones and activities were prepared in advance of each project year based on the proposal schedule. In general, we were successful to follow and achieve most of the major outputs and activities based on the schedule of the proposal. However, we also encountered some unexpected difficulties in the process of the project implementation. Particularly during early second year of the project (February 2017), when we had trouble to establish communication with our local partners at Laos despite our repeated attempts to contact them. Therefore, based on discussion within project committee and staff and APFNet, we discontinued the process-based modelling work in Laos, as it required great amount of contribution from the local partners to collect information essential for the process-based modeling. To offset the loss of Laos work, we added an additional important ecosystem type (*Rhizophora apiculata* mangrove forest plantation) in Matang region of Malaysia.

Moreover, during the fall field visit in Myanmar pilot site 2017, there was minor disturbances in two plots because of the illegal logging and thinning of the teak. We reported this to the concerned authority and no such issue occurred afterwards. Other technical issue was experienced while developing economy-specific google web platforms particularly for China due to firewall against Google Maps. However, a breakthrough was achieved in making the Google Maps-based tool accessible and useable in China.

Additionally, we also experienced delay in finalizing the agreements with all of the partner organizations during Year 1 because of different formalities and requirements for each institutions and local partners involved. However, we managed to convince our partners to begin working on the project while the agreements are pending, so that there will be no further delay in the project progress and implementation. Developing the agreement with Myanmar was further complicated due to the Canadian Government's sanctions against the economy during first few years. These sanctions inhibit any party from transferring funds to organizations or residents of Myanmar. This issue was addressed (thanks to the APFNet) with the help of APFNet to transfer funds to the Ministry of Environmental Conservation and Forestry in Myanmar on behalf of UBC after receiving the invoices of their contributions to the project. This will ensure that the local partners receive proper and timely compensation for their work and avoids UBC facing legal charges

and fines for contravening Canadian Government sanctions. The Canadian sanction against Myanmar was lifted as of October 2016. Thereafter, travel and payment related to the project occurred directly and smoothly that certainly helps to speed up implementation of the project activities.

Furthermore, there was challenges in general invoicing procedure with local partners resulting delay in receiving adequate invoices and transferring funds to the partners. To address the issue, an invoicing protocol, template, and wire transfer form were created and distributed to local partners.

Regardless of the different technical, administrative and management challenges, nonetheless, project implementation and progress has not been delayed and has remained on track.

2.2 Project resources and costs

A funding agreement was signed between APFNet and Executing Agency (EA), Faculty of Forestry, University of British Columbia, Vancouver and endorsed by the Project Supervisory Committee, the Canadian Forest Services on June 18th, 2015. The project implementation period was 36 months. The total budget of the project was US \$ 899,200, of which, APFNet granted US \$ 499,200 where as EA contributed US \$ 400,000 in cash and kind. USD 4,500 is in balance. The project's financial details are provided in Annex B.

UBC has a rigorous financial management system controlled centrally by professional accountancy staff, and an effective financial and research management control framework for the monitoring of the use of funding. UBC developed and implemented effective policies, administrative systems, procedures, and controls to ensure that all activities funded by and the Agency were conducted in compliance with all:

- 1) Legislated requirements;
- 2) Agency policies and procedures; and
- 3) Other agency requirements specific to a particular Grant or Award

The faculties and departments in UBC are required to follow UBC established policies and procedures for the management of grant and award funds. Aside from the UBC policies and procedures, there are also specific human resources, Payment and Procurement, Payroll, Research and Trust Accounting guidelines that they need to abide by.

At the department of Forestry Resource Management, there is a structured workflow to ensure a transaction from initiation to approval and processing is in a

proper sequence to ensure they are performed in according to the EA's policies and the Funding Agreement.

The field activities cost represent 30% of all the reported expenses followed by travel and related cost (15%). Higher proportion of expenses in these categories occurred mainly because our focus was to conduct field activities effectively so that quality data required for tools and model building can be collected with the help of our local partners.

The overall budget variance was 0.90%. All the budget variance was well within the range except the meeting and training cost, which consists of higher variance (-17.14%) and was accrued excess expenses than the anticipated budget (see Annex B for financial detail). This occurred because the project focused on capacity building and sharing project outcomes, tools and models and their application as widely as possible in Asia-Pacific. Since aforementioned costs heavily involved traveling (flight), accommodation and other related expenses, which has increased substantially compared to when we estimated these costs at the beginning of the project.

To ensure compliance, following categories of the budget were examined during the project period. 1) Project staff cost; 2) travel and related costs; 3) field activities cost; and 4) Operating expenses. For salary expenses, all reported expenses, and samples of the employees' appointment forms and contract were selected and examined. In addition, these transactions were examined to ensure proper approvals processes were followed, including proper Human Resource approval steps. The travel expenses claims were examined to ensure they are in compliance with the EA's travel policy. Similarly, all reported expenses related to the field activities cost were examined to ensure the use of the funding is in compliance with the purposes described in the Funding Agreement and the annual work plan. In conclusion, the EA used funding for the purposes intended in the Funding Agreement and Project Proposal.

2.3 Procurement and consultant recruitment

All services were performed under approved work plans and were used directly and only by the project and contributed to the achievement of project goals and objectives. Several data such as climate data, satellite image and digital maps were purchased required for climate niche and FORECAST Climate models. Similarly, local inventory data, hydrological data and other biological data were also purchased for local partners required for the research activities.

UBC has developed and implemented effective policies, administrative systems, procedures and controls to ensure that all activities funded by and the Agency are

conducted in compliance with all:

- 1) Legislated requirements;
- 2) Agency policies and procedures; and
- 3) Other agency requirements specific to a particular Grant or Award

2.4 Monitoring & evaluation and reporting

A systematic and comprehensive reporting, review, monitoring, and evaluation has been developed and adopted by the EA for effective monitoring, evaluation and reporting of the project progress. We developed a logical framework matrix to identify any gaps between the planned situation and the actual situation, depending on the indicators related to each activity listed in the logical framework matrix. Annual Work Plan (AWP) was prepared in advance for each project year with milestones and anticipated activities intended for the year. Two periodic progress reports were prepared and submitted to APFNet twice annually at the middle and end of the each year to guarantee that the project implementation is on track to achieve the anticipated objectives. The progress report summarized the activities that had been implemented for the year and compared with the associated logical framework matrix and work plan as a reference to track the project progress. When needed, corrective actions were adapted to ensure the efficiency and effectiveness of project implementation, to achieve the objectives of the project, to avoid encountering unexpected delays in such areas as output delivery, and to ensure the timing and actual availability of planned input items (e.g., personnel, equipment, funds).

A mid-term progress report was prepared and submitted for the period from January 1st, 2016 to July 30th, 2017. This report summarized the research and activities completed for each output, the results of the application of models/tools, indicated the next steps to be taken for each component, evaluated whether the project implementation was on track, and outlined the actions to be taken for any sections that not had progressed as far as anticipated. Frequent communication and interactions with APFNet staff greatly contributed to ensure the progress on the track. A mid-term project evaluation led by external APFNet was conducted on September 2017. During this evaluation, a workshop was conducted when the external evaluator met with all the involved staffs and researchers from Faculty of Forestry at UBC and discussed about various aspect of project implementation followed by series of meetings. Recommendations and suggestions from the mid-term evaluation such as to do more outreach and training were achieved by organizing two hands on training workshops: one in Myanmar on November 2017 and second one in Guangzhou, China on July, 2018 accompanied by sharing project outcomes in international conferences, seminars and hosting visiting scholars in UBC. These training workshops were participated by forest management practitioners, decision makers and researchers from various organization in Asia-Pacific such as

Myanmar, Malaysia, Cambodia, Thailand and China (please see 2.5, output five and Annex D4-D7 for detail).

To ensure effective implementation of the project activities, regular project meetings (every month and as per need) was organized with the team members to report the progress, to discuss issues encountered and to present plans for the next step followed by series of brainstorm sessions to explore solutions for research problems. Similarly, project site visits and regular contact with the local partners were achieved to guarantee effective implementation of the project activities in the pilot sites.

2.5 Dissemination and knowledge sharing

Dissemination and knowledge sharing of the project outcomes is one of the main activities of the project. To achieve this, a comprehensive network involving scientists, policymakers, decision-makers, practitioners and other stakeholders was established, and the capacity of stakeholders enhanced through a suite of approaches designed to address the needs of different types of stakeholders. In particular, the capacity of government officials and local forest managers enhanced in the area of policy making and policy implementation related to forestry adaption to climate change using the methods described below (Table 1). Additionally, the research team organized and participated in various events to share the research and knowledge acquired from the project with broader community mostly in Asia-Pacific region. This project generated six peer review papers, at least another five under review and preparation, two training handbooks, which contributes our understanding of the adaptation of Asia-Pacific forests to climate change.

Table 1: A summary of the dissemination and knowledge sharing activities

Description	Number	Total number of people involved	Remarks
Training and Workshops	4	124	One week
Conferences	11	410	Half day seminars
Seminars	18	~ 750	Half day seminars
Peer review publications	6		5 more are under review/ preparation
Training manual publications	2		Prepared and shared during the training workshops
Visiting Delegates	20	250	Less than a week

Academic training, graduate students and visiting scholars	6	60	3 months and up

To develop network, we have continued with the existing network established in the Phase I and extended gradually with the stakeholders of the project and wider society through organizing and participating various activities and events in the partner economies as well as in the Asia-Pacific region. As a transitional event between Phase I and Phase II, project team members attended the World Forestry Congress (7-11 September 2015) in Durban, South Africa. Here, they highlighted the Phase I achievements and discussed how they would be built upon in Phase II. Similarly, to educate about the Phase II climate change adaptation project among the stakeholders, an inception meeting was held over two days (February 23rd and 26th, 2016) as a side event at Asia-Pacific Forestry Week (APFW), hosted by the FAO in the Philippines. The meeting focused to ensure that all the team members as well as local partners of the phase II fully understand the project's goals, objectives, their roles and responsibilities. Five representatives from UBC and nine representatives from our partner economies attended the meeting. During the meeting, UBC team members shared the achievements of Phase I as well as the goals and objectives of Phase II. Further, annual milestones and monitoring and evaluation guidelines were also set and discussed followed by outlining research and objectives to be achieved in Year 1. This meeting provided an opportunity to educate our local partners about the project as well as strengthen relationships with them. Similarly, our team members visited pilot site several occasions not only to collect data required for the project but also to build capacity and strengthen relationships with the local partners.

Moreover, to share outcomes, tools and models developed by the project, team members organized and actively participated in the at least eleven international conferences and workshops in various parts of Asia-Pacific regions. Project team members attended the 124th annual IUFRO Asia-Oceania Conference in Beijing, China from October 22nd-24th, 2016 and organized a two-hour side session entitled "Tackling climate change adaptation in tropical and subtropical forests". In this session, scholars from Australia, Canada, China, Chinese Taipei (local partner), Nepal, and Malaysia (local partner) presented six oral presentations. These oral presentations focused on the best practices to address future climate impacts in Asia-Pacific forest ecosystems, including strategies such as the implementation of a cost-benefit framework to analyze prospective practices, integration of climate and ecological modeling tools in adaptive forest management development, as well as methodologies to quantify ecosystem services and carbon budgets. Over 30 participants attended this workshop followed by discussion on adaptive forest management through application of innovative tools and models to tackle climate change issues in tropical and sub-tropical forests in Asia-Pacific. Project achievements and its application were further presented at two international conferences: one at XIX Common Wealth Forestry Conference in Dehradun, India (3-5 April 2017) and other at IUFRO 125th Anniversary Congress in Freiburg,

Germany (18-22 September 2017). In Common Wealth Conference, two papers on Adaptation of Asia-Pacific Forest to Climate Change were presented under the session Adaptation to Climate Change. The audience showed their keen interest on tools and modelling that has been developed in this project and their application to understand adaptation of forest to changing climate.

In the IUFRO 125th Anniversary Congress in Freiburg, a presentation entitled “Integration of Climate and Ecological Modelling tools for Adaptive Management in Asia-Pacific Forests” was presented under the theme “Climate Change Adaptation in Forest Management: From Applied Science to Implementation”. The audience showed their interest particularly on the tools and modelling and their applicability to understand the effect of changing climate on forest. Additionally, project achievements and its application were presented at three international conferences: first one at the Tenth International Conference on Climate Change: Impacts and Responses organized by University of California at Berkeley, USA from 20-21 April 2018 and the second one at International Conference on “Promotion of Agroforestry for Rural Income Generation, Climate Change Mitigation and Adaptation” 27-29 April 2018 in Kathmandu, Nepal. Apart from these two conferences, a parallel session entitled “Bamboo Forest Ecology and Management in Changing Climate” was organized in Global Bamboo and Rattan Congress from June 25-27, 2018, Beijing, China. In this conference, ten papers were presented which attracted more than 30 attendees including academics and industry professionals whose work/research pertains to the bamboo ecology and climate change in Asia-Pacific region. This event particularly focused on multifaceted issues of bamboo forest ecology and sustainable management under effect of climate change on bamboo management. Our team members highlighted the integration of the use and application of tools and models developed in this project to understand impact of climate change on bamboo forest management. The audience showed their keen interest on the tools and modelling such as ClimateAP, Climate Niche Modeling and FORECAST model and their applicability to generate data and apply the outcome to address effect of changing climate on the bamboo for sustainable forest management. Project achievements and applications further promoted in the 4th International Congress on Planted Forests, which was held from 23rd to 27th October, 2018, Beijing China. Our team member, Dr. Guangyu Wang organized a session entitled “Impacts of climate change and air pollution on forest ecosystems: Impacts, adaptation and management options”. Eight scholars presented their research on the topic, which were attended by more than 35 individuals who showed their keen interest on these tools and models and further collaborations. In this workshop, Dr. Wang shared the outcomes, use and potential application of climate tools and models developed in this project to address climate change adaptation and mitigation of the planted forest in Asia-Pacific forests.

Research seminars were conducted at several universities and research institutions based in Asia Pacific and beyond to extend our network while at the same time-sharing the project outcomes and its application to address effect of climate change on the forest. Our team members conducted research seminar and

interacted with several scholars: Kyoto University, Tokyo University and Kyushu University in Japan; National Ilan University, National Taiwan University and National Taiwan Normal University, Taiwan Forestry Research University, Chinese Taipei; University in Philippines Los Banos, Bangor University, Indonesia; Department of Forest and Forest Research Institute, Myanmar; Viet Nam National University of Forestry in Vietnam and University of British Columbia, Canada. For wider outreach of the project outcomes, our management team organized several seminars at university in South America: Peru (Universidad Nacional Agraria La Molina and Universidad Nacional Del Centro Del); Chile (Universidad de Chile, Pontificia Universidad Católica de Chile and Universidad Austral de Chile). These events were organized in the forms of presentations, workshop and seminars attended by audience (Academics, students, policy makers and practiceners) ranges from 30-80 individuals and very well received.

Additionally, to expand our network and strengthen our relationship with researchers in the Asia-Pacific region, the University of British Columbia has been hosting 10-15 young research scientists each year from multiple universities in China (with varying lengths of stay). These visiting scholars have been researching topics including forest management, remote sensing, forest inventory, climate change policy and economic evaluation, soil science, and wood products processing; 5 of which were directly involved in this project. Each year, various training programs were also conducted in order to acclimate the visiting scholars to various aspect of sustainable forest management, academic writing standards at UBC and research opportunities. Similarly, a series of field trips have been organized to familiarize the scholars with forest management in British Columbia – including field trips to nurseries, orchards, woodlots, and the BC Ministry of Forests, Lands and Natural Resource Operations. This exchange program was funded partly by the University of British Columbia's Faculty of Forestry, with the remainder of expenses were covered by the visiting scholars' home university, where they research and study in a similar field.

Three comprehensive hands on training workshops were organized aiming to enhance capacity of government officials, local forest managers and researchers in terms of using tools and models developed in the project and applying them to the area of policy making and policy implementation related to adaptation of forest to climate change. Additionally, one hands on training on field inventory methods and incorporation of the data to models was also conducted (please see details below).

The first training workshop “Modelling Climate and Forest Ecosystems in a Changing Climate” was held in Kunming, China from May 31st- June 7th, 2016; it was co-organized with the Research Institute of Resources Insects of the Chinese Academy of Forestry. The objective of this 8-day workshop was to introduce the models and tools developed in Phase I to the local partners so that they will be able to effectively and accurately implement the research for their respective pilot site and economy. The workshop focused on the technical application of the models and management and decision-making methods in order to increase the capacity of

participants to conduct research on forest adaptation to climate change in their own economies. There were 20 trainees from seven economies Chinese Taipei, Laos, Malaysia, Myanmar, China, Japan and Canada, representing 10 institutions. A detailed training handbook containing background readings and application of tools/models was prepared and distributed to the workshop participants before the workshop (digital book) and printed book later during the workshop. Participants were actively trained in how to use ClimateAP and FORECAST Climate so that they can independently use these models to contribute to the project's research.

The second training was conducted during site visits in the spring 2017 in Myanmar, where undergraduate level forestry students were incorporated into field research activities. Project team members Dr. Brad Seeley and Ms. Lianzhen Xu in collaboration with local partners trained the students how to conduct accurate field measurements and data collection, including the use of industry-standard measurement instruments such as clinometer and GPS instrument. They were also educated how these data can be incorporated into models that contribute understanding of effect of climate change on productivity of the forest, Teak in this case. Students participated and aided in the collection of data, by providing information such as tree diameter-at-breast-height (DBH), tree height, and density difference. Additionally, volunteer students were able to aid in the marking of measured trees within research plots and help record GPS coordinates for future visits. Incorporating future forestry professionals in recent field research has allowed students to gain valuable, hands-on experience while learning standard industry techniques and applications, while further providing students with exposure to this research project. It is critical that future forest and land managers, particularly in the Asia-Pacific, understand the importance of climate change and adaptive forest management for the future viability of regional forests.

The third training workshop was organized in Forest Research Institute of Myanmar from November 13-16, 2017. Twenty-two researchers and officials representing Forest Research Institute and Forest Department of Myanmar were provided comprehensive hands on training on how to use, set up and run FORECAST Climate modeling followed by application and interpretation of the outcomes from the model. Further, our team members also shared the results of Teak plantation pilot site on how the model can be implemented and used for generation of relevant information. The training was well received and beneficial to the participants so that the trainees will be able to independently use these models effectively and efficiently in their research for developing adaptive forest management strategies.

The fourth training workshop entitled "Adaptation of Asia-Pacific Forests to Changing Climate: Modeling Climate and Forest Ecosystems" was organized in partnership with the Guangdong Academy of Forestry from July 4-9, 2018 in Guangzhou, China. The main objective of the workshop was to enhance the capacity of forest managers, policy makers and researchers from Asia-Pacific Region by training them on application of the models and tools developed in the project for effectively and accurately conduct research and formulate adaptive forest

management strategies against changing climate. A comprehensive updated handbook/training manual (pages 197) containing background readings and application of tools/models was prepared and distributed to the workshop participants prior to the workshop (digital book) and printed book later during the workshop. Sixty-two participants from seven economies (China, Myanmar, Malaysia, Thailand, Cambodia, Chinese Taipei and Canada) representing various organization from Department of Forest, Research Institute, University as well as private organizations received a comprehensive education in the application of ClimateAP and FORECAST Climate so that they can independently use these models to contribute to the project's research. In addition, we also discussed about way forward related to the project and likelihood of application of tools and models developed in the project. Many participants emphasized the importance of these models and tools and their application while at the same sought more hands on training and outreach on the tools/models and their application in their economies for coping with changing climate to the valuable species and vulnerable ecosystem.

In addition to the aforementioned activities, we also shared the project outcomes to the wider public through setting up the freely available online and desktop modeling tool, and the project website that allow stakeholders, policy makers, forest managers, and the general public to access the work and tools/models developed by the project. An online google based ClimateAP is available through the web browser (<http://climateap.net/>). Through this site, users can generate climate data as well as spatial visualization of climate maps, and spatial projections of climate niches models for our local partner's ecosystems and 10 key species for different time-periods and climate scenarios. Similarly, a free desktop version of ClimateAP is available through subscription. This tool can generate much needed scale free climate data for developing climate niche models for different time periods and climate scenarios. Moreover, we also set up the project website (<http://asiapacific.forestry.ubc.ca>) which serves as a gateway to know about the projects, events, project outputs and most importantly get access to peer reviewed publications and reports published during the entire project period.

3. PROJECT PARTNERES' PERFORMANCE

3.1 Performance of Supervisory Agency

The APFNet committee successfully fulfilled its role of reviewing and providing feedback on the project's annual reports, midterm and annual work plans. The reviews were timely, detailed, and invaluable for planning and project management that contributes executing the project activities. The Canadian Forest Service as a technical supervising agency played a key role particularly providing comments and suggestions on the research activities, and helped ensure all activities were carried out successfully. Their feedbacks were timely and relevant that helps to plan, implement and management of the research activities in efficient manners.

3.2 Performance of Executing Agency

Faculty of Forestry at the University of British Columbia (UBC), Canada was the Executing Agency (EA) for the project. The EA has been responsible for the planning, implementation of the project, financial management, and the coordination with the local partners in China, Chinese Taipei, Malaysia and Myanmar. The main project management team has been Dr. John Innes, Dr. Guangyu Wang, Dr. Tongli Wang and Dr. Brad Seely at the Faculty of Forestry, UBC throughout the project. A project coordinator was placed throughout the project period to coordinate research and enhance coordination between the project, the APFNet and the local partners. A Ph.D. student Lianzhen Xu based in Faculty of Forestry, UBC has been conducting her research in this project. Additionally, eight work and learn undergraduate students were also engaged in this project to conduct research, data entry and train them about the tools and models developed in the project.

The project managers completed their responsibilities and tasks successfully with respect to plan, implement, manage and disseminate the project activities and outcomes. The project management team prepared annual work plans, implement them, monitor their progress and address the issues as soon as it appeared after consultation with APFNet, local partners and supervisory agency depending on the situation. Regular meeting with team members and local partners have been arranged to communicate about the plan, implementation status and monitoring of the project activities. Throughout the project period, project team members have been actively engaged to disseminate the project outcomes and tools/models developed during the project by organizing training workshops, seminars as well as participating in the international conferences and seminars along with publishing peer reviewed papers for wider audiences. The project team successfully collaborated with the local partners and other stakeholders in China; National Ilan University and Taiwan Forestry Research Institute, Chinese Taipei; Forest Department and Forest Research Institute, Myanmar and Universiti Putra Malaysia, Malaysia to get kind support for the project that contribute to achieve project outcomes. Similarly, project team members successfully collaborated with Research Institute of Resources Insects of the Chinese Academy of Forestry, Kunming, China and Guangdong Forest Academy, Guangdong, China to co-organize two training workshops (May 31- June 7, 2016 in Kunming and 4-9 July, 2018 in Guangdong) that helps to build capacity of the academician, researcher, policy makers and practitioner in the Asia-Pacific region and disseminate the project outcomes, tools and models developed in the project across wider community.

3.3 Performance of Implementing Agency, consultants (technical assistants), contractors, and suppliers

The EA, the Faculty of Forestry, UBC, Canada carried out most of the research activities, which was not possible without the contribution of our collaborators: particularly our local project partners from National Ilan University and Taiwan Forestry Research Institute, Chinese Taipei; Forest Department and Forest Research Institute, Myanmar; Faculty of Forestry, Universiti Putra Malaysia (UPM), Malaysia and Chinese Academy of Forest, China. Our local collaborators fulfilled their responsibility at the highest level particularly contributing the collection of the primary and secondary data, arranging logistics while doing fieldwork and bridging connection with the local experts. Additionally, they were also active in dissemination of the project outcomes to wider communities in their respective jurisdictions. Moreover, we also collaborated with several renowned researcher active in tropical forestry in Southeast Asia. Professor Nobuya Mizoue (PhD) from National Kyushu University, Japan was instrumental to assist in our research in Myanmar, particularly his vast knowledge about tropical forest and research in Myanmar. Dr. Qinglin Li from Ministry of Forest, Lands, and Natural Resource Operations, British Columbia, Canada provided his expertise on our research work. They successfully fulfilled their role at the highest level, which contributed to achieve the outcomes of the project.

3.4 Performance of APFNet

APFNet was supportive and constructive throughout the entirety of the project. Their contributions were met and exceeded the expectations of the project's management team. The APFNet provided useful and constructive feedback on the project planning, implementation and management of the project whenever needed, mainly through Annual Work Plan and Annual Progress Report. Their constructive feedbacks helped Project team for clear guideline to implement and manage the project activities. With respect to the grant disbursement, it was provided in a timely manner without any delay during the entire project period. Their communication with project team was prompt, efficient and in detail. This good communication between both parties enabled the project to be carried out smoothly, and the project's objectives to be successfully met. Moreover, the project managers met with APFNet representatives in Beijing repeatedly to discuss the project progress, and were given constructive feedbacks to improve project outputs. APFNet facilitation during mid-term evaluation of the project was also remarkable in terms of providing feedback and arrangement of necessary logistic for evaluation of the project. The project management team received support from the APFNet while organizing international training workshops that helps to organize the training workshops successfully and disseminate the project outcomes widely in the Asia-Pacific region.

4. PROJECT PERFORMANCE

4.1 Project achievements

Output 1: ClimateAP with future annual climate projections

The main objective of this part of the project is to add annual projections for the future and to add time series function that can generate annual time series projections for historical (1901-2017) and future (2011-2100) years for any location in the region in a single run.

Activity 1.1 Data collection and processing:

Monthly climate data (max and min temperature, and precipitation) have been downloaded for the three GCMs: ACCESS1-0, CanESM2 and CCSM4. Downloaded datasets include 36 monthly climate variables for two GHG emissions scenarios (RCP 4.5 and RCP 8.5) and cover 90 years from 2011 throughout 2100, resulting in a total of 19,440 climate data layers.

Activity 1.2 Calculations of anomalies:

ClimateAP uses anomaly data to downscale future climate projections through a delta approach. Thus, the values of the downloaded data have been converted into anomalies relative to a 1961-1990 normals and formatted for the use of ClimateAP.

Activity 1.3 Programming and debugging:

All the climate layers have been integrated into ClimateAP. Time-series functions have also been added to the software package for the historical and future years, respectively. The methods and improvements of ClimateAP over the climate data generated by other models (PRISM and WorldClim) are described in our recent publication (Wang et al. 2017).

As a result, the improved ClimateAP (v2.12) can generate monthly climate data for each year from 2011 to 2100 instead of three normal periods (2020s, 2050s and 2070s) as illustrated for mean annual temperature (MAT) Figure 2).

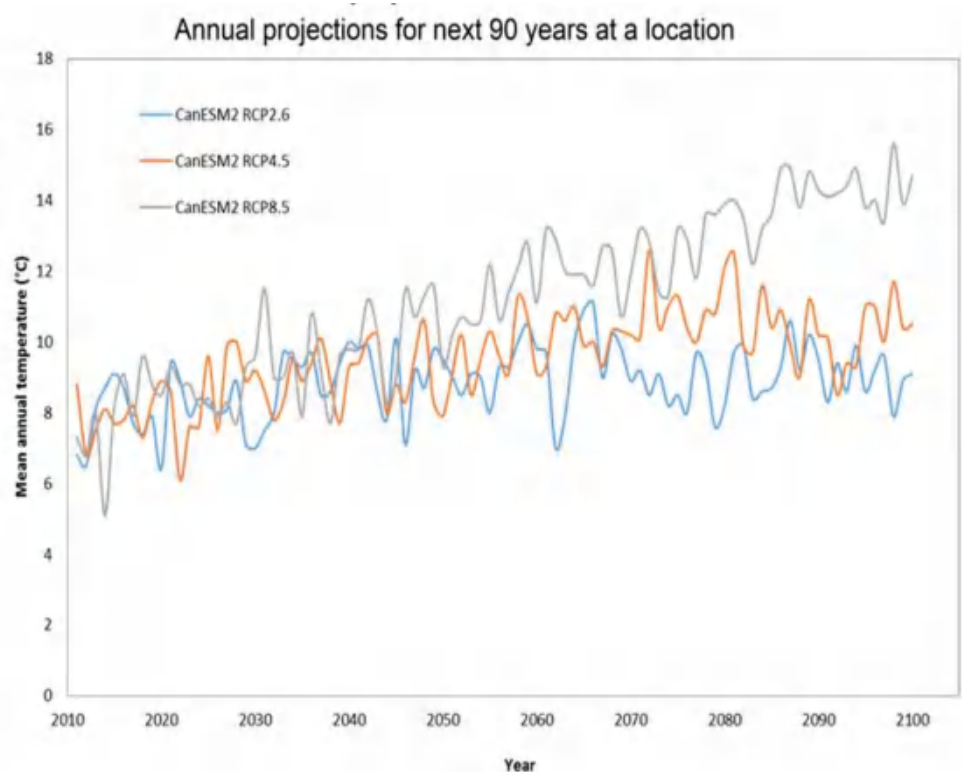


Figure 2. Future climate projections for individual years (curves) vs. normal (bars) periods using GCM CanESM2 for three greenhouse gas emission scenarios

The newly added time series functions for historical and future periods allow users to obtain climate data for multiple years and multiple locations in a single run as illustrated in

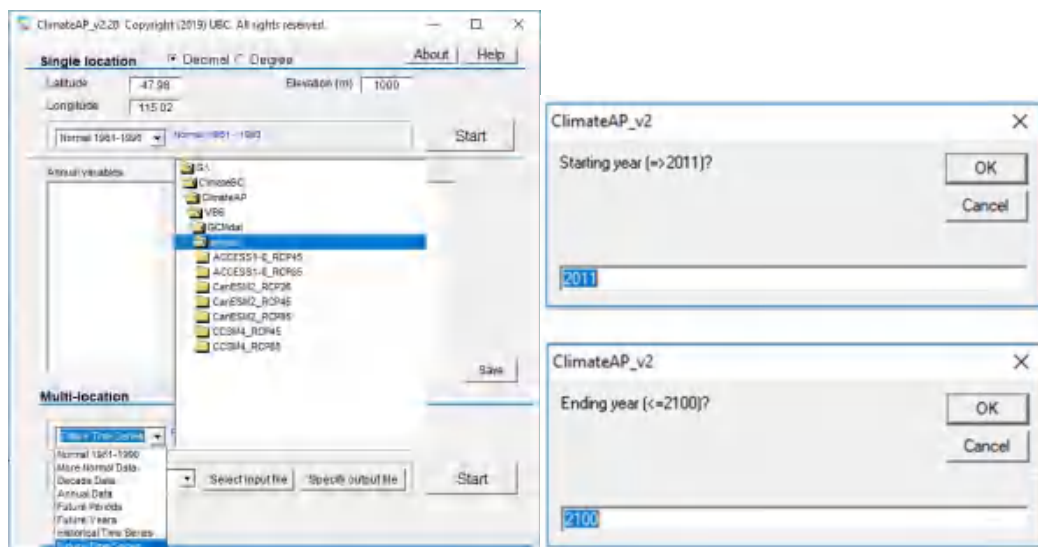


Figure 3 and Figure 4. These functions can save users a tremendous amount of time.

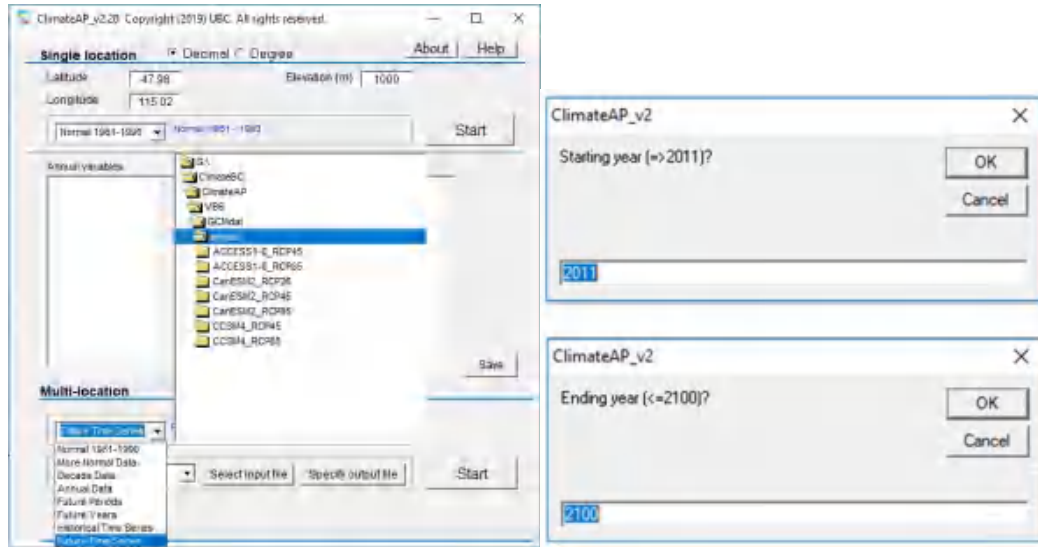


Figure 3. Illustration of using the Time-Series function for future period.

Year	id1	id2	Latitude	Longitude	Elevation	MA1	MWMT	MMMT	TD	MAP	AHM	DD_0	DD5	DI
2011	1	11	49	115.02			0.5	21.1	-23.2	44.2	248	42.3	2408	1723
2011	2	12	50.98	120.02	1000		-2	18.9	-24.4	43.3	899	16.1	2870	1361
2011	3	13	49	115.02	600		0.5	21.2	-23.4	44.6	245	42.7	2424	1740
2011	4	14	49	115.02	-9999		0.5	21.1	-23.2	44.2	248	42.3	2408	1723
2011	5	15	32.05	118.7667	26		15.7	31.1	-3.1	34.3	889	38.9	126	4284
2011 weform	TYHKK		14.7657	98.39141	311		25.6	28.1	21.9	6.2	2190	16.3	0	7399
2011	7	dyfdj	48	-125	800		-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
2012	1	11	49	115.02			2.4	23	-20.6	43.6	233	53.1	1973	1934
2012	2	12	50.98	120.02	1000		-1.1	21.1	-24.1	45.2	316	38.3	2720	1537
2012	3	13	49	115.02	600		2.4	23.2	-20.7	43.9	231	53.6	1989	1951
2012	4	14	49	115.02	-9999		2.4	23	-20.6	43.6	233	53.1	1973	1934
2012	5	15	32.05	118.7667	26		17.1	30.7	4.6	26	1351	22	11	4479
2012 weform	TYHKK		14.7657	98.39141	311		25.8	28.1	23	5.1	2013	17.8	0	7483
2012	7	dyfdj	48	-125	800		-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999
2013	1	11	49	115.02			3	21.9	-17.4	39.3	244	53.2	1862	2031
2013	2	12	50.98	120.02	1000		-0.5	20.3	-24.1	44.4	427	22.4	2719	1699
2013	3	13	49	115.02	600		3	22	-17.7	39.7	241	53.9	1879	2049
2013	4	14	49	115.02	-9999		3	21.9	-17.4	39.3	244	53.2	1862	2031
2013	5	15	32.05	118.7667	26		16.4	29.8	2.9	26.9	1385	19.1	16	4291
2013 weform	TYHKK		14.7657	98.39141	311		25.7	27.8	23.6	4.2	3005	11.9	0	7420
2013	7	dyfdj	48	-125	800		-9999	-9999	-9999	-9999	-9999	-9999	-9999	-9999

Figure 4. Output of ClimateAP using the time-series function.

In addition, we have updated historical climate data from Climate Research Unit (CRU) from the version ts3.23 to ts3.24, ts4.01 and ts4.01. At the same time, we have also extended the years of coverage from 1901-2012 to 1901-2017. Climate baseline data has also been replaced for Chinese Taipei with a better, locally developed baseline dataset. This dataset is more accurate for the given region and therefore will improve model accuracy and capabilities for projections. Several minor bugs in the model have been reported by users, all of which have been successfully fixed.

Based on the same methodology, a R version of ClimateAP for Chinese Taipei, *clim.regression*, has been developed to take the use of more locally available climate data. Huan et al. (2018) have published a peer-reviewed scientific paper describing the methodology and the improvement over the original climate data.

Significance of ClimateAP

Climate data from all climate models are presented in raster format, which gives an average of a certain area depending on the spatial resolution of the raster files with the highest at 800 x 800 m. Even with the highest spatial resolution, the accuracy of the climate data can be substantially compromised in mountain areas. ClimateAP is the only exception that provides climate data for specific point locations (i.e., scale-free) in the Asia Pacific. As the focus of climate change studies is shifting from global and regional scales towards local applications, climate data representing the exact location becomes critical. In addition, this tool is user-friendly and does not require GIS or other sophisticated computing skills to use it. Thus, ClimateAP will be an essential tool for climate change studies in the region.

During this project period, we have added the monthly climate data for individual years for the future period (2011-2100) in addition to 30-year normal periods. This addition allows users to study climate variability and extreme events over the years beyond the 30-year average. We have added the time-series functions for historical and future years. With these functions, users can generate climate data for multiple locations and multiple years in a single run and save users' tremendous amount of time. ClimateNA for North America, the precursor of the ClimateAP, has gained over 1,300 subscribers over the last two years as more and more users (mostly researchers) have realized the importance of the scale-free and the user-friendly feature this model. However, we have only 170 subscribers for ClimateAP up to date. People in Asia Pacific are still using WorldClim, which is generally considered inferior to PRISM, let alone ClimateAP. We believe that more and more users in the Asia Pacific region will discover this useful tool in the future for their climate change related studies. Meanwhile, we also hope that this tool can be maintained, updated and improved to facilitate the increasing demand for accurate climate data to tackle the challenges in forest adaptation to climate change.

Output 2: Assessments of the impact of climate change on forest ecosystems, key species and vegetation types

The objective of climate niche modeling in this project is to include additional species and forest vegetation types in more economies (China, Chinese Taipei, Laos, Malaysia, and Myanmar). Climate niche models and their future projections for ecosystems will be particularly important as they can serve as a reference for all species associated with those ecosystems. Meanwhile, we will take advantage of our modeling expertise to improve the current classifications of the ecosystems. These projections will provide assessments of the impact of climate change on forest ecosystems and key species in terms of the shifts in geographic distribution of suitable climate niches, species selection and vulnerability to abiotic and biotic stresses.

Species, ecosystems and vegetation types to be projected are as follows:

China: two larch (*Larix gmelinii* and *L. olgensis*) species, Scots pine (*Pinus sylvestris*),

Yunnan Pine (*Pinus yunnanensis*), black locust (*Robinia pseudoacacia*), Chinese cork oak (*Quercus variabilis*), aspen (*Populus tremula*), moso bamboo (*Phyllostachys edulis*) and entire ecosystems.

Chinese Taipei: *Cyclobalanopsis longinux* (syn. *Quercus longinux*), *Chamaecyparis formosensis* and entire ecosystems.

Lao, Malaysia and Myanmar: Vegetation types.

Activity 2.1 Vegetation data collection and climate data generation:

Distribution data for the eight tree species in China were collected from the digital achieve of Chinese Vegetation and Global Biodiversity Information Facility (GBIF). The species distribution vectors were rasterized at the spatial resolution of 1 x 1 km. The pixels with the species occurring were considered as presence of the species and remaining pixels as absence of the species, which was demonstrated in Figure 5. The species distribution data for other species are shown in Annex D1. The two species from Chinese Taipei were obtained from the ecological plot data of Forest Service Bureau of Chinese Taipei. The plots with the occurrence of the species were considered presence and the remaining as absence of the species.

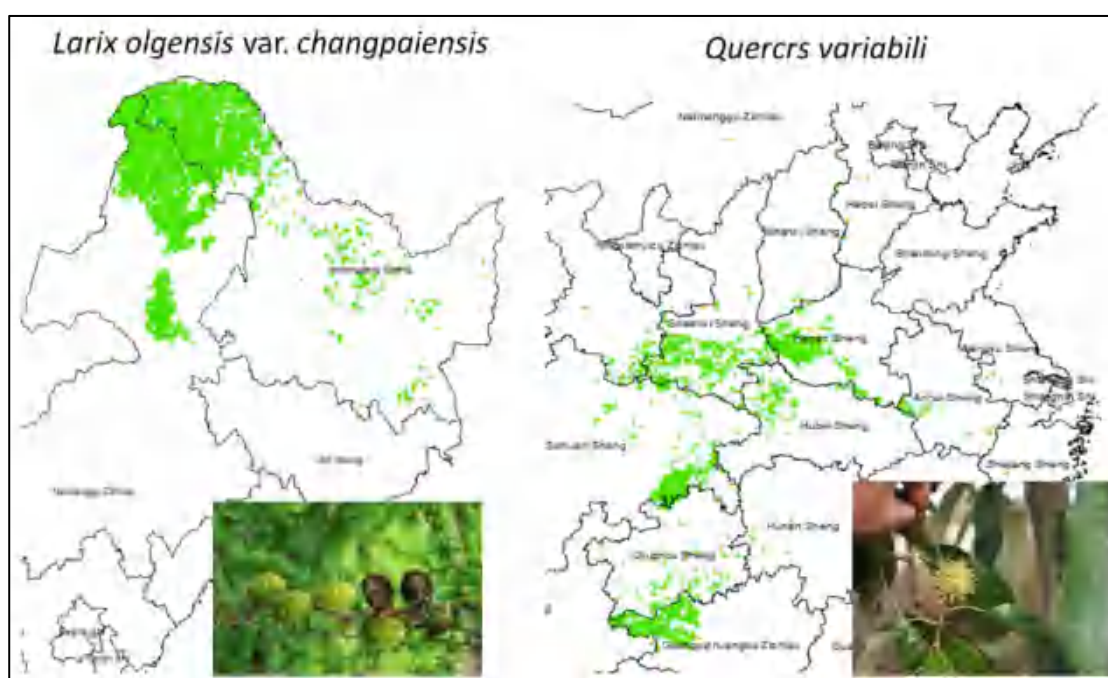


Figure 5. Distributions of occurrence data of *Larix olgensis* var. *changpaiensis* and *Quercus variabilis*.

For forest ecosystems in China and Chinese Taipei, the level 3 vegetation classification from the digital achieve of Chinese Vegetation, with 56 ecotypes, were used to represent the forest ecotypes of the country as shown in Figure 6. The spatial data of forest type data for Malaysia was obtained from Federal Forestry Department

Peninsular Malaysia. While the forest type maps for Myanmar were obtained from the Ministry of Environmental Conservation and Forestry of Myanmar, and Chinese Academy of Forests. Digital information forest ecotypes were also rasterized at 1 x 1 km resolution as for species mentioned above.

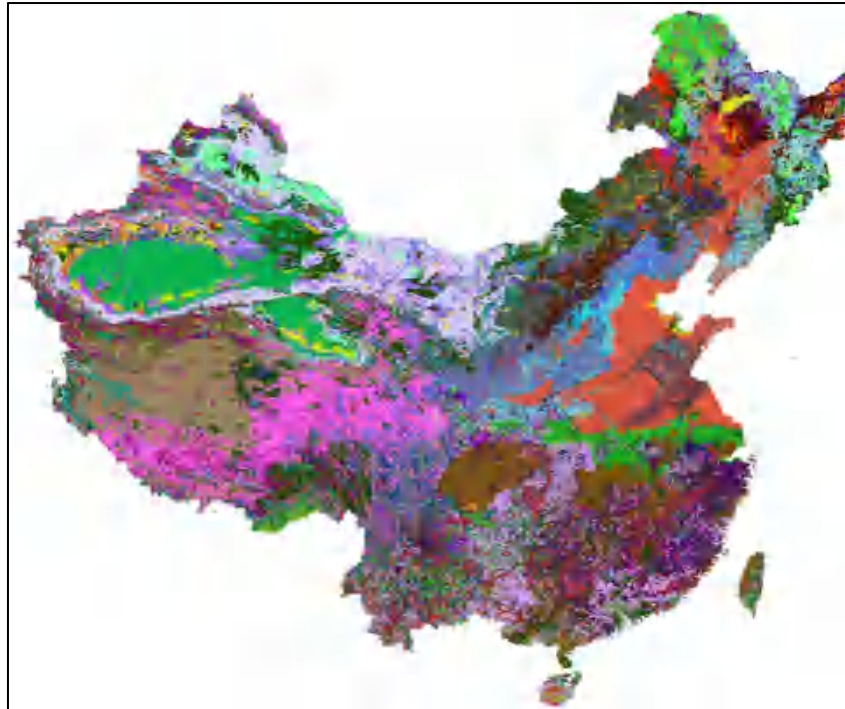


Figure 6. The 56 ecotypes at the level of 3 vegetation classification in China.

ClimateAP was used to generate annual and seasonal climate variables (69 in total) for all the presence and absence data points of all the 10 species and ecotypes for the reference period 1961-1990. Climate and species data were then processed and formatted for modelling. To deal with an uncertain future climate, we need to project future distributions using multiple climate change scenarios and to generate consensus projections. Thus, we generated spatial climate data for 15 GCMs and 2 greenhouse gas Representative Concentration Pathways (RCP 4.5 and RCP 8.5), resulting in 30 climate change scenarios using ClimateAP.

Activity 2.2 Development of climate niche models:

Random Forest, the machine-learning modeling approach used in Phase I of the project, was used to build climate niche models for each of the 10 species, ecosystems and vegetation types. Key climate variables from ClimateAP were selected to optimize the models. These models were then refined for some of the pseudo absent sample locations considering human impact on the species distribution. We then generate climate niche spatial distributions with the refined models for the 10 species and the ecosystems using the spatial climate data generated from ClimateAP for the reference period of 1961-1990.

The predicted classification of ecosystems in China and Chinese Taipei are supposed

to be improved over the original ones. This is because some errors existing in the original classifications of the ecosystems can be corrected based the plant-climate relationships built in the models through the machine-learning process.

Based ecological plot data and climate data generated from ClimateAP, a new classification of forest ecosystem was established using our niche modeling approach. A manuscript was submitted to Applied Vegetation Science.

Activity 2.3 Consensus projections using multiple climate scenarios:

Consensus projections of the species and forest ecosystems have been generated for three future periods: 2020s, 2050s and 2080s. **Our consensus projections are supposed to be more robust than those using a single or a small number of climate change scenarios.** Four maps using the consensus projections were generated for each species for the reference and three future periods as shown in Figure 7 and the maps for all the species can be found in Annex D2. These projections have also been uploaded to our web-based platform for spatial visualization (more details see Output 4).

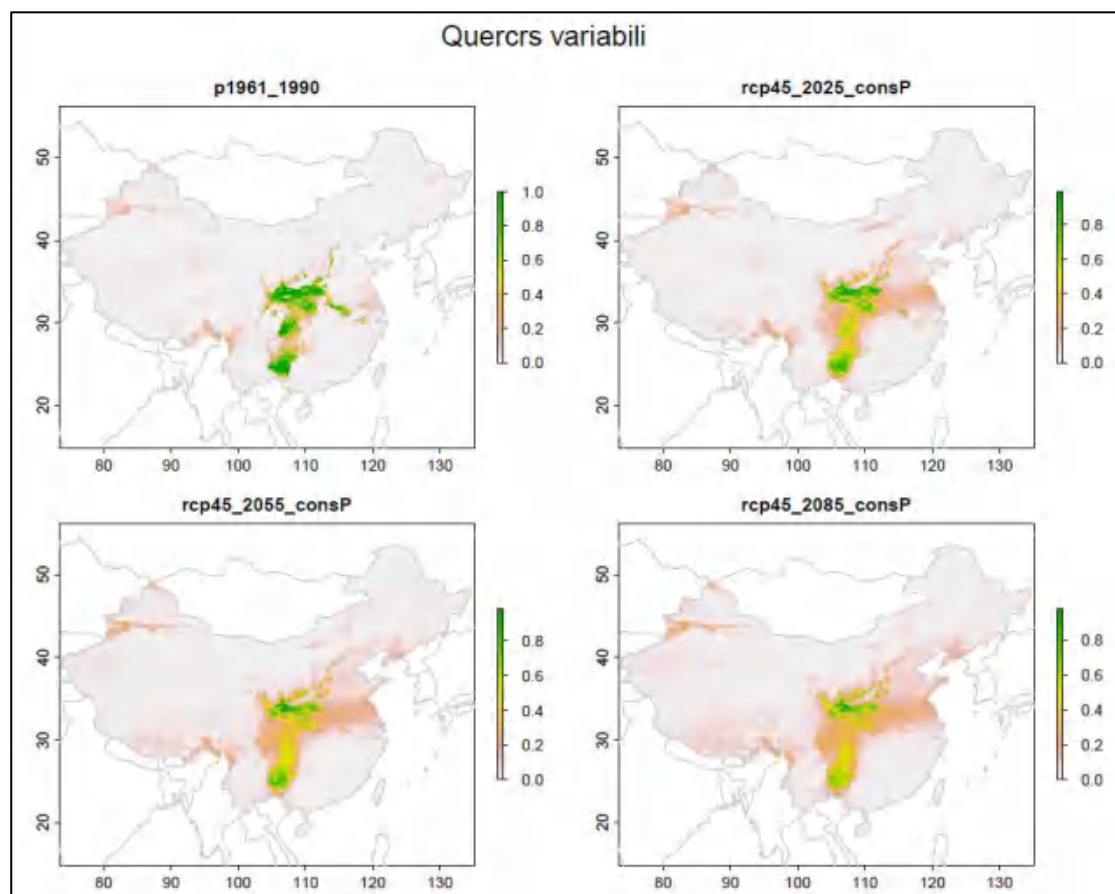


Figure 7. The probability of occurrence of *Quercus variabilis* for current and the three future periods 2020s, 2050s and 2080s.

According to our consensus projections, we found that almost all the eight tree species in China are projected to contract to some extent. **The contraction is**

particularly serious for conifer species in the north including two larch and one pine species. *Larix gmelinii* is mainly distributed in the north of Heilongjiang province and Inner Mongolia Autonomous Region, but also spread throughout Heilongjiang province. Our projections indicate that the areas with suitable climate conditions for this species would contract dramatically, occurring in the near future (2020s) and leaving almost no areas suitable for this species at the end of the century (See Appendix D2 page 101-102 for figure). *Larix olgensis* var. *changpaiensis*, mainly distributed in Liaoning and Jilin provinces, shows a similar trend, but the magnitude of contraction is much less severe (See Appendix D2 page 103-104 for figure). The pine species, *Pinus sylvestris* var. *mongolica*, distributed in Heilongjiang province, was projected to contract in a magnitude comparable to *Larix gmelinii*. The areas with suitable climate conditions would be almost all disappeared in the end of this century (See Appendix D2 page 105-106 for figure). However, some regions in Southwest (Tibet and Qinghai) show some potential for these three species to grow there in the future. This is particularly promising for *Pinus sylvestris* var. *mongolica* (See Appendix D2 page 105-106 for figure).

The two broadleaf species *Robinia pseudoacacia* and *Salix matsudana*, distributed in Middle-east China, show a similar pattern under future climates, the spatial distributions of their climate niches were projected to contract and shift northeastward (See Appendix D2 page 109-110 for *Robinia pseudoacacia* and page 111-112 for *Salix matsudana*). Another broadleaf species *Quercus variabilis*, distributed in central and southern China, shows small potential of shifting its spatial distribution under future climates, but contractions were predicted to occur in the future (Figure 7).

Phyllostachys pubescens, widely distributed in southeast China, was projected to contract in its spatial distribution and show no sign of shifting anywhere (See Appendix D2 page 113-114). The future of this species is comparable to *Cunninghamia lanceolata* that we projected in Phase I of this project. The impact of climate change on these two species is probably the most dramatic as they are economically and ecologically important species in China.

Among all the species that we assessed, the least impacted species appears to be *Pinus yunnanensis*. Its distribution covers Yunnan, Sichuan and Guizhou provinces. Our projections indicate that the areas suitable for this species would contract under future climates; however, the magnitude of the contraction is less severe than other species. It also shows some potential to grow in northern China in future climates as shown in Figure 8.

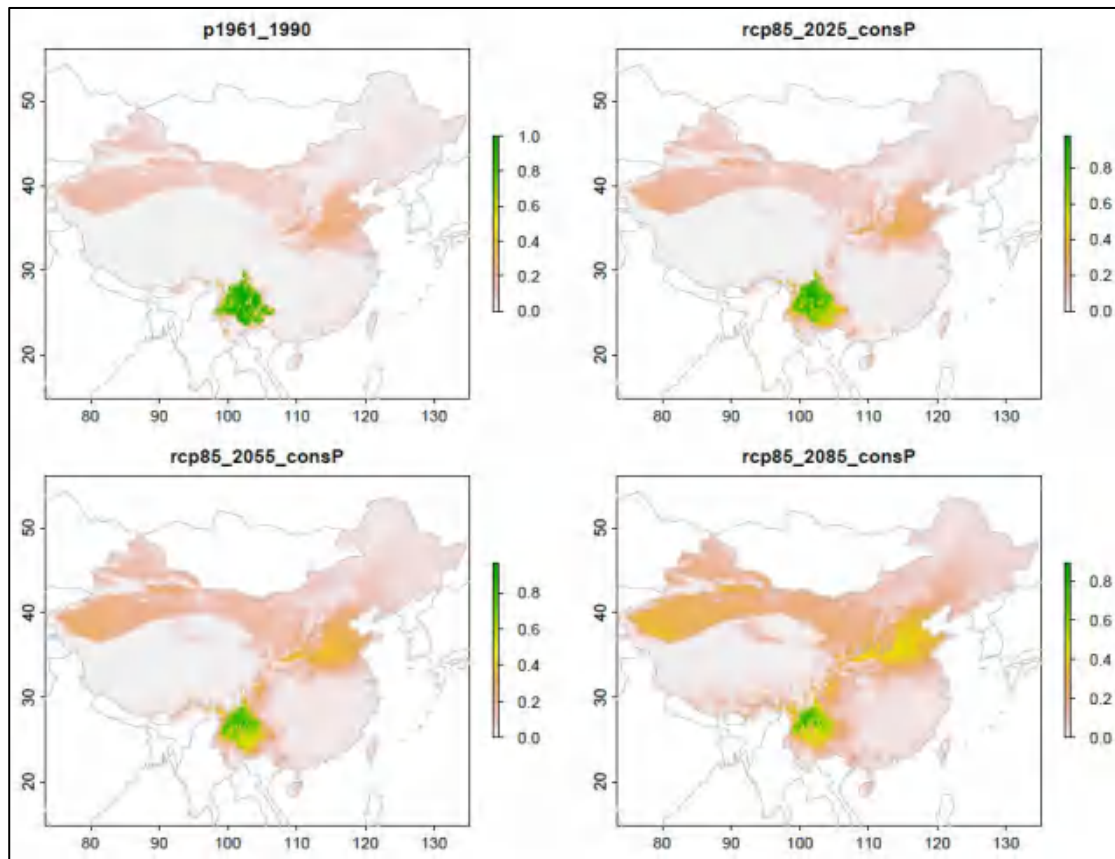


Figure 8. The probability of occurrence of *Pinus yunnanensis* for current and the three future periods 2020s, 2050s and 2080s.

For the impact of climate change on the climate niche of these two species in Taiwan, *Chamaecyparis formosensis* (Taiwan cypress) is distributed at high altitude with an average elevation of 2100 m (910 - 3100 m), occurring at the tops of the mountains (Figure 9). We projected that climate change would push the climate niche of this species even higher on average, resulting in a moderate contraction of the total areas suitable for this species based on our consensus projections from the 15 GCMs. For the other species, *Cyclobalanopsis longinix* (*Quercus longinix*) is distributed in a mid-range of altitude in Taiwan, not occurring at the tops of the mountains (Figure 10). Climate change would substantially reduce the size of the climate niche of this species at lower elevations and push this species to higher elevations in Taiwan. Some areas near the tops of the mountains would become suitable for this species. Thus, some areas currently occupied by Taiwan cypress may become more suitable for *Quercus longinix* in future climate.

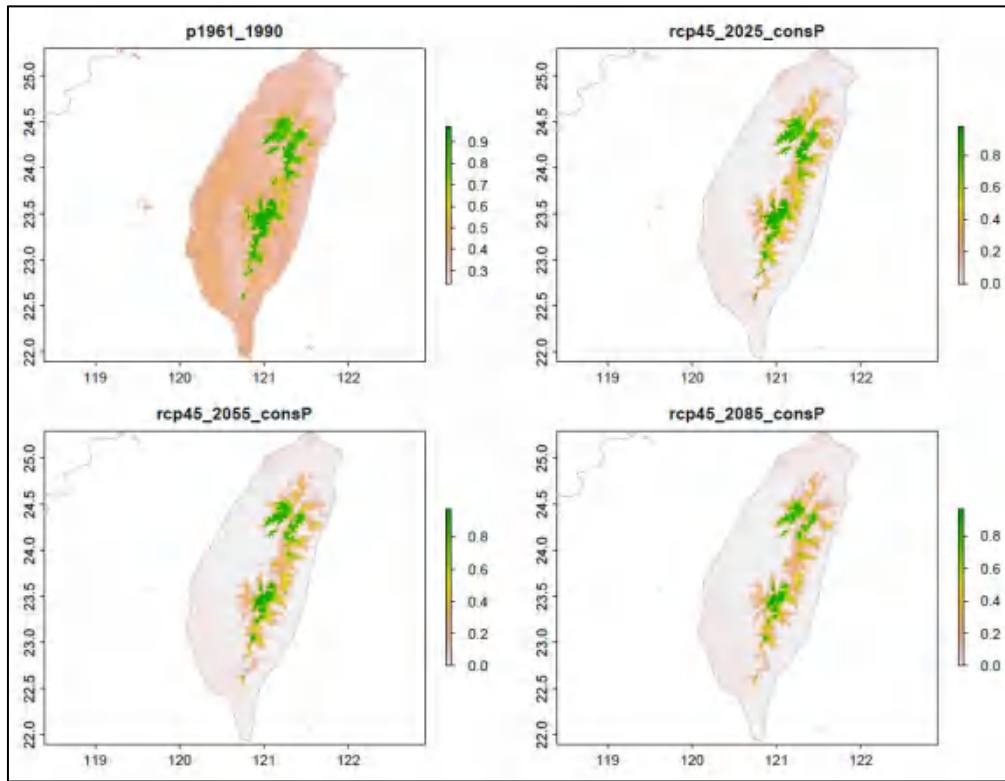


Figure 9. The probability of occurrence of *Chamaecyparis formosensis* for current and the three future periods 2020s, 2050s and 2080s.

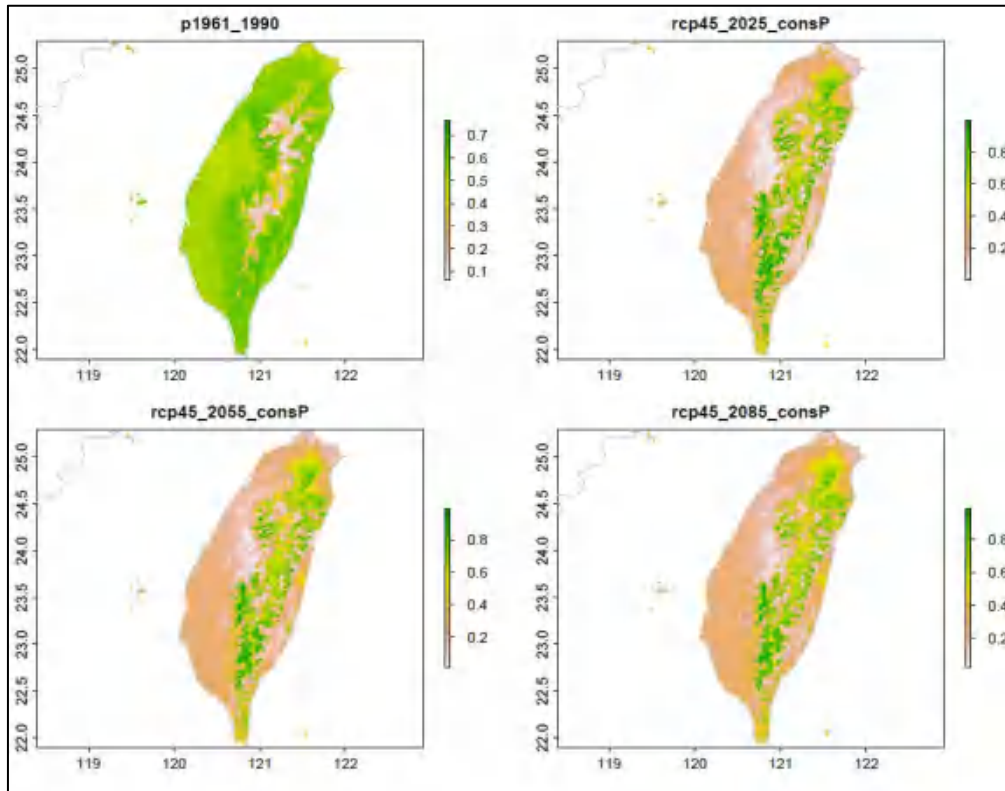


Figure 10. The probability of occurrence of *Cyclobalanopsis longinux* for current and the three future periods 2020s, 2050s and 2080s.

The consensus projections for the forest ecosystem in China is shown in Figure 11. These maps have also been uploaded to our web platform for easy spatial visualization. We found a trend of northward shifting in general. However, some ecotypes are projected to expand substantially, including the “multiple ripens grain fields and deciduous orchards” (in dark brown) in Mideast China, and the “multiple ripens grain fields and evergreen orchards and subtropical economic plantations” (in dark green) in the south. Such shifts and expansion may have dramatic impact on the land use and forest resources management in the future.

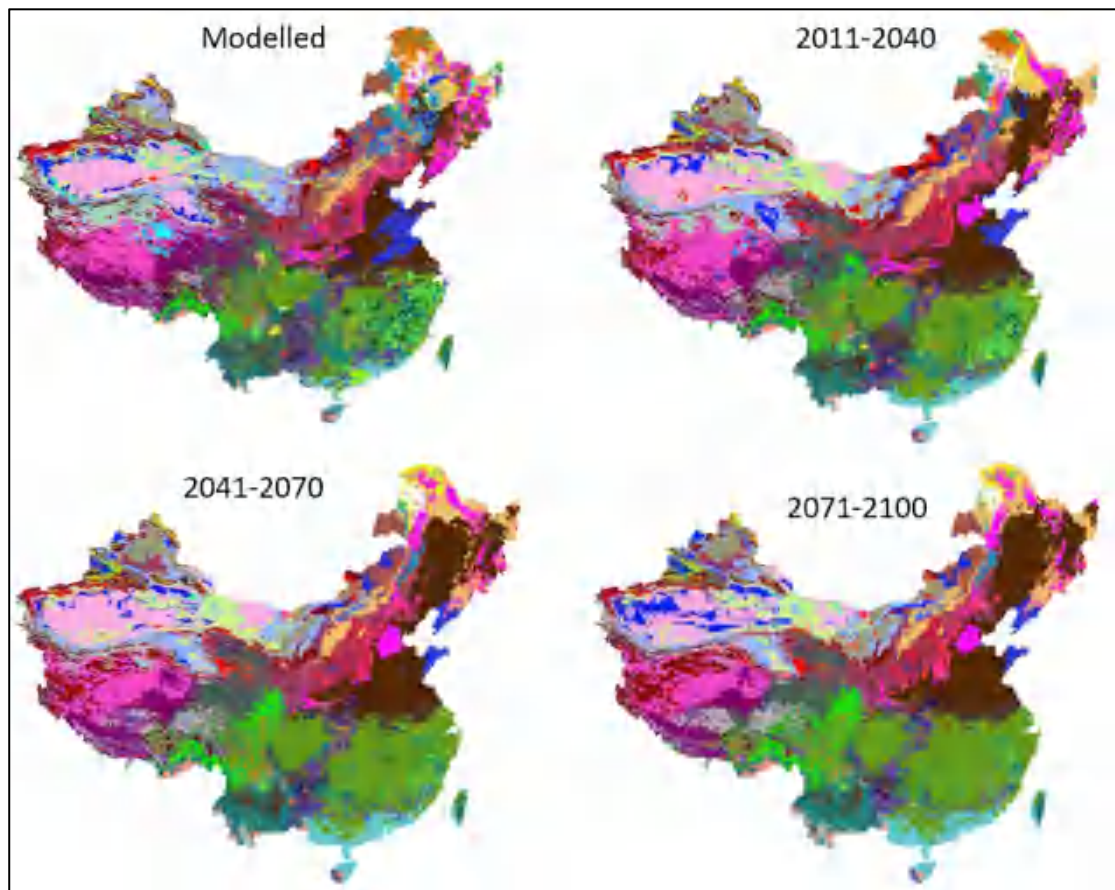


Figure 11. Consensus projections of the forest ecosystem classifications in China based on 15 GCMs and 2 greenhouse emission scenarios (RCP 4.5 and RCP 8.5).

For forest ecosystem in Malaysia, our consensus projections show that the dramatic expansion of the “Inland forest” (in dark green) ecotype is the dominant feature under climate change. On the other hand, the “Hill Dipterocarp Forest” (in golden) is projected to contract to a small fraction of its original size. Figure 12 shows the projected shift for 2080s. The projections for all the three periods can be visualized in our web platform for Malaysia (ClimateMalaysia).

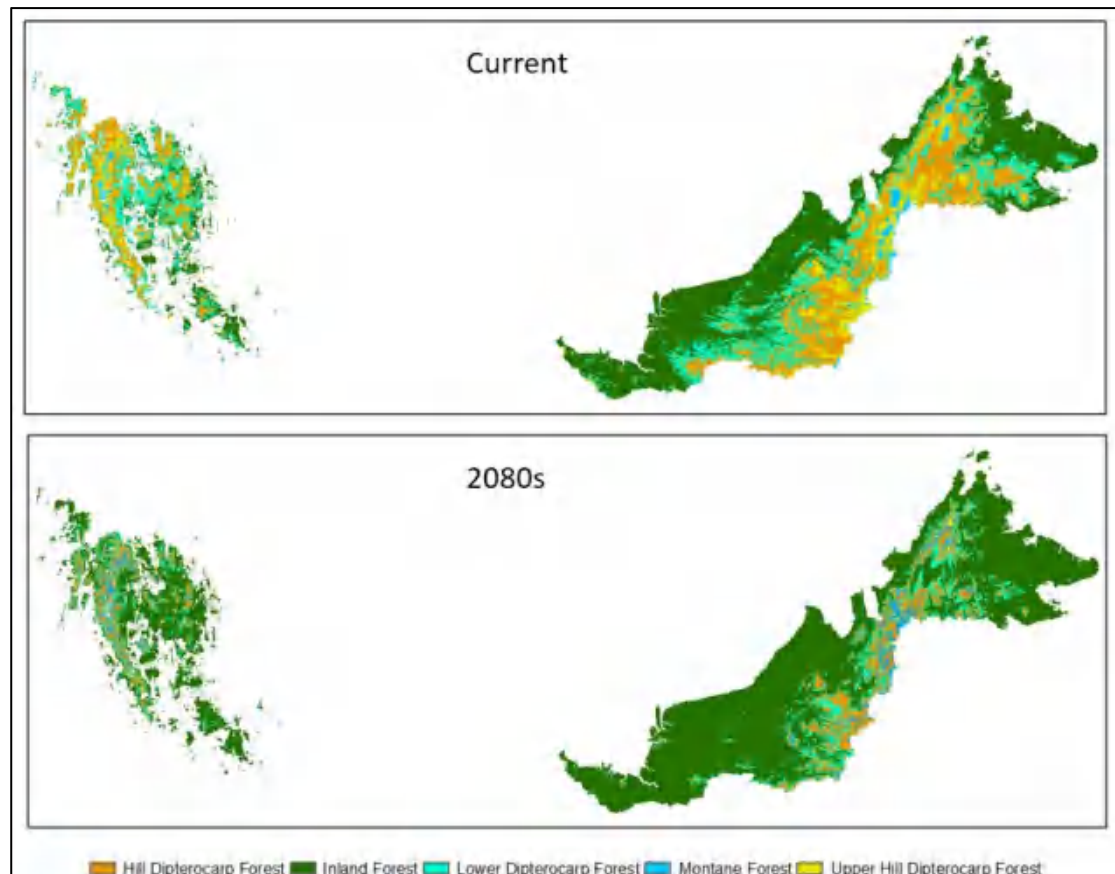


Figure 12. Consensus projections of the forest ecosystem classifications in Malaysia based on 15 GCMs and 2 greenhouse emission scenarios (RCP 4.5 and RCP 8.5).

The forest ecosystem in Myanmar is also projected to shift substantially (Figure 13). The climate conditions suitable for the “Crop Land” (in yellow) is projected to expand considerably. Meanwhile, the areas for the “Sand” (in brown) and the “Grass” (in red) are also to expand. On the other hand, areas suitable for broadleaf (in green) and needle leaf (in dark green) forests are projected to contract. All projections have been uploaded to the web platform (ClimateMyanmar) for online visualization.

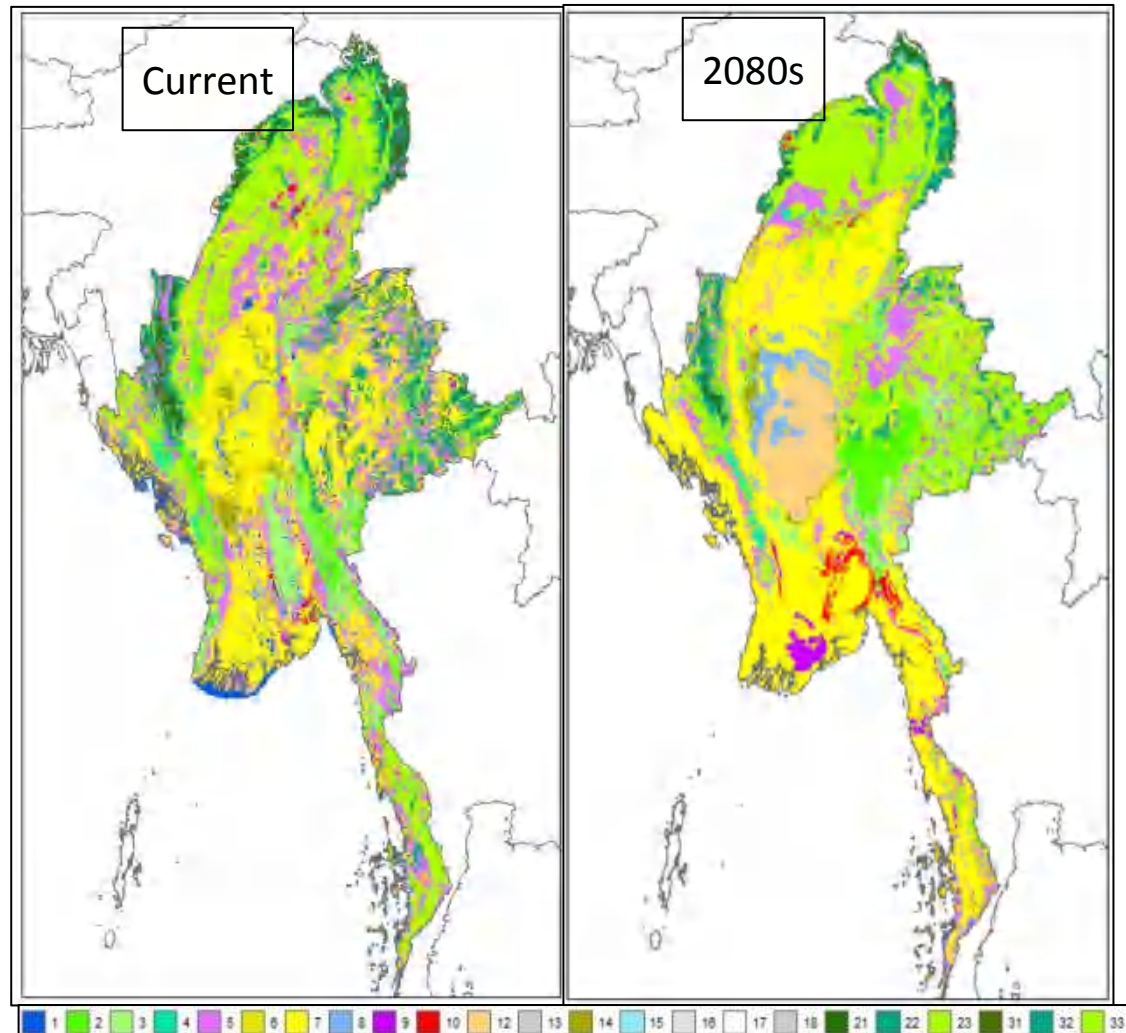


Figure 13. Spatial distributions of forest ecotypes in Myanmar under the current and a future period (2080s) based on our consensus projections.

Significance of climate niche models and their projections

One of the major challenges for forest trees under climate change is the mismatch between the climate that a tree species has adapted to in the past and the climate that the species will experience in the future. Such a mismatch can considerably compromise the health and productivity of our forests, and even convert them from a carbon sink to a carbon source. Climate niche models can define the realized climate niche of a tree species or a forest ecotype, and project the shift in future climate conditions. The importance of climate niche models have been well recognized, however, the model accuracy and future climate uncertainty remain a challenge for researchers and practitioners.

Through this project, we have developed climate niche models for 10 important forest tree species and for economic specific forest ecosystems in this region. We have applied the most advanced state-of-art modeling technologies, such as multiple-forest machine-learning modeling algorithm and consensus projection approach, to secure the accuracy of our models and to deal with uncertainty in future climates. Thus, our model projections provide a solid scientific basis for assessing the impact of climate change and for developing adaptive strategies including assisted migration for the major forest tree species in the region.

Our climate niche models for forest systems provide an effective alternative to modeling individual species. The high richness of forest tree species in the tropical and subtropical regions imposes a challenge in developing climate niche models for individual species, especially the species occurrence data are often not available. With projections for forest ecotypes, it is possible to associate individual tree species with the shift of each forest ecotypes to predict the shift for individual species, which would be our next objective.

Our model projections for forest ecosystem and tree species in North America have been used for developing climate-based species selection (CBSS) and climate-based seed transfer (CBST) tools. Such tools have not been developed yet in the Asia Pacific region. With most important tree species modeled in an economy, such as in China, we can develop similar tools to serve as a template for this region.

Output 3: Evaluations of adaptive forest ecosystem management strategies through model integration, development of indicators and trade-off analysis

The primary objective of the work in this section of the project was to use the well-established forest ecosystem management model FORECAST Climate (Seely et al. 2015) as a vehicle to facilitate policy discussions through a scientifically credible evaluation the potential response of regional forest ecosystems to alternative climate change scenarios and management options. By leading them through the detailed process of calibrating and applying this modelling tool, developed at the University of British Columbia, we provided insight for local scientists and forest managers to help them understand the complex systems they are dealing with, as well as provide opportunities for addressing policy and data gaps to formulate alternative adaptive forest management strategies in the context of climate change. The work was focused on three ecosystems types located in two different economies including:

- 1) Teak (*Tenctona grandis*) / Bamboo plantations in located in the Bagoyoma region in south central Myanmar. Project partners included representatives from Forest Research Institute in Yezin and the Ministry of Environmental Conservation and Forestry in Nay Pi Taw.
- 2) Acacia (*Acacia mangium*) plantations located in peninsular Malaysia, and the

Sabah and Sarawak regions in Borneo. Project partners included scientists from the Institute of Tropical Forests and Forest Products (INTROP) at the Universiti Putra Malaysia, forest managers from Acacia Forest Industries (AFI) in Sabah, and forest managers from Sarawak Planted Forest (SPF) in Sarawak.

- 3) Mangrove (*Rhizophora apiculata*) plantations in the Matang region of peninsular Malaysia. Project partners included scientists from the Institute of Tropical Forests and Forest Products (INTROP) at the Universiti Putra Malaysia.

The following sections provide summaries for work completed for each ecosystem type.

Teak (Tectona grandis) / Bamboo plantations in Myanmar

Site visits and establishment of field plots

Mar 2017

A total of 11 field plots were established in a series of teak plantations varying in age in site quality in the Yedashae township area of the Tuangoo Forest District. Measurements in the teak stands included height and diameter at breast height (1.3m) for all trees. Information with respect to crown length, forest floor conditions and minor vegetation was also recorded. Forestry students from The Forest Research Institute participated in the fieldwork and were trained with respect to methodology for establishing plots and the use of digital hypsometer from measuring tree heights.

Nov 2017

The UBC team met with partners from the Myanmar Forest Research Institute and re-visited all 11 plots established in the spring of 2017. Conditions during the fall visit reflected the end of the wet season whereas the spring visit was conducted at the end of the dry season. During the fall visit, soil samples were collected from each plot and under-canopy photos were taken for determination of leaf area index (LAI) for use in the calibration of FORECAST Climate. During the visit we found that most of the plots had been maintained very well, however, 2 plots had been disturbed by illegal logging and thinning. Forestry students from The Forest Research Institute participated in the fieldwork.

Model calibration and validation activities

In terms of dataset development, a teak dataset has been developed for the FORECAST model using data from the literature and plots established Myanmar. A bamboo dataset has been completed and added to the general teak ecosystem calibration dataset based on a detailed literature review. Bamboo is recognized as a considerable competitor in teak plantations and also provides ecosystem services for local people. The teak dataset including calibration of climate relationships was

completed and tested using plot data. A comparison of model projections for teak productivity with no thinning against measured plot data is shown in Figure 14. As expected, the model shows greater levels of biomass accumulation relative to stands older than 15 years after which thinning would have occurred. When we implement thinning in the model, the levels of biomass accumulation are consistent with those measured.

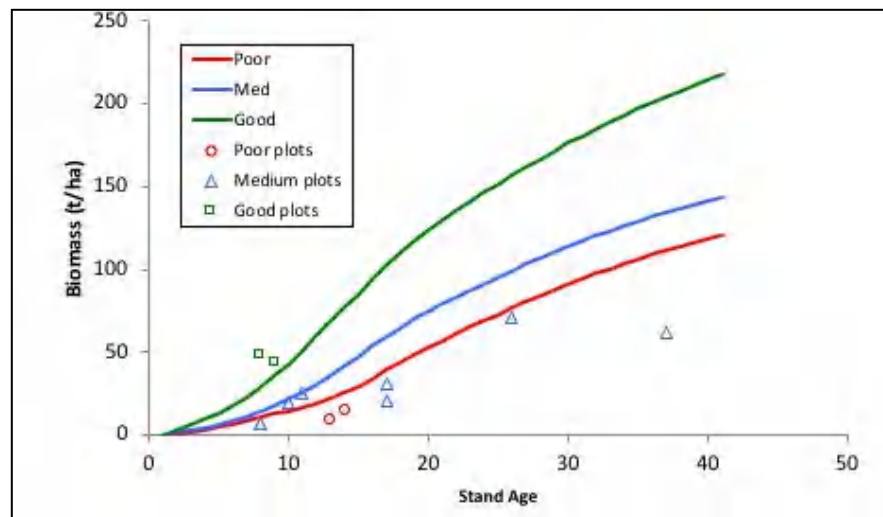


Figure 14. A comparison of model projections of stem biomass accumulation using 3*3m spacing with no thinning against measured values in field plots.

The capability of the model to simulate the effect of climate on teak growth rates was evaluated using tree-ring data from a dendroclimatology study conducted in central Myanmar (D'Arrigo et al. 2011). The results (see Figure 15) suggest the model is able to represent the effect of climate on tree growth with growing season precipitation as a key factor.

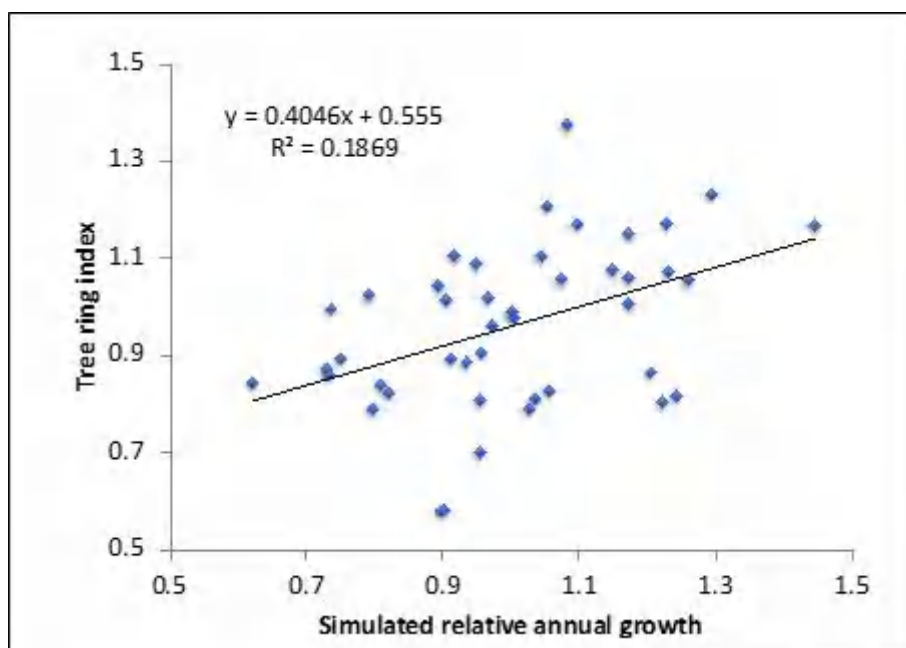


Figure 15. A comparison of relative simulated annual tree productivity by FORECAST Climate using historical climate data vs. tree ring indices (1961-2006) derived from a study conducted in central Myanmar.

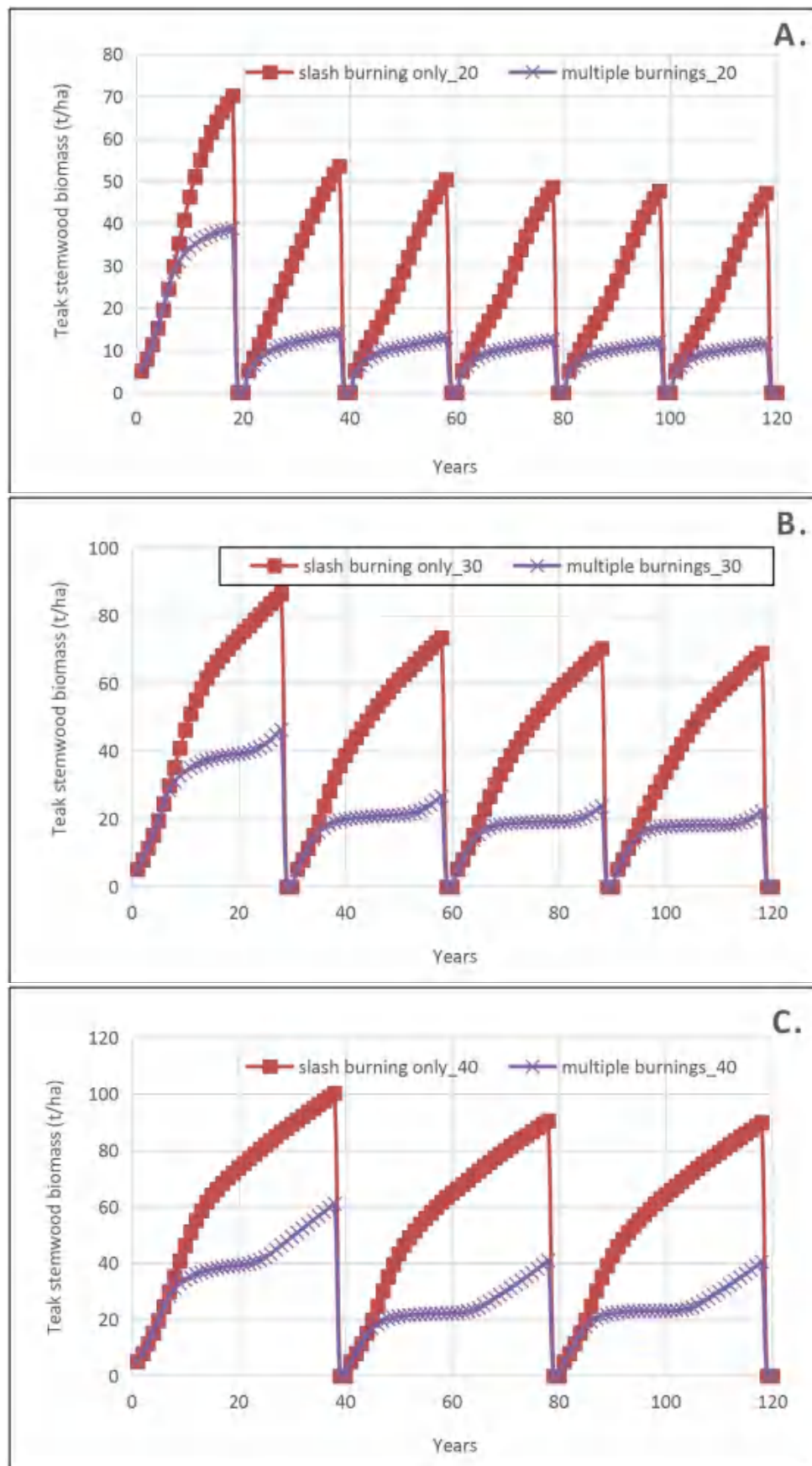
Model application

The calibrated FORECAST Climate model was used to evaluate the impact of fire frequency, rotation length, and bamboo competition in teak/bamboo ecosystems, and was used to project the potential impacts of climate change (especially, the intensity and frequency of drought events) on the long-term productivity and health of teak plantations in Myanmar.

Evaluating Management Alternatives in Teak/Bamboo Ecosystems in Myanmar

Burning is considered as a necessary procedure for the successful establishment of teak plantation. However, burning may cause soil degradation and site yield decline because of accelerated loss of nutrients and topsoil. The **rotation** age of plantation teak in its natural range has varied between 50-90 years, however, in 1998, the Forest department of Myanmar launched a special teak plantation program, which adopts a 40-year rotation and clear-cutting at the end of the rotation. In the near future, there will be extensive teak plantations, will be clear-harvested, and consequently, large-scale of second-rotation of taungya teak reforestation will be undertaken. So, there is a concern that the “second rotation problem”.

Simulation results of impact of frequency and rotation length on teak growth are shown in Figure 16 and Figure 17.



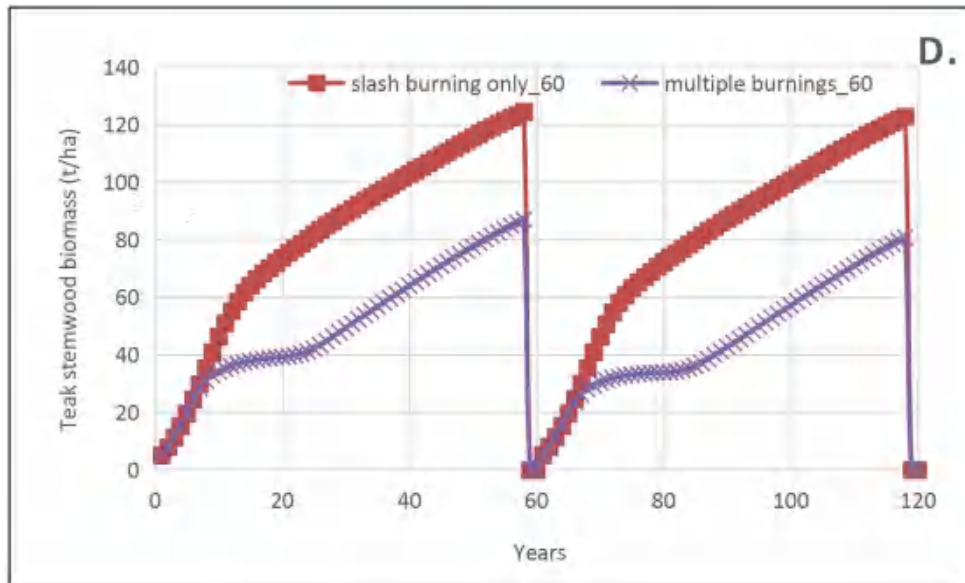
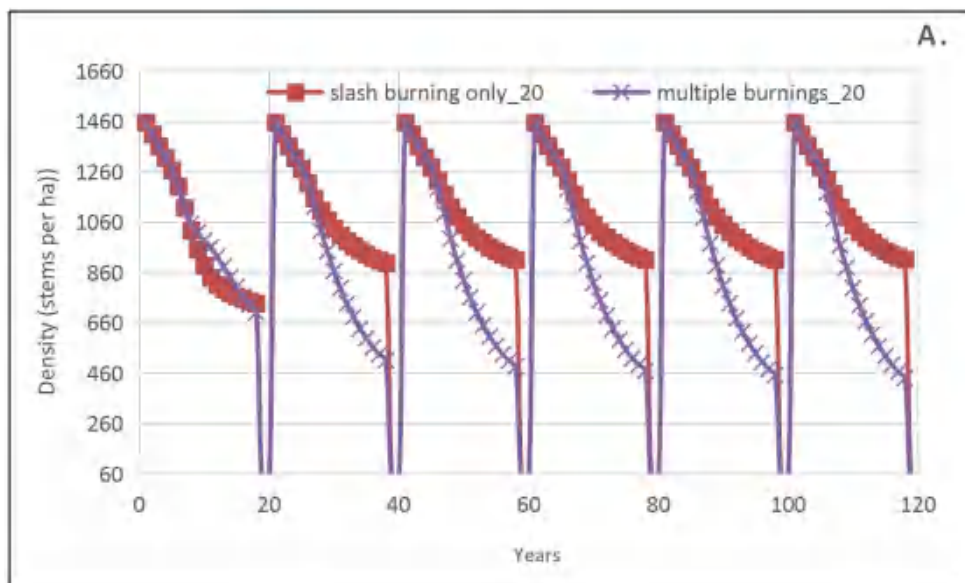


Figure 16. Simulation of impact of frequency and rotation length on teak productivity. A) 20 years rotation, B) 30 years rotation, C) 40 years rotation and D) 60 years rotation. Fire Frequency: Slash burning only(i.e., burning after harvesting); Multiple burnings(i.e., multiple control burnings till 18 years old and slash burning after harvesting). Simulation scale is 120 years with multiple rotations.



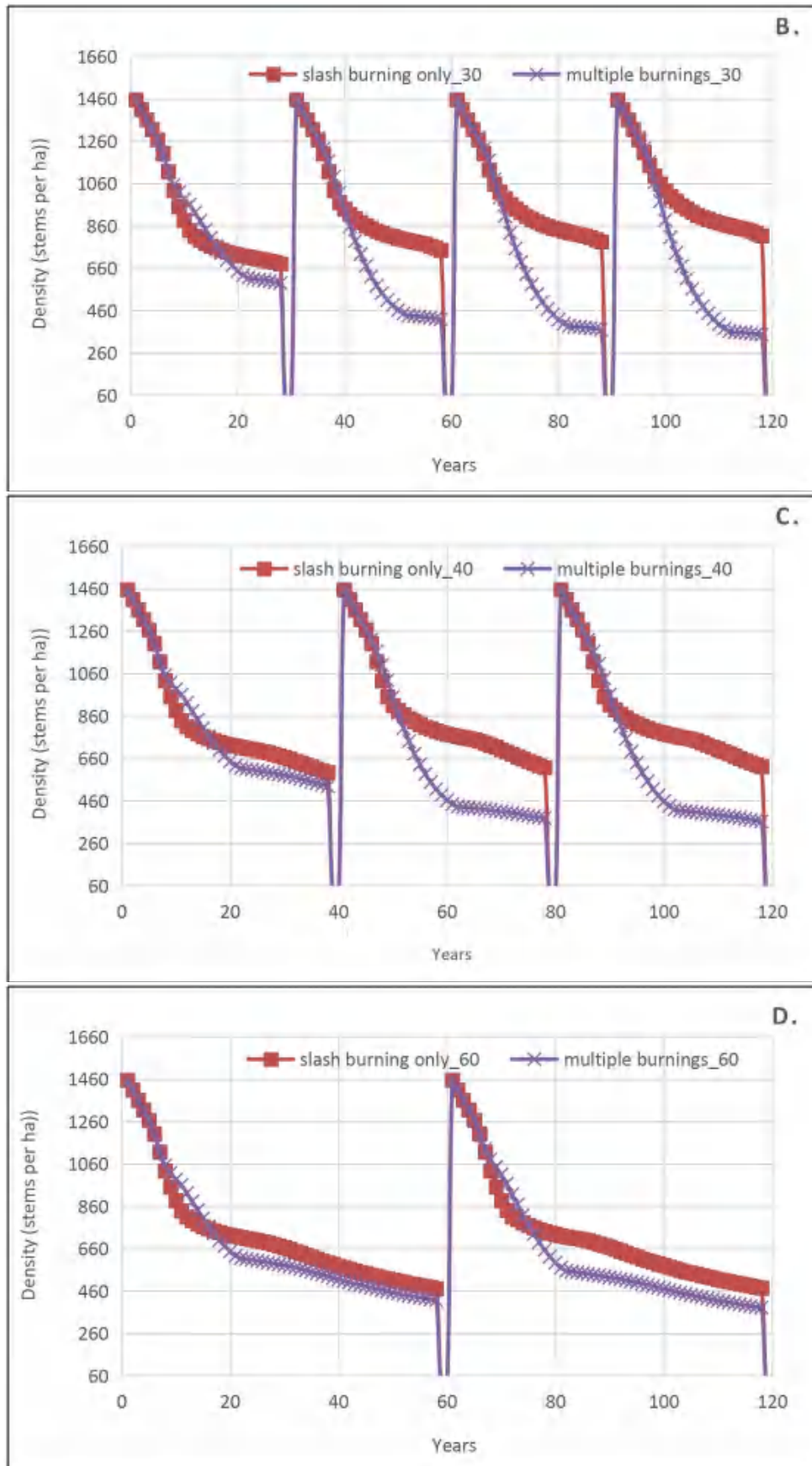


Figure 17. Simulation of impact of frequency and rotation length on teak mortality. A) 20 years rotation, B) 30 years rotation, C) 40 years rotation and D) 60 years rotation. Fire Frequency: Slash

burning only(i.e., burning after harvesting); Multiple burnings(i.e., multiple control burnings till 18 years old and slash burning after harvesting). Simulation scale is 120 years with multiple rotations.

Frequently burning, especially with short rotation, will deteriorate the soil fertility (see Figure 18) and result in declining productivity of teak. With slash burning only, the rotation length would be at least 40 years. With multiple burnings, lengthening the rotation age to 60 years even could not recover the productivity. The large losses of organic matter are due to multiple burnings removed almost all the logging slash and forest floor litter, and some of the root biomass.

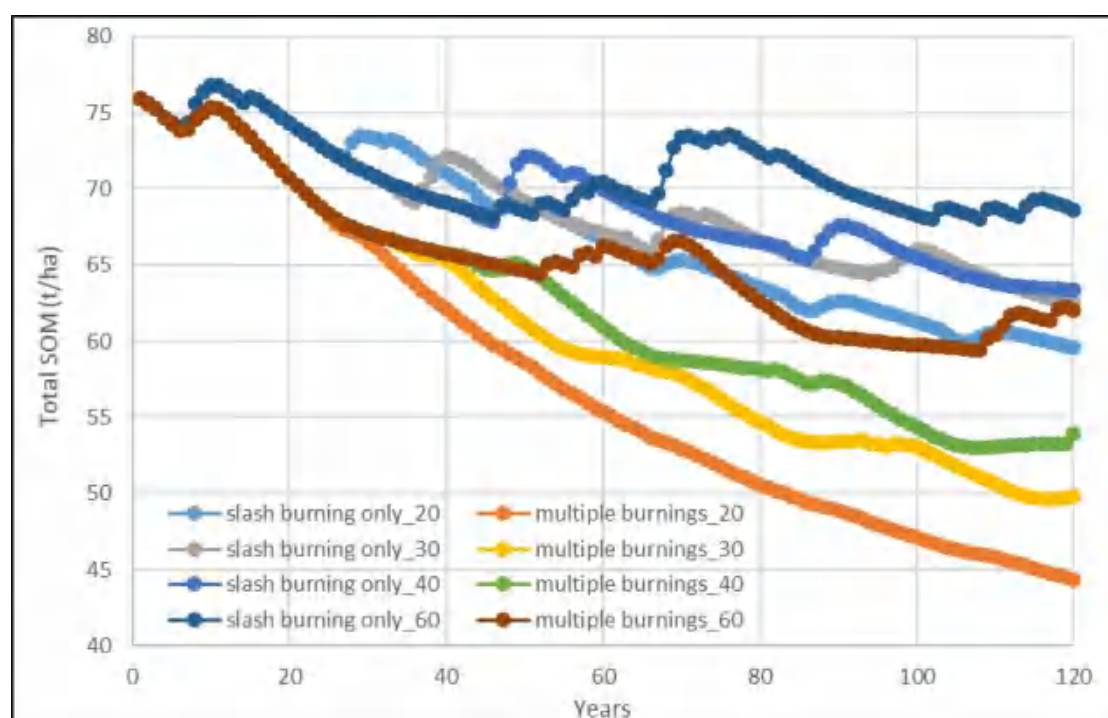
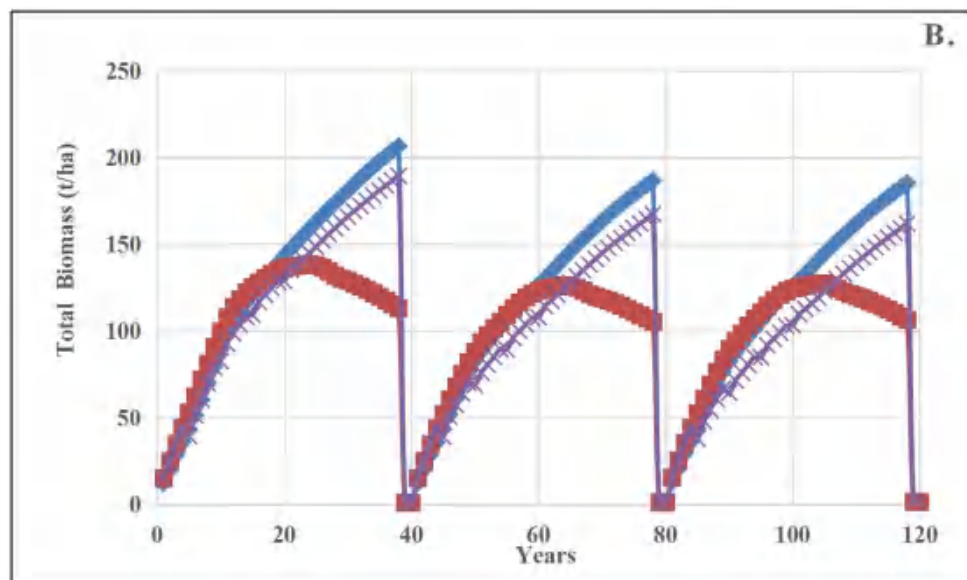
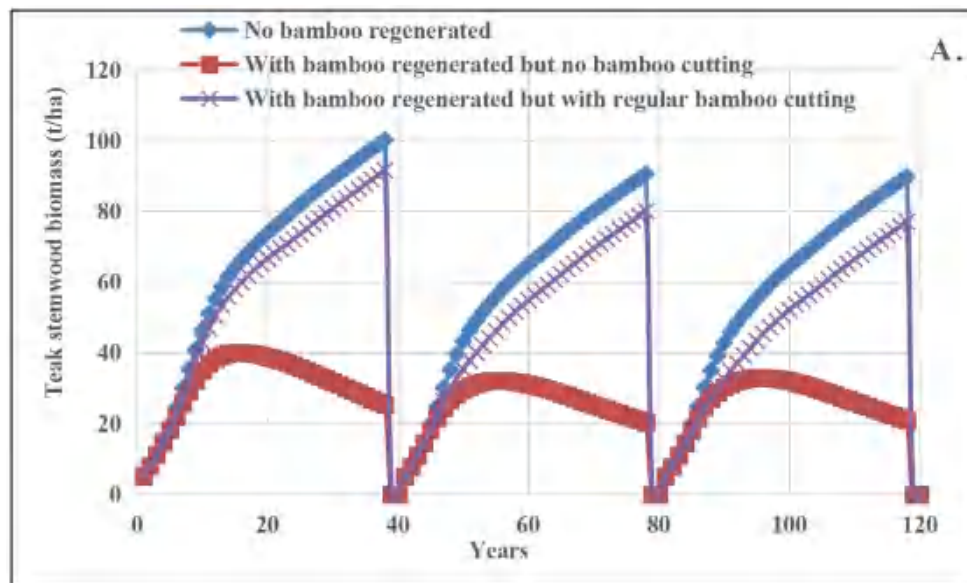


Figure 18. Simulation of impact of fire frequency and rotation length on total soil organic matter mass. Simulation scale is 120 years with multiple rotations (i.e., 20, 30, 40 and 60 years) with two burning regimes (i.e., slash burning only and multiple burnings).

Bamboo is commonly associated with teak in the study area, and it is seen as an indicator of deep, rich, well-drained soils on which teak also develops well. Many studies indicates that retaining or intercropping bamboo in teak plantations may help in improving soil fertility thus making the plantation more productive. Simulation results of impacts of bamboo competition on teak plantation are illustrated in Figure 19. Model results suggest that bamboo competition will result in reduction of teak productions. Without regular bamboo cutting, bamboo would out-compete teak. Compared to pure teak plantation, the survival rate of teak was higher in the plantation with bamboo regenerated+ cutting across three rotations. Although Bamboos could lead to reduction in teak productivity, they can increase the soil organic matters (SOM) thus improve soil fertility. Appropriate control of the

compatibility and interspecific competition between bamboos and tree species should be done for full use of the available resources.



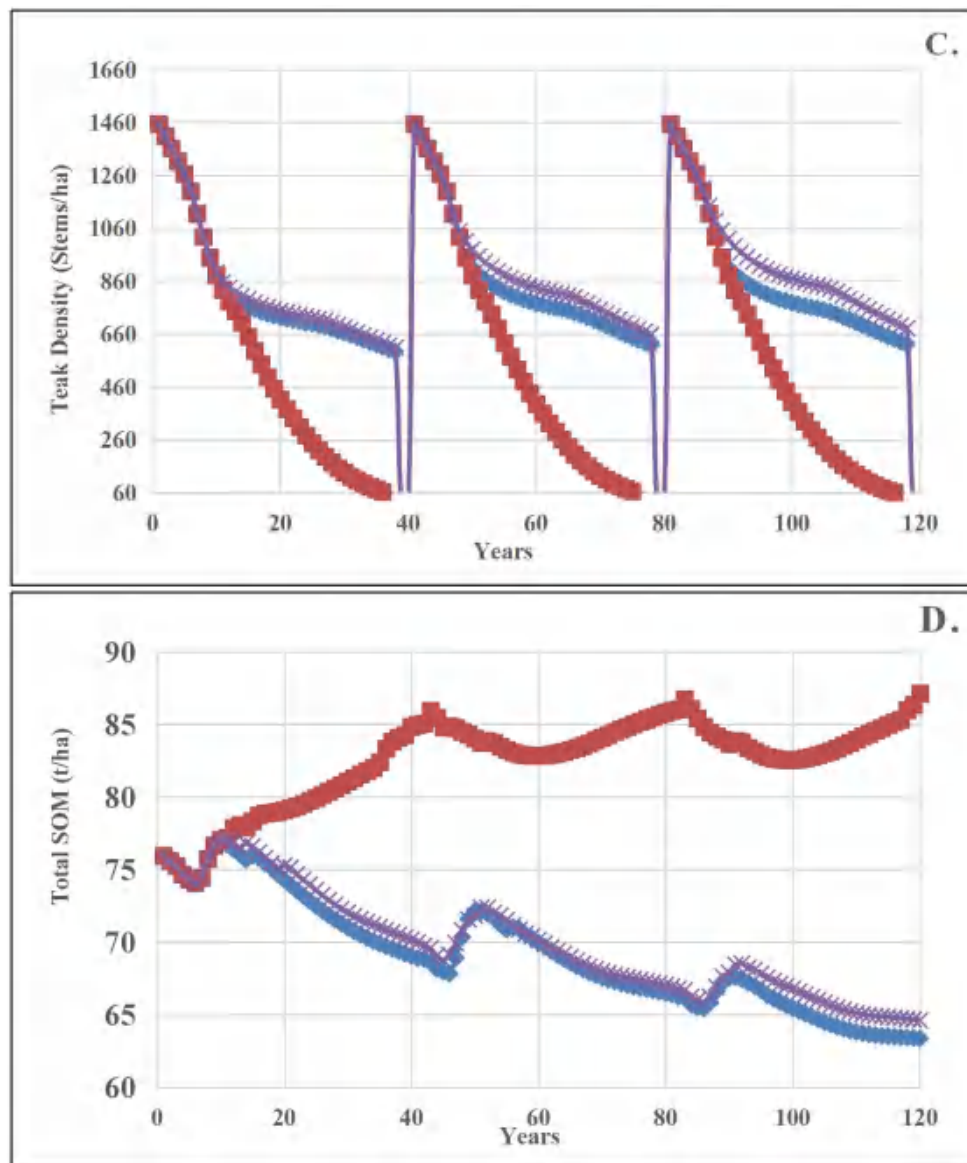


Figure 19. Simulation of impact of bamboo competition on A) teak stemwood biomass, B) total biomass, C) teak mortality, and D) total soil organic matters.

Simulating Climate Change Impacts on Long-term Teak Productivity and Health

The calibrated and verified FORECAST Climate Model was employed to simulate the long-term impact of climate change on stand growth and development for teak plantations using three different approaches. The three-pronged approach provided greater insight on the extent to which climate change (particularly changes in drought frequency and intensity) may affect the long-term health and productivity of teak plantations in central Myanmar.

Development of climate change scenarios: 1st approach

In the first approach, climate change scenarios were developed based upon the output from one of the IPCC AR5 General Circulations Models (GCMs), CanESM2, based upon the RCP 4.5 and 8.5 emissions scenario. Monthly climate data was

downloaded from ClimateAP model for the study area (Wang et al. 2012). The monthly temperature and precipitation were then converted to daily values using MarkSim DSSAT weather file generator (<http://gisweb.ciat.cgiar.org/MarkSimGCM/>). Monthly air temperature and monthly rainfall for the historical years (1901-2016) and future years (2021-2100) based on CanESM2 RCP 4.5 & 8.5 scenarios are shown in Figure 20.

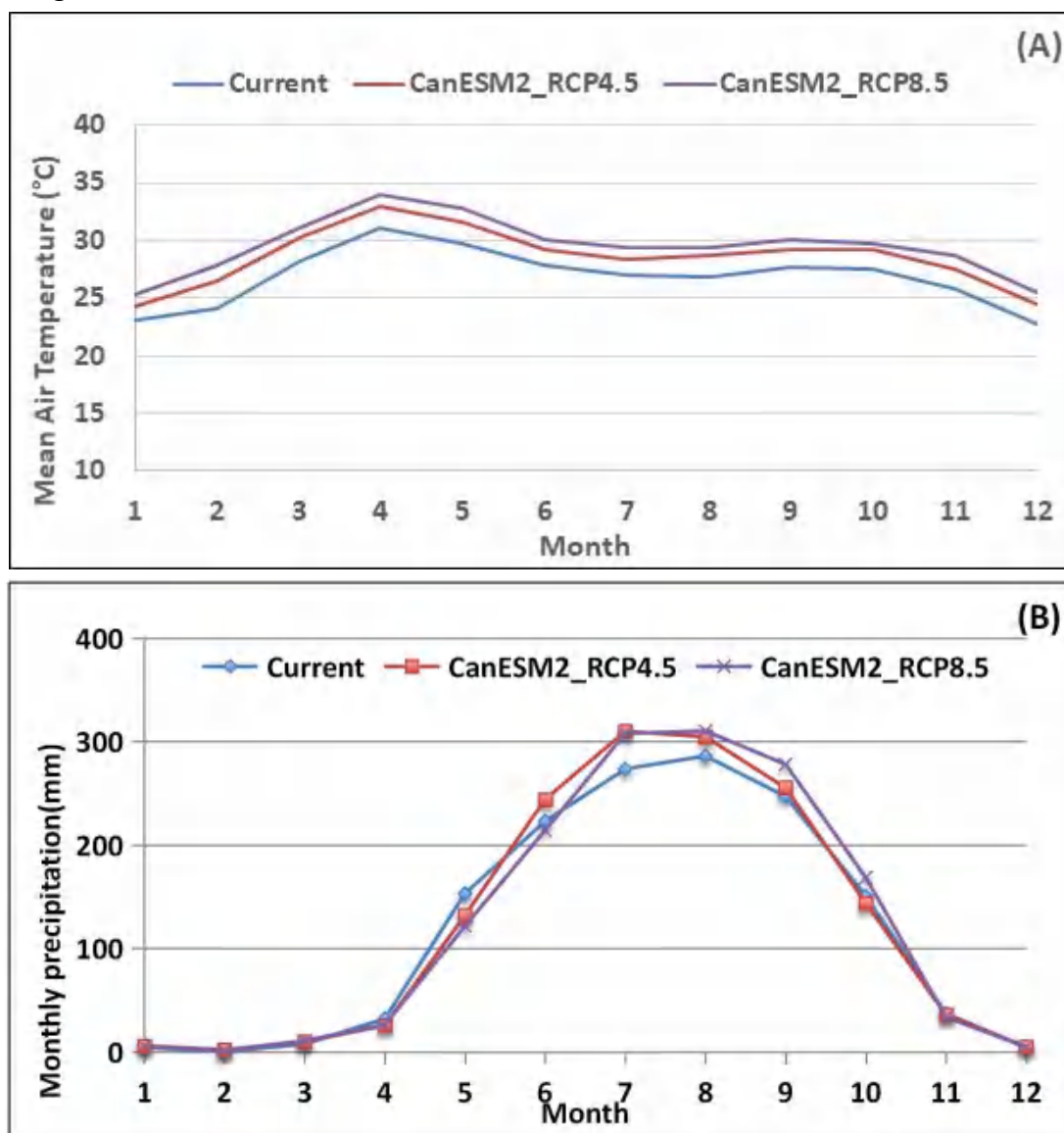


Figure 20. Climate change scenarios based on CanESM2. (A) Mean monthly temperature. (B) Mean monthly precipitation. Current climate is from 1901 to 2016, CanESM2 RCP4.5 and RCP8.5 climate projections are from 2021-2100.

Development of climate change scenarios: 2nd approach

In the second approach, we created the drought events based on the historical climate from 1901-2016. We used the historical patterns of temperature and only modify the precipitation patterns by reducing wet days of shoulder months (May or October) or growing season (GS) using climate modification features available in the Statistical DownScaling Model (SDSM) software package (Wilby et al. 2002, 2004,

2013). The resulting 117-yr (from 1901 to 2016) climate scenarios are represent a set of scenarios with increasing drought severity (Figure 21).

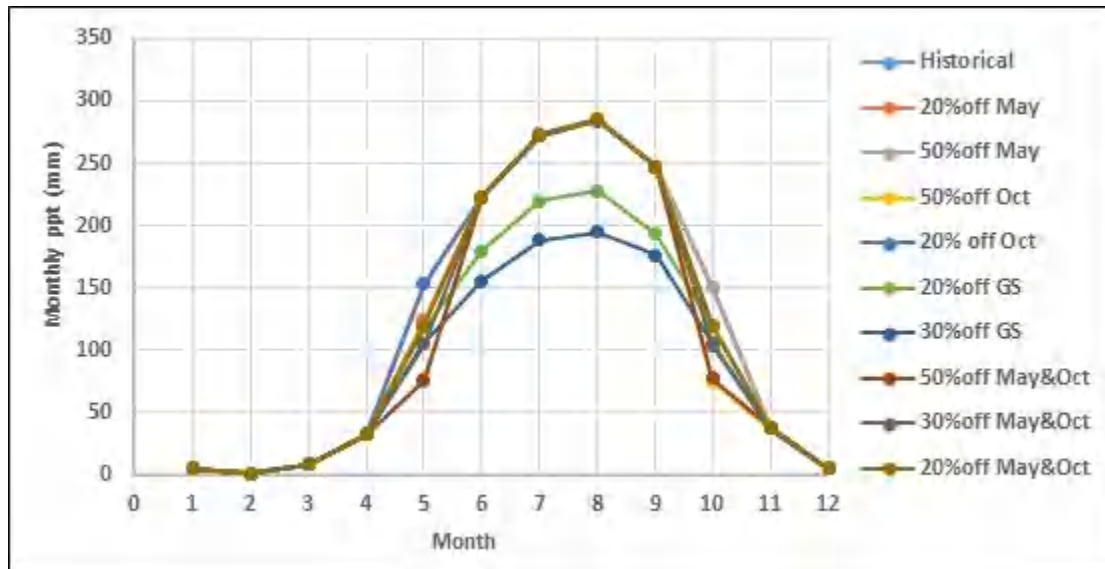


Figure 21. Climate change scenarios based on the historical climate from 1901-2016 by reducing wet days of shoulder months (May or October) or growing season (GS).

Development of climate change scenarios: 3rd approach

In the third approach, we used the projected patterns of temperature deviations determined as part of the first approach in combination with a gradient of artificially enhanced drought events. Precipitation patterns were derived from projected CanESM2 RCP 8.5 scenario. To exclude the high inter-annual variability of annual precipitation, we used the mean precipitation patterns of CanESM2 RCP 8.5 scenario and then systematically increased the intensity and frequency of extreme drought years. The extreme drought conditions of each month were from the most drought months from CanESM2 RCP 8.5 scenario from 2020 to 2100. The resulting 80-yr (2021-2100) climate scenarios are represent a set of scenarios with increasing drought severity (Figure 22).

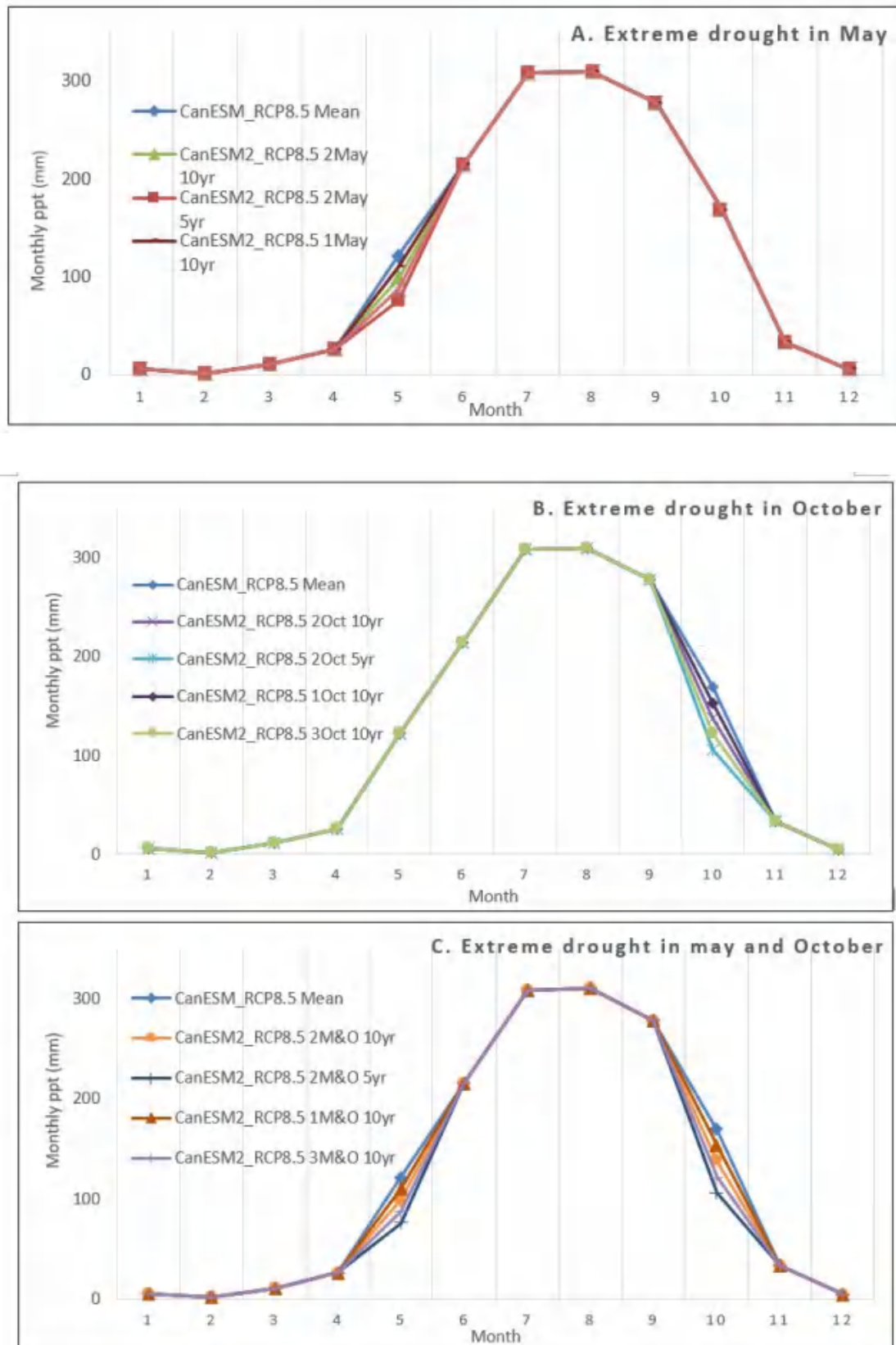
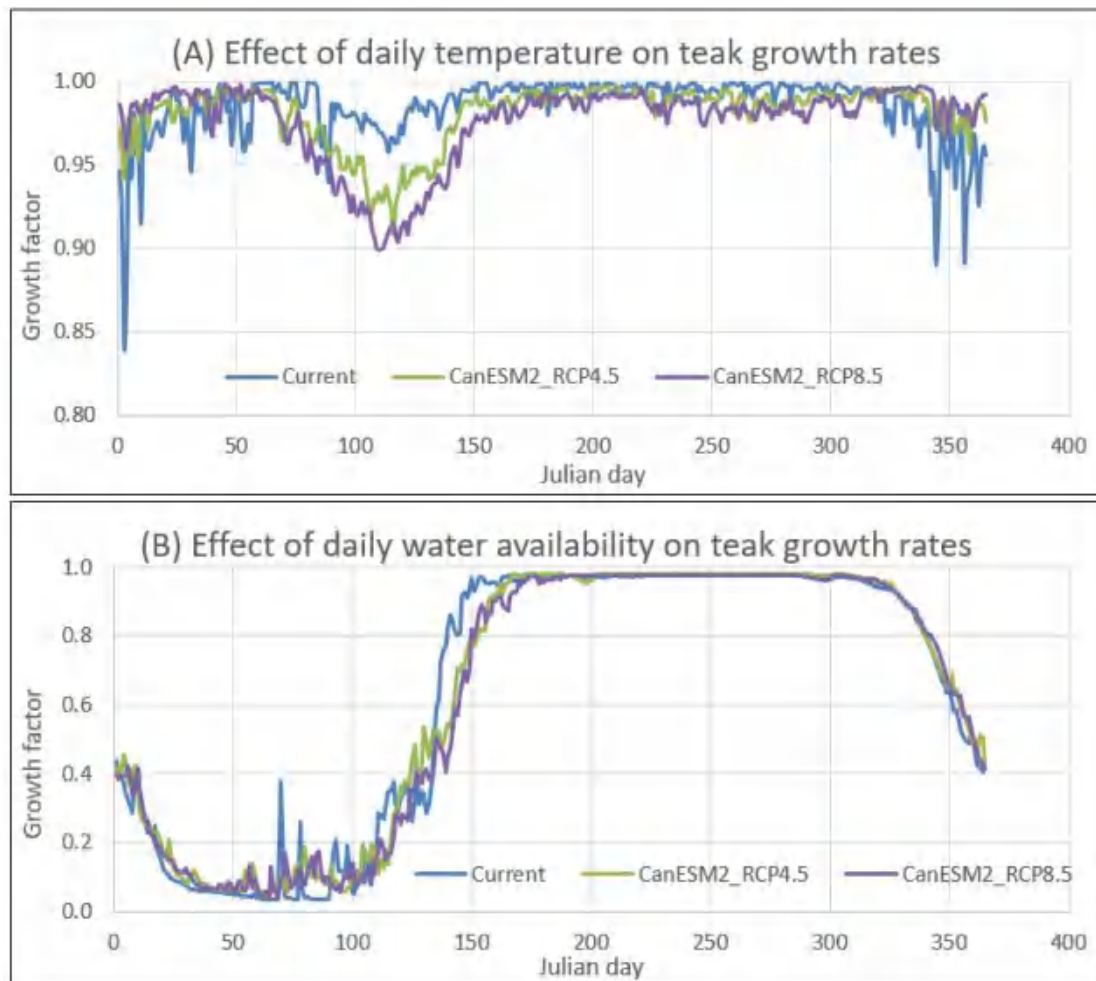


Figure 22. Climate change scenario based on CanESM2 RCP 8.5 from 2020 to 2100 A) Extreme drought in May, B) Extreme drought in October, and C) Extreme drought in May and October.

Simulation results of climate change impacts: 1st approach

The calibrated and verified FORECAST Climate model was run in climate change mode to simulate the impact of climate on net primary productivity. The model calculates a climate response factor that represents both the impact of water stress and temperature on growth rates. Projected impacts in newly planted stands of the current climate and climate change (CanESM2 RCP4.5 and 8.5) scenarios on the growth factor is shown in Figure 23. The model predicts that the average growth factor tended to show slight decline in the climate change scenarios relative to the current climate.



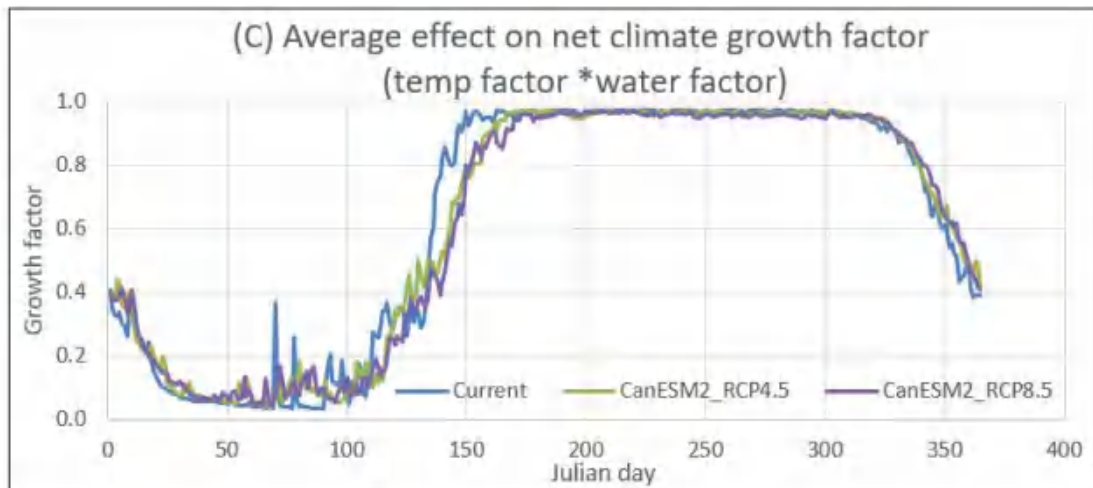
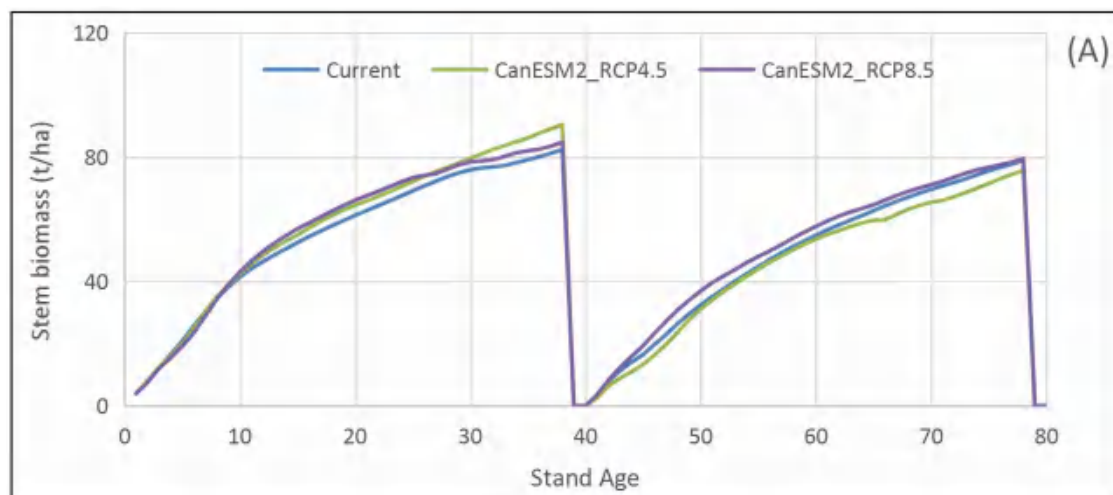


Figure 23. Simulated impact of climate change (A) daily temperature, (B) daily water availability and (C) daily temperature and daily water availability on the average daily growth factor. The growth factor is used a multiplier on NPP and thus lower values translate to reduced growth. Results for the average daily growth factor are show for newly established teak stands and reflect data from two sequential 40-year (coinciding with each rotation) historical climate data (1901-2016) and future time periods based upon the CanESM2 RCP4.5 and RCP8.5 climate scenarios from 2020 to 2100.

The impact of climate change on stemwood biomass production and mortality is shown in Figure 24. Both climate change scenarios had a net positive impact on teak stemwood biomass production in the first 40-year rotation, however, had a net negative impact in the second rotation. These results may be due to heat induced drought-related mortality during the growing season.



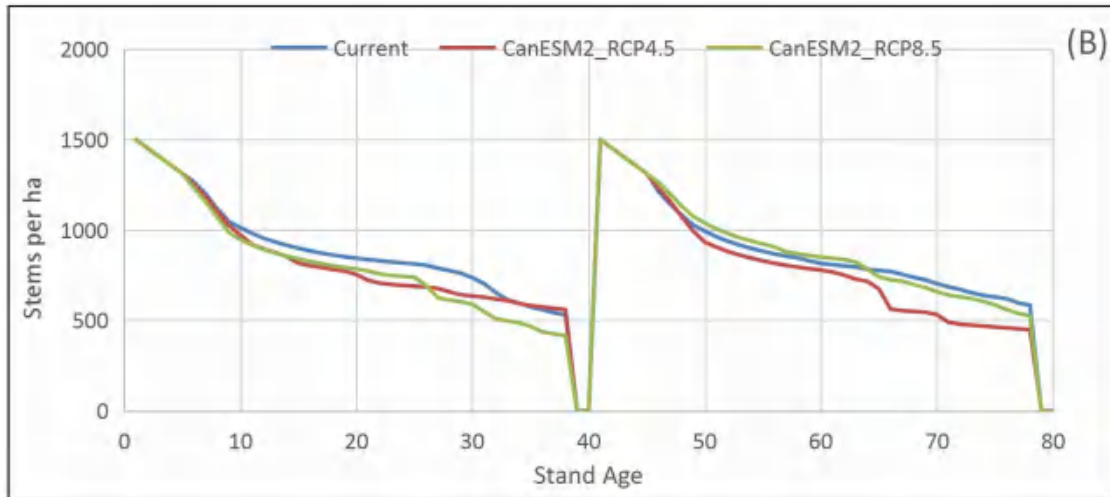
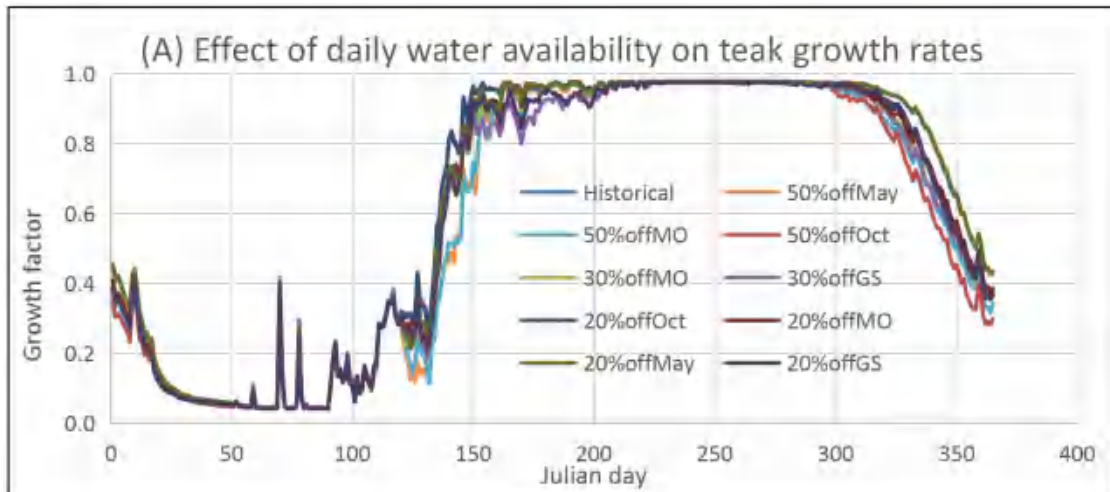


Figure 24. Simulation results showing the impacts of climate change on (A) stemwood biomass production, and (B) teak mortality. Based on two sequential 40-year (coinciding with each rotation) historical climate data (1901-2016) and future time periods based upon the CanESM2 RCP4.5 and RCP8.5 climate scenarios from 2020 to 2100.

Simulation results of climate change impacts: 2nd approach

In this approach, we used the historical patterns of temperature and only modified the precipitation patterns by reducing wet days of shoulder months (May or October) or growing season (GS) based on the historical climate from 1901-2016. Simulation results are shown in Figure 25 and Figure 26. The growth factor and stemwood biomass production declined in all climate change scenarios relative to current climate. We also found that reducing wet days in October resulted in less productivity than in May, but more productivity than in both May and October. Increasing water stress during the months of growing season shortened the moisture-limited growing season, and led to higher drought-related mortality.



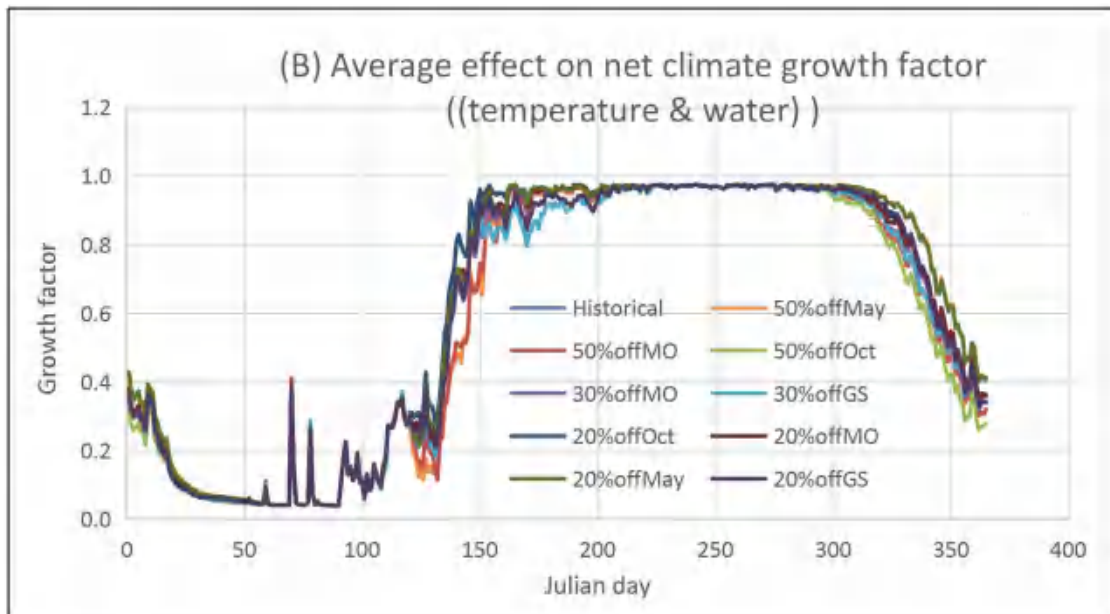
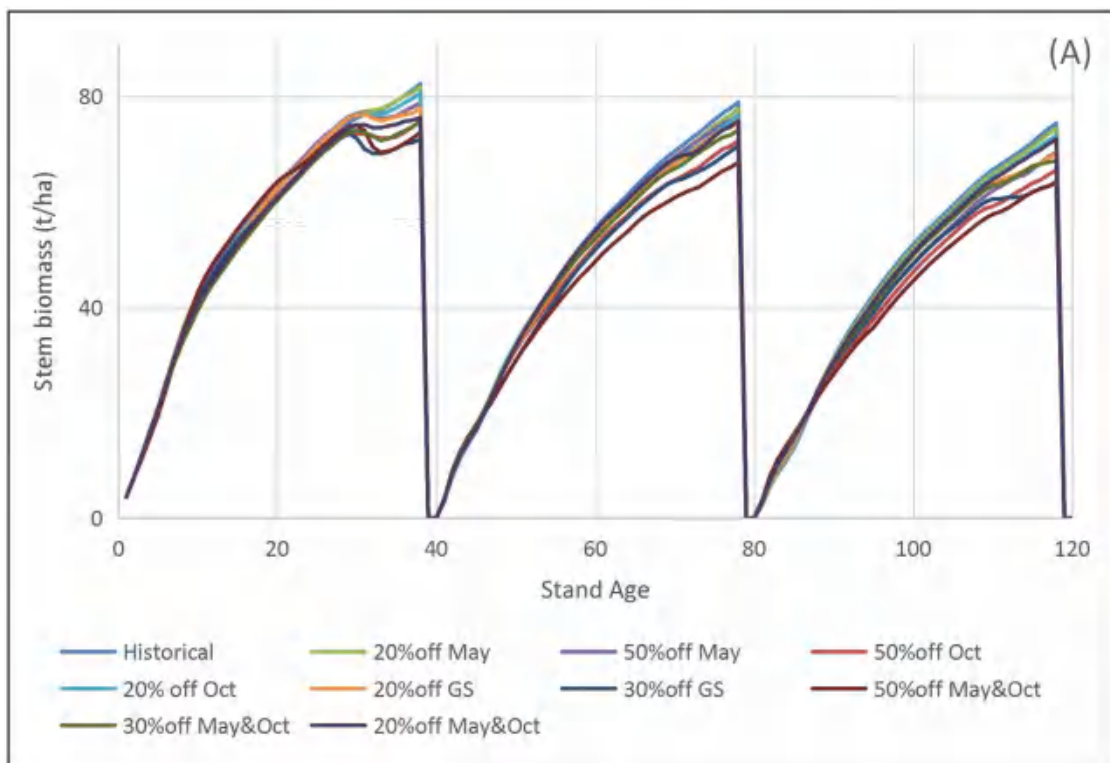


Figure 25. Simulated impact of climate change (A) daily water availability and (B) daily temperature and daily water availability on the average daily growth factor. The growth factor is used a multiplier on NPP and thus lower values translate to reduced growth. Results for the average daily growth factor are shown for newly planted stands and reflected data from three 40-year time periods (coinciding with each rotation) from the historical climate data and modified historical climate data from 1901 to 2016.



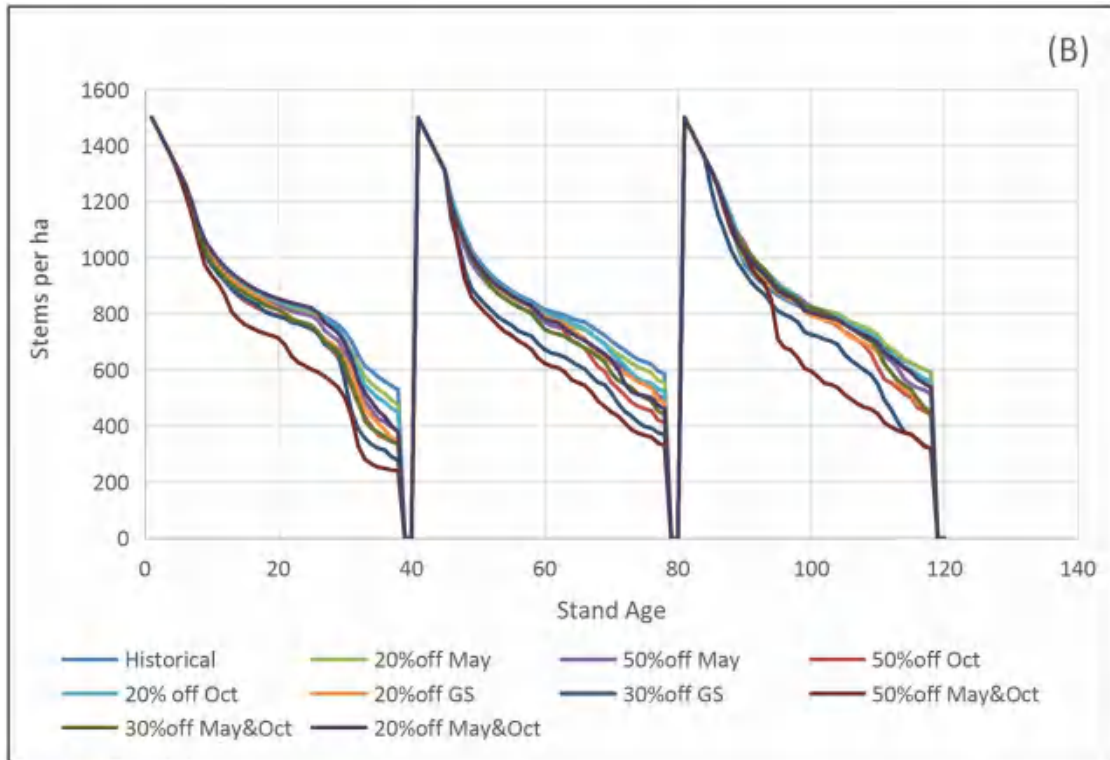


Figure 26. Projected impact of climate change on: (A) teak stemwood biomass, and (B) teak mortality. Results are shown for newly planted stands and reflected data from three 40-year time periods (coinciding with each rotation) from the historical climate data and modified historical climate data from 1901 to 2016.

Simulation results of climate change impacts: 3rd approach

In this approach, we used the mean precipitation patterns of CanESM2 RCP 8.5 scenario and then systematically increased the intensity and frequency of extreme drought years to create El Nino scenarios. Simulated impact of different intensity and frequency of drought events on teak are shown in Figure 27 (daily growth factor), Figure 28 (stemwood biomass) and Figure 29 (mortality). Simulation results showed that increasing the intensity and frequency of El Nino events had a negative impact on teak productivity with declines in growth factor, stemwood biomass productivity and increases in mortality.

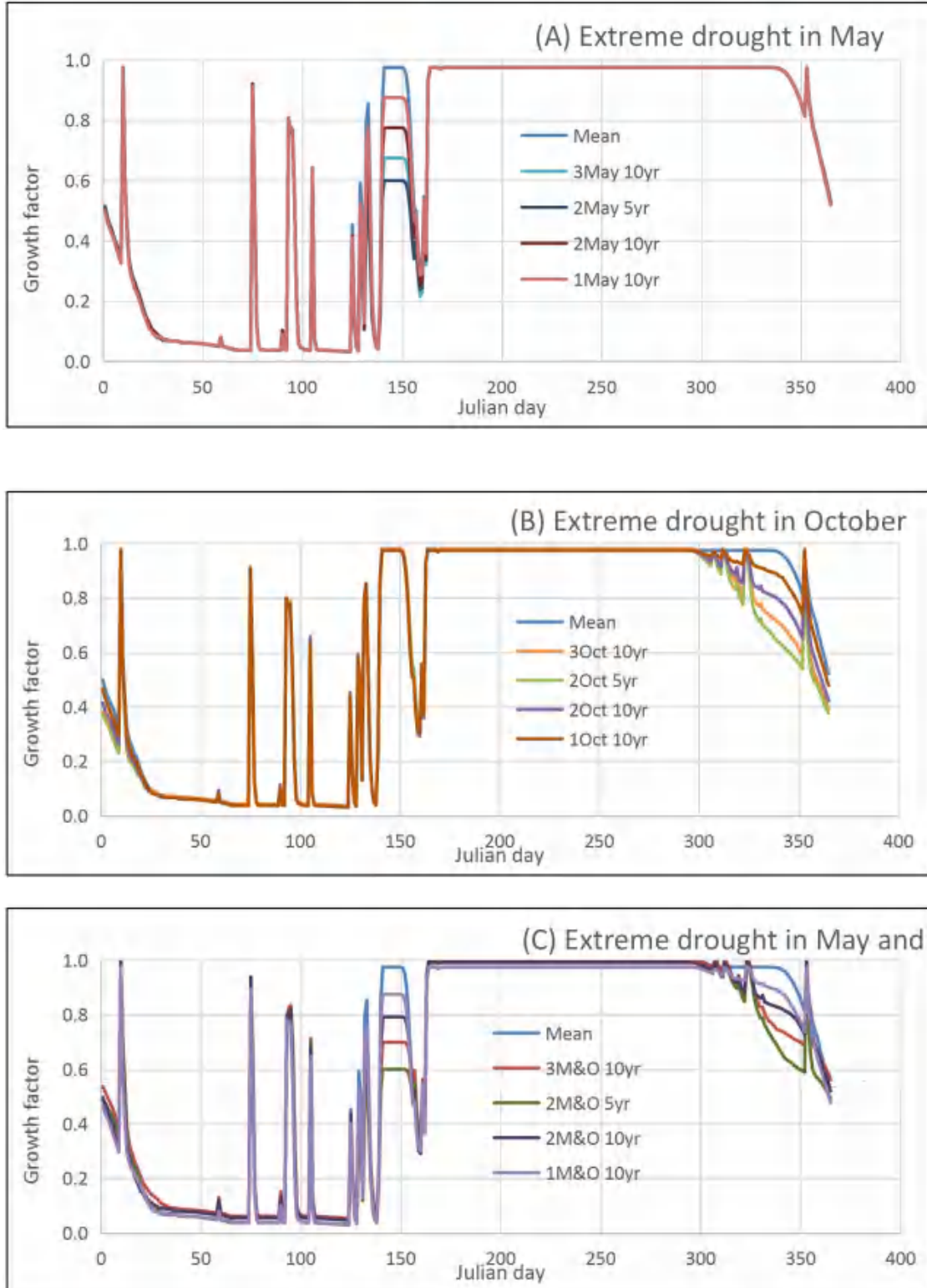


Figure 27. Simulated impact of different intensity and frequency of drought events on the average daily growth factor (A) Extreme drought in May, (B) Extreme drought in October, and (C) Extreme drought in May and October. Climate change scenarios based on CanESM2 RCP 8.5 scenario from 2020 to 2100 by systematically increasing the intensity and frequency of extreme drought years.

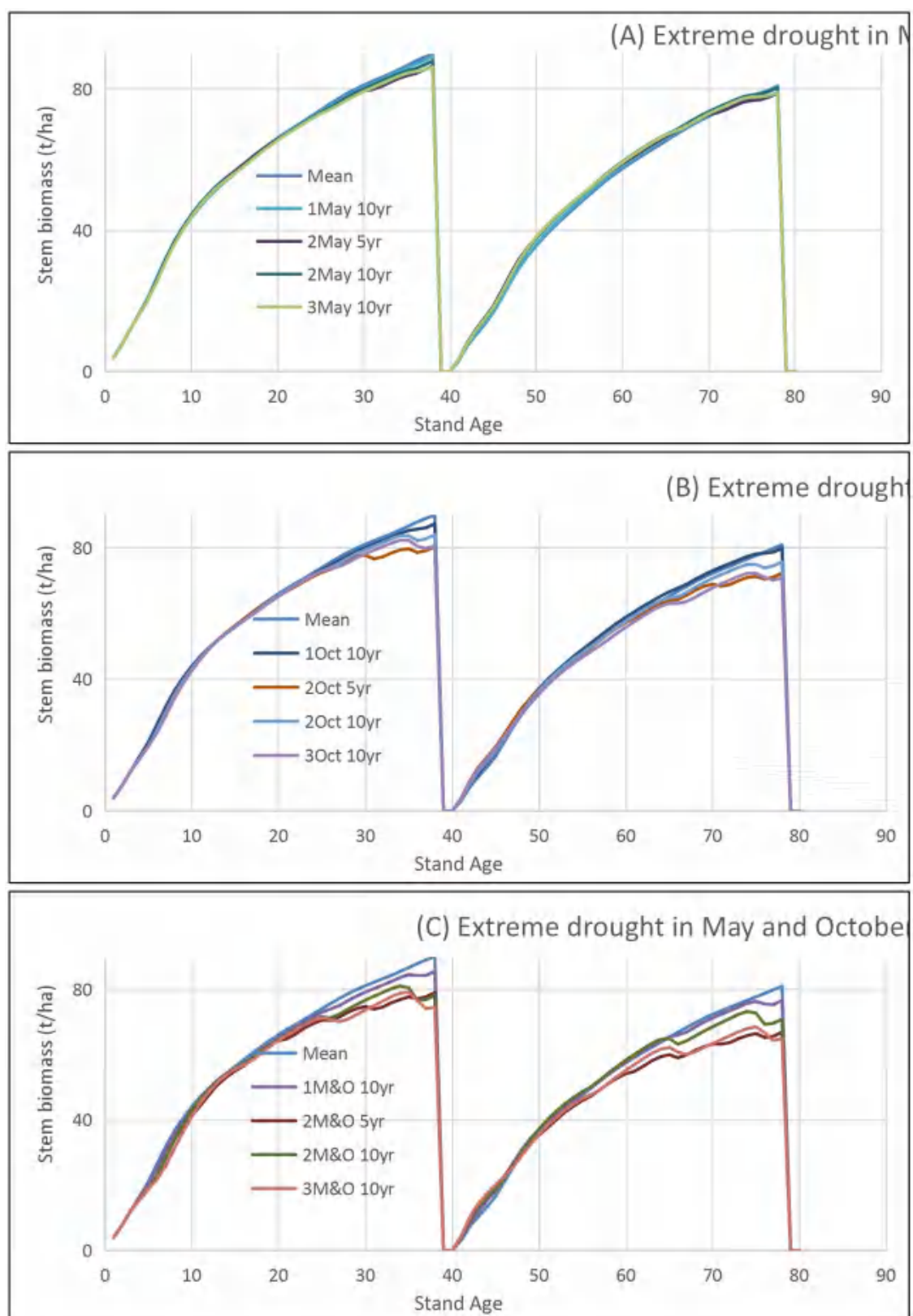


Figure 28. Simulated impact of different intensity and frequency of drought events on teak stemwood biomass (A) Extreme drought in May, (B) Extreme drought in October, and (C) Extreme drought in May and October. Climate change scenarios based on CanESM2 RCP 8.5 scenario from 2020 to 2100 by systematically increasing the intensity and frequency of extreme drought years.

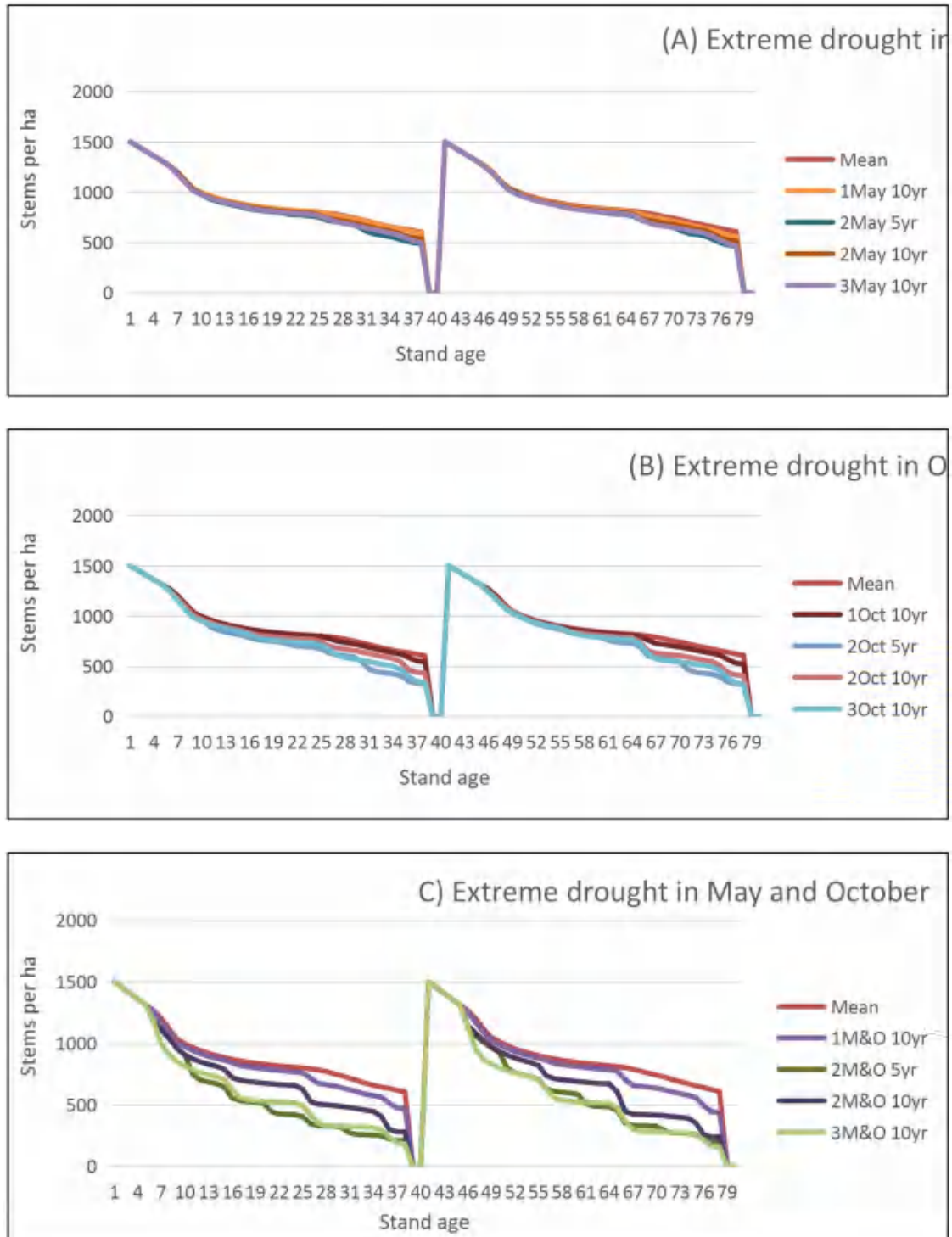


Figure 29. Simulated impact of different intensity and frequency of drought events on teak mortality (A) Extreme drought in May, (B) Extreme drought in October, and (C) Extreme drought in May and October. Climate change scenarios based on CanESM2 RCP 8.5 scenario from 2020 to 2100 by systematically increasing the intensity and frequency of extreme drought years.

Acacia (Acacia mangium) plantations located in Malaysia

Site visits and establishment of field plots

Mar 2017

We met with project partners at University Putra Malaysia (UPM) and visited *Acacia mangium* plantations visited in Peninsular Malaysia (Kemasul Plantation in Pahang) in the Saba region of Borneo (SAFODA plantation near Kota Kinabalu). We were able to explore the different types of plantations and learned about local management techniques employed for *Acacia* stands. We discussed the project with local managers but but were unable to convince the SAFODA managers to establish plots and participate in the study.

Nov 2017

Dr. Seely met with colleagues from UPM to review progress on the development of an *Acacia mangium* calibration dataset based upon a literature review. We traveled to the Samarakan plantation in the Sarawak region of Borneo and established 5 plots in plantations ranging in age and site quality. Plot measurements included top heights, DBH, and crown length estimates for all trees. In addition, under-canopy photos were taken for determination of leaf area index (LAI). All data of the collected during the fieldwork has been summarized and was used further calibration and verification of FORECAST Climate.

Dec. 2017

In Malaysia, project partners at University Putra Malaysia (UPM) The UPM partners returned to the Samarakan plantation (in Sarawak) and establish 5 additional plots in *Acacia mangium* stands. These data have been processed at UBC in were included for use in model calibration and verification.

Model calibration and validation activities

The FORECAST calibration data set for *Acacia mangium* was completed using regional data from an extensive literature review in combination with field data. An example of the calibration data for stem biomass is shown in Figure 30 where it is compared against biomass accumulation data from other locations in SE Asia and data from the Samarakan plot measurements completed in this project. It is evident from this comparison that the calibration data are consistent with both regional and local productivity data.

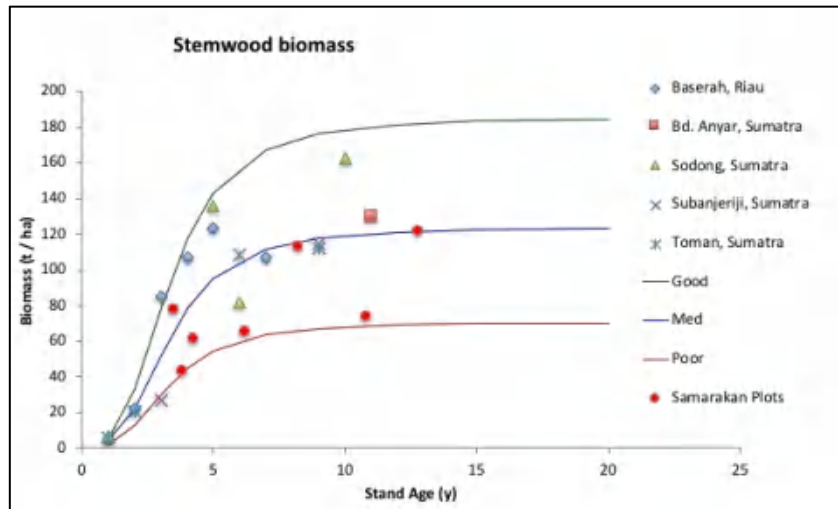
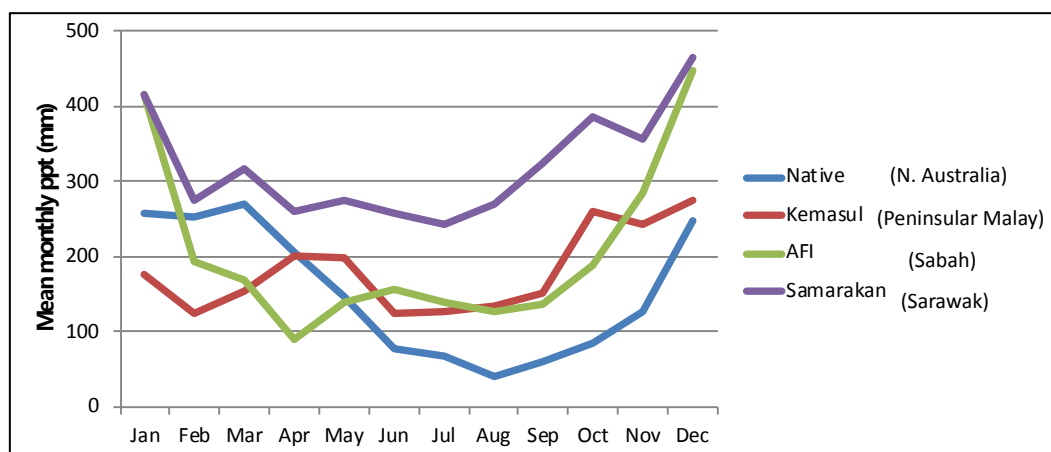


Figure 30. A comparison of literature-derived growth data from regional acacia plantations against data from the Samarakan plots and the model calibration curves.

Model application

The calibrated FORECAST climate model was used to explore both the effect of regional climate differences on the productivity of acacia plantations the potential impacts of climate change on acacia productivity.

The effects of regional climate differences on acacia productivity were explored using climate data from three distinct regions within Malaysia including northern Sabah, peninsular Malaysia, and Sarawak. The variation of climate among these regions is illustrated in Figure 31. The model was run in climate change mode to simulate the impact of climate on net primary productivity. The model calculates a climate response factor that represents both the impact of water stress and temperature on growth rates. The differences of regional climate data on the climate growth factor is shown in Figure 32. These results show that the climate is most favorable for acacia growth in Sarawak followed by northern Sabah and peninsular Malaysia, respectively. Water stress during the mid-part of the year was the primary factor limiting growth.



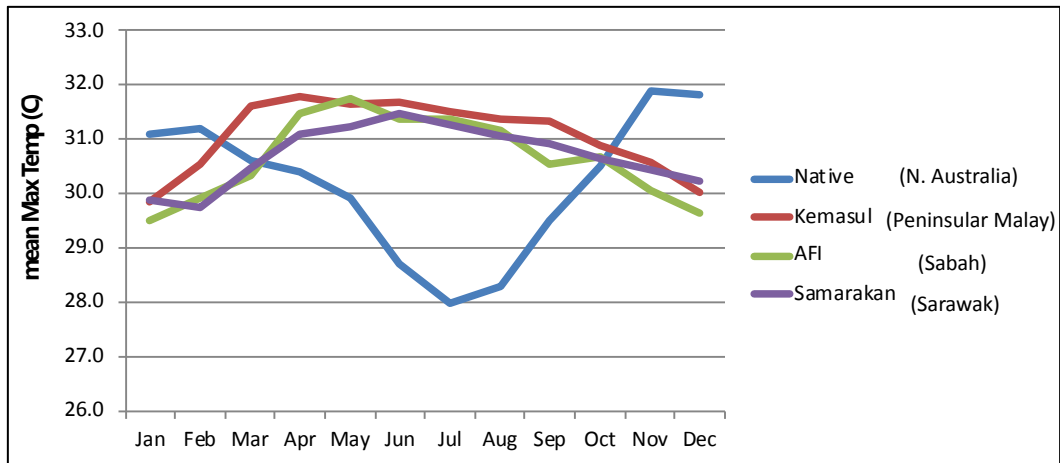


Figure 31. Mean monthly precipitation in 3 regions in Malaysia relative to that in native range of acacia in N. Australia (top panel). Mean monthly temperature in 3 regions in Malaysia relative to that in native range of acacia in N. Australia (bottom panel).

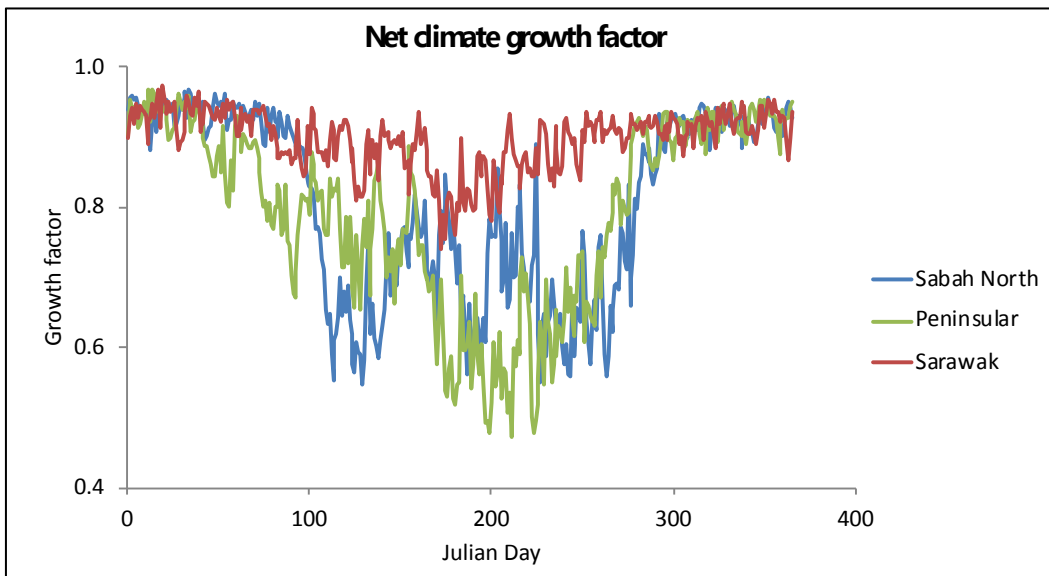


Figure 32. Simulation results showing impact of regional climate on the net climate growth factor. The growth factor is used a multiplier on NPP and thus lower values translate to reduced growth.

The potential impact of climate change and an associated increase in the frequency of El Nino events was explored using the model in each of the three climate regions. Three different climate scenarios were simulated including a representation of 2050, and 2080 climates under the RCP 8.5 scenario using combined output from a range of GCM models. A third scenario termed an El Nino scenario was constructed by repeating the driest year (out of 99 runs) back to back with a frequency of every 12 years. A series of 4*6-yr rotations were simulated for each run. The results of the runs on simulated water stress (a key indicator of stand productivity) are shown in Figure 33.

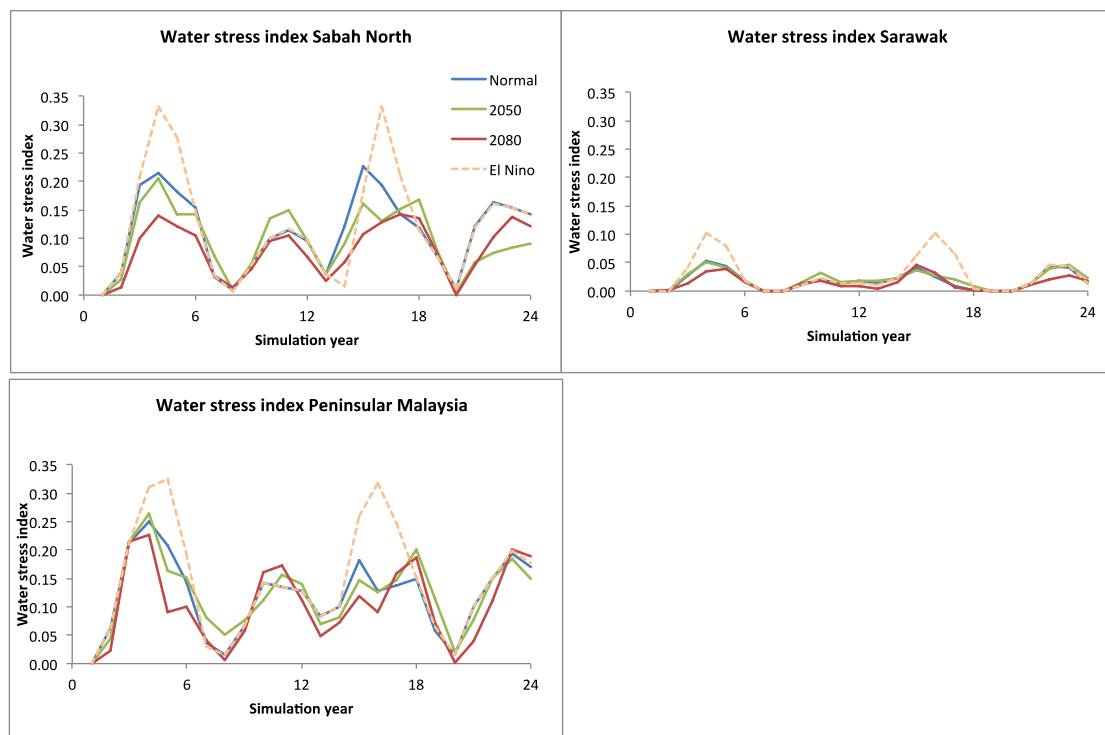


Figure 33. Projected impacts of the different climate change scenarios on annual water-stress growth response indices in *Acacia mangium* stands located in different regions of Malaysia for each year of the 24-year simulation periods (4*6yr rotations). Notice the difference in the Sarawak site, which has much lower water stress, even during the El Nino years.

The greatest impacts of El Nino climate occurred in the peninsular Malaysia region where average annual NPP declined by 16-20% (Figure 34). There was little impact in the wetter Sarawak region.

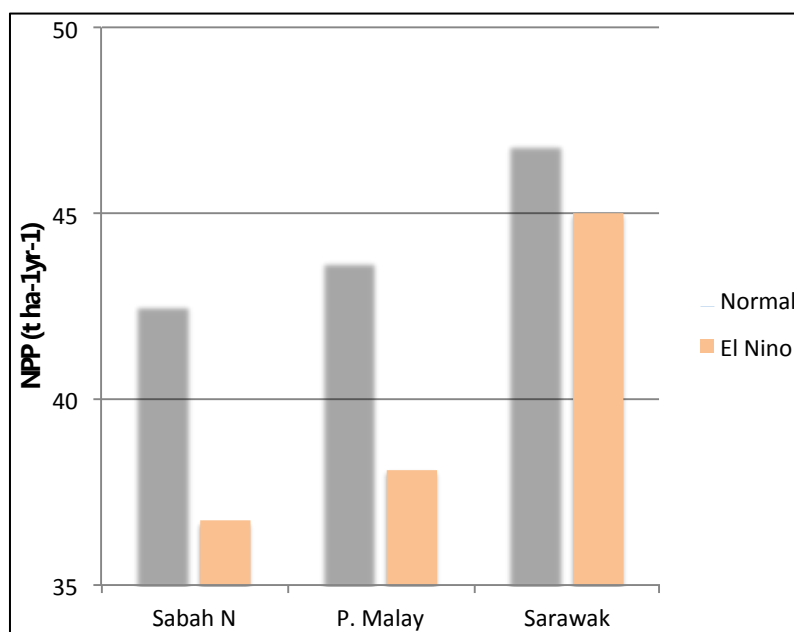


Figure 34. The simulated effect of increased frequency of extreme El Nino events on average

annual acacia plantation productivity (NPP).

Mangrove (Rhizophora apiculata) plantations in Malaysia

Site visits and establishment of field plots

Nov 2017

Dr. Seely met with colleagues from UPM to review progress on the development of an *Acacia mangium* calibration dataset based upon a literature review. We discussed the availability of biomass and growth data from a mangrove study being conducted by researchers from UPM. It was determined that these data would be suitable to prepare a FORECAST calibration dataset representative of the Matang mangrove forests on the west coast of peninsular Malaysia.

Model calibration and validation activities

The FORECAST calibration data set for *Rhizophora apiculata* was completed using regional data from an extensive literature review in combination with research plots established by UPM researchers in plantations within the Matang Mangrove Forest Reserve.

Model application

Mangrove ecosystems are critical areas from a habitat and biodiversity perspective. They provide a wide range of ecosystem services including protection from erosion, nurseries for many aquatic species, production of biomass for charcoal and timber, and storage of carbon particularly in soils. Forecast Climate was used to examine the potential impacts of climate change on ecosystem productivity and soil organic matter storage in *Rhizophora apiculata* plantations within the Matang Mangrove Forest Reserve.

A series of climate change simulations were conducted using 2 different climate change scenario and a normal climate scenario. The climate change scenarios included a representation of 2050, and 2080 climates under the RCP 8.5 scenario using combined output from a range of GCM models. In each scenario, the model was run for 90 years simulating 30 consecutive 30-yr rotations with clear-cut harvest.

Model results suggest that climate change will have a negative impact on mangrove productivity with declines in average annual NPP ranging from 5 to 15% below those observed under the normal climate scenario Figure 35. The main factor leading to the decline in productivity is the negative effect of increased temperatures on growth rates. Another, more troubling result was the effect of climate change on the loss of soil organic matter, which was predicted to decline by as much as 11% over the 90-year period (Figure 36). This loss of soil organic matter would lead to a significant release of CO₂ into the atmosphere adding to greenhouse gas (GHG)

effects.

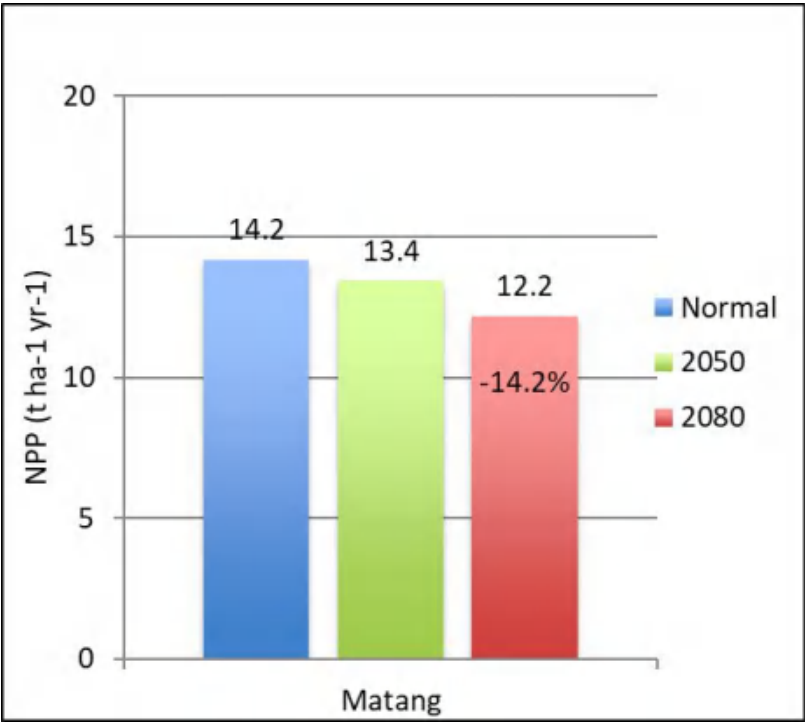


Figure 35. Projected impacts of climate change on average annual NPP in Rhizophora mangrove plantations in the Matang region of Malaysia.

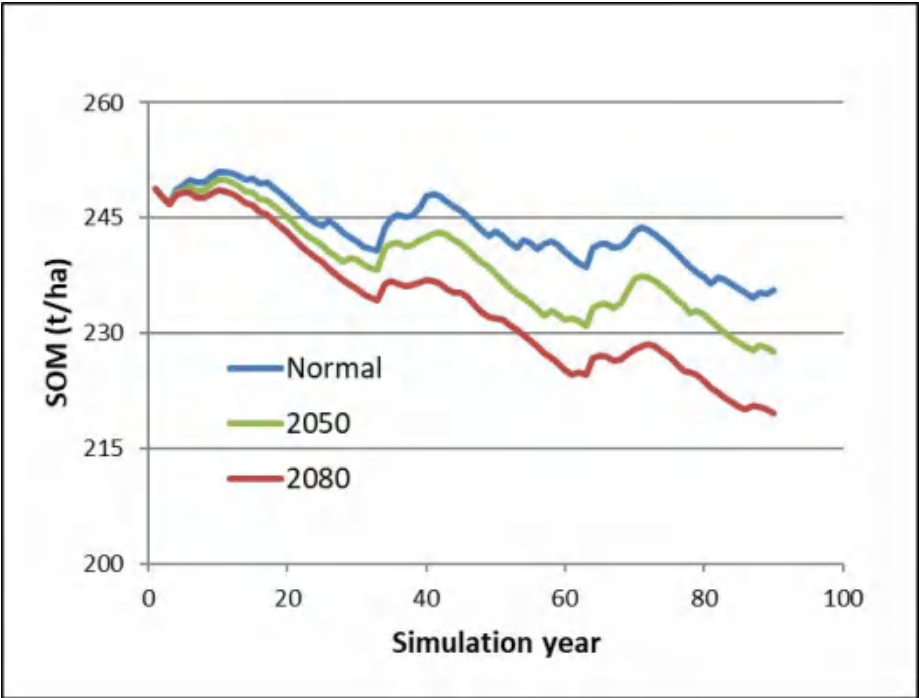


Figure 36. Projected impacts of climate change on soil organic matter (SOM) content in Rhizophora mangrove plantations in the Matang region of Malaysia.

Significance of Output 3

The primary objective of the work in this section of the project was to use the well-established forest ecosystem management model FORECAST Climate as a vehicle to facilitate policy discussions through a scientifically credible evaluation the potential response of regional forest ecosystems to alternative climate change scenarios and management options. The significance of the work conducted in support of Output 3 is twofold. First, the project provided an in-depth educational experience for the project participants with world-class experts in the field. Second, the output from the completed modelling work provided valuable insight in terms of how each of the target ecosystem types might respond to a changing climate.

From an educational perspective, project participants were allowed to take part in multiple workshops discussions about all aspects of the application of the FORECAST model, starting with data acquisition, processing, and finishing with actual experience in using the tool and understanding the output. In addition to the time spent in the classroom, participants were taken through the steps of establishing field plots, taking measurements and using the data to help calibrate the model. Each group was provided with the calibrated model for future use. By leading them through the detailed process of calibrating and applying this modelling tool, we provided information for local scientists and forest managers to help them understand the complex systems they are dealing with, as well as to provide opportunities for addressing policy and data gaps to formulate alternative adaptive forest management strategies in the context of climate change.

In addition to the educational aspects, the work conducted in support of Output 3 helped to inform an ongoing discussion about the potential impacts of climate change in local ecosystems. In all three systems where the tool was applied, the results revealed some of the potential implications and complications of forest resource management in the context of changing climates. While the tool clearly does not provide any definitive answers to specific management questions, its output provided valuable insight with respect to how different species and ecosystem types might respond to a changing climate. Such insights can help the project participants, all local scientists and forest managers, work with their regional peers and superiors to design meaning adaptation strategies.

Output 4: A web platform for data access and visualization for specific economies

A Google Maps based web tool has been developed (climateap.net) to provide a platform for data access and spatial visualization of model outputs. In order to increase the effectiveness of spatial visualization and data access, economy-specific web platforms have been developed for each of the five pilot economies. With the new platforms, climate data and forest ecosystem and/or species distributions can be accessed and visualized for individual economy.

Activity 4.1 Generation of maps:

For visualization of climate and species/ecosystems distributions, maps depicting the two basic climate variables (mean annual temperature and mean annual precipitation) have been generated for each of the five pilot economies.

Activity 4.2 Development of economy-specific web platforms:

The economy-specific web-based climate models have been built for China, Chinese Taipei, Malaysia, Laos, and Myanmar. These models have the complete functions of the ClimateAP version. Maps depicting mean annual temperature and mean annual precipitation have been overlaid onto the web platform, facilitating the spatial visualization of climatic conditions. As the web-based platform is an integration of spatial visualization and ClimateAP, the economy-specific web platform will have the same functions, but it will zoom in on the specific area for each economy, without overlays for other economies. More importantly, the Google Maps-based tool is now accessible and useable in China. All the economy-specific web platforms are hosted on at sub-domains of the domain for climateap.net. They can be accessed through ClimateAP as shown in Figure 37 and Figure 38, or alternatively using the following links:

ClimateChina: <http://climateap.net/china.aspx>

ClimateMalaysia: <http://climateap.net/malaysia.aspx>

ClimateMyanmar: <http://climateap.net/myanmar.aspx>

ClimateTaiwan: <http://climateap.net/taiwan.aspx>

ClimateLaos: <http://climateap.net/laos.aspx>

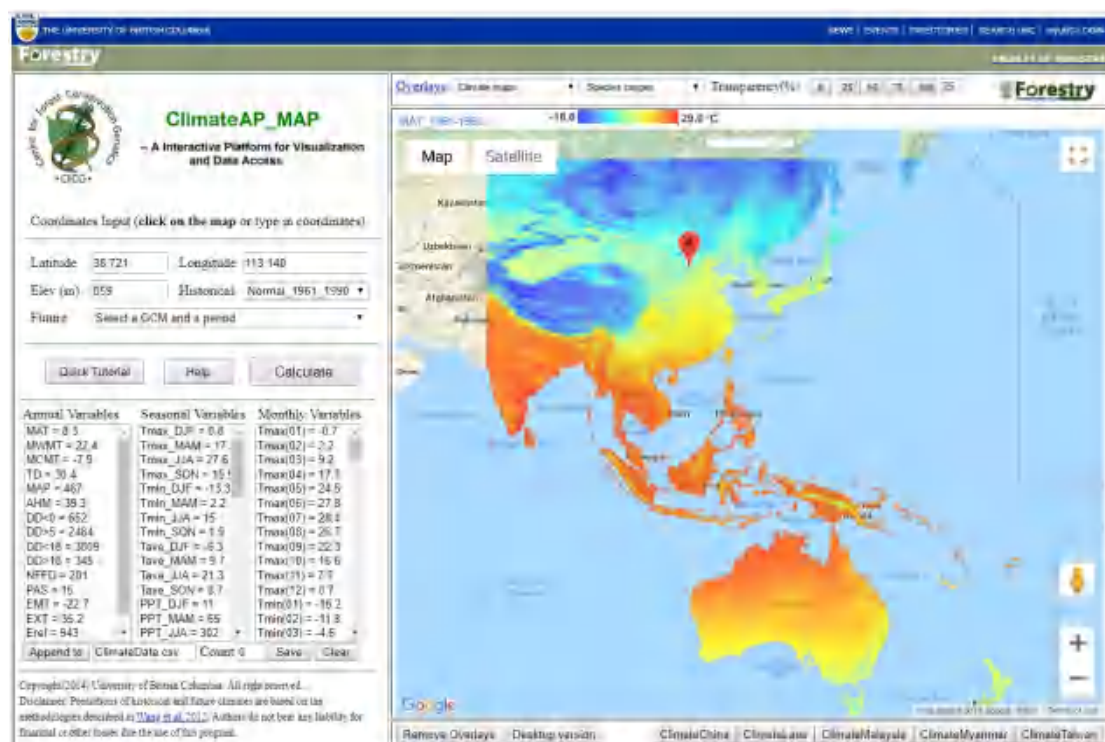


Figure 37. A screenshot showing the access to economy-specific web platform through the web-based ClimateAP.

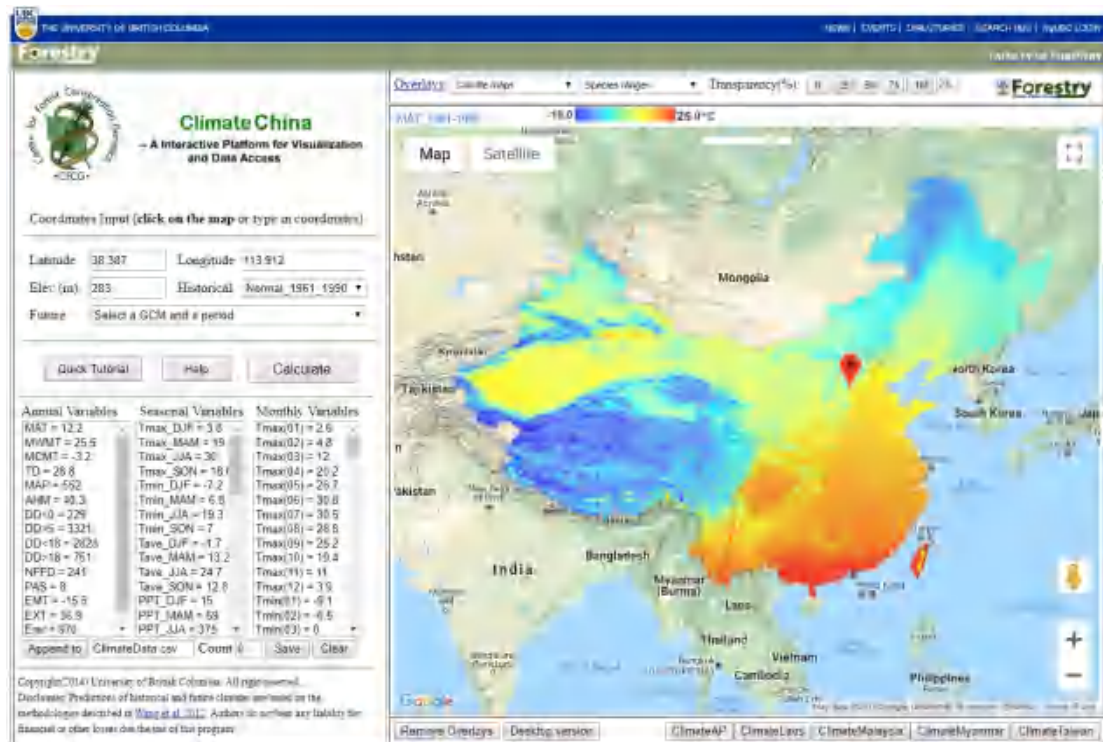


Figure 38. A screenshot of ClimateChina built on Google Maps (<http://climateap.net/china.aspx>) accessible in China.

Activity 4.3 Map uploading and web maintenance:

Maps of climate variables (MAT and MAP), forest tree species and forest ecotypes have been uploaded and integrated into the Google Maps through the Google Map API. Users can visualize the current species distributions and their future projections as illustrated in Figure 39, Figure 40, Figure 41 and Figure 42).

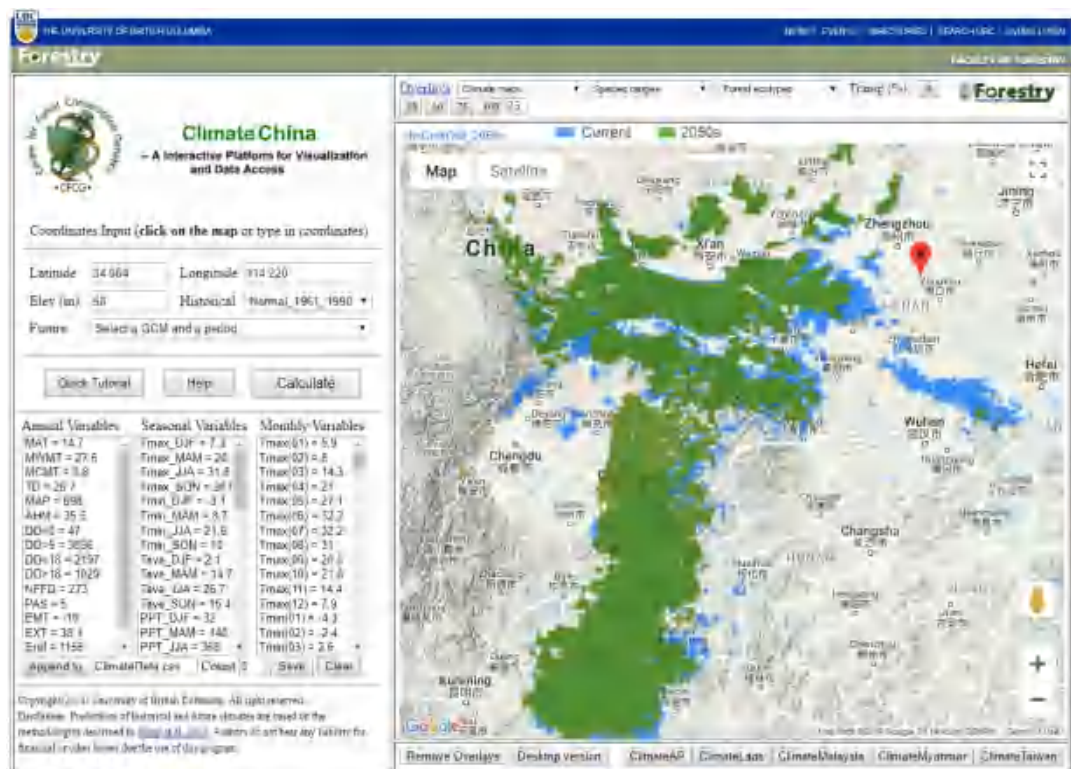


Figure 39. Screenshot showing the distributions of Chinese cork oak for current and 2050s.



Figure 40. Consensus projection of forest ecotypes in China for 2050s.

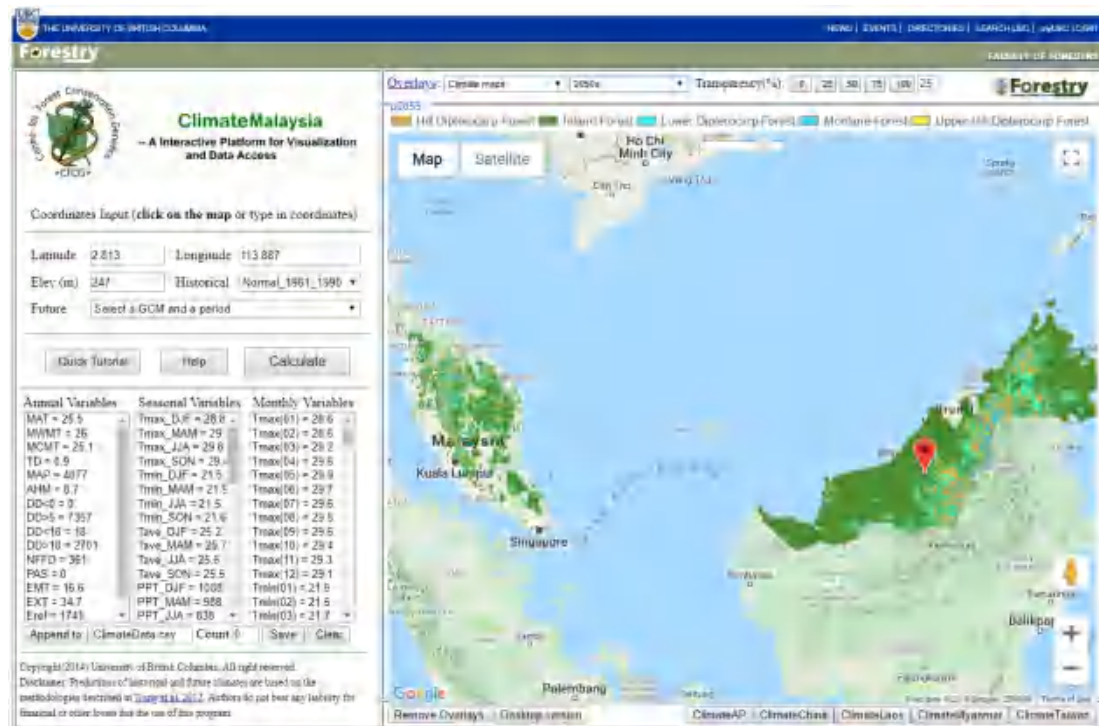


Figure 41. Consensus projection of forest ecotypes in Malaysia for 2050s.

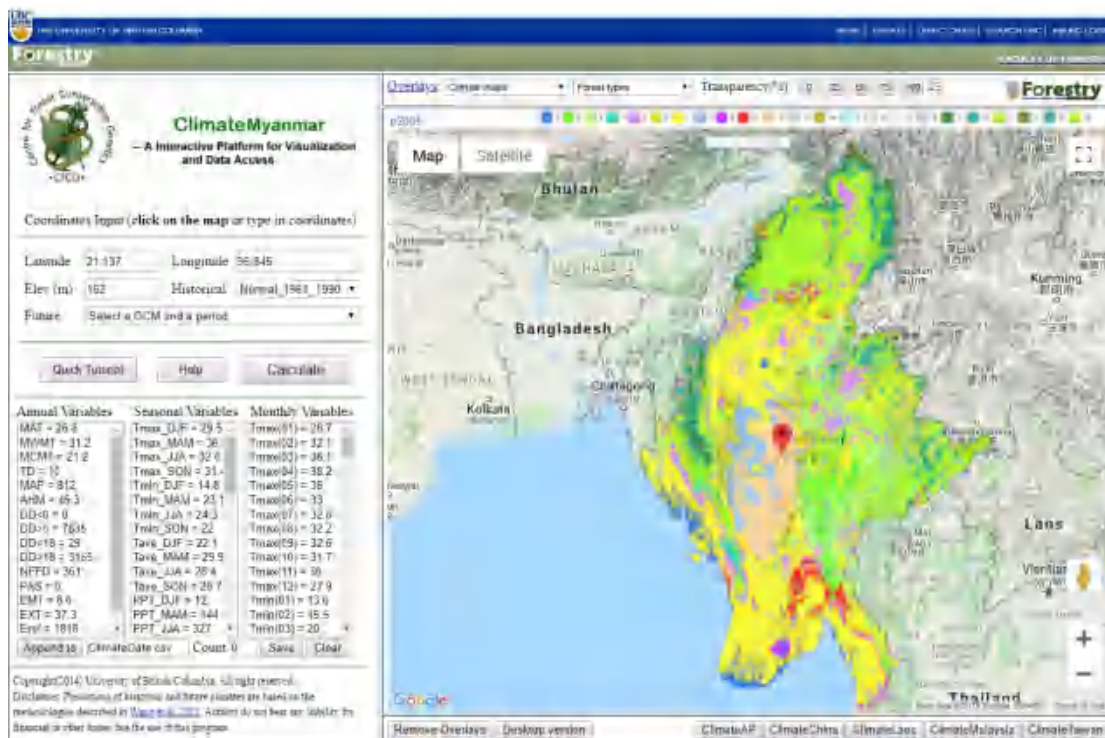


Figure 42. Consensus projection of forest ecotypes in Myanmar for 2050s.

Significance of the web platforms

We have developed a web platform based on the Google Map API to facilitate interactive accesses to the tools and information generated from this project by researchers, forest managers, policy makers, and stakeholders from the Asia Pacific and around the world. To improve the accessibility and make the platform locally

specific, we have developed a specific platform for each economy during the Phase II of this project. The economy-specific platform allows users to interactively access to the scale-free climate data simply by clicking on the Google map and to visualize the spatial projections of major climate variables and climate niche for a species and/or a forest ecotype. It can be used by researchers to conduct studies and by the public to visualize the impact of climate change on individual tree species and a forest ecotype for education purposes. However, it takes time for users to discover these powerful tools and we hope the tools are maintained, updated and improved.

Output 5: Networking and capacity building

Network building

Building network and capacity particularly related to adaptation of Asia-Pacific forest to changing climate is one of the key area of this project. To achieve this, we formed a diverse research team and advisory committee and active communication was maintained throughout the project period. This team and committee consist of scholars from Canada, China, Chinese Taipei, Myanmar and Malaysia representing ranges of organization from university professor/researcher, government policy makers as well as practitioners.

Throughout the entirety of the project, the network of scientists, policy makers, decision-makers, practitioners, and other stakeholders continuously expanded. We built upon the existing network established in the Phase I and extended gradually through organizing and participating various activities and events in the partner economies as well as in the Asia-Pacific region. For instance, project team members attended the World Forestry Congress (7-11 September 2015) in Durban, South Africa, where we invited experts across the globe including partner economies to highlight about the Phase I achievements and discussed how the Phase II would be built upon. Similarly, to educate about the Phase II climate change adaptation project among the stakeholders, an inception meeting was held over two days (February 23rd and 26th, 2016) as a side event at Asia-Pacific Forestry Week (APFW), hosted by the FAO in the Philippines. In this event, nine representatives from our partner economies and five representatives from UBC participated and discussed about upcoming activities, roles and responsibilities to implement the project efficiently and effectively. Similarly, our team members visited pilot sites and local partner's

institutions initially and set up local communication network, which were further expanded and enhanced throughout the project period.

Additionally, to expand our network and strengthen our relationship with researchers in the Asia-Pacific region, the University of British Columbia has been hosting 10-15 young research scientists each year from multiple universities in China (with varying lengths of stay, see detail in Annex D 3.1). These visiting scholars have been working with members of the research team and researching topics including forest management, remote sensing, forest inventory, climate change policy, scientific writing, soil science, and wood products processing. A series of field trips were also organized to familiarize the scholars with forest management in the context of British Columbia – including field trips to nurseries, orchards, woodlots, and the BC Ministry of Forests, Lands and Natural Resource Operations. Additionally, during 2018, various research scientists and professors representing different university of China and other university of Asia-Pacific actively participated in several programs such as forestry field school, forestry online course development workshop and several other courses (see details in Annex D 3.2). These exchange opportunities strengthened the relationship between the project team members and increased collaboration on research, bringing together knowledge from different backgrounds and forestry practices to yield the best possible results.

Significance of Network Building

A comprehensive network of scientists, policy makers, practitioners and stakeholders across the Asia-Pacific region and beyond allowed this project to contribute APFNet's goals of dissemination and exchange of knowledge and capacity building. The international collaboration with the local partners and the wider scientific community related to forest adaptation to climate change benefited the researchers, institutions, and economies involved and strengthened the project team, through sharing knowledge and skills with respect to tools, models, technology and management planning crucial for delving adaptive forest management policy in the context of changing climate.

Training workshop

Series of comprehensive training workshops were conducted to enhance capacity of government officials, local forest managers and researchers in terms of using tools and models developed in the project and applying them to the area of policymaking and implementation related to forestry adaption to climate change in the region. The first training workshop "Training Workshop on Modelling Climate and Forest Ecosystems in a Changing Climate" was held in Kunming, China from May 31st- June 7th, 2016. Twenty trainees attended this workshop from seven economies: Canada, China, Chinese Taipei, Japan, Laos, and Malaysia representing 10 institutions and learned about application of ClimateAP and ecological models to develop adaptive forest management strategies to address effect of climate change (See details in

Annex D4). The second training was conducted during site visits in the spring 2017 in Myanmar in which undergraduate level forestry students were trained on how to conduct accurate field measurements and data collection, including the use of industry-standard measurement instruments such as clinometer and GPS instrument. They were also educated how these data can be incorporated into models that contribute our understanding of effect of climate change on productivity of the forest, Teak in this case (See details in Annex D5). The third workshop was organized in the Forest Research Institute, Myanmar from November 13-16, 2017 (See details in Annex D6). Twenty-two researchers and officials representing Forest Research Institute and Forest Department of Myanmar were trained. A final and the fourth training was held in Guangdong, China from July 4-9, 2018. Sixty-two participants from seven economies (China, Myanmar, Malaysia, Thailand, Cambodia, Chinese Taipei and Canada) representing various organization Department of Forest, Research Institute, University as well as private organization participated in this training (See details in Annex D7). These workshops provided hands on training on using ClimateAP, climate niche model and FORECAST Climate model and their application to the forest managers, policy makers and researchers from Asia-Pacific Region for effectively and accurately conduct research and formulate adaptive forest management strategies against changing climate.

Significance of the training workshop

These hands on training workshops contributes to achieve APFNet goals of capacity building and knowledge sharing through enhancing the capacity of forest managers, policy makers and researchers from Asia-Pacific Region by training them to use ClimateAP and FORECAST Climate model and their application independently for effectively and accurately conduct research and formulate adaptive forest management strategies against changing climate. Thus, this workshop allowed the outputs and technological advances made by this project to become available to the research community in the Asia-Pacific region. Additionally, two comprehensive training handbooks were published and distributed among the trainee which contains background readings and application of tools/models and available upon the request for future use.

Seminars

Several research seminars were organized at universities, research institutions and government organization particularly but not limited to in Asia-Pacific region to extend our network while at the same time sharing the project tools and its application to address the effect of climate change on the forest. These seminars typically held for half a day, when project team members presented series of presentations targeted towards the project's findings, the tools that were available and how to use them, and their application to understand the impacts of climate change on the forests with example from the pilot sites and beyond. Presenters further extended discussion towards effect of climate change on forestry, including job security, forest productivity, fire risk, ecosystem services and resilience, and

carbon storage with focus on local region, being relevant to the adaptation of the local ecosystems coordination with the local host. These seminars were attended by range of audience ranges from 30-80 individuals.

During the project period, our team members successfully organized more than 18 research seminars located in various locations: Kyoto University, Tokyo University and Kyushu University in Japan; National Ilan University, National Taiwan University and National Taiwan Normal University, Taiwan Forestry Research University, Chinese Taipei; University in Philippines Los Banos, Bangor University, Indonesia; Department of Forest and Forest Research Institute, Myanmar and Viet Nam National University of Forestry in Vietnam; University of British Columbia Canada. For wider outreach of the project outcomes, our management team organized several seminar at South American University, namely Universidad Nacional Agraria La Molina and Universidad Nacional Del Centro Del in Peru; Universidad de Chile, Pontificia Universidad Católica de Chile and Universidad Austral de Chile in Chile.

Significance of Seminar

These seminars enhanced dissemination of knowledge, project outcomes, available tools and their application addressing impact of climate change on forest and society but also our team members had opportunity to exchange ideas and learn from the host organizations about their ongoing researches on the topic that benefited to improve our research. Moreover, these research seminars improve project's network, which helps to achieve project's outcomes and promote long lasting regional collaborations on climate change research.

International conferences and peer reviewed publications

The project team members organized and actively participated in the at least eleven international conferences in various parts of Asia-Pacific regions to share outcomes, tools and models developed by the project. Team member organized a side event "Innovative Tools for sustainable forest management under climate change" at Asia-Pacific Forestry Week (APFW), hosted by the FAO in the Philippines (February 26th, 2016, see detail Annex 8.2). Similarly, Phase II Inception Workshop was organized during this conference to ensure that all the local partners of the phase II fully understand the project's goals and objectives and their roles and responsibilities. Five representatives from UBC and nine representatives from our partner economies attended the meeting (See details in Annex 8.3). Project team members also attended and organized a two-hour side session entitled "Tackling climate change adaptation in tropical and subtropical forests" in the 124th annual IUFRO Asia-Oceania Conference in Beijing, China (October 22-24, 2016). In this session, scholars from Australia, Canada, China, Chinese Taipei (local partner), Nepal, and Malaysia (local partner) presented six oral presentations and attended by over 30 participants followed by discussion on the adaptive forest management through application of innovative tools and models to tackle climate change issues in tropical and sub-tropical forests in Asia-Pacific (See details in Annex 8.3). A parallel session

entitled “Bamboo Forest Ecology and Management in Changing Climate” was organized in the Global Bamboo and Rattan Congress from June 25-27, 2018, Beijing, China. In this session, ten papers related to bamboo and sustainable management in the context of changing climate were presented, which attracted more than 30 attendees including academics and industry professionals, whose work/research pertains to the bamboo ecology and climate change in Asia-Pacific region (See details in Annex 8.4). Additionally, our team member, Dr. Guangyu Wang organized a session entitled “Impacts of climate change and air pollution on forest ecosystems: Impacts, adaptation and management options” in 4th International Congress on Planted Forests Beijing China (23rd to 27th October 2018). The main objective of this session was to integrate climate change and air pollution impact on forest ecosystem. Our team members also participated in the several international conferences (Table 2) and orally presented and discussed about the outcomes of the project, tools, models and their application.

Table 2: List of international conference participated and organized during project duration.

SN	Name of conference	Mode of participation	Date	Location
1	World Forestry Congress	A session organized /Oral presentation	7-11 September 2015	Durban, South Africa
2	Asia-Pacific Forestry Week	A session organized/Oral presentation	23-26 February 2016	Philippines
3	IUFRO Asia-Oceania	A session organized/Oral presentation	22-24 October 2016	Beijing, China
4	XIX Common Wealth Forestry	Oral presentation	3-5 April 2017	Dehradun, India
5	IUFRO 125th Anniversary Congress	Oral presentation	18-22 September 2017	Freiburg, Germany
6	Tenth International Conference on Climate Change: Impacts and Responses	Oral presentation	20-21 April 2018	University of California at Berkeley, USA
7	International Conference: Promotion of Agroforestry for Rural Income Generation, Climate Change Mitigation and Adaptation	Oral presentation	27-29 April 2018	Kathmandu, Nepal

8	Global Bamboo and Rattan Congress	A session organized/Oral presentation	June 25-27, 2018	Beijing, China
9	International Forum on Dryland Ecological restoration and desertification	A forum organized/ oral presentation	29-Jun-18	Xinjiang, China
10	Forest Rehabilitation in the Asia-Pacific Region	Oral presentation	26 March, 2018	Beijing, China
11	International Congress on Planted Forests	A session organized/Oral presentation	23-27 October, 2018	Beijing, China

To share the knowledge and outcomes of the project to wider audiences, our team members successfully published six peer review papers related to various aspect of climate change adaptation to Asia-Pacific forests as follows (See Annex 9 for published papers) and at least five papers are under preparation and under review.

Lists of published papers

- (1) ClimateAP-an application for dynamic local downscaling to historical and future climate data in Asia-Pacific published in *Frontiers of Agriculture Science and Engineering* <https://doi.org/10.15302/J-FASE-2017172>
- (2) Simulating the impact of climate change on the Growth of Chinese Fir Plantations in Fujian Province, China published in *New Zealand Journal of Forestry Science* (2017) 47:20 DOI 10.1186/s40490-017-0102-6
- (3) Spatial modelling of fire drivers in urban-forest ecosystems in China published in *Forests* 2017, 8, 180; doi:10.3390/f8060180
- (4) Understanding fire drivers and relative impacts in different Chinese forest ecosystems published in *Science of the Total Environment* 2017 411-425 <http://dx.doi.org/10.1016/j.scitotenv.2017.06.219>
- (5) A dynamic downscaling approach to generate scale-free regional climate data in Taiwan in *TAIWANIA* 2018 63 (3) 251-266 DOI: 10.6165/tai.2018.63.251
- (6) Climate change impacts and forest adaptation in the Asia-Pacific region: from regional experts' perspectives in *Journal of Forestry Research* 2019 30 (1) 277-293

List of papers under preparation and review

- (1) Impact of climate change on the distribution of Teak within its natural distribution range using Climate Niche Analysis
- (2) Impact of changes in the frequency and intensity of drought events on long-term Teak productivity and health in Yedaeshe Township in Myanmar
- (3) Evaluate future ecosystem services from Teak plantations under climate change in Yedaeshe Township in Myanmar

- (4) Development of forest ecosystem classifications using ClimateAP and Random Forest in Taiwan
- (5) Climate niche models for forest ecosystems and their future projections in China
- (6) *Acacia mangium* plantations feasibility in Malaysia under climate change

Similarly, two comprehensive handbooks were also published (one in 2016 and second one in 2018, see Annex 10 for published handbooks) as training manuals and distributed during the trainings. These manuals contained background readings and application of models and tools developed in the project served as an important guide for trainings.

Significance of international conference and publications

Organization and participation in the international conferences contributed to achieve sharing knowledge, tools and models developed in the project as well as building networks among wider audiences particularly in Asia Pacific and globally. Publishing peer review papers not only helps to share and promote the project outcomes, tools and models but also confirm the scientific credibility of the project outcomes, tools and models.

4.2 Project Impacts

The Adaptation of Asia-Pacific Forests to Climate Change II phase has produced extensive scientific knowledge and practice on present and future climate impacts on the tree species and ecosystems in sub-tropical and tropical region at two scales (local and national) through advancing state of the art the technology and capacity building required to mitigate and adapt forests to climate change in the Asia-Pacific region.

The project addressed the lack of publicly available high-resolution climate data in the region to generate accurate prediction of climate change impacts on the region's forest. ClimateAP, a tool developed during this project can generate historical and future monthly climate data for specific point locations (i.e., scale-free) in the Asia Pacific. Such scale free data is critical, as the focus of climate change studies has been shifting from global and regional scales towards local applications. Additionally, this tool is user-friendly and does not require GIS or other sophisticated computing skills as other available lower resolution climate data does. Thus, the high accuracy and quality of the data produced by ClimateAP will allow forest managers, resource planners, and policy developers to generate more targeted and adaptive management strategies, and more successful long-term forestry policy. Currently, there are 170 subscribers of ClimateAP and anticipated to increase looking at the previous trend as its growing popular in the region.

The project also addressed the lack of models for important tree species and forest ecosystem in the region essential to understand effect of changing climate on the

distribution and productivity in the region. Climate niche model for 10 important forest tree species provide the a solid scientific basis for assessing the impact of climate change on their distribution and for developing adaptive strategies including assisted migration for the major forest tree species in the region. While climate niche models for forest ecosystem provide an alternative to modeling individual species especially when the species occurrence data for individual species are not available, which is often the case in the region. Moreover, from our experience in North America, these models can be used for developing climate-based species selection (CBSS) and climate-based seed transfer (CBST) tools. This is particularly very relevant to integrate the effect of changing climate in the restoration activities that has been taking place in the region.

Pilot sites based process-based model such as FORECAST Climate enabled the development of adaptive strategies and potential tradeoff for climate change through the integration of model prediction with local forest management practices in Teak/bamboo plantation forest in Myanmar, *Acacia mangium* plantation in Saba region of Borneo and *Rhizophora apiculata* in Matang mangrove reserve. The output from the completed modelling work provided valuable insight in terms of how each of the target ecosystem types might respond to a changing climate. Such information from generated by FORECAST Climate provide a decision-support tool to forest managers to develop strategies that consider both the environmental and economic costs, which will help forest managers to achieve their management targets. Overall, these models will lead to environmental, economic, and social benefits, through improved forestry policies, and adaptive management strategies at the regional and local scale.

The project increased scientific capacity among the researchers, policy makers and forest managers particularly from the partner economies as well as from Asia-Pacific region through the workshops, training programs, seminars, and network building. Sharing tools and models developed during the project enhanced research capability of the stakeholders that has further advanced the research in the field of climate change impact. For instance, our partner from the Chinese Taipei has been developed a R version of ClimateAP for Chinese Taipei, *clim.regression*, to take the use of more locally available climate data and applied these data for predicting effect of climate change on forest ecosystem in Chinese Taipei. Transfer of knowledge and skills targeting participant's local region made sharing knowledge generated during the project much more impactful so that the forest managers, government officials, and researchers, are then able to use the tools and models independently to make decisions that are the most appropriate for their unique situation. Furthermore, these components of network building have improved regionally specific knowledge of climate change impacts on forests to people in a broad range of professions, which should improve future research and adaptive capacity throughout the Asia-Pacific.

This project has significantly contributed to advance science and technology related to climate change adaptation of Asia-Pacific forests, as well as management and policy development through its publications in peer review journals, reports, training books as well as participation/organization of conferences and seminars. The project's published work includes six peer-reviewed papers (several under preparations/under reviews), several reports and two books (handbooks on training workshops) along with participation/organization of several conferences and workshops. These publications and activities improve the development of sustainable forest management under the climate change context, help to make informed policy and management decisions in the Asia-Pacific. The work produced by this project and the subsequent work in the future will lead to improve research and strategy development regarding climate change mitigation and adaptation, which will allow continued environmental, social, and economic prosperity throughout the region.

This project has produced extensive scientific knowledge on tree species, ecosystems, and current and future climate impacts in the Asia-Pacific region, as well as increased scientific capacity through training relevant stakeholders on cutting-edge models and tools for national and local predicted climate change scenarios, forest adaptation strategies, and ecosystem dynamics. This work will facilitate and promote the study of climate change in the region, allowing the identified lack in science, technology, and policy with respect to adapting forests to climate change to continue to be addressed. This will ensure continued social, economic, and environmental benefits into the future, through the maintenance of forestry dependent industry, jobs, and communities, and continued gains from the ecosystem and cultural services provided by forest ecosystems.

4.3 Sustainability

Sustainability is a significant feature of this project so that the benefits of the project will continue well after this project. The tools and models developed in the project are accessible online. ClimateAP is available for download as a desktop version and is accessible online as a Google Maps based version. Similarly, economic specific projections map for species and forest ecosystem ranges in current and future climates are also available for spatial visualization and download. These tools and outputs will still be available to users, including policy makers and practitioners in the region that will provide high-resolution climate data as well as range map of species and forest ecosystem under different climate, essential for making policy and adaptive forest management strategies in the region. The project enriched the knowledge base on forestry adaptation to climate change for this region and available for future use. The project web site will be maintained and promoted as a knowledge hub through which, interested stakeholders will be able to access large number of peer-reviewed journal publications, technical reports and other relevant

educational materials that have been produced by the project. The handbooks that were developed for the Kunming and Guangdong training workshop is also publicly available, and contains detailed information regarding the development, application and relevance of models and tools related to sustainable forest management. This handbook can be used as great resources for capacity building in the region. Additionally, there will be continual opportunities for those involved in the project to deliver training to stakeholders, policy makers, and forest managers regarding the tools developed from the project. Most importantly, the capacity building carried out through the project and the partnership with local stakeholders have created a strong ownership of the process and recognition of what is in their own interest that would strengthen the sustainability of the results in the partner economies.

4.4 Future development

“Phase I and II of the project have developed very useful tools that can be utilized and accessed by a range of users to inform decision-making regarding forest adaptation to climate change and possible response options/trade-offs” (Mid-term Report by Gabrielle Kissinger, 2017). The tools include: 1) ClimateAP; 2) Climate niche models and their projections for forest tree species and forest types; 3) Process-based ecological models; and 4) Web-based spatial-visualization and data-access platform. These tools have laid out a foundation to facilitate and promote climate change adaptation related research and applications at regional and local scales.

However, “Without the necessary long-term funding to keep up the maintenance of the system and its more targeted application in target economies, the risk is that the tools sit on the shelf and the investment value is not realized to the fullest degree possible. **Both UBC and APFNet are encouraged to consider how a long-term funding mechanism can be established**” (Mid-term Report by Gabrielle Kissinger, 2017). This is particularly true, as the field of climate change adaptation is very active, and the data and technologies supporting the tools are updated at a rapid pace. For example, the climate data supporting ClimateAP is updated annually. The new version of GCMs will become available in one or two years. The tools will also need to adapt new technologies to make them more useful. This is particularly true for ClimateAP, climate niche models and the web-based platform.

4.4.1 ClimateAP

ClimateAP generates scale-free climate data for specific locations. This unique feature makes it stand out from all other climate models that use pixel means instead. The scale-free climate data substantially improve the accuracy of ecological models at both regional and local scales. ClimateAP has gained 170 subscribers, which is relatively small in comparison to ClimateNA (>1500) as it is largely undiscovered. This number is expected to increase exponentially with time if the tool is well maintained.

The following are the areas for future development and maintenance.

- **Developing a data portal to host gridded climate data.** ClimateAP can generate climate data for specific locations to build niche-based or process-based models. Gridded raster data are also needed for ecological models to generate spatial projections. The data portal can provide such data for historical and future periods. The climate data portal develop for ClimateNA has over 20,000 downloads per year, suggesting the popularity of such a data portal.
- **Adding a map-to-maps function to allow ClimateAP to read DEM maps and output climate maps directly.** To generate climate maps using current version of ClimateAP is not a straightforward task. Users need to generate an input dataset from a digital elevation model (DEM) file to run ClimateAP and then to convert the CSV output files into ArcGIS maps, which are challenging for many users. The map-to-maps function will be a significant step in the improvement of this tool.
- **Adding paleo climate data,** including Last Glacial Maximum (LGM) (21,000 year ago), MidHolocene (6,000 year ago) and the last 1,000 year. Paleo climate data are useful to validate ecological models and to understand the long-term evolutionary process driven by climate.
- **Essential maintenance to keep its historical (1901 -) and the GCM (CMIP6) climate data updated.** To keep the tool updated is critical for the tool to be useful with time. During the project period, historical climate data have been updated to the tool every year. This work should be continued in the future. For future climate projections, ClimateAP has included GCMs from the CMIP5 (IPCC 5th Report). The CMIP6 is to be released soon and ClimateAP should be updated with the CMIP6 on time.

4.4.2 Climate niche models

Climate niche models are widely used to provide scientific basis for developing forest adaptive strategies. However, this approach is also criticized due to low accuracy and misinterpretations of such models. The combination of the scale-free climate data from ClimateAP and our comprehensive expertise make our climate niche models stood out for their credibility. For example, a climate niche model built for Douglas-fir using gridded climate data from WorldClim completely failed to predict the areas suitable for this species in Europe (Boiffin et al. 2017), while our scale-free-climate-based niche model can predict it at a very high accuracy (nearly 90%). Climate niche models for forest ecosystems in Asia Pacific can serve as a framework to incorporate individual species for assessing the impact of climate change and for developing adaptive strategies.

- **Improving ecosystem classifications.** Current ecosystem classifications in the Asia Pacific region are coarse and they are generated mostly based on vegetation types, political boundaries and approximation. Thus, climate

gradients are poorly reflected in the classifications. Our model predictions have improved them to some extent through machine-learning process. However, the ecosystem classifications can be further improved through a combination of using remote-sensing vegetation data, scale-free climate data from ClimateAP and an intensified machine-learning process. The improved systems can serve as a framework for conservation and adaptation to climate change in the region.

- **Associating species to the ecosystems.** Ecological models have been built and used to predict for the future periods. Associating individual species to the ecosystem framework (just like putting passengers into a train) is a critical step to put the systems in action for climate change adaptation. This is particularly important for tropical and sub-tropical regions where the number of species is large and the modelling for individual species is difficult.
- **Ranking of species selection for future climates.** We have built climate niche models for 15 major tree species in the region (Phase I and Phase II). It is important to build such a model for the major species if occurrence data are available (e.g., in China) or to associate them to the ecosystem frameworks if species occurrence data are lacking. Then, we will be able to provide information to rank species climatic suitability for afforestation/reforestation for a given planting site in future climates. We can also evaluate species richness and identify potential refugia in future climates, which is important for genetic conservation of forest tree species in the region.

4.4.3 Map-based visualization tool

The web-based ClimateAP is a Google Map-based platform that allows users to access climate data simply by clicking on the map. It also facilitates visualization of spatial distributions of climate variables and ecological niches for forest tree species and forest ecotypes. This tool brings the output of scientific research to a wide range of users including policy makers and forest resource managers. To maintain the tool updated and more powerful, we need to:

- **Keep the platform updated.** The web-based climate data need to be updated as for the desktop version of ClimateAP. Meanwhile, model projections for ecosystem and species generated from the above-mentioned studies will also need to be integrated into the map-based tool for easy access.
- **Migrate the Google Map based system to ArcGIS online system.** The current Google map-based system is good for providing coordinates and elevation to feed ClimateAP to generate climate data for any specific location. However, the ArcGIS online system can make the spatial layers for climate variables and species distributions truly interactive and more professional. This migration will bring the web-based platform to a new level and considerably improve the usefulness of this too.

4.4.4 Reach out

The sister program of ClimateAP, called ClimateNA, went through a long way to reach out for a broad audience. After recognition of the advantage of the scale-free climate data, more and more users have switched from using WorldClim and PRISM climate models to ClimateNA. There are now over 1500 subscribers and over 1700 citations for ClimateNA. ClimateAP is just at the starting period and has already gain over 170 subscribers during last two years. We need more effort to reach out for the tool to serve more users by organizing workshops, attending conferences and local visits to help users to use the tools.

5. CONCLUSION, LESSONS LEARNED AND RECOMMENDATIONS

5.1 Conclusion

The project successfully achieved the outputs/objectives and fully completed all the activities within the allocated time. User friendly and scale free high-resolution data generation tools have developed and improved. Such scale free data is critical, as the focus of climate change studies has been shifting from global and regional scales towards local applications. Tools such as this with high accuracy and quality climate data will allow forest managers, resource planners, and policy developers to generate more targeted and adaptive management strategies, and more successful long-term forestry policy while facilitate and improve the accuracy of future climate research in the region. Climate niche model for important forest tree species and ecosystem provide the a solid scientific basis for assessing the impact of climate change on their distribution and for developing adaptive strategies including assisted migration for the major forest tree species in the region. While these climate niche models provide effect of climate change on species and ecosystem distribution in large scale (national), pilot sites based FORECAST Climate model provide effect of climate change on the productivity of important tree species and target ecosystem under different management scenarios at local scale. Thus, these models provided valuable insight in terms of how each of the target ecosystem types might respond to a changing climate, thus will enable the development of adaptive strategies and potential tradeoff for climate change through the integration of model prediction with local forest management practices. The project further increased scientific capacity among the researchers, policy makers and forest managers particularly from the partner economies as well as from Asia-Pacific region through the workshops, training programs, seminars, and network building. Moreover, this project has significantly contributed to advance science and technology related to climate change adaptation of Asia-Pacific forests, as well as management and policy development through its publications in peer review journals, reports, handbooks as well as participation/organization of conferences and seminars.

The models, tools and research outcomes from this project are crucial for understanding the impacts of climate change on Asia-Pacific forests, and developing

successful strategies at different scale to ensure the forest remain environmentally and economically viable, and continue to provide social and ecosystem services. Our project team has secured remarkable achievement and exceeding our objectives, and have significantly contributed to capacity building, the science and application in forestry adaptation to climate change in the region.

5.2 Lessons learned and recommendations

The management and research team learned valuable lessons throughout the project duration. In the research front, we have learnt that the impact of climate change on the species and ecosystem of Asia Pacific will have diverse effect as shown by climate niche models. Some species expand their distribution while other species contract their range in response to future climate. Similarly, our pilot sites research highlighted the importance of including other competitive species into account while modeling. Thus, models need to be tailored to the specific issues, relationships, and species for the location of interest to ensure that they are accurate and useful, and needed to be adapted to the local situation. Additionally, we also learned about challenges of acquiring latest data that are required for model building, validation and simulation. However, these latest data were collected by the concerned authority of the government, but are not openly available to the scientific community. To address this, working and collaborating with those authorities is essential as well as keep emphasizing the benefits of open access to data and results. Involving decision makers would allow the developed research and management objectives to be shared and increased ownership of the project as well as improve government decision-making capacity. Though, such type of participation was done in this project but the management team felt more should have been done.

Similarly, we have also learned that in our more developing partner economies, most researchers are struggling to acquire sufficient financial resources to conduct research activities. Appropriate monetary compensation should be provided to benefit the organization and researchers in the field for their time and contribution, while also benefitting participating individuals' subsequent skillsets. It has become increasingly clear that the project budget allotment aimed to fund partner research is too low, as our developing partner countries are in severe lack of any preliminary resources and supplies. Hence, we must provide research partners with adequate supplies and monetary funds to perform such tasks. Additionally, we also noticed diverse capacity among the researchers in partner economies, and is generally low among the more developing partner. In this respect, other important lesson that we have learned is that investment of more resources for capacity building for those partners early in the project, who has less capacity in order to achieve anticipated project outputs so that they will be able to use and implement the project outcomes independently and efficiently earlier and would contribute greatly for achieving project objectives. Moreover, we have learned that frequent direct in person contact

with local project partner is very important for executing project efficiently and successfully as such direct communication enhances personal relationship, trust building, and also help to avoid differences in working culture. Consequently, we get more support, personal trust and feedback on timely manner from our project partners. In doing so, we also know their capacity and what they can support us while at the same time; we also know what they expect from us.

Other important lesson learnt was due consideration must be paid while selecting partner and site in case of pilot site study. Selecting good and committed partner is essential for efficient implementation of the project activities, thus successful achievement of the project outcomes. Similarly, selection of secured pilot sites (in terms of forest) should be also very important so that there is no illegal felling of the trees required for the repeated measurements.

We also learned that through phase I and II of the project with the support from APFNet, we have developed state of the art models and tools that can be utilized and accessed by a range of users to inform decision-making regarding forest adaptation on temperate, sub-tropical and tropical forest of Asia-Pacific region to climate change and develop possible response options/trade-offs. Therefore, these models and tools should be maintained and updated regularly to get their full uptake. While we will maintain the webpage and these models and tools, there should be a long-term funding mechanism to update, promote and provide training of these tools and models for their long-term use by wider users in Asia-Pacific region.

Annexes

- A. Project Implementation status
- B. Financial statement(including balance sheet, source and use of Funds statement, and expenditure details) by both category and activity
- C. Project audit report
- D. Project outputs, such as technical reports, key project documents (workshops, field visits, technical visits, trainings etc.), publications, brochures, webpages, etc.
- E. 2-3 Feature stories from the project for promotion
- F. Photos, media cliffs and other materials used/available for project outreach

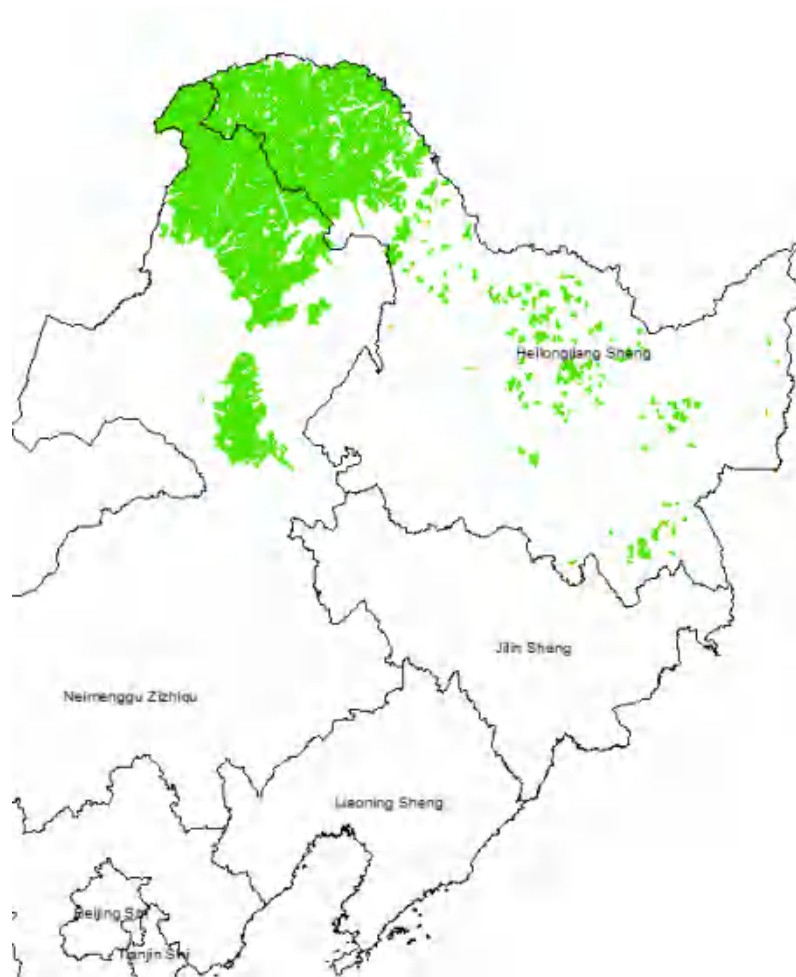
Annex A Implementation status (scheduled versus actual)

Project Objective/Outputs/Activities (in line with PD/AWPs)	Indicators (in line with PD/AWPs)	Baseline of activities	Progress made (%completion of activities and degree of output/objective achievement)	Appraisal time	Actual time
Objective 1	To enable ClimateAP to generate monthly climate data for 2011-2100		The objective has been achieved		
Output 1	ClimateAP with future annual climate projections		Software package, ClimateAP v2.0 has been released, 100%		
Output 2	Assessments of the impact of climate change on forest ecosystems, key species and vegetation types		Niche based models for 10 key species and forest ecosystems in four economies and projections, 100%		
Output 3	Evaluations of adaptive forest ecosystem		FORECASTClimate model calibrated, validated and simulated for Teak		

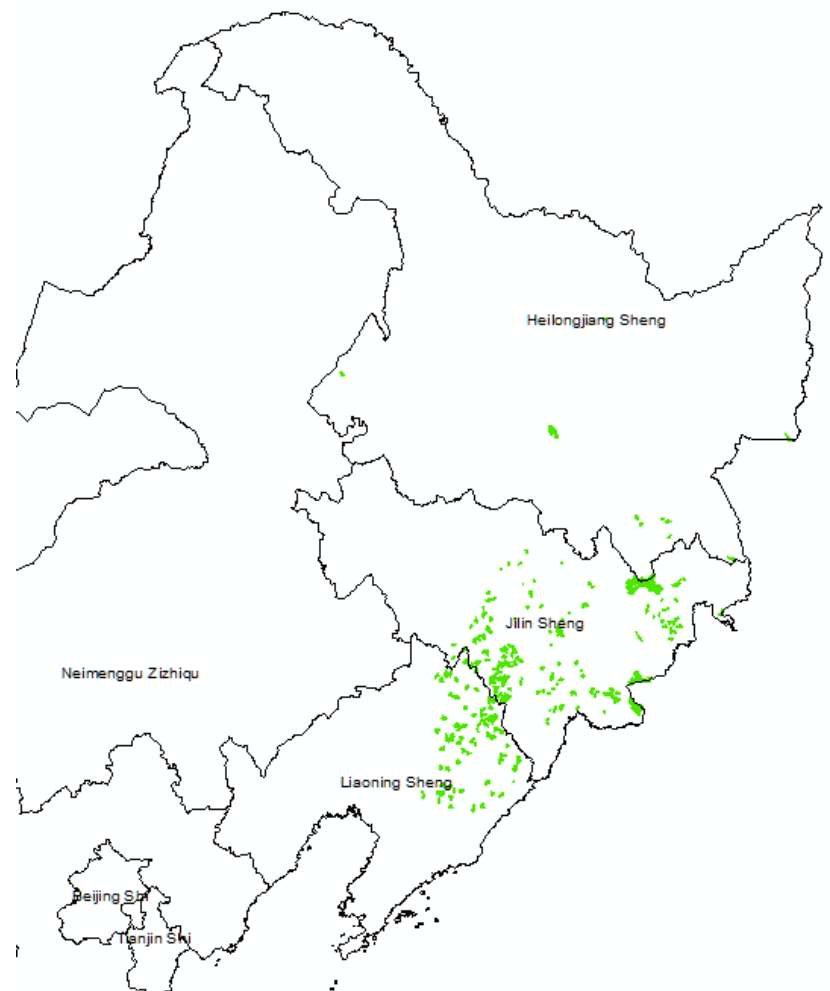
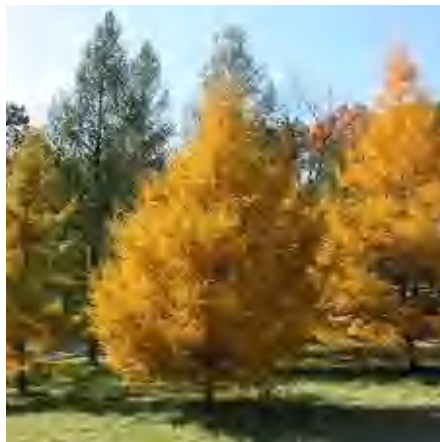
	management strategies through model integration, development of indicators and trade-off analysis		(<i>Tenctona grandis</i>) / Bamboo plantations in the Bagoyoma region in south central Myanmar; <i>Acacia</i> (<i>Acacia mangium</i>) plantations in peninsular Malaysia, and the Sabah and Sarawak regions in Borneo and Mangrove (<i>Rhizophora apiculata</i>) plantations in the Matang region of peninsular Malaysia; 100%		
Output 4	A web platform for data access and visualization for specific economies		Development of four economy-specific web platforms for data access and visualization of climate, climate niche models and projection for key species and ecosystems; 100%		
Output 5	Networking and capacity building		Networking, capacity building in local partner and Asia-Pacific region and peer review publications, 100%		

Annex D1: Species distribution data for all species

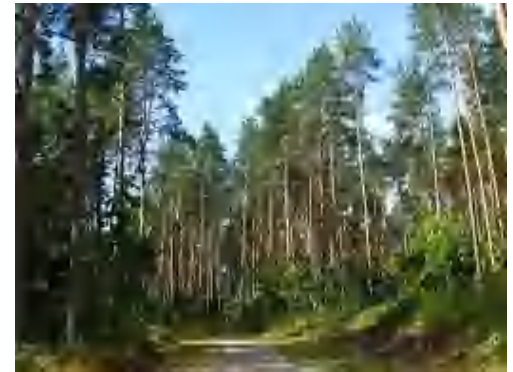
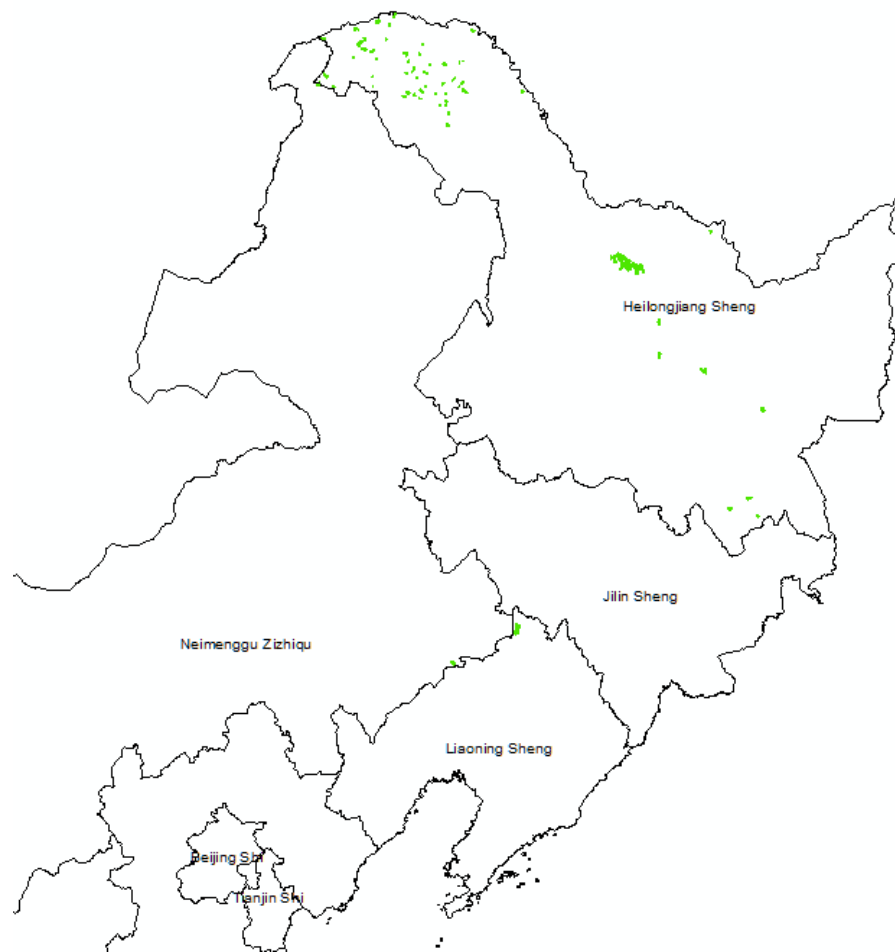
Larix gmelinii



Larix olgensis var. *changpaiensis*

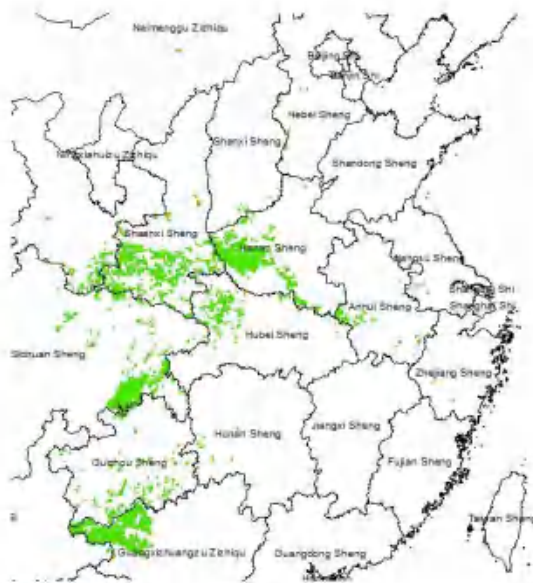


Pinus sylvestris var. *mongolica*



Annex D1: Species distribution data for all species

Quercus variabilis



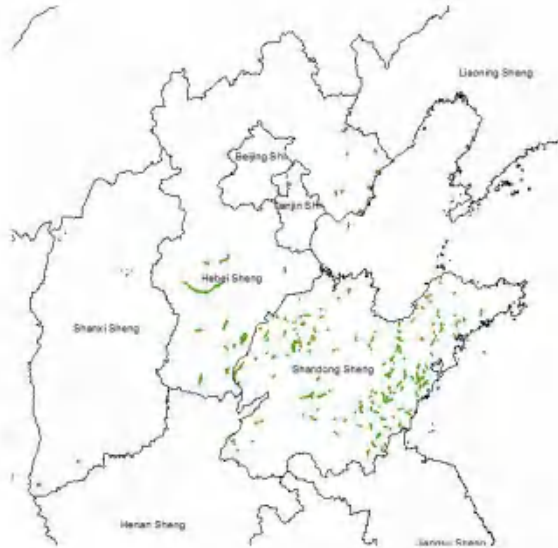
Annex D1: Species distribution data for all species

Robinia pseudoacacia



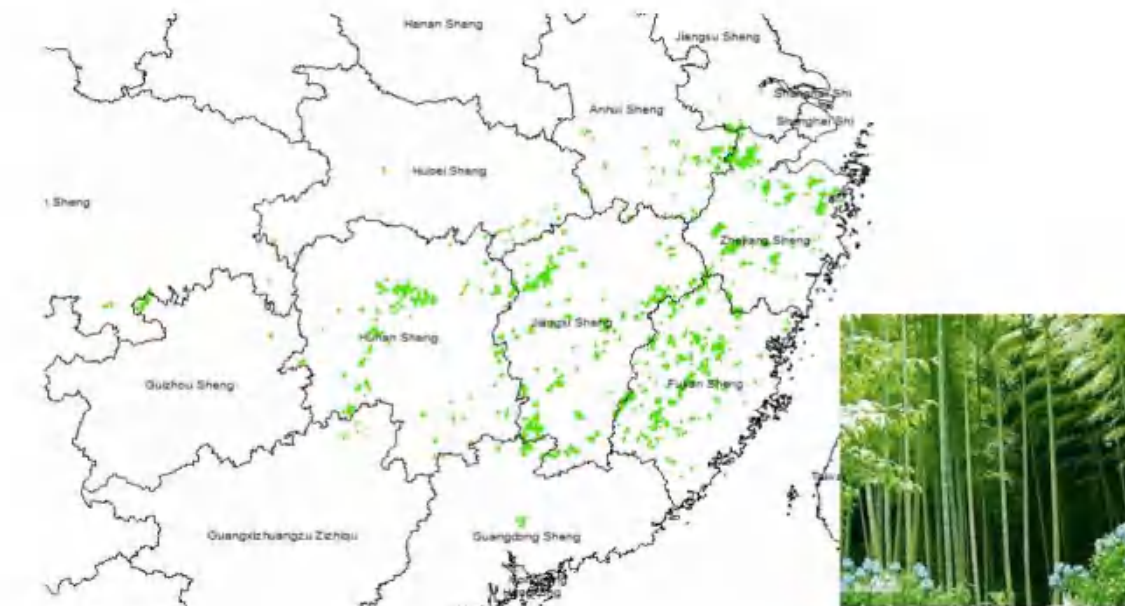
Annex D1: Species distribution data for all species

Salix matsudana



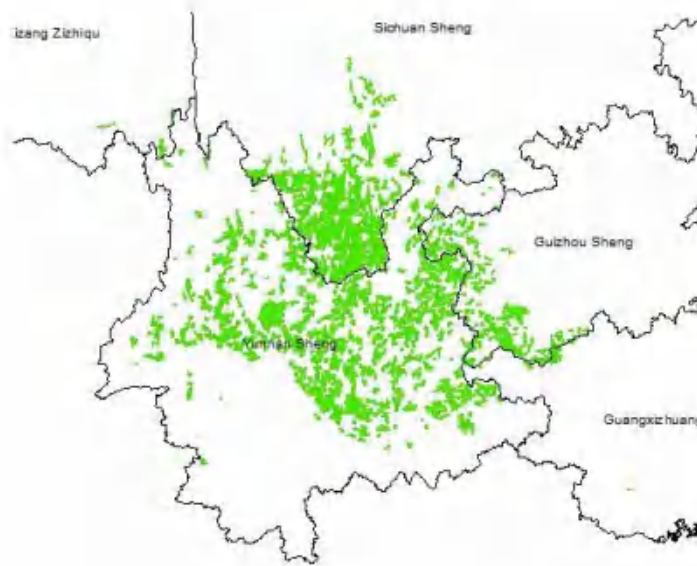
Annex D1: Species distribution data for all species

Phyllostachys pubescens



Annex D1: Species distribution data for all species

Pinus yunnanensis



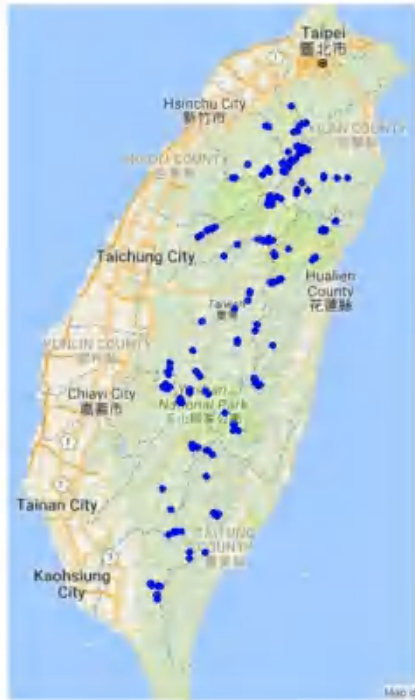
Annex D1: Species distribution data for all species

Cyclobalanopsis longinux
(*Quercus longinux*)

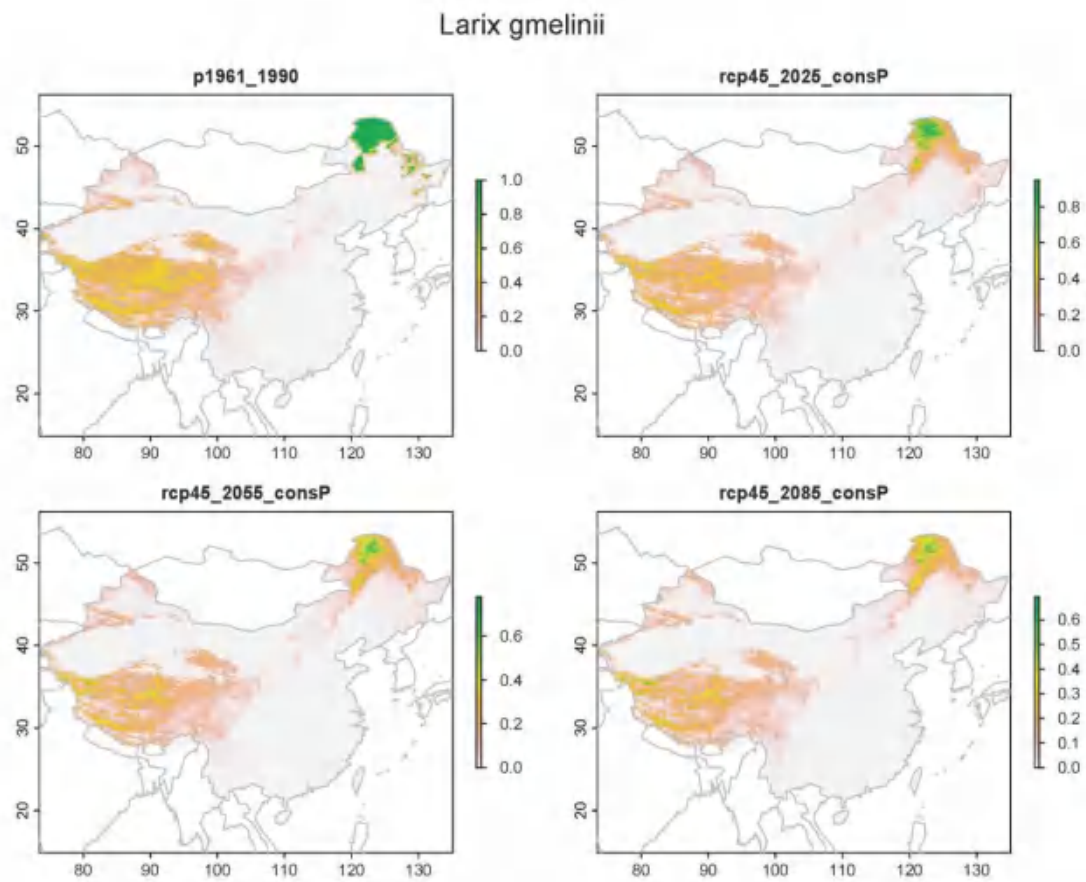


Annex D1: Species distribution data for all species

Chamaecyparis formosensis
(Taiwan cypress)

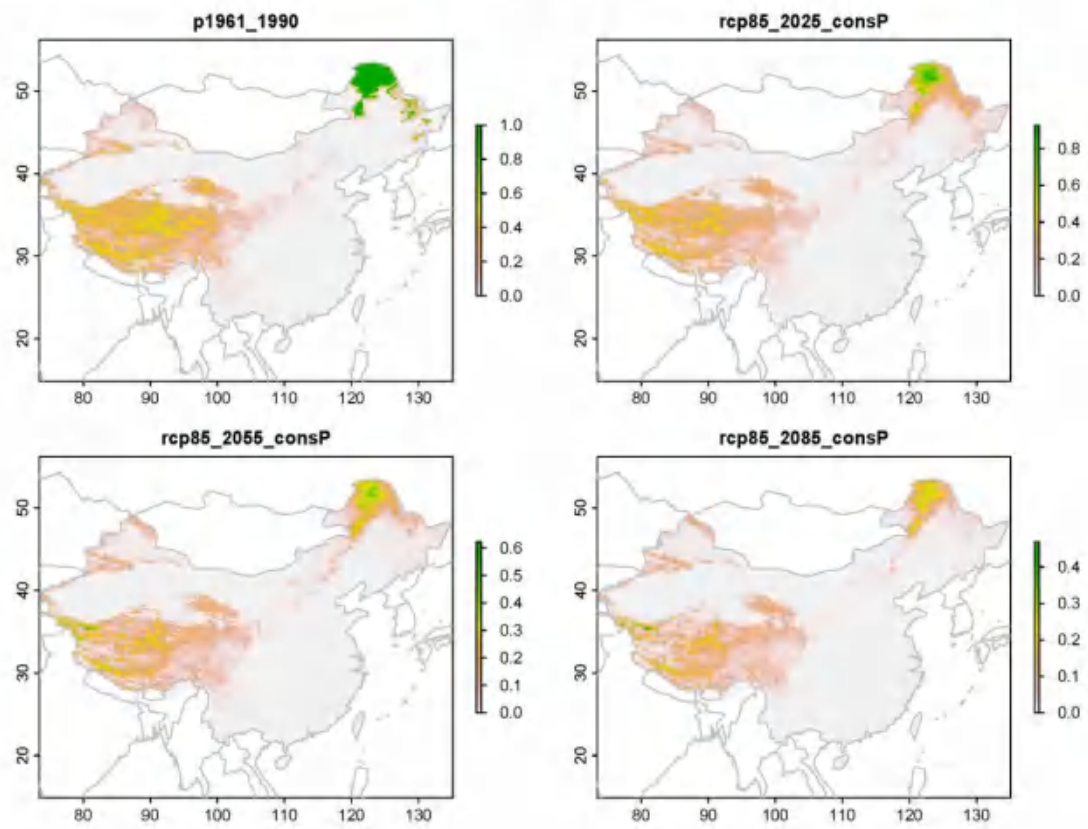


Annex D2: Species projection maps under climate change for all species



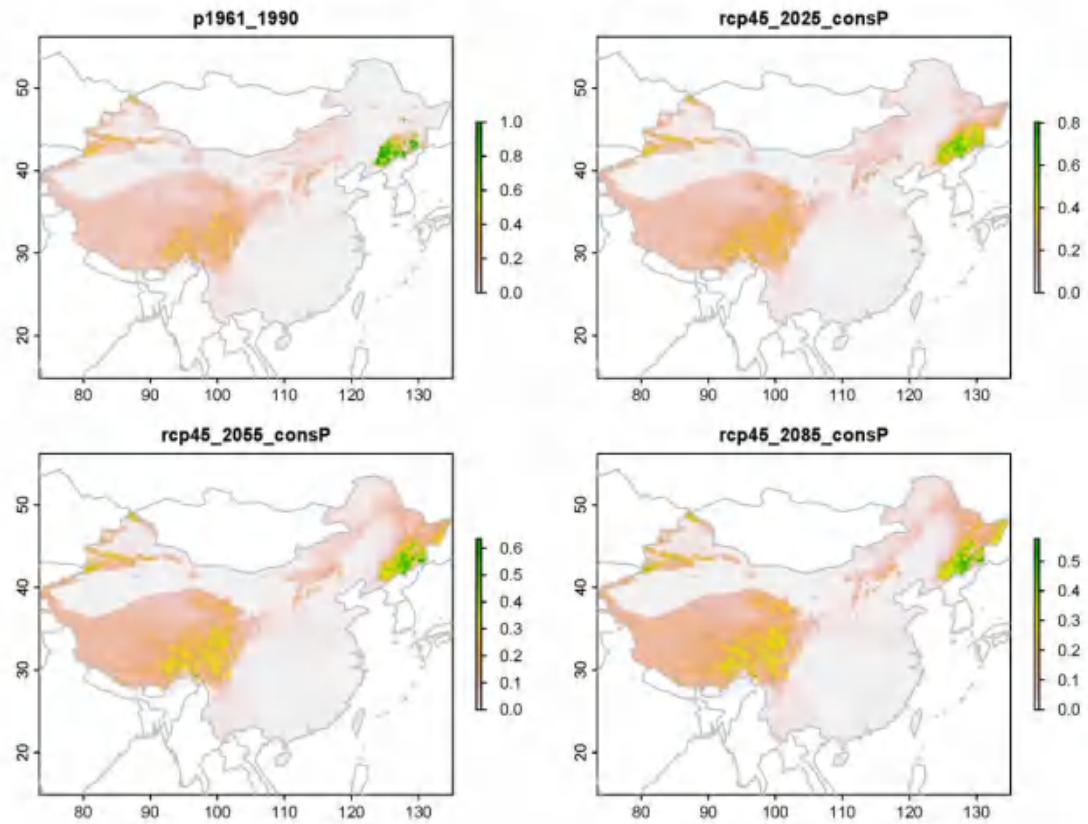
Species projection maps under climate change for all species

Larix gmelinii

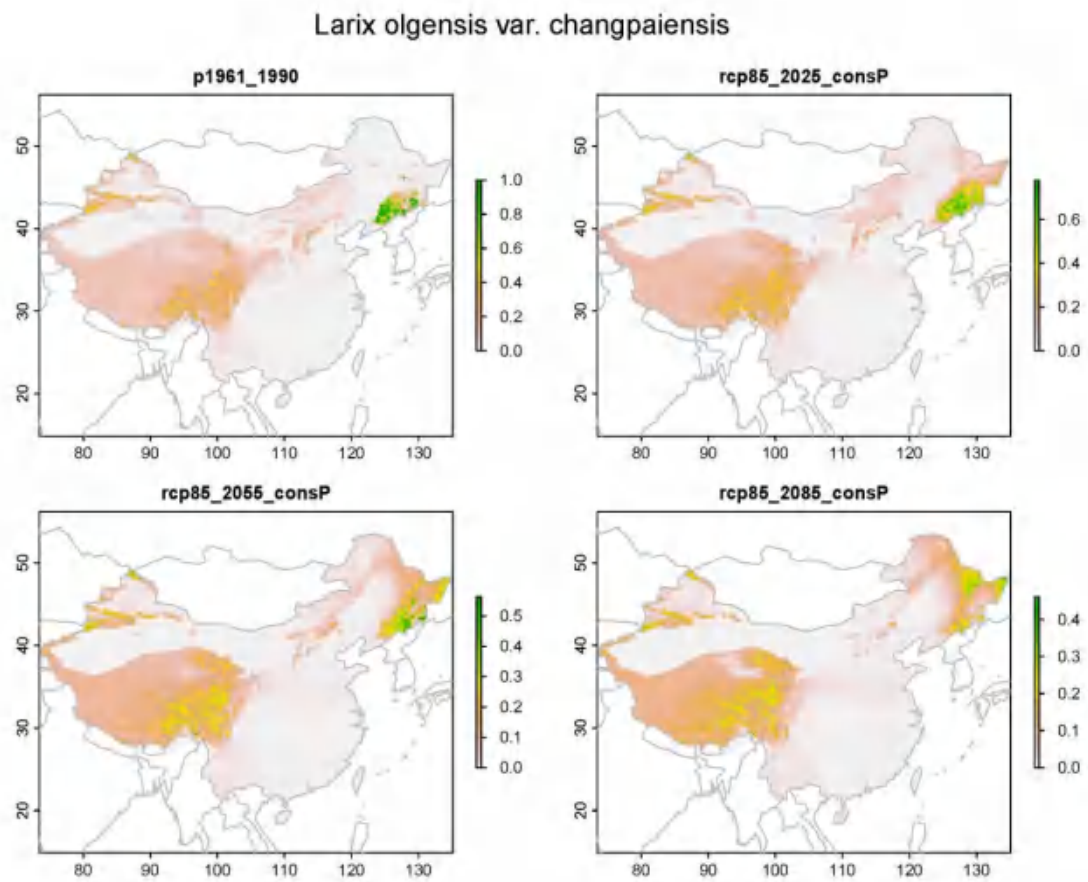


Species projection maps under climate change for all species

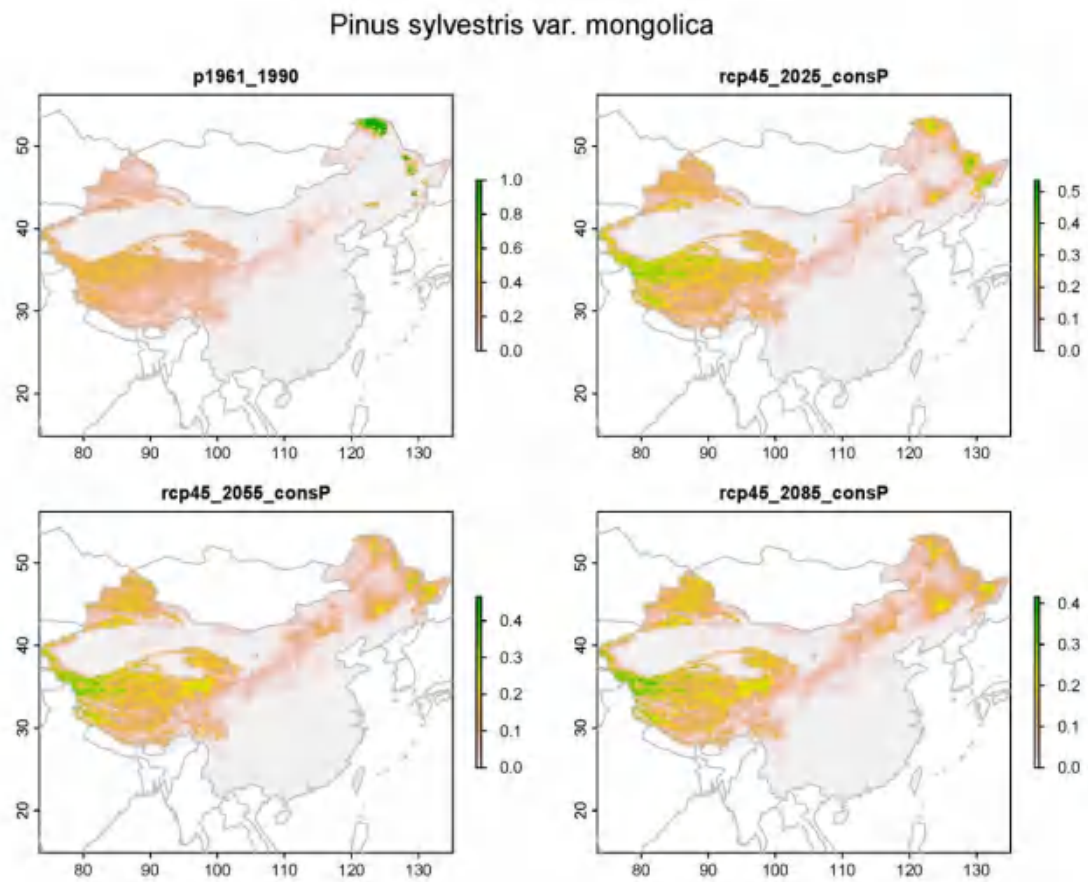
Larix olgensis var. *changpaiensis*



Species projection maps under climate change for all species

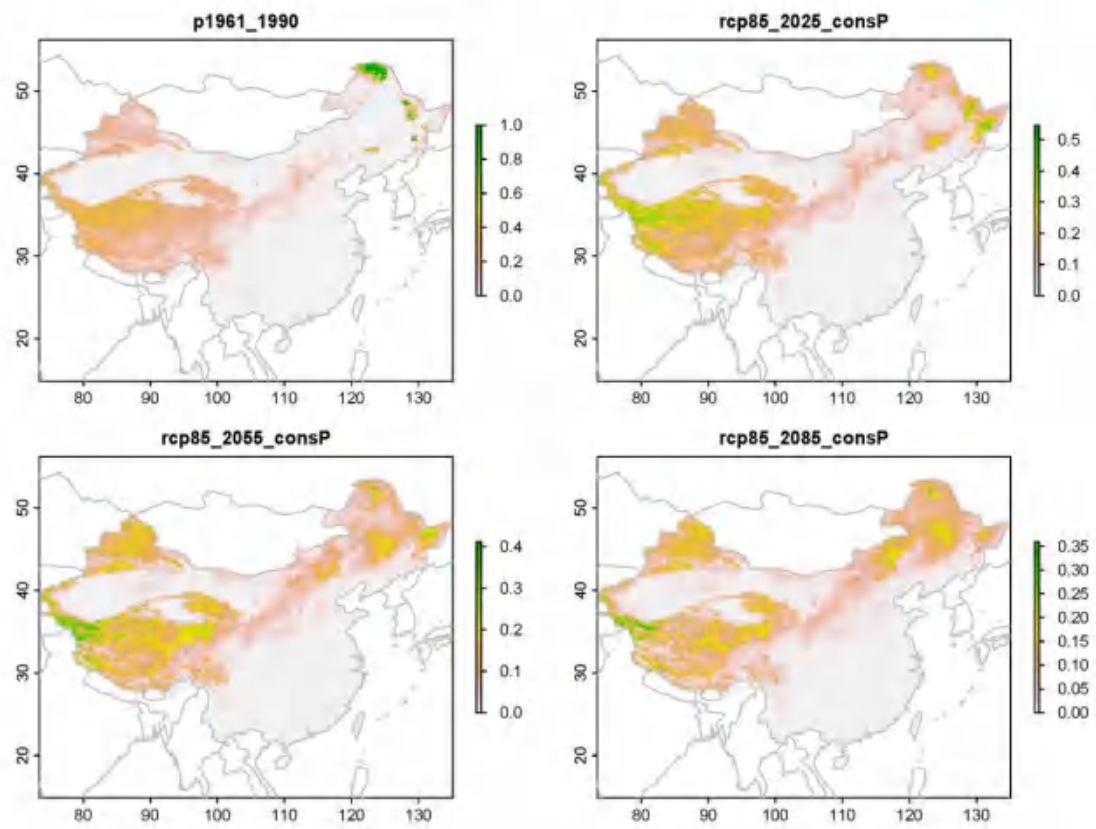


Species projection maps under climate change for all species

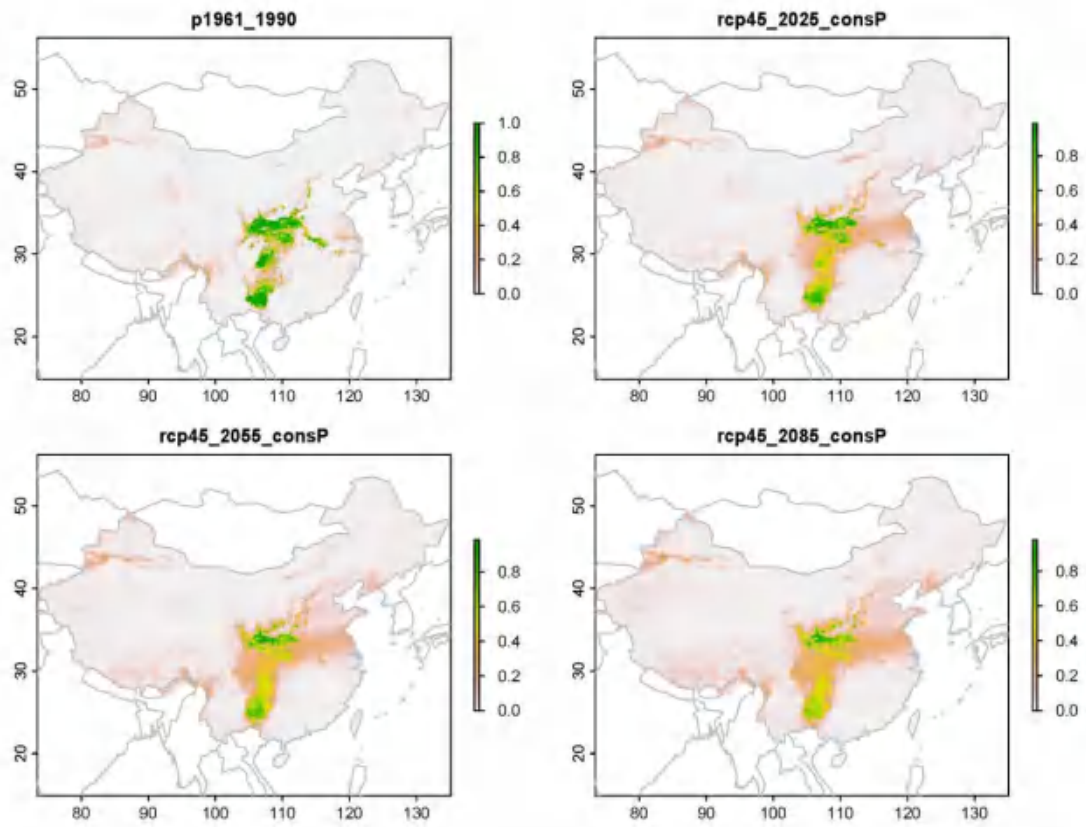


Species projection maps under climate change for all species

Pinus sylvestris var. *mongolica*

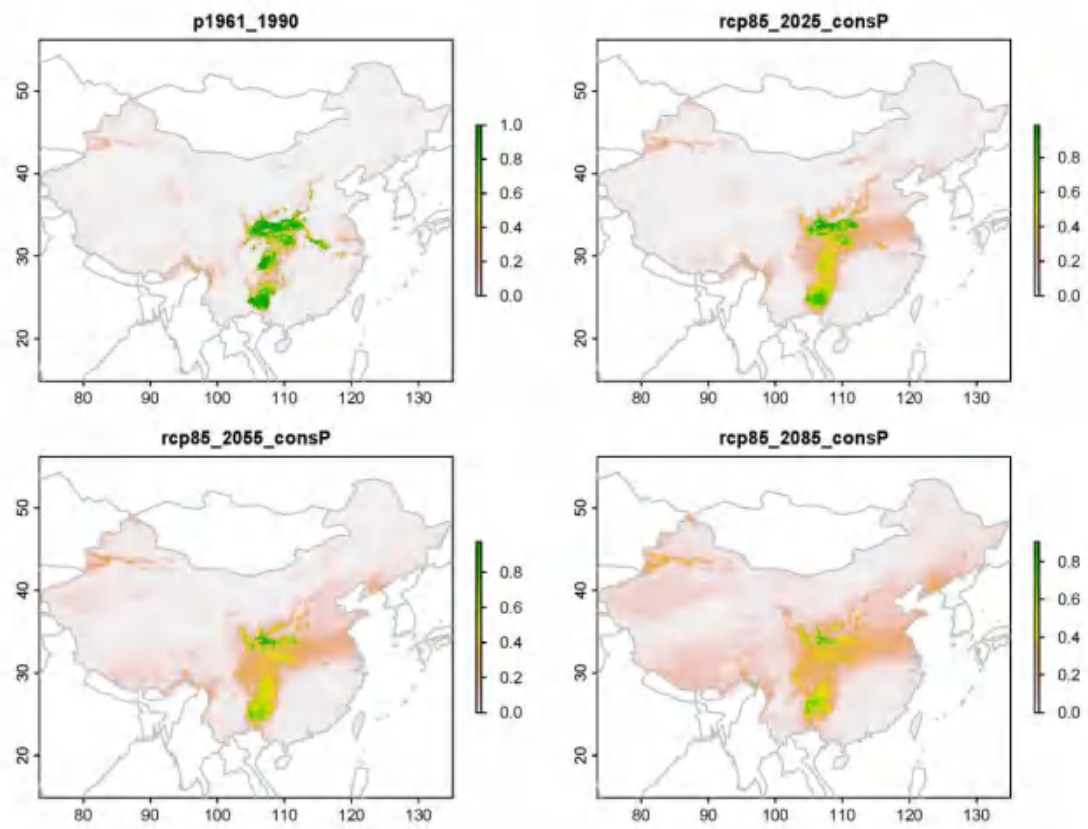


Quercrs variabili



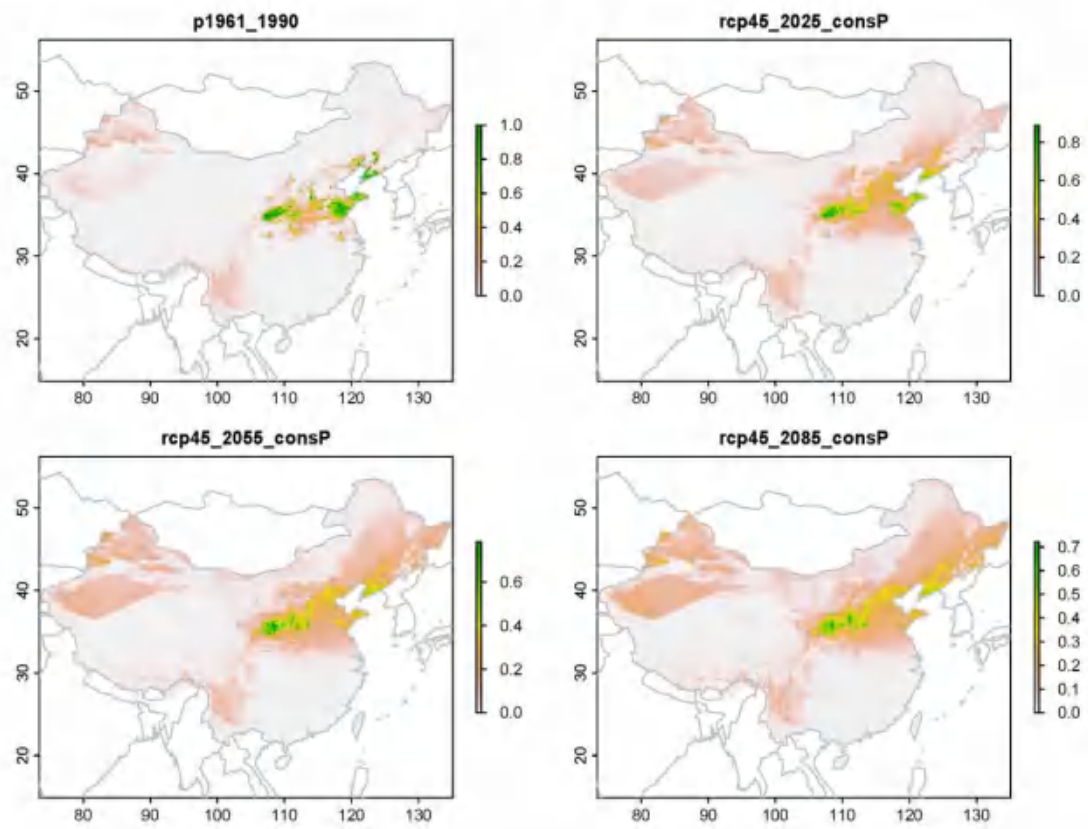
Species projection maps under climate change for all species

Quercus variabilis



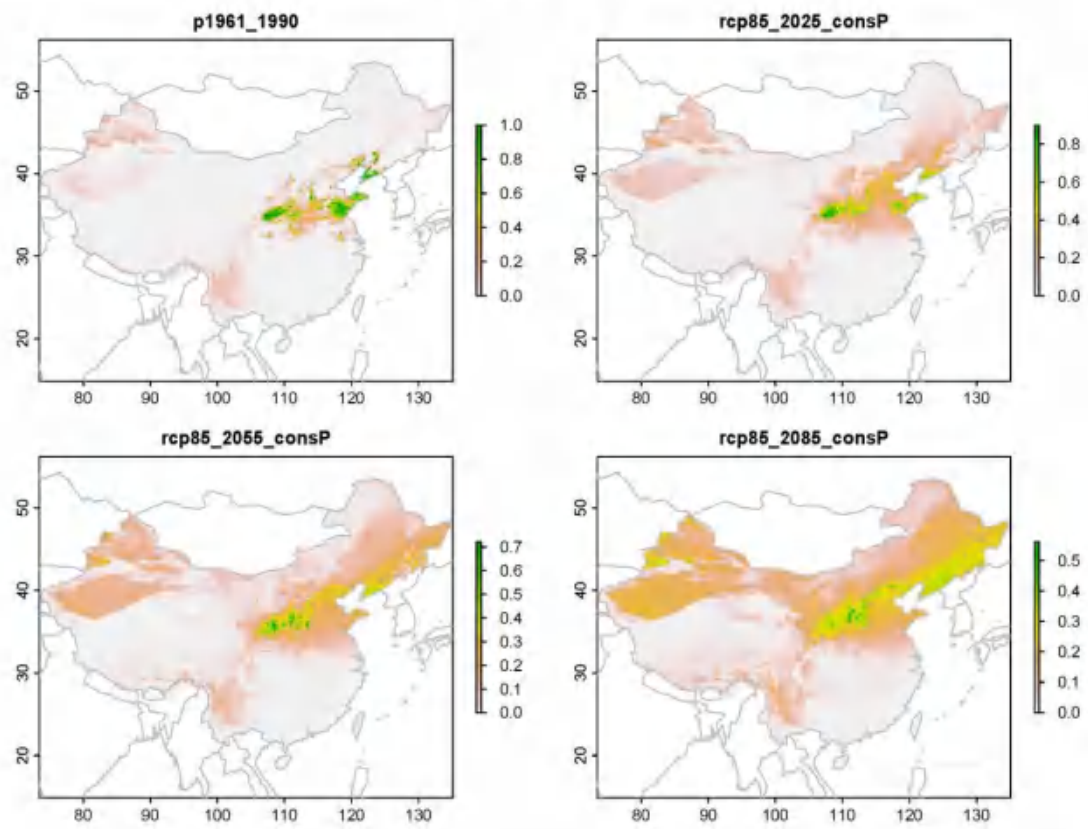
Species projection maps under climate change for all species

Robinia pseudoacacia



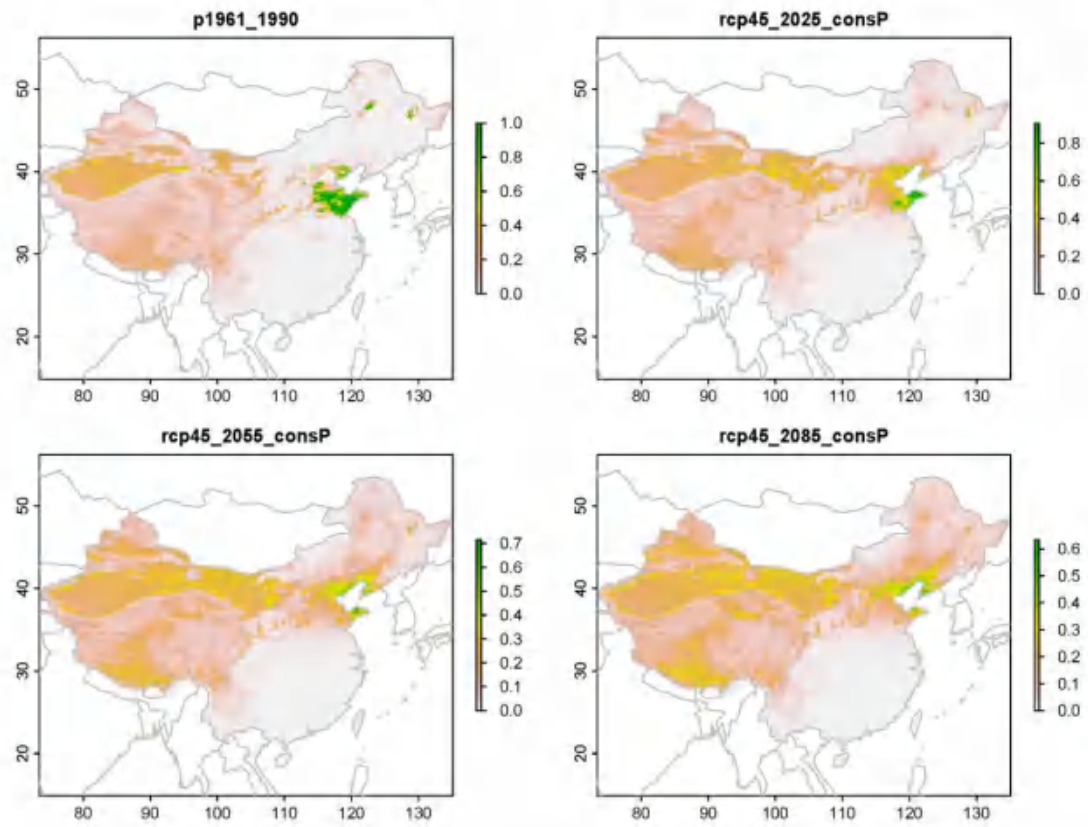
Species projection maps under climate change for all species

Robinia pseudoacacia



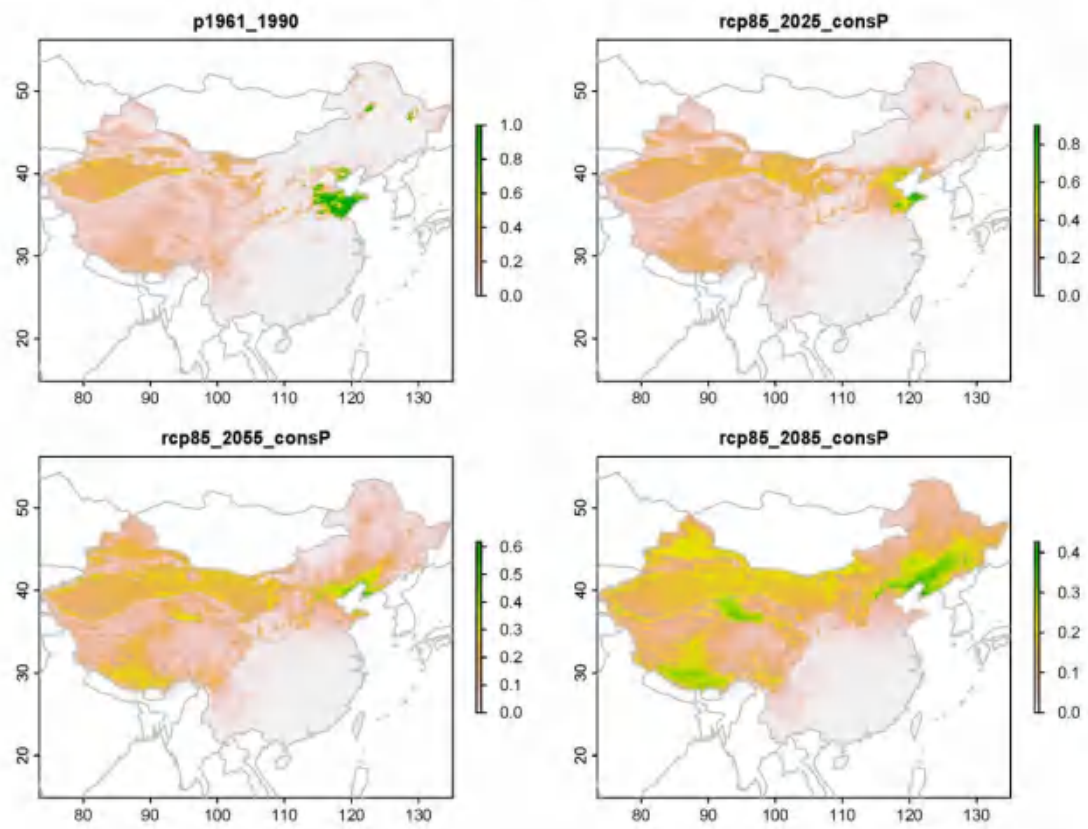
Species projection maps under climate change for all species

Salix matsudana



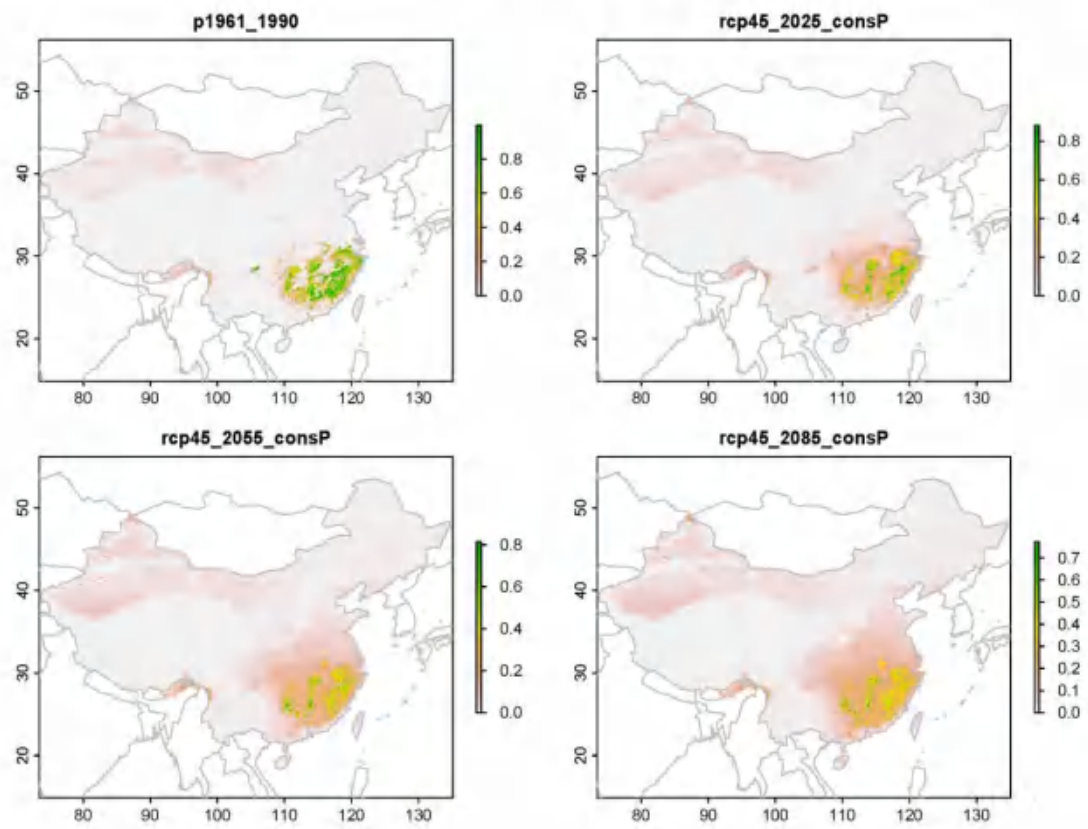
Species projection maps under climate change for all species

Salix matsudana



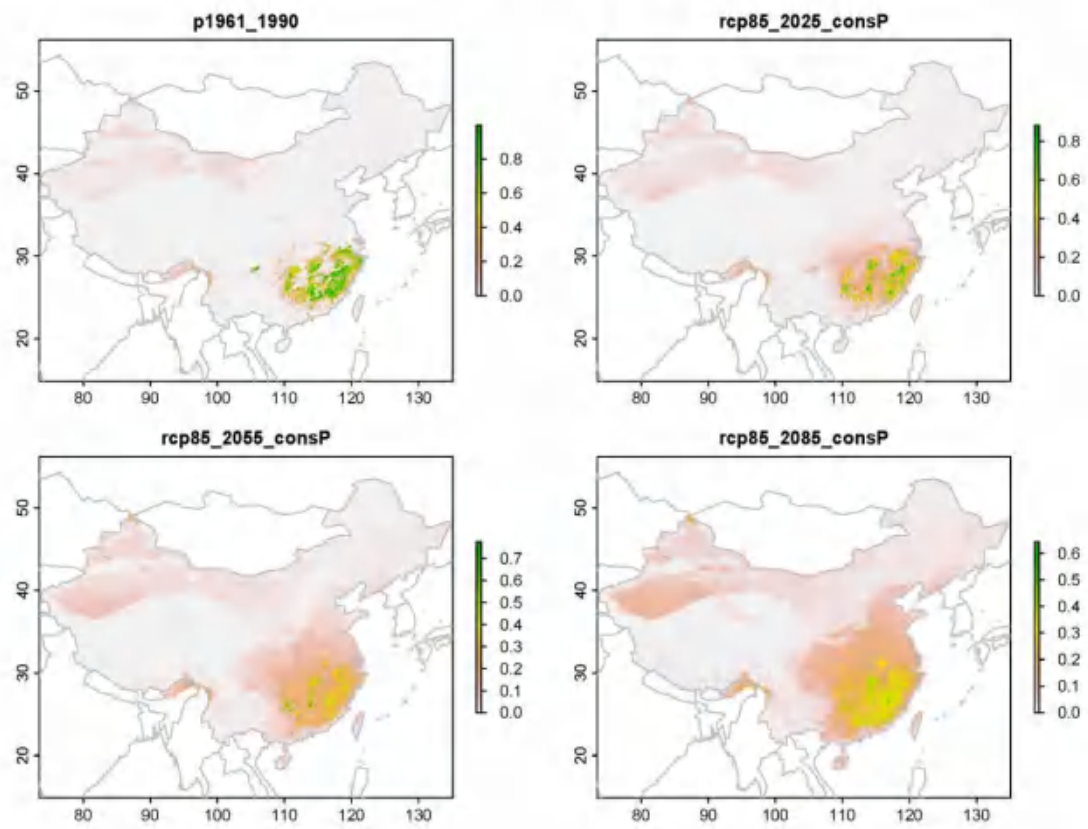
Species projection maps under climate change for all species

Phyllostachys pubescens



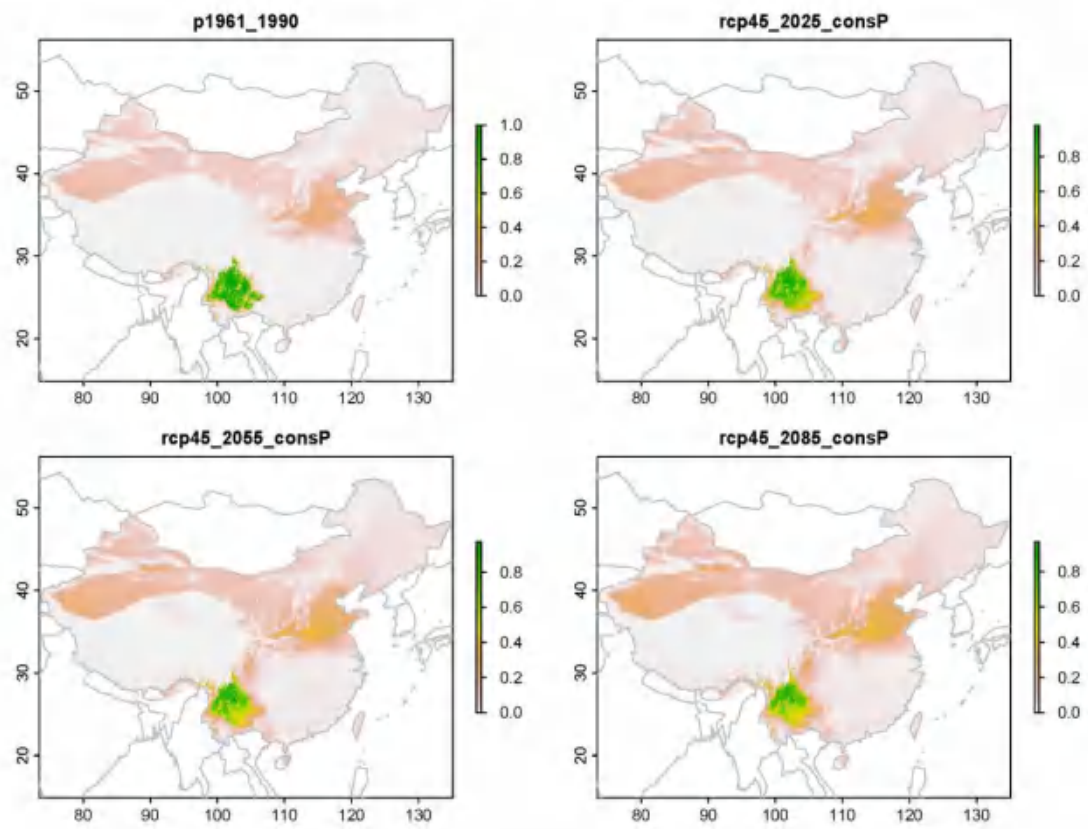
Species projection maps under climate change for all species

Phyllostachys pubescens



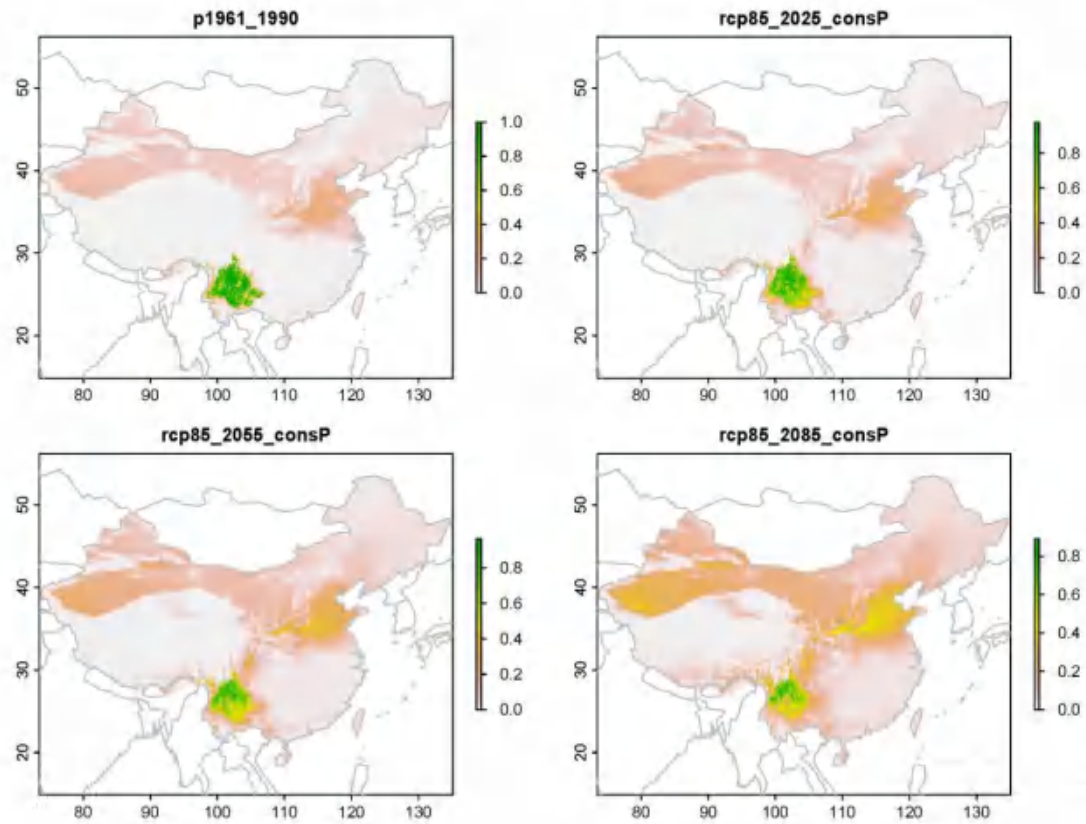
Species projection maps under climate change for all species

Pinus yunnanensis



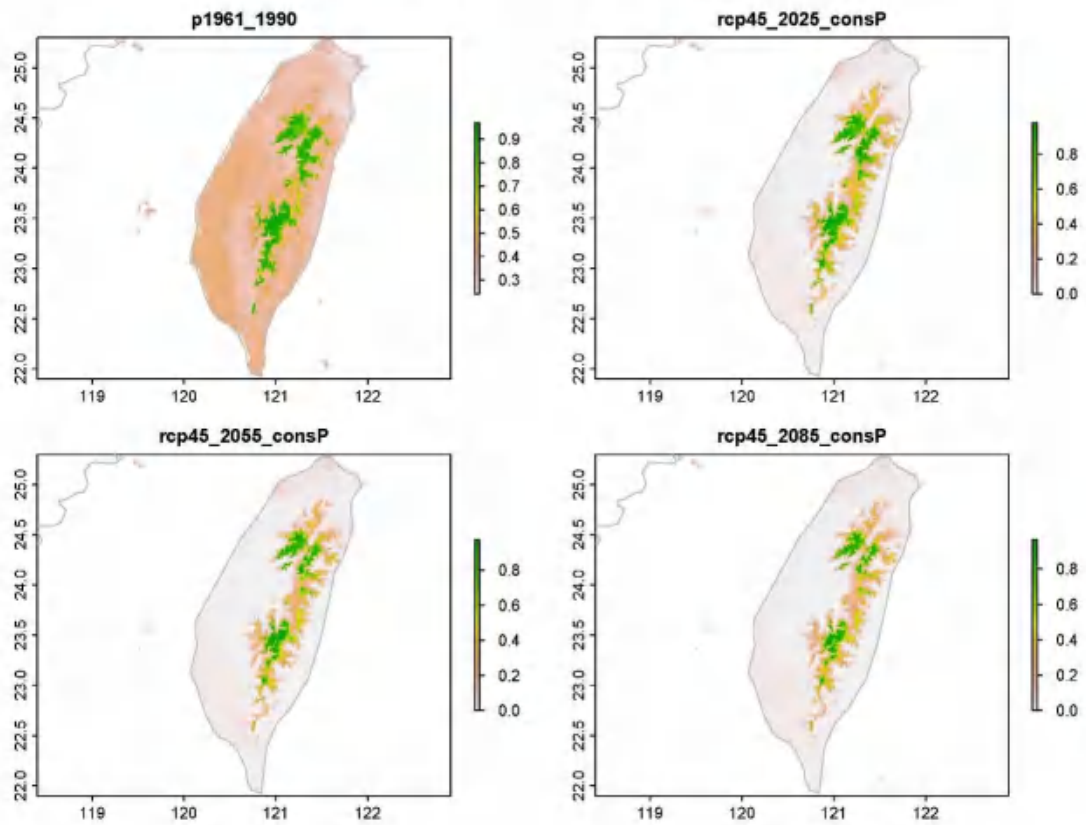
Species projection maps under climate change for all species

Pinus yunnanensis



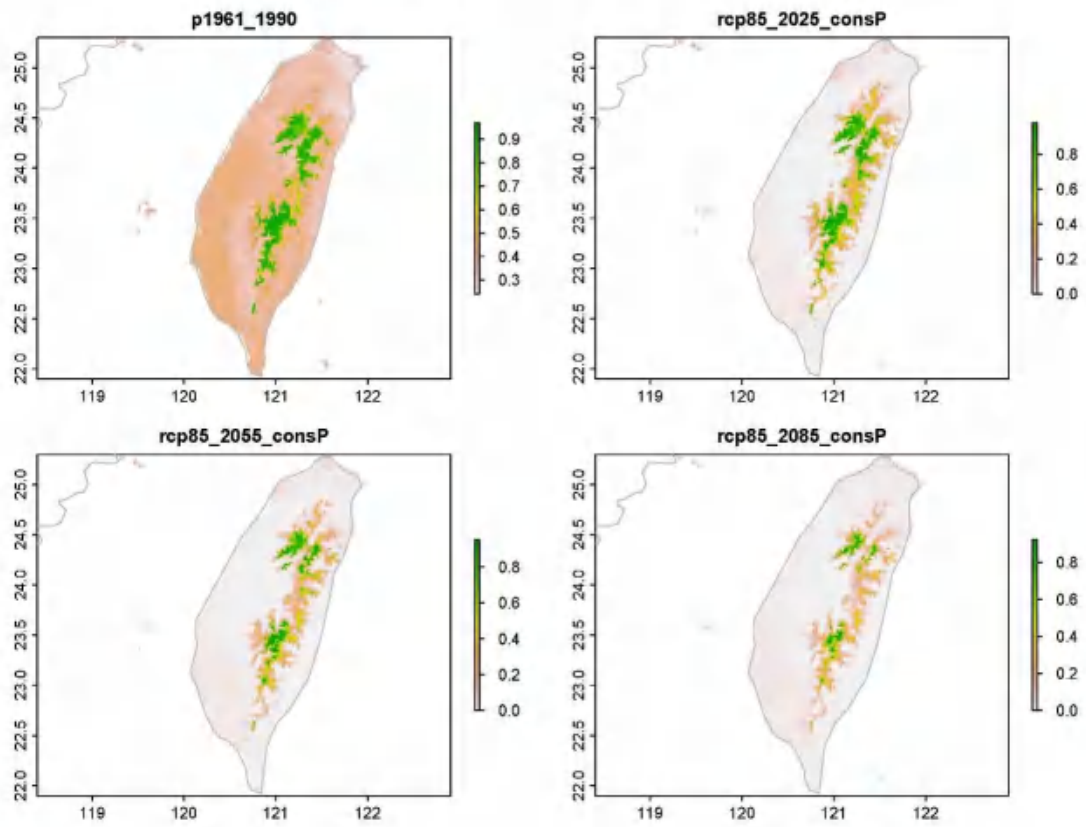
Species projection maps under climate change for all species

Chamaecyparis formosensis

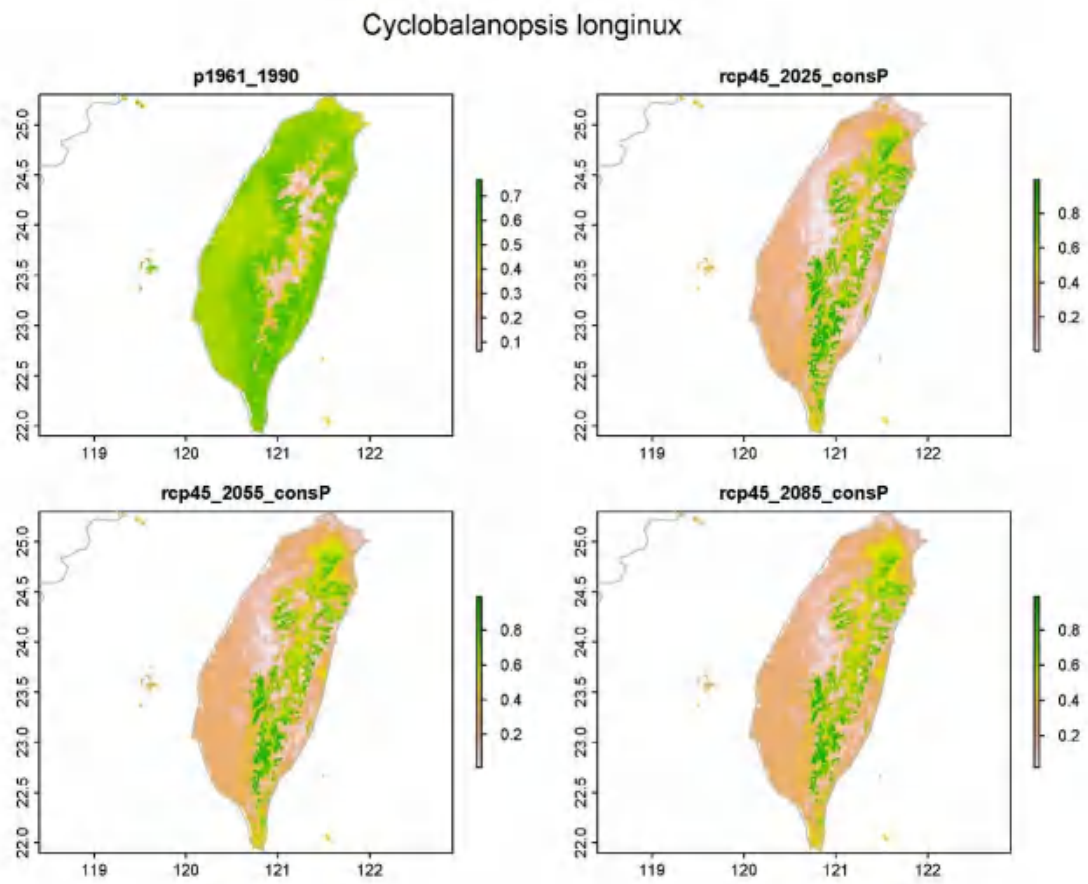


Species projection maps under climate change for all species

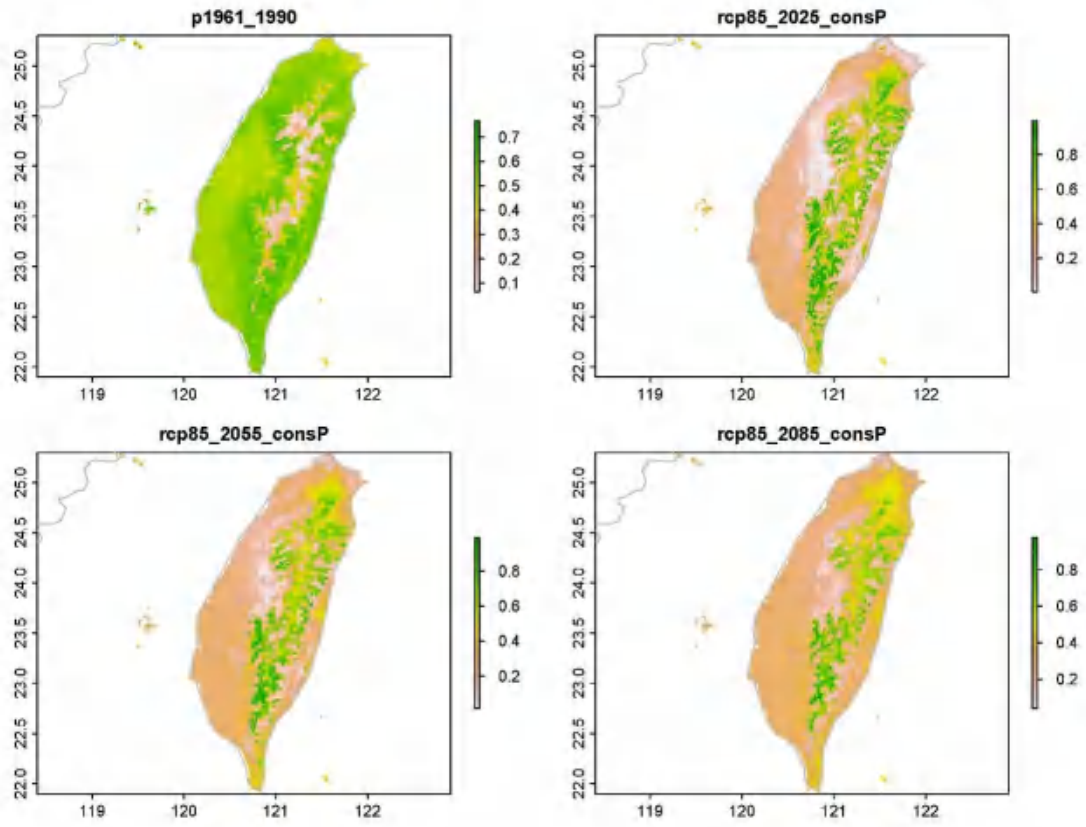
Chamaecyparis formosensis



Species projection maps under climate change for all species



Cyclobalanopsis longinux



Annex D3: Visiting Scholar Seminar and Training in UBC Faculty of Forestry

D3.1 Weekly Seminars, every Friday 2017

Weekly seminars are provided to all visiting scholars as a part of a training program to acclimate scholars to forestry in BC, research and applications spearheaded by the Faculty of Forestry, UBC policies, standards, and resources, as well as provincial forest policy. These talks are primarily given by Forestry Faculty, which additionally familiarizes visiting scholars with professors. These training seminars are complimented by a series of field trips to provide a more hands-on approach to learning about forestry and forest practices in British Columbia.

Schedule for 2017:

Dates	Instructors	Topics	#Attendances
Feb 17	Ms. Sally Taylor, Acting Head, Woodward Library	Introduction to UBC Library resources, how to use the journal database, and what is Mendeley	10
Feb 24	Dr. Nicholas Coops Associate Dean, Research	New Methods for Remote Sensing of Forest Inventory	11
Mar 3	Dr. Suzie Lavallee Senior Instructor	Discussion techniques for the university classroom	10
Mar 10	Dr. Janette Bulkan Assistant Professor	Community/Aboriginal Forestry in a Global Context	10
Mar 17	Dr. Peter Marshall Professor	Selected Administrative Approaches Within the University of British Columbia	12
Mar 24	Dr. Taraneh Sowlati Professor	Supply Chain Management	N/A
Mar 31	Dr. Verena Greiss,	Forest Resources Management	N/A
Apr 28	Dr. Guangyu Wang	MOOCs in Forestry and SFM online courses	11
May-June	Working with their own supervisors	Research and self-study time	N/A
July-Aug	Urban Forestry: Sara Barron (Graduate Research Assistant) and Owen Croy (Sessional Lecturer) Forest Management:	Auditing courses offered in the Vancouver Summer Program (http://www.forestry.ubc.ca/students/undergraduate/vancouver-summer-program/)	N/A

	Dr. Clive Welham (Research Associate) and Dr. Gregory Paradis (Post-Doctoral Research Fellow)		
Sep 8	Chris Crowley/Hailan Chen Center for Teaching, Learning and Technology	Use of technology for teaching	12
Sep 15	Chris Crowley/Hailan Chen	Teaching approach and developing MOOCs	11
Sep 22	Dr. Sue Watt	Forestry management in British Columbia: Challenges and Opportunity	10
Oct 6	Dr. John Innes, Professor/Dean	Sustainable Forest Management in Changing World	10
Oct 13	Dr. Guangyu Wang	Forest Carbon	12
Oct 20	Dr Guangyu Wang/Dr. Anil Shrestha	State of National Parks in the world: Issues and Opportunities in Changing Environment	10
Nov 3	Dr. Guangyu Wang	Not and bolts of writing peer review paper for Journal	12
Nov 10	Dr Harry Nelson	Critical analysis of forest policy in Canada	10
Dec 1	Working with their own supervisors	Research and self-study time	
Dec 8	Dr. Guangyu Wang	Forest Research Methods	12

D3.2 Visiting Scholar Seminar and Training in UBC Faculty of Forestry during 2018

During 2018, we continued hosting young research scientists from multiple universities in China and beyond (with varying lengths of stay) to expand our network and strengthen our relationship with emerging young researchers in Asia-Pacific region. This exchange program is mostly funded partly by the University of British Columbia's Faculty of Forestry, with the remainder of expenses are covered by the visiting scholars' home university, where they research and study in a similar field. During 2018, various research scientists and professors representing different university of China as well as other university of Asia-Pacific actively participated in the following programs.

Forestry Field School: Seven professors from four university in China (Beijing Forestry University, Nanjing Forestry University, Fujian Agriculture and Forestry University and Zhejiang Agriculture and Forestry University) participated in the summer forestry field school that was lasted from 26th of August to 3rd September, 2018. This course exposed visiting professors honing field skills training in forest measurement, biodiversity monitoring and ecology of the forest in British Columbia. As a part

of the training, they were exposed to ecology of Coastal Western Hemlock Zone, Mountain Hemlock Zone, Interior Douglas Fir Zone and Ponderosa Pine Zone of Forest in British Columbia.



Visiting professors from China in Malcolm Knapp Research Forest in Vancouver, British Columbia.

Forestry Online Course Development Workshop: We partnered with the Executive Office of Asia-Pacific Forestry Education Coordination Mechanism for forestry online course development workshop to conduct workshop on developing 11 forestry online course, held from July 26th to August 3rd, 2018. In this workshop, apart from UBC professors/staffs, 17 professors across 6 University in Asia-Pacific participated and actively engaged in development of online courses that meets the challenges of sustainable forest management in the context of climate change and forest destruction. Among the 17 professors, 4 were from Beijing Forestry University, China; 2 were from University of Melbourne, Australia; 1 from Kasetsart University, Thailand; 2 from University of Philippines, Philippines; 4 from Nanjing Forestry University, China and 4 from Fujian Agriculture and Forestry University, China. Please see lists of participants for details below.



A group photo of online course participants in UBC

List of the participants

Institutions	Name
Beijing Forestry University	Yong Liu
	Xinna Zhang
	Dawei Yin
	Jie Duan
University of Melbourne	Chris Weston
	Luba Volkova
Kasetsart University, Thailand	Damrong Pipatwattanakul
University of the Philippines Los Banos	Juan M. Pulhin
	Roberto B. Figueroa
The University of British Columbia	John Innes
	Guangyu Wang
	Nicholas Coops

	Terry Sunderland
	Tongli Wang
	Michelle Zeng
	Anil Shrestha
	Cindy Cheng
	Lorien Nesbitt
	Weicong Fu
Nanjing Forestry University	Xiaoyan Zhou
	Jingquan Han
	Xin Zhou Wang
	Lv Zhiying
Fujian A&F University	Futao Guo
	Xiaolong Hou
	Houxi Zhang
	Jianfeng Huang

Training Team and Presenters

UBC CTLT

Dr. Christina Hendricks, Academic Director, CTLT & Professor

Dr. Andrea Han, Associate Director, Curriculum and Course Services, CTLT

Chris Crowley, Manager, Learning Design, CTLT

Carrie Hunter, PhD Curriculum Consultant, CTLT

Hailan Chen, PhD Learning Designer, CTLT

Bosung Kim, PhD Learning Designer, CTLT

UBC Faculty of Forestry

Dr. John Innes, Dean, Faculty of Forestry & Chair of Asia Pacific Forestry Education Coordination Mechanism

Dr. Guangyu Wang, Associate Dean & Asian Strategies, Director of Asia Forest Research Centre, Faculty of Forestry

Michelle Zeng, Manager, Executive Office of AP-FECM & Online Course Running Manager, Faculty of Forestry

Dr. Anil Shrestha, Lecturer, Online Course Instructor & Research Coordinator, Faculty of Forestry

UBC Experts

Patty Hamblen, Director, Health Promotion and Education, UBC Student Development & Services

Dr. Leah May Ver, Lecturer, Faculty of Science

Saeed Dyanatkar, Executive Producer, UBC Studios

Michael Sider, Producer, UBC Studios

Nadia Picco, Team Lead, UBC Studios

Peter James, Intellectual Property & Copyright, Librarian

Forest Management and the effect of carbon: Several young researcher from Chinese Universities participated in this course. This short course provided an introduction of ecology of carbon i.e. where the carbon is, how carbon recycles through the living and non-living world along with in-depth discussion on how carbon can be managed to maximize benefits while at the same time minimizing the emission. The scientists were further exposed to not only ecology but also interface of politics and economics at national and international arena. This programme conducted for four weeks from July 14th to August 14th, 2018.

Urban Forestry: In this Forestry course several young researchers from Chinese Universities participated which was conducted from July 28th to August 3rd, 2018. This course provided knowledge of concept and significance of urban forest and how to establish healthy urban forest ecosystems with the changing context of increased population, climate change, urban heat island, flooding and pollution.

Urban green spaces and wellbeing: This course provided research scientists planning and managing urban green spaces and ecosystem for human welfare, ecological health, and protection of cities' support systems. Learners gained theoretical and practical knowledge about maintaining urban forest networks, parks, wetlands, and other green infrastructures which play key role in moderating heat waves and cooling demands, maintaining biodiversity and carbon sinks, controlling forest fires, storm-water flood mitigation, bio-energy production essential for wellbeing of the city dwellers.

Annex D4: Summary Report - Training Workshop on Modelling Climate and Forest Ecosystems in a Changing Climate

Adaptation of Asia-Pacific Forests to Climate Change – Phase II
Kunming, China, May 31 – June 7, 2016

1. Introduction to the Workshop

This workshop was modelled after the training workshop that was successfully held during Phase I of this project in Kunming in 2013. The objective of the workshop was to introduce the models and tools developed in Phase I to the local partners so that they will be able to effectively and accurately implement the research in their respective pilot site and economy. The workshop focused on the technical application of the models and management and decision-making methods in order to increase the capacity of participants to conduct research on forest adaptation to climate change in their own economies.

The workshop ran for 8 days and covered several facets of forestry, climate change, forest management, and technological and modelling advancements. Lecture topics included the impacts of climate change on forest ecosystems and current policy around climate change mitigation and adaptation; a review of forest inventory techniques, applications, and analysis; an overview of the concepts of stand dynamics and growth and yield; an introduction to the development and application of models used in Phase I including ClimateAP, climate niche modelling, and FORECAST Climate; the use of technology such as LiDAR and artificial intelligence in forestry research and management; and results from research on the drivers of forest fires. Participants received a comprehensive education on these topics and were actively trained in the use of ClimateAP and FORECAST Climate so that they can independently use these models to contribute to the project's research. A summary of each day's activities and lectures is provided in Section 2.

Workshop attendance was higher than initially anticipated; present were 20 trainees, 7 instructors, 1 guest lecturer (who also participated as a trainee), and 2 APFNet representatives. Overall, the workshop successfully achieved its objectives; we successfully increased the knowledge and capacity of participants to use the models and tools developed in Phase I that will be employed in Phase II which will enable them to help achieve the project's research objectives and help address climate change adaptation. Based on the feedback from the workshop evaluation, the training was well received and beneficial to participants. The evaluation form and a summary of the responses can be found in Annex C and D, respectively.

Prior to the workshop, from May 28 to 30, the five participants from UBC visited Shangri-La, Yunnan with Dr. Shuaifeng Li of the Research Institute for Resources Insects. The purpose of the trip was to gain a greater appreciation for the ecosystem diversity in Yunnan, in particular, to observe how the elevation gradient in the region is reflected by changes in vegetation. The valley ecosystem was observed during the trip to Potatso National Park, while the variety of mountainous vegetation was observed during the trip to Shika Snow Mountain. The trip expenses were covered by the Research Institute for Resources Insects, so there were not costs incurred by the project for the time spent in Shangri-La.

2. Summary of Workshop Activities

2.1 Day 1: May 31, 2016

Opening remarks

The workshop began with open remarks from a panel including Dr. Chen Xiaoming from the Research Institute of Resources Insects, Mr. Zoufeng Zhuang from the Asia-Pacific Network for Sustainable Forest Management and Rehabilitation (APFNet), Dr. Peter Marshall from the University of British Columbia (UBC), Dr. Linsen Zhao from Southwest Forestry University, and Dr. Guangyu Wang from UBC. Each welcomed participants to the workshop and gave an introduction to their institution and involvement with the project.

Presentation: Introduction to program, activities, instructors, and participants, presented by Dr. Guangyu Wang

Dr. Guangyu Wang opened the workshop by welcoming participants to the training program and introducing them to Kunming. He discussed each of the organizations involved in hosting the workshop – APFNet, UBC, and the Research Institute of Resources Insects. As well, Dr. Wang introduced all of the lecturers and gave a brief summary of their research expertise and what they would focus on during their lectures. Lastly, he reviewed the weeks schedule to provide participants with a clear understanding of what would be covered and expected of them during the workshop.

Lecture: Climate change and forest management policy under the context of COP21, presented by Dr. John Innes

Dr. John Innes presented on the current science of climate change and climate policy, particularly as it relates to forestry via Skype, as he was unable to attend the workshop in person. His presentation comprehensively covered the progress of policy and international agreements related to forests and climate change from the inauguration of the UNFCCC to COP21 in 2015. Dr. Innes familiarized participants with the IPCC's Assessment process and discussed the results and observations of the assessments and how they have changed over the years. Additionally, he spoke to the changes in climate that have already occurred and the data and observations that support the fact that anthropogenic climate change is already occurring. Dr. Innes walked participants through the policies and international agreements that have been or are currently in place, giving particular emphasis to those that relate to the participants' local economies. Lastly, he highlighted the impacts that the recent discussions at COP21 in Paris will have on forests and forest related climate change policy. Overall, participants were given a clear overview of how the climate is changing, how changes in climate will affect forest ecosystems, forests' roles in mitigating climate change, and the current policies and initiatives aimed at tackling climate change and how these action plans compare to their objectives.

Presentation: Project Overview and Phase II Arrangement, presented by Dr. Guangyu Wang

Dr. Guangyu Wang's second presentation focused on familiarizing participants with both Phase I and Phase II of the project, as not all attendees were present at the inception meeting in the Philippines. He reviewed the outcomes of Phase I and how Phase II will build upon them. Dr. Wang also discussed the logistics of the project including the Year I work plan and what is expected from the project's partners in order to achieve the expected outcomes. As well, he discussed the need for participants to share the information and skills learned at the workshop with their colleagues and pointed out that effort needs to be made by all parties to increase the funding sources for the project.

Lecture: Part 1. Overview of forest inventory techniques and applications, presented by Dr. Peter Marshall

Dr. Peter Marshall presented an overview of forest inventory techniques and applications in two parts, with the first being the afternoon of the opening day. He described what forest inventory is, the challenges in implementing forest inventory, and the attributes of good and effective inventory. Dr. Marshall discussed the recent developments in technology and tools, highlighting the pros and cons of various tools and reviewed the appropriate setting for using these tools and methods to reduce error and improve data reliability. As well, he discussed the recent trends in data analysis related to forest inventory and summarized the current state of forest inventory at a broad scale. Overall, Dr. Marshall's presentation provided an excellent and comprehensive introduction and overview to the importance of forest inventory and the best tools and technologies that participants can use to improve their data collection and forest inventory analysis.

Presentation: Introduction to modelling with artificial intelligence, presented by Dr. Guoliang Liu

As there was additional time at the end of the day, Dr. Guoliang Liu gave a brief introduction to the technology he's developed to store and analyze forest inventory data. He walked through some examples using his cloud data technology to model various economic and ecological factors related to the selected forest management plan. This presentation acted as a brief introduction to the lecture he would give at the end of the week.

2.2 Day 2: June 1, 2016

Lecture: Part 2. Remote sensing data collection and analysis, presented by Dr. Peter Marshall

The second day of the workshop opened with Dr. Peter Marshall carrying on with his lecture on forest inventory, expanding it to touch on remote sensing data collection and analysis. In this lecture, he highlighted the importance of maps in forest inventories and how the geographic information system (GIS) can be used to not only generate maps for inventories, but also analyze various relationships among the data and extract information. Dr. Marshall covered the basics of remote sensing to ensure all participants had the same level of understanding of the technology and its application. He covered satellite imagery, touching on the physics of the electromagnetic radiation spectrum and the type of information that can be gained for remote sensing data at various spatial resolutions and from different satellite technologies. Dr. Marshall then introduced Light Detection and Ranging (LiDAR); he explained the mechanics behind the technology and highlighted the importance of this technology for digital terrain modelling and digital surface models. He provided a comprehensive explanation of how to use LiDAR and the information that can be gleaned from the data gathered.

Lecture: Stand dynamics and growth and yield, presented by Dr. Peter Marshall

For his final presentation, Dr. Marshall gave a thorough lecture focused on stand dynamics and growth and yield. He discussed the key elements of stand dynamics including the concepts of growing space, competition, and the influence of disturbances. He walked participants through the development of single age stands and complex stand and the various elements of management associated with them. Dr. Marshall closed with a presentation on modelling growth and yield of both even and uneven aged stands.

Lecture: ClimateAP and its applications, presented by Dr. Tongli Wang

Dr. Tongli Wang introduced trainees to the climate model ClimateAP which he developed in Phase I. He walked them through other available climate models and explained how ClimateAP differs from

them and how these differences result in ClimateAP being more accurate than other available models. Dr. Wang went through the steps in developing ClimateBC, the predecessor to ClimateAP, and justified the importance and necessity of each of the steps to generating high accuracy and low-resolution climate data. As well, Dr. Wang explained how to use both the GoogleMaps based version and desktop version of ClimateAP. Trainees downloaded the desktop version to their computers so that they could follow along as Dr. Wang went through some examples. He showed them step-by-step how to run the model for various periods and climate scenarios with different variable outputs.

2.3 Day 3: June 2, 2016

Lecture: Climate niche modelling, presented by Dr. Tongli Wang

Dr. Wang opened the third day of the workshop with an overview of the evidence of climate change and how these changes are expected to impact forest ecosystems through shifts in the climate niches of tree species resulting in less optimal growing conditions for the species. He discussed options for assisted migration as the climate is expected to change faster than tree species can migrate. Dr. Wang then went through the model he's develop to predict the changes in the climatic niche of tree species. This included the development of the Random Forest model and the steps he's taken to overcome several issues associated with this type of model. Dr. Wang then went through the results from the model application in Phase I to highlight the type of information that can be gleaned from the model projections. There was a great discussion among Dr. Wang, trainees, and other lecturers on the application and limitations of the climate niche models. Dr. Wang also discussed some recent research he's done on the potential use of this model beyond climate niches, which again led to discussion among the group and proved to be beneficial to the groups understanding and Dr. Wang's future evaluation and research on the subject.

Presentation: Overview of FORECAST Climate Workshop Kunming, presented by Dr. Brad Seely

As Dr. Brad Seely was the primary lecturer over the remainder of the workshop, he began with an overview of the agenda for the next few days and explained his objectives and what is expected from the participants both in the workshop and through the duration of the project.

Lecture: Review of climate change impacts on forest growth and development: toward the application of FORECAST Climate, presented by Dr. Brad Seely

Dr. Seely's first lecture focused on some of the expected changes in climate that may impact forest productivity. He also touched on the importance of ENSO events and how they may be impacted by climate change. This is of particular importance, as El Niño events can results in severe drought in Southeast Asia, and the impacts of drought on forest productivity is one of the possible research questions being explored in the pilot sites. Dr. Seely conducted a comprehensive literature review on the research already carried out in the pilot site economies to better understand what has been done and areas of research that still need to be explored; he presented this information to participants as a way to familiarize everyone with the issues being faced in each region and to get them thinking about the sort of questions they want to address.

Lecture: An overview of FORECAST model, presented by Dr. Brad Seely

Dr. Seely introduced the FORECAST model which FORECAST Climate was built upon. He outlined the data requirements for the model and the ecosystem and management processes that it can represent. Dr. Seely discussed the application and outputs of the model and used the results of previous research in Fujian, China to demonstrate how the model can be implemented and the

information it generates. Dr. Seely spent the last part of the afternoon installing FORECAST software onto participants' computers so that in the following days they would be able to work with the model.

2.4 Day 4: June 3, 2016

Lecture: Evaluating management trade-offs between economic fibre production and other ecosystem services in Chinese fir production in Fujian province, presented by Dr. Haijun Kang

Dr. Haijun Kang presented the methodology and findings from his research paper “Landscape-scale trade-off analysis of Chinese-fir plantations”. He outlined his method for using FORECAST and the Landscape Summary Tool (LST) to evaluate different management scenarios and compare the trade-offs between economic production and ecosystem services. Dr. Kang went through his development of different management scenarios and analysis units, the trade-off analysis indicators that were used, the framework of the LST model, and the application of the model. He then went through the results of the model and how they can be interpreted and used to improve forest management plans. This was an effective presentation in highlighting how FORECAST can be used and the type of analysis it can be used for; it provided participants with an example of what was accomplished in Phase I and got them thinking about how they could use this tool in their own study region.

Lecture: Overview of FORECAST Data Requirements and Key Simulation Algorithms, presented by Dr. Brad Seely

In this lecture, Dr. Seely focused on introducing the structure of the FORECAST model and the data requirements. He walked through the various components of the model; he discussed in detail the data inputs and steps involved in the setup of the model, how this information is interpreted in the ecosystem simulation component, and ultimately the outputs that are generated by the model. Dr. Seely then focused on specific elements of the model, starting with the data requirements for the input files; he clearly indicated the various data categories and potential data sources for each. He went through the core ecosystem processes represented in FORECAST ESM and discussed the feedbacks and relationships that are incorporated in the model and the importance of the inclusion of these relationships. Dr. Seely then walked participants through the simulation algorithms that are used in the model, focusing on Net Primary Production as an example. As well, he provided a schematic illustrating all the components and relationships represented just within the nutrient cycling component of FORECAST. The detailed description of the workings of the model gave trainees a thorough understanding of the capacity of the model and what ecosystem components are considered and simulated.

Following the lecture, Dr. Seely then went through all of the data files he'd previously provided to participants; this included published work for their reference, detailed instructions on how to run the model, and sample data sets. He provided detailed instruction on what information needs to be input, what that information is used for, and its importance to the model. Dr. Seely also indicated moments where they could check the accuracy of their data, such as generating intermediate stage graphs, in order to avoid potential errors in their input data and to catch any mistakes or missing data before they run the model.

Activity: Using FORECAST, led by Dr. Brad Seely, assisted by Dr. Haijun Kang

With participants following on their own computers, Dr. Seely used the example data set he'd provided them to go through the set up and running of FORECAST. He went through each element in fine detail, including the model setup, where data should be stored, the various codes used for different

simulations, and how to interpret outputs. After his demonstration, participants spent some time working with the model on their own while Dr. Seely and Dr. Kang assisted them and addressed any questions that arose.

2.5 Day 5: June 4, 2016

Field Trip: Stone Forest and Yunnan Nationalities Village

For the full day field trip, participants visited the Stone Forest just outside of Kunming as well as the Yunnan Nationalities Village. This field trip allowed them to become more familiar with the ecosystems in Yunnan province and gain a greater appreciation of the cultural diversity of the region. This also served as an opportunity to project partners to bond and gave them a well-deserved break from the intense training workshop.

2.6 Day 6: June 5, 2016

Lecture: Simulating the impact of climate change on forest growth rates with FORECAST Climate: A case study from British Columbia, presented by Dr. Brad Seely

Dr. Seely began the morning by reviewing the key points from his lecture on June 3 and doing another demonstration with FORECAST, this time using various cohorts of the same species. He then moved on to introduce FORECAST Climate; this included presenting the ForWaDy hydrological model that is incorporated into FORECAST Climate. Dr. Seely went through the key components of FORECAST Climate, the required data, and how FORECAST was adjusted to become FORECAST Climate. Dr. Seely then went through a case study from British Columbia to illustrate how the model can be applied and the information that can be gleaned from model outputs. He also discussed the application and results from the use of this model in Phase I on the pilot site in British Columbia. This lecture very clearly informed participants of the modelling advancements made by the development of FORECAST Climate and provided great insight as to what can be achieved through the application of the model.

Activity: Using FORECAST Climate, led by Dr. Brad Seely, assisted by Dr. Haijun Kang

In the afternoon, Dr. Seely carried out another interactive example with participants following along on their computers, this time using ForWaDy and FORECAST Climate. He went through all of the required inputs, the different variables that need to be included for each file, what these variables are used for in the model, and how to generate the appropriate input values. Dr. Seely clearly explained variables that need to be calculated from the field, those that can be estimated, and those that can be found in literature. He then went through how data in the excel files are represented and then input into the model itself. Dr. Seely then performed some demonstration runs using the data sets he just reviewed to illustrate the information generated by the model and how to interpret the results. This activity effectively summarized the type of data and information the partners need to obtain, how they will use it, and the type of simulations the model can run with that information. Furthermore, it gave participants a clear understanding of the steps they need to take following the workshop to gather appropriate and accurate data, and it further clarified the type of research questions that FORECAST Climate is capable of addressing.

2.7 Day 7: June 6, 2016

Meetings with partner economies

In the morning, Dr. Brad Seely and Ms. Shari Mang met with the participants from each partner

economy to finalize the research questions for each pilot site and develop a work plan for the rest of Year 1. The focus was on setting concrete steps to work towards completing the project's activities and establishing deadlines for each step. The project's agreements and financial compensation were also discussed. All meetings concluded with clear goals and activities for the partners and UBC team, which will be reflected in Schedule B that was drafted as part of the agreement.

Lecture: LiDAR and its application in forest ecosystems, presented by Dr. Lin Cao

Dr. Lin Cao introduced participants to LiDAR technology, how it works, and the various uses of LiDAR. He reviewed the different technological options for airborne and satellite based LiDAR and explained how the data is interpreted. Dr. Cao then went through the pros and cons of LiDAR and the best uses for this type of technology. He discussed situations when it is important to have more high quality data (e.g. if you want a high accuracy DTM you need high density data) and how to transform data to generate the information needed. Dr. Cao then discussed how LiDAR can be used for forestry specifically and illustrated this using an example of his research that applied LiDAR in China to estimate forest biomass and develop maps based on those estimations.

Lecture: Tree and plot biomass estimation using LiDAR data, presented by Dr. Lin Cao

Following his lecture, Dr. Cao gave a demonstration on the area-based approach and individual tree crown approach for estimating biomass using LiDAR, FUSION, and ArcGIS. For each approach, he walked participants through each step of the process from the initial processing of data points through to the final model validation. Dr. Cao performed the calculations and analysis in real time to illustrate exactly how these approaches are carried out.

Lecture: Forest Simulation Optimization System (FSOS) – Artificial Intelligence + HPC Cloud Computing, presented by Dr. Guoliang Liu

Dr. Guoliang Liu gave an overview on his artificial intelligence technology for modelling and managing forests at the stand level. He then went through various forest models that can be used to balance the various elements of forest management. Dr. Liu went through the function of FSOS, all the forest ecosystem and management components that can be evaluated by it, and the outputs from the model. He went through several applications of his models from both China and Canada, including how the research aided in resolving forest management issues after the Mountain Pine Beetle outbreak in BC. Dr. Liu showed participants how to access and use the website where all of these tools are located and illustrated how to conduct various types of analysis. He demonstrated the types of graphs, maps, and reports the model generates and discussed how this information can be interpreted to improve forest management.

2.8 Day 8: June 7, 2016

Lecture: Investigation in Characteristics Driving Factors in Resultant Emissions of Forest Fires in China, presented by Dr. Futao Guo

Dr. Futao Guo's presentation focused on his research examining forest fire occurrence in China. He discussed the history of fire occurrence in China and the impact it has throughout the region. Dr. Guo then discussed the importance of understanding the driving factors causing forest fires and how, through his research, he has come to identify these factors. He discussed the methodology and results from several of his projects, explaining the tools he used for each analysis and the type of information he was able to generate. This lecture was an excellent way for participants to see other kinds of work done by project partners in Phase I and a way to get them thinking about ways to expand the research they'll be carrying out during this phase.

Work Plan presentations by local partners:

Each partner economy was responsible for giving a 10 minute presentation on any work they had done thus far and their work plan and goals for the remainder of the year. The presentations were largely based on the previous day's meeting with Dr. Seely and Ms. Mang where these elements had been blocked out. As well, participants used this time to familiarize everyone with their economy and pilot site as not all workshop attendees were present at the Inception Meeting in the Philippines where this information was first presented.

- ***Malaysia: Presented by Dr. Siti Nurhidayu Abu Bakar***

Dr. Bakar gave an introduction to Malaysia and the pilot site, Danum Valley Conservation Area. She outlined the various sources of meteorological data available to them and showed the results from running ClimateAP with this data. Dr. Bakar also discussed some of the issues they've come across thus far. Malaysia lacks detailed forest type maps, as they only consist of three broad forest classes: inland forests, peatland forest, and mangrove. As such, the team from Malaysia plan on developing more detailed maps and validating the information available on current maps through a literature review and using Landsat images. Dr. Bakar then gave an overview of the climate and ecological conditions in Danum Valley. She reviewed the research being conducted at Danum Valley and the type of data available from these projects. Lastly, Dr. Bakar reviewed their work plan laid out at the previous day's meeting and accurately summarized the next steps that will be taken to achieve the Year 1 objectives.

- ***Myanmar: Presented by Mr. Thein Suang***

Mr. Suang opened by discussing what he gained from the workshop, such as an increased interest in the models and collaboration with UBC, a clearer understanding of the data that's needed, and a need to practice using FORECAST with their local data. He outlined the research questions they want to focus on at the Myanmar pilot site, which were in line with the ones proposed by Dr. Seely and discussed at the previous meeting. Mr. Suang familiarized participants with the pilot site in Myanmar, including the major forest type in the region and other projects being conducted there. He went through the steps for the work plan that were discussed in the previous day's meeting, and they were in agreement with the ideas put forward by UBC team members.

- ***Laos: Presented by Dr. Sithong Thongmanivong***

Dr. Thongmanivong described the study site in Laos to familiarize everyone with the ecosystem and research potential of the area. He outlined the tree species selected as the focus species for this research project and discussed their importance in the region. Dr. Thongmanivong gave a detailed outline of the work plan for the remainder of the year, including deadlines for each step and a detailed description of how these steps will be achieved. All of the steps and objectives outlined were in agreement with those laid out at the previous day's meeting.

- ***China: Presented by Dr. Shuaifeng Li***

Dr. Li presented on previous research he conducted on afforestation and carbon stock. He outlined the study site and methods they used to study the carbon stock in *Pinus kesiya* plantations. Dr. Li reviewed the research results and the implications in forest management development. Dr. Li did not include information on his work plan and objectives in his presentation; however, in the previous day's meeting he indicated that he would build upon

the data set and research that he presented on for the work being carried out in this project.

- ***Chinese Taipei: Presented by Dr. Huan-Yu Lin***

Dr. Lin introduced us to the state of forests on Taiwan Island and the various ecosystems and climate conditions that occur there. He discussed the type of vegetation data they have available and the work they've done with it thus far. Dr. Lin and his colleagues have already performed some validation analysis of ClimateAP using data from the meteorological stations on the island. They found that ClimateAP is highly accurate for the lowland areas in Taiwan, whereas in the mountain areas, the model tends to overestimate the average monthly temperatures. They also found that ClimateAP does not accurately reflect the regional effect of northeastern monsoons. Dr. Lin has already contacted Dr. Tongli Wang about how to resolve this disparity and improve the ClimateAP model. Dr. Lin also outlined their plan for the climate-niche modelling component of the project at the species level and for ecoregions. They also plan to apply FORECAST Climate; this was discussed with Dr. Seely in the previous meeting and where a plan was developed to carry out the research.

Presentation: Closing to the Training Workshop on Modelling Climate and Ecosystems in a Changing Climate, presented by Ms. Shari Mang

To close the workshop, Ms. Shari Mang gave a presentation summarizing the week's events and outlining the steps moving forward. She began with a review of the key points from all of the lectures and linked these to the main objectives of the workshop. This was a way to help participants digest the extensive amount of information they received over the week and remind them of the key elements that the organizers aimed to have them gain from the workshop. As well, Ms. Mang discussed the remaining milestones in the Year 1 Work Plan and how the local collaborators are expected to participate in achieving these objectives. She discussed the steps local partners are expected to take to share the information and skills gained at the workshop with their colleagues and collaborators and reminded them of the individual work plans and timelines they'd set for themselves. Ms. Mang closed the presentation with a montage of photos from the workshop and extended her sincere thanks for their hard work and attention during the week.

Participants and Instructors at the Training Workshop on Modelling Climate and Forest Ecosystems in a Changing Climate

	Name	Economy	Institution	Attendance Date
<i>Trainees</i>				
1	Dr. Siti Nurhidayu Abu Bakar	Malaysia	Universiti Putra Malaysia	May 31 – June 7
2	Dr. Ahmad Ainuddin Bin Noruddin	Malaysia	Universiti Putra Malaysia	May 31 – June 7
3	Dr. Norizah Kamaruddin	Malaysia	Universiti Putra Malaysia	May 31 – June 7
4	Dr. Sithong Thongmanivong	Laos	National University of Laos	May 31 – June 7
5	Mr. Fongkeo Boualapha	Laos	National University of Laos	May 31 – June 7
6	Mr. Chittana Phomphila	Laos	National University of Laos	May 31 – June 5
7	Mr. Thein Saung	Myanmar	Forest Research Institute	May 31 – June 7
8	Mr. Billy Ne Win	Myanmar	Forest Research Institute	May 31 – June 7
9	Mr. Soe Myint Thein	Myanmar	Forest Research Institute	May 31 – June 7

10	Dr. Huan-Yu Lin	Chinese Taipei	Taiwan Forestry Research Institute	May 31 – June 7
11	Dr. Tze-Ying Chen	Chinese Taipei	National Ilan University	May 31 – June 7
12	Ms. Chia-I Kuo	Chinese Taipei	Taitung Sustainable Development Society	May 31 – June 7
13	Dr. Shuaifeng Li	China	Chinese Academy of Forestry	May 31 – June 7
14	Dr. Jianrong Su	China	Chinese Academy of Forestry	May 31 – June 7
15	Dr. Wande Liu	China	Chinese Academy of Forestry	May 31 – June 7
16	Dr. Xiaobo Huang	China	Chinese Academy of Forestry	May 31 – June 7
17	Dr. Shusen Wang	China	Inner Mongolia Agriculture University	May 31 – June 4
18	Dr. Nobuya Mizoue	Japan	Kyushu University	June 2 – June 5
19	Ms. Lianzhen Xu	Canada	University of British Columbia	May 31 – June 7
<i>Guest Lecturer and Trainee</i>				
1	Dr. Guoliang Liu	Canada/China	Wenzhou Carbon Academy and Nanjing Jialin System Engineering Ltd.	May 31 – June 6
<i>Instructors</i>				
1	Dr. Guangyu Wang	Canada	University of British Columbia	May 31 – June 7
2	Dr. Tongli Wang	Canada	University of British Columbia	May 31 – June 2
3	Dr. Brad Seely	Canada	University of British Columbia	May 31 – June 7
4	Dr. Peter Marshall	Canada	University of British Columbia	May 31 – June 4
5	Dr. Futao Guo	China	Fujian Agriculture and Forestry University	June 6 – June 7
6	Dr. Haijun Kang	China	Fujian Agriculture and Forestry University	June 2 – June 7
7	Dr. Lin Cao	China	Nanjing Forestry University	June 6
<i>APFNet Representatives</i>				
1	Mr. Kebiao Huang	China	APFNet	May 31 – June 3
2	Mr. Zuofeng Zuang	China	APFNet	May 31 – June 1

Workshop Schedule

Date	Time	Activity	Activity leader(s)
May 30	Whole day	Participants arrive and check in to Expo Garden Hotel	
May 31	7:30 – 8:00	BREAKFAST	
	9:00 – 9:30	Opening Ceremony	Dr. Chen Xiaoming (IRI); Mr. Kebiao Huang and Mr. Zoufeng Zhuang (APFNet); Dr. Peter Marshall (UBC); SWFU Representative; Dr. Guangyu Wang (UBC)
	9:30 – 9:45	Group photo	
	9:45 – 10:15	Introduction to program, activities, instructors, and participants	Dr. Guangyu Wang
	10:15 – 10:30	TEA BREAK	
	10:30 – 12:00	Lecture: Climate change and forest management policy under the context of COP21	Dr. John Innes
	12:00 – 13:30	LUNCH	
	13:30 – 14:30	Project Overview and Phase II Arrangement	Dr. Guangyu Wang
	14:30 – 15:00	Overview of data requirements and training workshop activities	Dr. Tongli Wang and Dr. Brad Seely
	15:00 – 15:15	TEA BREAK	
	15:15 – 17:00	Lecture: Forest Inventory I	Dr. Peter Marshall
	17:30	DINNER	
June 1	7:30 – 8:00	BREAKFAST	
	8:15 – 8:30	Morning welcome and daily review	
	8:30 – 10:00	Lecture: Forest Inventory II	Dr. Peter Marshall
	10:00 – 10:15	TEA BREAK	
	10:15 – 12:00	Lecture: Modelling Stand Dynamics	Dr. Peter Marshall
	12:00 – 13:30	LUNCH	
	13:30 – 15:00	Lecture: ClimateAP	Dr. Tongli Wang
	15:00 – 15:15	TEA BREAK	
	15:15 – 17:00	Lecture: ClimateAP Continued	Dr. Tongli Wang
	17:30	DINNER	
June 2	7:30 – 8:00	BREAKFAST	
	8:15 – 8:30	Morning welcome and daily review	
	8:30 – 10:00	Lecture: Climate Niche Modelling	Dr. Tongli Wang
	10:00 – 10:15	TEA BREAK	
	10:15 – 12:00	Lecture: Climate Niche Modelling Continued	Dr. Tongli Wang
	12:00 – 13:30	LUNCH	
	13:30 – 15:00	Lecture: Overview: Forest response to climate change	Dr. Brad Seely
	15:00 – 15:15	TEA BREAK	
	15:15 – 17:30	Lecture: Introduction to FORECAST & FORECAST Climate	Dr. Brad Seely
	18:00	DINNER	
June 3	7:30 – 8:00	BREAKFAST	
	8:15 – 8:30	Morning welcome and daily review	

	8:30 – 10:00	Lecture: Review Data requirements & Algorithms	Dr. Brad Seely
	10:00 – 10:15	TEA BREAK	
	10:15 – 12:00	Lecture: Review Data requirements & Algorithms	Dr. Brad Seely
	12:00 – 13:30	LUNCH	
	13:30 – 15:00	Working with FORECAST software	Dr. Brad Seely
	15:15 – 15:30	TEA BREAK	
	15:30 – 17:00	Working with FORECAST software	Dr. Brad Seely
	17:30	DINNER	
June 4	7:00 – 8:00	BREAKFAST	
	8:00 – 17:30	Field trip to Stone Forest and Yunnan Nationalities Village. See page 27 for the trip itinerary	
	18:00	DINNER	
June 5	7:30 – 8:00	BREAKFAST	
	8:15 – 8:30	Morning welcome and daily review	
	8:30 – 10:00	Lecture: Review FORECAST Climate data requirements & Simulation Algorithms	Dr. Brad Seely
	10:00 – 10:15	TEA BREAK	
	10:15 – 12:00	Lecture: Review FORECAST Climate data requirements & Simulation Algorithms	Dr. Brad Seely
	12:00 – 13:30	LUNCH	
	13:30 – 15:00	Working with FORECAST Climate software	Dr. Brad Seely
	15:00 – 15:15	TEA BREAK	
	15:15 – 17:00	Working with FORECAST Climate software	Dr. Brad Seely
	17:30	DINNER	
June 6	7:30 – 8:30	BREAKFAST	
	8:30 – 10:00	Meet with individual groups 8:30 – 9:10: Malaysia 9:20 – 10:00: Myanmar	Dr. Brad Seely
	10:00 – 10:15	TEA BREAK	
	10:15 – 12:00	Meet with individual groups 10:15 – 10:55: Laos 11:00 – 11:20: China 11:20 – 11:40: Chinese Taipei	Dr. Brad Seely
	12:00 – 13:30	LUNCH	
	13:30 – 14:30	Lecture: LiDAR and its application	Dr. Lin Cao
	14:30 – 14:45	TEA BREAK	
	14:45 – 16:00	Lecture: Tree and plot biomass estimation using LiDAR data	Dr. Lin Cao
	16:00 – 17:30	Lecture: Optimizing and balancing carbon storage and other values of a forest	Dr. Guoliang Liu
	18:00	DINNER	
June 7	7:30 – 8:00	BREAKFAST	
	8:15 – 8:30	Morning welcome and daily review	
	8:30 – 10:00	Lecture: Climate change and forest fire management	Dr. Futao Guo
	10:00 – 10:15	TEA BREAK	
	10:15 – 11:45	Group Presentations	
	11:45 – 12:30	Closing presentation and workshop evaluation	Ms. Shari Mang
	12:30 – 14:00	LUNCH	
	14:00 – 17:30	Free afternoon to explore Kunming or to arrange meetings to discuss the project's next steps.	
	18:30	DINNER	

Workshop Evaluation Form

Evaluation Form: Training Workshop on Modelling Climate and Forest Ecosystems in a Changing Climate

A. Workshop Evaluation

Please rank the following statements from “1 – Strongly Agree” to “5 – Strongly Disagree”.

	Strongly Agree				Strongly Disagree
1. Overall, the workshop was very useful.	1	2	3	4	5
2. The program was well paced within the allotted time.	1	2	3	4	5
3. The instructors were knowledgeable about the topics.	1	2	3	4	5
4. The workshop, lectures, and activities were well organized.	1	2	3	4	5
5. The supplementary material provided prior to the workshop was useful in preparing for the workshop lectures.	1	2	3	4	5
6. The workshop has greatly improved your knowledge and skills regarding the tools/models presented.	1	2	3	4	5
7. You feel confident to independently use ClimateAP to carry out the project’s research.	1	2	3	4	5
8. You feel confident to independently use FORECAST/FORECAST Climate to carry out the project’s research.	1	2	3	4	5

Please select one response for each of the following questions:

9. The supplementary material (i.e. the Training Handbook) provided prior to the workshop contained:
- ☐ a) Not enough detail ☐ b) An appropriate level of detail ☐ c) Too much detail
10. The technical level of the information presented was:
- ☐ a) Too introductory ☐ b) At the appropriate level ☐ c) Too advanced
11. Was the workshop:
- ☐ a) Too short ☐ b) The right length ☐ c) Too long

B. Lecturer evaluation

Please rank the following statements from “1 – Strongly Agree” to “5 – Strongly Disagree” for each of the indicated lecturers.

1. DR. PETER MARSHALL

	Strongly Agree				Strongly Disagree
1. The lecturer was clear and understandable in their presentations.	1	2	3	4	5
2. The information presented was well organized and well explained.	1	2	3	4	5
3. The lecturer was knowledgeable about the topic.	1	2	3	4	5
4. The lecturer provided clear and helpful responses to questions that were asked.	1	2	3	4	5

2. DR. TONGLI WANG

	Strongly Agree				Strongly Disagree
1. The lecturer was clear and understandable in their presentations.	1	2	3	4	5
2. The information presented was well organized and well explained.	1	2	3	4	5
3. The lecturer was knowledgeable about the topic.	1	2	3	4	5
4. The lecturer provided clear and helpful responses to questions that were asked.	1	2	3	4	5

3. DR. BRAD SEELY

	Strongly Agree				Strongly Disagree
1. The lecturer was clear and understandable in their presentations.	1	2	3	4	5
2. The information presented was well organized and well explained.	1	2	3	4	5
3. The lecturer was knowledgeable about the topic.	1	2	3	4	5
4. The lecturer provided clear and helpful responses to questions that were asked.	1	2	3	4	5

4. DR. LIN CAO

	Strongly Agree				Strongly Disagree
1. The lecturer was clear and understandable in their presentations.	1	2	3	4	5
2. The information presented was well organized and well explained.	1	2	3	4	5

3. The lecturer was knowledgeable about the topic.	1	2	3	4	5
4. The lecturer provided clear and helpful responses to questions that were asked.	1	2	3	4	5

5. DR. GUOLIANG LIU

**Strongly
Agree**

**Strongly
Disagree**

1. The lecturer was clear and understandable in their presentations.	1	2	3	4	5
2. The information presented was well organized and well explained.	1	2	3	4	5
3. The lecturer was knowledgeable about the topic.	1	2	3	4	5
4. The lecturer provided clear and helpful responses to questions that were asked.	1	2	3	4	5

6. DR. FUTAO GUO

**Strongly
Agree**

**Strongly
Disagree**

1. The lecturer was clear and understandable in their presentations.	1	2	3	4	5
2. The information presented was well organized and well explained.	1	2	3	4	5
3. The lecturer was knowledgeable about the topic.	1	2	3	4	5
4. The lecturer provided clear and helpful responses to questions that were asked.	1	2	3	4	5

C. Additional Comments

Please write any additional comments you have regarding positive elements of the workshops and areas that need improvement.

Summary of Evaluation Responses

Summary of Responses to the Workshop Evaluation

The following results are based on the responses from 13 participants.

A. Workshop Evaluation

Response key Q1-8: Ranked on a scale from “1 – Strongly Agree” to “5 – Strongly Disagree”.

Question	Mean Response
1. Overall, the workshop was very useful.	1.31
2. The program was well paced within the allotted time.	1.31
3. The instructors were knowledgeable about the topics.	1.08
4. The workshop, lectures, and activities were well organized.	1.15
5. The supplementary material provided prior to the workshop was useful in preparing for the workshop lectures.	1.62
6. The workshop has greatly improved your knowledge and skills regarding the tools/models presented.	1.46
7. You feel confident to independently use ClimateAP to carry out the project’s research.	2.08
8. You feel confident to independently use FORECAST/FORECAST Climate to carry out the project’s research.	2.38

Response key Q9-11:

- Q9: 1=not enough detail; 2=an appropriate level of detail; 3=too much detail
- Q10: 1=too introductory; 2=at the appropriate level; 3=too advanced
- Q11: 1=too short; 2=the right length; 3=too long

Question	Mean Response
9. The supplementary material (i.e. the Training Handbook) provided prior to the workshop contained:	2.15
10. The technical level of the information presented was:	2.15
11. Was the workshop:	2.00

B. Lecturer evaluation

Response key for lecturer evaluation: Ranked on a scale from “1 – Strongly Agree” to “5 – Strongly Disagree”.

1. DR. PETER MARSHALL

	Mean Response
1. The lecturer was clear and understandable in their presentations.	1.23
2. The information presented was well organized and well explained.	1.23
3. The lecturer was knowledgeable about the topic.	1.31
4. The lecturer provided clear and helpful responses to questions that were asked.	1.23

2. DR. TONGLI WANG

	Mean Response
1. The lecturer was clear and understandable in their presentations.	1.31
2. The information presented was well organized and well explained.	1.46
3. The lecturer was knowledgeable about the topic.	1.23
4. The lecturer provided clear and helpful responses to questions that were asked.	1.23

3. DR. BRAD SEELY

	Mean Response
1. The lecturer was clear and understandable in their presentations.	1.31
2. The information presented was well organized and well explained.	1.15
3. The lecturer was knowledgeable about the topic.	1.31
4. The lecturer provided clear and helpful responses to questions that were asked.	1.15

4. DR. LIN CAO

	Mean Response
1. The lecturer was clear and understandable in their presentations.	1.08
2. The information presented was well organized and well explained.	1.08
3. The lecturer was knowledgeable about the topic.	1.31

4.	The lecturer provided clear and helpful responses to questions that were asked.	1.23

5. DR. GUOLIANG LIU

		Mean Response
1.	The lecturer was clear and understandable in their presentations.	1.46
2.	The information presented was well organized and well explained.	1.54
3.	The lecturer was knowledgeable about the topic.	1.38
4.	The lecturer provided clear and helpful responses to questions that were asked.	1.46

6. DR. FUTAO GUO

		Mean Response
1.	The lecturer was clear and understandable in their presentations.	1.31
2.	The information presented was well organized and well explained.	1.38
3.	The lecturer was knowledgeable about the topic.	1.38
4.	The lecturer provided clear and helpful responses to questions that were asked.	1.23

Annex D 5: Capacity-Building and Educational Outreach in the Asia-Pacific

The Asia-Pacific region has been identified as exceptionally vulnerable to climate change, as it contains more than 60% of the world's population - many of whom are impoverished and dependent on natural resources, such as forests, for their survival. With 18.3% of global forest cover and much of the world's biodiversity, the degradation and loss of natural forest ecosystems in the Asia-Pacific region would be detrimental to the local communities and economies dependent upon these systems, as well as global ecosystem stability and diversity. Thus, it is absolutely critical that capacity-building and educational outreach occur to ensure that beyond the implications of this research project, future foresters and land managers have sufficient knowledge and training to manage the land to ensure environmental and socio-economic stability in the region for future generations.

During site visits in spring 2017 to project research plots in Laos and Myanmar, undergraduate level forestry students were incorporated into field research activities through a brief training session provided by project team members Dr. Brad Seeley and Ms. Lianzhen Xu in collaboration with local partners. Students were taught how to conduct accurate field measurements and data collection, including the use of industry-standard measurement instruments such as clinometers. Students participated and aided in the collection of data, by providing information such as tree diameter-at-breast-height (DBH), tree height, and density difference. Additionally, volunteer students were able to aid in the marking of measured trees within research plots and help record GPS coordinates for future visits.

Incorporating future forestry professionals in recent field research has allowed for students to gain valuable, hands-on experience while learning standard industry techniques and applications, while further providing students with exposure to this research project. It is critical that future forest and land managers, particularly in the Asia-Pacific, understand the importance of climate change and adaptive forest management for the future viability of regional forests. Through including students in research and exposing them to applicable techniques and relevant adaptive management research projects, we are preparing the future of tomorrow to better manage and plan for regional forests, using the scientific knowledge that this project provides to integrate into forest management practices in order for forest ecosystems to adapt and mitigate the effects of climate change, maintaining the livelihoods of local people.



Undergraduate trainee students



Annex D6: Summary Report - Training Workshop on FORECAST Climate Modelling and its application in a Changing Climate

Adaptation of Asia-Pacific Forests to Climate Change – Phase II
Forest Research Institute, Myanmar, Nov 15, 2017

Opening remarks of the training workshop

The workshop began with open remarks from Dr. Thaung Naing Oo (Director of FRI). He welcomed participants to the meeting and gave an introduction to their institution and involvement with the project. As well, he stated the importance of learning and application of our tools to Myanmar. Dr. Guangyu Wang then welcomed the trainees and thanked FRI and FD for the all supporting. Dr. Nobuya Mizoue also gave a statement to the trainees. He emphasized the importance of such tool and encouraged all the trainees to learn it. Finally, all attendees from both FRI and FD self-introduced themselves.



Photo: Open remarks from Dr. Thaung Naing Oo (Director of FRI)

Presentation: Overview of FORECAST Climate Model Workshop in Forest Research Institute in Myanmar by Dr. Brad Seely

As Dr. Brad Seely was the only lecturer of the workshop, he provided a general introduction to the workshop in FRI. At the beginning, he explained his objectives and what is expected from the

participants in the workshop. He ended up with an overview of the agenda for the whole day training.



Photo: Overview of FORECAST Climate Model training workshop by Dr. Brad Seely

Lecture: An Overview of the FORECAST Model by Dr. Brad Seely

Firstly, Dr. Brad Seely briefly provided an overview of the FORECAST model. FORECAST is a powerful decision support tool that can be used to examine a wide variety of forest management alternatives. Hybrid calibration approach provides the flexibility of a process model with a strong empirical foundation and relatively simple calibration. He then reviewed the concept of ecological rotation and presented an example application of FORECAST Model to evaluate yield decline in Chinese fir plantations. He concluded that applications of FORECAST Model include assessments of: Ecosystem resilience, long-term flow of ecosystem services, multi-objective forest management.

Lecture: Overview of FORECAST Data Requirements and Key Simulation Algorithms

In this lecture, Dr. Seely focused on introducing the structure of the FORECAST model and the data requirements. He went through various components of the model; he discussed in detail the data inputs and steps involved in the setup of the model, how this information is interpreted in the ecosystem simulation component, and ultimately the outputs that are generated by the model. Dr. Seely then focused on specific elements of the model, starting with the data requirements for the input files; he clearly indicated the various data categories and potential data sources for each. He went through the core ecosystem processes represented in FORECAST ESM and discussed the feedbacks and relationships that are incorporated in the model and the importance of the inclusion

of these relationships. Dr. Seely then walked participants through the simulation algorithms that are used in the model, focusing on Net Primary Production as an example. As well, he provided a schematic illustrating all the components and relationships represented just within the nutrient cycling component of FORECAST. The detailed description of the workings of the model gave trainees a thorough understanding of the capacity of the model and what ecosystem components are considered and simulated.

Following the lecture, Dr. Seely then went through all of the data files he'd previously provided to participants; this included published work for their reference, detailed instructions on how to install and run the model, and sample data sets. He provided detailed instruction on what information needs to be input, what that information is used for, and its importance to the model. Dr. Seely also indicated moments where they could check the accuracy of their data, such as generating intermediate stage graphs, in order to avoid potential errors in their input data and to catch any mistakes or missing data before they run the model.



Photo: Dr. Brad Seely gives lectures on FORECAST Model

Activity: Using FORECAST Model, led by Dr. Brad Seely, assisted by Ms. Lianzhen Xu

Dr. Brad Seely used the results of current research of Teak to demonstrate how the model can be implemented and the information it generates. Dr. Seely spent the last part of the morning installing FORECAST software onto participants' computers so that they would be able to work with the model in the afternoon.

With participants following on their own computers, Dr. Seely used the example data set he'd provided them to go through the set up and running of FORECAST. He went through each element in fine detail, including the model setup, where data should be stored, the various codes used for different simulations, how to create an ecostate file, how to set up management regimes and how to interpret outputs. After his demonstration, participants spent some time working with the model on their own while Dr. Seely and Ms Lianzhen Xu assisted them and addressed any questions that arose.

Activity: Closing discussion to the Training Workshop on FORECAST Climate Model led by Dr. Brad Seely and Mr. Thein Saung

By the end of training workshop, the trainees raised a lot of questions by using FORECAST Model in Myanmar, such as how to apply it to natural forests, how to build up setup dataset, how to simulate it with climate component on, etc. Dr. Brad Seely patiently answered each of the questions. He suggested that natural forests could be classified into different groups based on ecotypes and knowledge of local expertise. However, it would be better to start with plantations (eg. Teak). In terms of input dataset, the setup data is built up on the literature review, field plot measurement, and experts' opinion.



Photo: Discussion on application of FORECAST Climate Model at the end of the training workshop



Photo: Group photo after training workshop

List of Training Workshop Attendance

No.	Name	Position	Department/Organization
1.	U Soe Min Thu	Range Officer	Training & Research Development
2.	U Tin Linn Aung	Range Officer	Natural Forest and Planting
3.	U Khaing Zaw Win	Staff Officer	Planning and Statistic
4.	U Thein Saung	Staff Officer	Forest Research Institute
5.	U Myo San	Range Officer	Planning and Statistic
6.	U Tet Nay Tun	Range Officer	Extension
7.	U Kyaw Sein Win Tun	Staff Officer	Wildlife Conservation
8.	Daw Ei Sandar Myint	Range Officer	Natural Forest and Planting
9.	Daw May Thet Htoo	Range Officer	Watershed Management
10.	Daw Thet Myat Yadanar Aye	Range Officer	Watershed Management
11.	Daw Shwe Lon	Research Assistant -3	Forest Research Institute
12.	Daw Kyi Khaing	Research Assistant -2	Forest Utilization
13.	Daw Win Win Nwe	Range Officer	Forest Research Institute
14.	Daw Tin Hnaung	Range Officer	Forest Research Institute

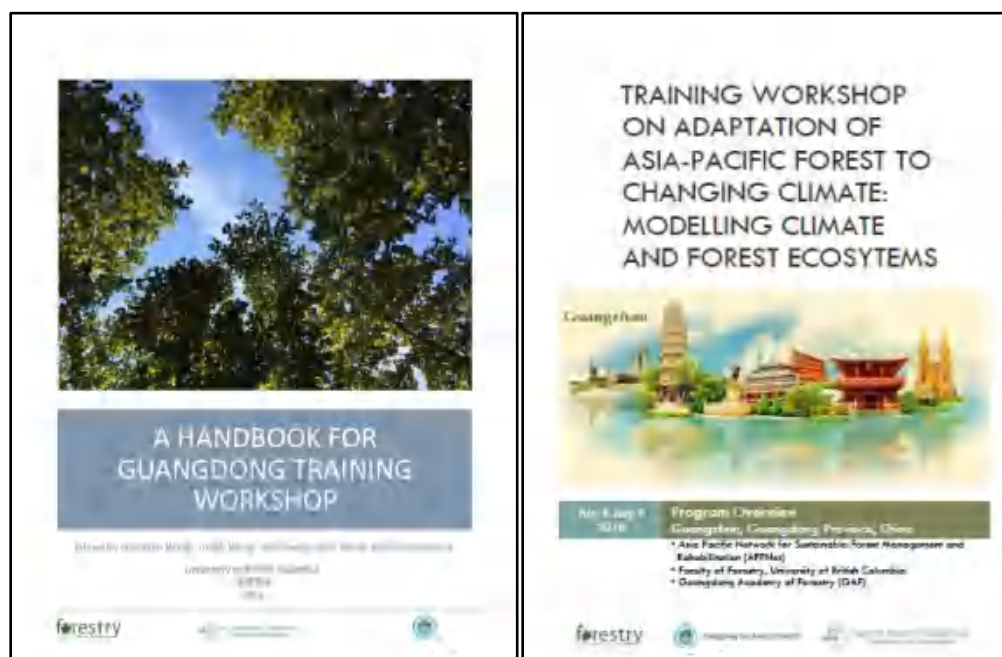
	Aye		
15.	Daw Ei Ei Zin	Research Assistant -3	Forest Research Institute
16.	Dr. Phyu Phyu Lwin	Staff Officer	Forest Research Institute
17.	Daw Ni Zin Phoo	Range Officer	Forest Research Institute
18.	U Ye Htet Aung	Project Assistant	KFS
19.	U Htet Swen Pyae	Project Assistant	KFS
20.	Daw Thae Cho Aye	Project Assistant	KFS
21.	Daw Ei Wah Wah Thet	Project Assistant	ICIMOD
22.	U Billy Nay Win	Research Assistant -2,	Forest Research Institute

Annex D7: Summary Report - Training Workshop on Adaptation of Asia-Pacific Forests to Climate Change: Modeling Climate and Forest Ecosystems

*Adaptation of Asia-Pacific Forests to Climate Change – Phase II
Guangzhou, China, July 4-9, 2018*

1. Introduction to the Workshop

The training workshop “Adaptation of Asia-Pacific Forest to Changing Climate: Modeling Climate and Forest Ecosystems” was organized by the University of British Columbia, Canada in partnership with the Guangdong Academy of Forestry, China from July 4-9, 2018 in Guangzhou, China. The main objective of the workshop was to enhance the capacity of forest managers, policy makers and researchers in the Asia-Pacific Region by training them on application of the models and tools developed in the project for effectively and accurately conduct research and formulate adaptive forest management strategies against changing climate. The workshop is one of several project components aimed at achieving APFNet’s goals of improving capacity and knowledge transfer in the Asia-Pacific region. A comprehensive updated handbook/training manual (pages 197) containing background readings and application of tools/models was prepared and distributed to the workshop participants before the workshop (digital book) and printed book later during the workshop.



A glimpses of Training handbook and Programme Overview for the workshop.

With this objective, the workshop was conducted for 4 days. Lecture topics focused on an introduction to the development and application of models and tools particularly ClimateAP, climate niche modelling, and FORECAST Climate models including technological and modelling advancements, the impacts of climate change on tree species/forest ecosystems and current forest policy regarding climate change mitigation and adaptation. Participants received a comprehensive education on these topics and were actively trained in the use of ClimateAP and FORECAST Climate so that they can independently use these models to contribute to the project’s research.

Workshop attendance was higher than initially anticipated. Altogether 62 participants from seven economies (China, Myanmar, Malaysia, Thailand, Cambodia, Chinese Taipei and Canada) representing various organization from Department of Forest, Research Institute, University as well as private organization participated in the workshop including six instructors from Faculty of Forestry, University of British Columbia, one instructor from Taiwan Research Centre, one guest lecturer from Chinese Academy of Forestry (who also participated as a trainee) and two representative from APFNet. Please see section 3 for complete list of participants and programme overview.



Group photo of workshop participants.

The array of topics and hand on exercise that were presented in the workshop ensured participants received a comprehensive understanding of the climate change and the research strategies and techniques that can be used to better assess climate change impacts on forests. The workshop successfully increased the knowledge and capacity of participants to use tools and models developed in the Adaptation of Asia-Pacific Forests to Climate Change project including technological and modelling advancements, which will enable them to achieve the Phase II research objectives and help address climate change adaptation in the Asia-Pacific region. A summary of each day's activities and lectures is provided **in the Section 2**.

2. Summary of Workshop Activities

2.1 Day 1: July 5, 2018

Opening remarks

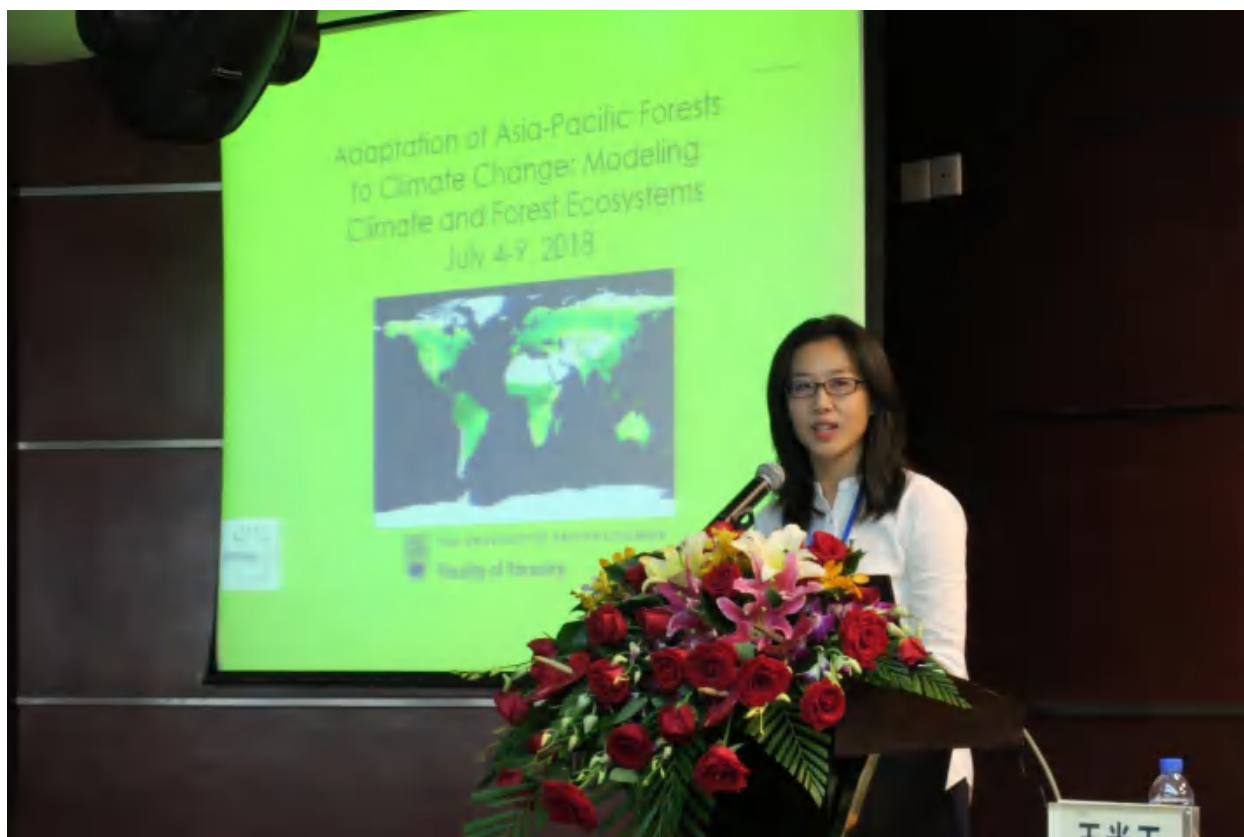
Dr. Guangyu Wang opened the workshop by welcoming participants to the training program and introducing them to Guangzhou followed by opening remarks from a panel including Dr. Wen Pan from Guangdong Academy of Forestry, Ms. Sun Weina from the Asia-Pacific Network for Sustainable Forest Management and Rehabilitation (APFNet), Dr. John Innes and Dr. Guangyu Wang from the University of British Columbia (UBC). Each welcomed participants to the workshop and gave an introduction to their institution and their involvement in the project.



A welcome address by Dr. Guangyu Wang, faculty of forestry, University of British Columbia.



A welcome addressed by Dr. Wen Pan from Guangdong Academy of Forestry, Guangzhou.



A welcome address by Ms. Sun Weina from the Asia-Pacific Network for Sustainable Forest Management and Rehabilitation (APFNet)

Presentation: Adaptation of Asia-Pacific forests to Climate change- PhaseII, presented by Dr. Guangyu Wang

Dr. Guangyu Wang's presentation including two parts. In the first part, he presented an overview of Climate Change in the Asia-Pacific Project: Adaptation of Asia-Pacific Forests to Climate Change (Phase II). He discussed the climate change in the Asia-Pacific region, the objectives of the project, and the key outcomes of the project. In the second part, he discussed each of the organizations involved in hosting the workshop – APFNet, UBC, and Guangdong Academy of Forestry. Dr. Wang further introduced all of the lecturers and gave a brief summary of their research expertise and what they would focus on during their lectures. Lastly, he reviewed the weeks schedule to provide participants with a clear understanding of what would be covered and expected of them during the workshop.



Dr Guangyu Wang presenting overview of the project and introduction of the workshop.

Presentation: Introduction to Faculty of Forestry, UBC and its partnership with APFNet, presented by Dr. John Innes

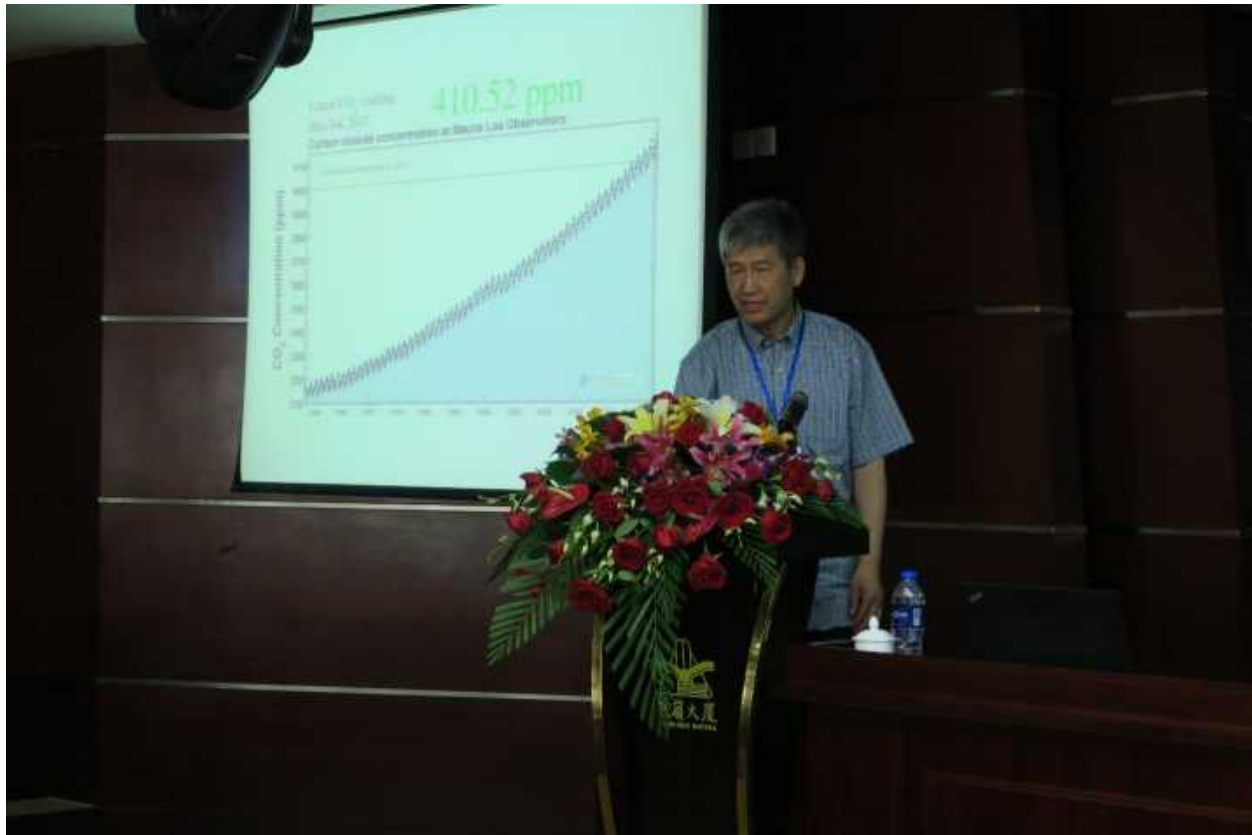
Dr. John Innes began with welcoming participants to the workshop, and then briefly introduced the programs, research groups, courses, and scholarships of Faculty of Forestry at UBC. He also summarized the partnership with the APFNet, including Adaptation of Asia-Pacific Forests to Climate change project, online courses on Innovative SFM Education, Capacity training for APFNet and member economies, and AP-FECM office. Lastly, he welcomed students, researchers, and officers to come to UBC for studying, training and visiting.



A welcome address by Dr. John Inness, Faculty of Forestry, University of British Columbia

Lecture: Introduction to climate and ecological modeling for forest adaptation to climate change, presented by Dr. Tongli Wang

Dr. Tongli Wang opened the first day of the training with an overview of the evidence of climate change and how these changes are expected to impact forest ecosystems through shifts in the climate niches of tree species resulting in less optimal growing conditions for the species. He discussed options for assisted migration as the climate is expected to change faster than tree species can migrate.



Dr. Tongli Wang lecturing about ClimateAP and its application.

Lecture: Introduction to ClimateAP and working with ClimateAP, presented by Dr. Tongli Wang

Dr. Tongli Wang introduced trainees to the climate model ClimateAP which he developed during the project. He described the features of ClimateAP, including scale-free, many ecologically relevant climate variables, incorporated and downscaled historical and future climates, and efficient and easy use. He walked them through other available climate models and explained how ClimateAP differs from them and how these differences result in ClimateAP being more accurate than other available models. Dr. Wang went through the steps in developing ClimateBC, the predecessor to ClimateAP, and justified the importance and necessity of each of the steps to generating high accuracy and low-resolution climate data. As well, Dr. Wang explained how to use both the GoogleMaps based version and desktop version of ClimateAP. Trainees downloaded the desktop version to their computers so that they could follow along as Dr. Wang went through some examples. He showed them step-by-step how to run the model for various periods and climate scenarios with different variable outputs.



Dr. Tongli Wang discussing with participants about ClimateAP tool.

Lecture: Local application of ClimateAP in Chinese Taipei, presented by Dr. Huanyu Lin

Dr. Huanyu Lin presented his use and local application of ClimateAP in Chinese Taipei. He described his experience of using the methodology of ClimateAP. According to local condition and data availability, he developed clim.regression which is a topographical-correspondent and scale-free climate downscaling model for Chinese Taipei. Overall, Dr. Lin provided an evident that ClimateAP is a very useful and accurate climate model, which could be applied to local forest ecosystem in the context of climate change.



Dr. Huanyu Lin presenting development and local application of ClimateAP in Chinese Taipei.

Lecture: Introduction to climate niche models for forest tree species and forest ecosystems, presented by Dr. Tongli Wang

In this part, Dr. Wang went through the model he has developed to predict the changes in the climatic niche of tree species and forest ecosystem. This included the development of the Random Forest model and the steps he has taken to overcome several issues associated with this type of model. Dr. Wang then went through the results from the model application to major species in the Asia-Pacific to highlight the type of information that can be gleaned from the model projections. Dr. Wang discussed the application and limitations of the climate niche models and how they differed from species distribution models. Dr. Wang also presented the use and application of this model using an ecosystem-based approach in BC, in China, and recently in Myanmar. At the end, he described how to work with the web platform for data access and visualization for specific economies.

Lecture: Applications of climate niche model in Chinese Taipei, presented by Dr. Huanyu Lin

Dr. Huanyu Lin demonstrated his application of Climate niche models for current and future distribution of montane forest vegetation in Chinese Taipei. He began with the introduction to the climate and vegetation of Chinese Taipei, followed by the objectives of his research. He then went through the methods and findings of modelling. He summarized that random forest could clearly demonstrate the upward and northward migration of vegetation under climate change scenarios. He further listed the limitation of climate niche model for modelling the change of monsoon forests. This provided participants with an example of what was accomplished in project and got them thinking about how they could use this tool in their own study region.

Day 2: July 6, 2018

Lecture: Review of climate impacts on forest growth and development: toward the application of FORECAST Climate, presented by Dr. Brad Seely

Dr. Seely's first lecture focused on some of the expected changes in climate that may impact forest productivity. He also explain the importance of ENSO events and how they may be impacted by climate change. This is of particular importance, as El Niño events can results in severe drought in Southeast Asia, and the impacts of drought on forest productivity is one of the research questions being explored in the Asia-Pacific Region. Dr. Seely then posed questions that how we can cope with the climate change and how we can use forest ecosystem models to evaluate long-term impacts and adaptation alternatives. Finally, he presented the issues with respect to model application. He presented this information to participants as a way to familiarize everyone with the issues being faced in each region and to get them thinking about the sort of questions they want to address.



Dr. Brad Seely presenting review of climate impacts on forest growth and development.

Lecture: An overview of FORECAST model and its application to examine management of teak plantation in Myanmar (model calibration), presented by Dr. Brad Seely

Dr. Seely's second presentation included two parts. During the first part, he briefly introduced the basic FORECAST model which FORECAST Climate was built upon; he reviewed the concept of ecological rotation; he then outlined the data requirements for the model and the ecosystem and management processes that it can represent; and he discussed the model application and outputs. In the second part, he presented his work on the application of FORECAST to examine management of teak (*Tectona grandis*) plantations in Myanmar. He briefly introduced teak forests in Myanmar, and described the field works has been done to calibrate the model for teak.

Lecture: FORECAST Model Application to Evaluate Impacts of Fire Frequency, Rotation Length, and Bamboo Competition on Teak Plantations by Ms Lianzhen Xu

Ms. Lianzhen Xu outlined her method and presented the results for using FORECAST to evaluate the impacts of different management scenarios on productivity and health of teak plantation in Myanmar. She went through some example outputs using FORECAST Model to simulate the impacts of fire frequency, rotation length, and bamboo competition on teak plantation. She concluded that short rotation and frequency burnings would deteriorate the soil, resulted in declining yield and degraded soil fertility in the successive rotations; although Bamboos could lead to reduction in teak productivity, they can increase the humus mass thus improve the soil fertility. This was an effective presentation in highlighting how FORECAST can be used and the type of analysis it can be used for.



Ms Lianzhen Xu presenting application of FORECAST model on Teak plantation in Myanmar.

Lecture: Regional forest observations for sustainable forest management, presented by Dr. Yong Pang

Dr. Pang's presentation included three major parts: introduction to remote measurement for forest management, GMS+ Project outputs and impacts, and RFO Project workplan and progress. Firstly, he provided background on the needs to forest resource observation. He walked us through different methods, techniques and tools of remote measurement. He introduced LiCHy (CAF's Lidar-CCD-Hyperspectral Airborne Observation System), and CHEOS (China High-resolution Observation

System). He discussed the issues on the application of the observed data to the tree level, stand level, and regional level and how to improve the results. During his second part of the presentation, he introduced the work he has done on GMS+ Projects which was mapping forest cover and carbon in the Greater Mekong Subregion and Malaysia. In the third part, he described his current RFO Project (i.e., Regional Forest Observations for Sustainable Forest Management), which covers most of Southeast Asian country in the Asia-Pacific Region. He mentioned that outcomes from the project have already been used in the climate adaptation project. For example, the ecosystem classification map of Myanmar which was used by Dr. Tongli Wang in the climate niche of Myanmar ecosystem. He summarized that more and more high resolution remote sensing data could provide information on forest mapping activities and aid forest monitoring and assessment of forest resources, and thus help make forest management plan. Overall, Dr. Pang's presentation provided insightful advanced tools and outcomes of mapping and monitoring forest resources, and most importantly, it provided an excellent example of how to link different outcomes of different projects and potential cooperation in the future cooperation.



Dr. Pang Yong presenting application of Remote Sensing for sustainable forest management in Asia-Pacific region.

Lecture: Review of climate change impacts on forest growth and development: toward the application of FOREST Climate, presented by Dr. Brad Seely

Dr. Seely introduced FORECAST Climate which included why and how to incorporate the ForWaDy hydrological model into basic FORECAST Model. Dr. Seely went through the key components of FORECAST Climate, data requirement, and how FORECAST was adjusted to become FORECAST

Climate. Dr. Seely then went through a case study from Myanmar to illustrate how the model was calibrated and validated. Dr. Seely conducted a comprehensive literature review on the analysis of teak rings in Myanmar forests shows impact of past climate on teak growth rates. He then presented the results of model validation by using tree ring data from Central Myanmar from period 1961-2006. This lecture very clearly informed participants of the modelling advancements made by the development of FORECAST Climate and provide an example of how to apply the model in the local region.

Lecture: Simulating climate change impacts on long-term teak productivity and health, presented by Ms. Lianzhen Xu

Ms. Lianzhen Xu presented the methodology and findings of her research work has been done in Myanmar. She outlined her method for using FORECAST Climate to evaluate different climate scenarios. Ms. Xu went through how she calibrate and validate the model, her method in downscaling climate data, and her development of different climate scenarios. She then went through the results of the model and how they can be interpreted and used. This lecture provided participants with an example and got them thinking about how they could use this tool in their own study research.

Lecture: Landscape-scale evaluation of alternative management strategies in the Yedashae Township region of Myanmar, presented by Dr. Brad Seely

Dr. Brad Seely presented the methodology and findings from his previous research paper “Landscape-scale trade-off analysis of Chinese-fir plantations”. He outlined his method for using FORECAST and the Landscape Summary Tool (LST) to evaluate different management scenarios and compare the trade-offs between economic production and ecosystem services. Dr. Seely went through his development of different management scenarios and analysis units, the trade-off analysis indicators that were used, the framework of the LST model, and the application of the model. He then went through the results of the model and how they can be interpreted and used to improve forest management plans. This provided participants with an example of what was accomplished in Phase I, which highlights how FORECAST can be used and what type of analysis it can be used for.

Lecture: Landscape scale analysis of teak forest management for Yedashae Township using FSOS, presented by Dr. Brad Seely

Dr. Brad Seely presented his application of Forest Simulation and Optimization System (FSOS) model for Yedashae Township in Myanmar. He introduced the FSOS, a spatially explicit forest planning software, to the trainees. Dr. Seely went through the function of FSOS, all the forest ecosystem and management components that can be evaluated by it, and the outputs from the model. He then went through its applications of FSOS to Yedashae Township, including how he developed the spatial data. Dr. Seely showed participants how to access and use cloud-based platform where all of these tools are located and illustrated how to conduct various types of analysis. He demonstrated the types of graphs, maps, and reports the model generates and discussed how this information can be interpreted to improve forest management. As time limited, Dr. Seely didn't show the simulation results. However, there is bright prospect of interoperating the FORECAST Climate Model into FSOS System, which allows for development of strategic forest management plan for multi-objective management.

Lecture: Application of FORECAST Climate for Acacia mangium plantations in Malaysia in Malaysia, presented by Dr. Brad Seely

Dr. Brad Seely presented the methodology and findings of application of FORECAST Climate to evaluate the impacts on long-term *Acacia Mangium* plantations in Malaysia. Firstly, he overviewed the background of *Acacia* plantations in Malaysia. He then went through how he developed the dataset

for calibrating and validating the model by using sample plots established in Kemasul and Samarakan. He presented the climate variation among Acacia sites and compared the effect of location on climate response. Dr. Seely also went through methods on generating daily climate data and development of different climate scenarios (including adding an El Nino scenario by selecting the driest year back to back with certain frequency). Finally, he showed some of the results of the model and how they can be interpreted and used. This lecture provided participants with another example of the application of FORECAST Climate model, which allows the participants to learn about variations of local application.



Dr. Brad Seely presenting application of FORECAST Climate for Acacia mangium plantation in Malaysia.

Lecture: Application of FORECAST Climate for mangrove forests (*Rhizophora apiculata*) in Malaysia, presented by Dr. Brad Seely

Dr. Brad Seely's last lecture presented the methodology and findings of application of FORECAST Climate to evaluate the impacts on long-term mangrove plantations in Malaysia. He began with the introduction to Matang Mangroves in Malaysia. He then went through how he developed the FORECAST Climate dataset to calibrate the model using extensive literature. Dr. Seely also went through methods on generating daily climate data and development of different climate scenarios. Finally, he showed some of the results of the model and how they can be interpreted and used. This lecture demonstrates that FORECAST Climate model can be applied to different forest ecosystem as long as it is calibrated and validated properly.

Presentation: Closing to the Training Workshop on Modelling Climate and Ecosystems in a Changing Climate, presented by Dr. Anil Shrestha

To close the workshop, Dr. Anil Shrestha gave a presentation summarizing the workshop and outlining the steps moving forward. He began with a review of the key points from all of the lectures and linked these to the main objectives of the workshop. This was a way to help participants digest the extensive amount of information they received and remind them of the key elements that the organizers aimed to have them gain from the workshop. Dr. Shrestha closed the presentation with photos from the workshop and extended her sincere thanks for their hard work and attention during the week.



Dr. Anil Shrestha summarizing the training workshop.

Activity: Closing discussion to the Training Workshop, led by Dr. Guangyu Wang

By the end of training workshop, the trainees from different countries expressed their thanks to the hosts of the workshop. They also raised a lot of questions on the application of the tools and models presented during the workshop. For example, how to apply ClimateAP to other region, how to validate the results of climate niche model, how to apply FORECAST Climate model to natural forests, how to learn the models and tools in detail, etc. Dr. Tongli Wang and Brad Seely patiently answered each of the questions. Dr. Guangyu Wang and Ms. Weina Sun also discussed the future extension of the outcomes from the climate change adaptation project. This closing discussion is very insightful which indicates that the participants gain the depth of the workshop and the workshop achieves its objectives.



Round table discussion about training workshop.

2.5 Day 4: July 8, 2018

Activity: Field Trip to Dinghu Mountain Forest Ecosystem Research Station

For the full day field trip, participants visited Dinghu Shan Forest Ecosystem Research Station and its experiment plots in Dinghu Mountain. The participant visited the museum of the Station, experimental plots of forest ecosystems transplanted down an elevation gradient, runoff observation field, coniferous and broadleaved mixed forest experimental plot, experimental plot of acid deposition, catchment in Monsoon evergreen broadleaved forests, and experimental plots of N deposition. This field trip allowed them to know the researches has been done and researches are currently conducted in this area, and also to become more familiar with the ecosystems in Guangdong province. Glimpses of photos during the workshop was presented below.









Programme Schedule for Training Workshop on Adaptation of Asia-Pacific Forest to Changing Climate: Modelling Climate and Forest Ecosystems.

Location: Yanling Hotel, Guangzhou, China

July 4 – July 9, 2018

Date	Time	Activity	Activity leader(s)
July 4	Whole day	Arrival of Participants, check in to hotel and registration for workshop	
July 5	7:30 – 8:00	BREAKFAST	
	9:00 – 10:00	Opening Ceremony	Dr. Wen Pan, Vice President Guangdong Academy of Forestry Dr. John Innes, Dean, Faculty of Forestry, UBC Ms. Sun Weina, Director, APFNet Dr. Guangyu Wang, Associate Dean, Faculty of Forestry, UBC
	10:00 – 10:30	Group photo/Tea Break	
	10:30 – 11:00	Introduction to programs, activities, instructors, and participants	Dr. Guangyu Wang, Associate Dean, Faculty of Forestry, UBC
	11:00-12:00	Introduction to climate and ecological modeling for forest adaptation to climate change	Dr. Tongli Wang, Faculty of Forestry, UBC
	12:00-13:00	LUNCH BREAK	
	13:00-15:00	Introduction to ClimateAP Working with ClimateAP Local application in Chinese Taipei Future development of ClimateAP	Dr. Tongli Wang, Faculty of Forestry, UBC Dr. Huan-Yu Lin, Taiwan Forest Research Institute, Chinese Taipei
	15:00-15:15	TEA BREAK	
	15:15-17:50	Introduction to climate niche models for forest tree species and forest ecosystems Applications of climate niche model in Chinese Taipei Working with climate niche model predictions on ClimateAP maps Where to go next?	Dr. Tongli Wang, Associate Dean, Faculty of Forestry, UBC Dr. Huan-Yu Lin, Taiwan Forest Research Institute
	17:50	DINNER	
June 6	7:30-8:45	BREAKFAST	
	8:45-9:00	Recap from participants	
	9:00-10:15	Review of climate impacts on forest growth dynamics Overview of the application of FORECAST/FORECAST Climate as decision support tools	Dr. Brad Seely, Faculty of Forestry, UBC

	10:15-10:30	TEA BREAK	
	10:30-12:00	Evaluating management alternatives in teak/ bamboo ecosystems in Myanmar: Model calibration, field work, simulation of stand management	Dr. Brad Seely, Faculty of Forestry, UBC Ms. Lianzhen Xu, Faculty of Forestry, UBC
	12:00-13:00	LUNCH BREAK	
	13:00-13:30	Regional forest observations for sustainable forest management	Dr. Pang Yong, Chinese Academy of Forest
	13:30-14:30	Simulating climate change impacts on long-term teak productivity and health	Dr. Brad Seely, Faculty of Forestry, UBC Ms. Lianzhen Xu, Faculty of Forestry, UBC
	14:30-15:00	TEA BREAK	
	15:00-16:45	Landscape-scale evaluation of alternative management strategies in the Yedashae Township region of Myanmar	Dr. Brad Seely, Faculty of Forestry, UBC Ms. Lianzhen Xu, Faculty of Forestry, UBC
	16:45-17:15	Review and Discussion	Dr. Brad Seely, Faculty of Forestry, UBC
	17:50	DINNER	
June 7	7:30-8:45	BREAKFAST	
	8:45-9:00	Recap from participants	
	9:00-10:30	Calibration and Application FORECAST climate to evaluate management of <i>Acacia mangium</i> plantations in Malaysia	Dr. Brad Seely, Faculty of Forestry, UBC Dr. Siti Nurhidayu Abu Bakar, Faculty of Forestry, Universiti Putra Malaysia
	10:30-10:45	TEA BREAK	
	10:45-12:00	Simulating climate change impacts on long-term Acacia productivity and health	Dr. Brad Seely, Faculty of Forestry, UBC
	12:00-13:00	LUNCH BREAK	
	13:00-14:30	Calibration and Application FORECAST climate to evaluate management of mangrove forests in Malaysia	Dr. Brad Seely, Faculty of Forestry, UBC
	14:30-14:45	TEA BREAK	
	14:45-15:15	Review and Future directions	Dr. Brad Seely, Faculty of Forestry, UBC
	15:15-16:00	Open discussion and Closing remarks	Dr. Guangyu Wang, Faculty of Forestry, UBC
June 8	7:30-9:00	BREAKFAST	
	FIELD TRIP TO DINGHU MOUNTAIN		
July 9	DEPARTURE		

List of participants in the workshop

Training Workshop on Adaptation of Asia-Pacific Forests To Climate Change			
Final Participants List			
No	Name	Organization	Country
1	Dy Lihong	APFNet RFO project, General directorate of Nature Protection and Conservation (GDANCP), Cambodia	Cambodia
2	Kraiwut Siri-On	Forest Survey and Assessment Division, Forest Land Management Bureau, Royal Forest Department	Thailand
3	Dr. Mohd Nazre Bin Saleh	Department of Forest Management, Faculty of Forestry, Universiti Putra Malaysia	Malaysia
4	BILLY NE WIN	Forest Research Institute, Forest Department	Myanmar
5	DR.PHYU PHYU LWIN	Forest Research Institute, Forest Department	Myanmar
6	ZAW MIN AYE	Forest Research Institute, Forest Department	Myanmar
7	Dr. John Innes	University of British Columbia	Canada
8	Dr. Guangyu Wang	University of British Columbia	Canada
9	Dr. Tongli Wang	University of British Columbia	Canada
10	Dr. Anil Shrestha	University of British Columbia	Canada
11	Dr. Brad Seely	University of British Columbia	Canada
12	Lianzhen Xu	University of British Columbia	Canada
13	Dr. Tze-Ying Chen	National Ilan University	Chinese Taipei
14	Dr. Wei-Chun Chao	National Chiayi University	Chinese Taipei
15	Dr. Huan-Yu Lin	Taiwan Forestry Research Institute	Chinese Taipei
16	Dr. Shuaifeng Li	Research Institute of Resource Insects, CAF	China
17	Dr. Xiaobo Huang	Research Institute of Resource Insects, CAF	China
18	Deng Guang	Research Institute of Forest Resource Information Techniques, Chinese Academy of Forestry (CAF)	China

19	Xia Xiaoyun	Research Institute of Forest Resource Information Techniques, Chinese Academy of Forestry (CAF)	China
20	Dr. Pang Yong	Research Institute of Forest Resource Information Techniques, Chinese Academy of Forestry (CAF)	China
21	Sun Weina	APFNet Beijing	China
22	Pisey	APFNet Beijing	Cambodia
23	Hongbo Zhai	Asia-Pacific Network for Sustainable Forest Management and Rehabilitation	China
24	Yalin Xie	Beijing Forestry University	China
25	Shiliang Liu	Beijing Forestry University	China
26	Dr. Jie Duan	Beijing Forestry University	China
27	Dr.Zhuo Wu	Guangzhou University	China
28	Dr.Li Dai	School of Geography and Environmental Science, Guizhou Normal University	China
29	Jin Hu	Guangdong Eco-engineering Polytechnic	China
30	Honghong Wang	Guangdong Eco-engineering Polytechnic	China
31	Wen Pan	Guangdong Academy of Forestry	China
32	Xianhua Gan	Guangdong Academy of Forestry	China
33	Weiqiang Zhang	Guangdong Academy of Forestry	China
34	Yuhui Huang	Guangdong Academy of Forestry	China
35	Fangfang Huang	Guangdong Academy of Forestry	China
36	Jian Cai	Guangdong Academy of Forestry	China
37	Changjun Gao	Guangdong Academy of Forestry	China
38	Yongfeng Wang	Guangdong Academy of Forestry	China
39	Long Wei	Guangdong Academy of Forestry	China
40	Yan Wu	Guangdong Academy of Forestry	China
41	Shihong Xiao	Guangdong Academy of Forestry	China
42	Xiaoqing Yi	Guangdong Academy of Forestry	China
43	Yongjian Cao	Guangdong Academy of Forestry	China
44	Zepeng Wu	Guangdong Academy of Forestry	China
45	Linyishu Yang	Guangdong Academy of Forestry	China
46	Zhongrui Zhang	Guangdong Academy of Forestry	China
47	Zhenshi Wang	Guangdong Academy of Forestry	China
48	Xiaogang Ding	Guangdong Academy of Forestry	China
49	Dehuo Hu	Guangdong Academy of Forestry	China
50	Minghuai Wang	Guangdong Academy of Forestry	China
51	Zhe Wang	Guangdong Academy of Forestry	China
52	Runhui Wang	Guangdong Academy of Forestry	China
53	Qingsong Bai	Guangdong Academy of Forestry	China
54	Boxiang He	Guangdong Academy of Forestry	China
55	Peiwu Xie	Guangdong Academy of Forestry	China

56	Haiyan Yang	Guangdong Academy of Forestry	China
57	Wanju Li	Guangdong Academy of Forestry	China
58	Dongxian Xu	Guangdong Academy of Forestry	China
59	Yufei Zhou	Guangdong Academy of Forestry	China
60	Baozhu Zhu	Guangdong Academy of Forestry	China
61	Ledong Guo	Guangdong Academy of Forestry	China
62	Shujing Wei	Guangdong Academy of Forestry	China

Annex D 8: Summary reports on session organized in international conferences

Annex D8.1: Summary Report - Innovative Tools for Sustainable Forest Management under Climate Change

Adaptation of Asia-Pacific Forests to Climate Change

26 February 2016 Pampanga Philippines

The open event *Innovative Tools for Sustainable Forest Management under Climate Change* took place on Friday February 26th as a Stream 2 event at Asia-Pacific Forestry Week in Clark Freeport Zone, Philippines. The event successfully attracted 81 participants including academics and industry professionals from all over the Asia-Pacific (AP) region. Members of the UBC research team presented on the research completed as part of the research project *Adaptation of Asia-Pacific Forests to Climate Change*, including explanations and demonstrations of the tools developed in Phase I of the project in order to provide knowledge and capacity building to all participants of the event. The purpose of the event was to share the outcomes and achievements of Phase I of this project, which are very applicable and beneficial to the AP region. Outcomes include the development of a high resolution, high accuracy climate model, ClimateAP, development of a climate niche model for five key forest tree species in the AP region, and integration of multiple ecological models in five pilot sites throughout the region to develop locally-specific sustainable forest management recommendations. This event successfully promoted this project and allowed for effective communication of project findings and their significance to many stakeholders in the region.

This event provided a valuable opportunity to share project findings and to encourage collaboration between the project and regional stakeholders. The key message concluded from the event was that specific, localized climate and ecological modeling tools can help the AP region to address uncertainty related to forest management under a changing climate. All participants left the event with a better understanding of the climate and ecological modeling tools available for them to complete climate change adaptation research in their local region. Participants were also provided with the resources needed to find more information about the project and tools online. A post presentation survey, distributed to all participants, provided the UBC research team with valuable information regarding which modeling tools are most likely to be used by stakeholders in the AP. The event was successful in meeting the objectives of project promotion, networking and capacity building, and provided a positive initial foundation for Phase II of the project.

A summary of each presentation is provided below.

Presentation 1: Overview of climate change and policy in the Asia-Pacific

Dr. John Innes, Dean in the Faculty of Forestry at UBC, presented on current climate change impacts and climate change policy in the AP. Dr. Innes reviewed the main commitments made by AP economies in the Paris Agreement after COP21, including the implications of those commitments for the AP region. He focused on the importance of meeting those commitments (particularly relating to Articles 5.2, 7.1, 7.6, 7.7 and 7.9) and discussed how each output of this research project is designed to provide AP economies with the capacity to do so.

Presentation 2: Adaptation to climate change in the Asia-Pacific

Due to a conflict in travel plans, Dr. Rod Keenan, Professor in the Faculty of Ecosystem and Forest

Sciences at the University of Melbourne, was unable to attend the meeting as originally planned, and Dr. Brad Seely from UBC presented on his behalf. Dr. Seely provided an overview of the key vulnerabilities to climate change for forests and people in the AP region. He discussed adaptation principles, specifically focusing on decision-led adaptation, as well as discussed a systems approach to vulnerability assessment. Dr. Seely provided a description of options for climate change adaptation in the context of forest management and stressed the importance of sustainable forest management and the key role that policy plays in effective sustainable forest management.

Presentation 3: Climate modeling for the Asia-Pacific

Dr. Tongli Wang, Assistant Professor in the Faculty of Forestry at UBC, presented on the development and application of ClimateAP. Dr. Wang explained how forest types are associated with climate types and how ClimateAP can be used to classify ecosystems and map the climate-niche distribution of species with climate change. He provided a detailed explanation of how ClimateAP was developed and how it works to provide high-accuracy, high-resolution climate data for any location in the AP. Dr. Wang also explained the importance of ecosystem classification and climate-niche mapping with climate change and encouraged participants to visit online sources of information and modeling tools.

Presentation 4: Selecting and applying modelling tools to evaluate forest management strategies in the context of climate change

Dr. Brad Seely, Research Specialist in the Faculty of Forestry at UBC, discussed how climate change will influence the growth and development of forest ecosystems in the AP region. He presented the implications of increased atmospheric CO² concentrations and of an increased frequency and intensity of extreme events associated with climate change. Dr. Seely then provided a framework for determining what factors are important when analyzing changes in forest processes with climate change, as well as how to choose what model to use based on the data available and the research question of interest. He provided the audience with a basic understanding of how process-based modeling is useful and how and when they can incorporate it into their research.

Presentation 5: Issues and solutions for SFM in a changing climate in the Asia-Pacific region

Dr. Guangyu Wang, Assistant Dean in the Faculty of Forestry at UBC, reiterated the general impacts of climate change on forests in the AP region and then presented the results of a survey of forestry experts in the AP region. Dr. Wang revealed that forestry is a top concern among experts in terms of the environmental and economic impacts of climate change in the AP region. He then provided a framework for developing adaptation and sustainable forest management strategies in forestry and explained how this research project follows the framework to improve the capacity of AP economies to achieve sustainable forest management.

Conclusion

Dr. John Innes facilitated a question and answer period where the UBC Research Team addressed all audience questions. Dr. Innes then concluded the event by summarizing the topics covered and emphasizing the promising ability of this research project to help improve the capacity of the AP region to achieve sustainable forest management under a changing climate. He closed the meeting by thanking all presenters and attendees for their participation.

Attendance List

Name	Position	Institution
Presenters and UBC Staff		
Dr. John Innes	Dean, Faculty of Forestry	University of British Columbia
Dr. Guangyu Wang	Assistant Dean, Faculty of Forestry	University of British Columbia
Dr. Tongli Wang	Assistant Professor, Faculty of Forestry	University of British Columbia
Dr. Brad Seely	Research Associate, Faculty of Forestry	University of British Columbia
Ms. Brianne Riehl	Project Coordinator, Faculty of Forestry	University of British Columbia
Ms. Michelle Zeng	Manager, Executive Office of APFECM, Faculty of Forestry	University of British Columbia
Audience		
Siti Nurhidaya Abu Bakar	Professor	UPM
Prof. A. K. Sahoo	Professor	Orissa University of Agriculture and Technology
Xiao Wenfa	Professor	Chinese Academy of Forestry
Huan-Yu Lin	Researcher	Taiwan Forestry Research Institute
Tze-Ying Chen	Professor	Ilan University
Roberto Oliver		
Alejandrino R. Sibucan Jr.	DA	NAMRIA
Aung Myn	Member	MFCC
Yahweleen R. Tan	Environmental Officer	Philippines Business for Social Progress
Janbern Barel	Project Officer	Philippines Business for Social Progress
Rochelle Bantigne	SPO	Philippines Business for Social Progress
Elizabeth I. Tolentino	Owner of a nursery	IL Forest Nursery
Virtito C. Natural Jr.	KBAs Coordinator	Mindoro Biodiversity Conservation Foundation
Nelissa Rocas	FMB II	Forest Management Bureau (FMB)
Edna Nuestro	Division Chief	FMB - Department of Environment and Natural Resources
Ivy Niwle A. Galla-Angeles	PED II	FMB - Department of Environment and Natural Resources

Adi Gangga		International Forestry Students Association (IFSA)
Wing Tuen Veronica Luey		International Forestry Students Association (IFSA)
Alicia L. Castillo	Chief of Watershed Section	FMB
Alma Lanzo	Legal Officer	FMB - Department of Environment and Natural Resources
Marjorie C. Pamplona	Project Officer	Philippine Tropical Forest Conservation Foundation (PTFCF)
Diane Bagui	Project Officer	Philippine Tropical Forest Conservation Foundation (PTFCF)
Hazel Consunji	Phils. Coordinator	ELTI (Environmental Leadership and Training Initiative?)
Eric Buduan	Sr. Project Officer	Philippine Tropical Forest Conservation Foundation (PTFCF)
Melissa Baromo	PA	Philippine Tropical Forest Conservation Foundation (PTFCF)
Jerome L. Montemayor	OIC/Program Director	IIFF Regional Centre for Asia
Bounchanh Lattanavongkot		LPTP/Lao
Houngphet Chanthavong		National University of Laos
Daovorn Thongphanh		National University of Laos
Thein Saung		Forest Research Institute
Sithong Thongmanivong		National University of Laos
Ben Viches		FAO
Hilda Waga	SSO	Department of Forests
Elizabeth Kaidong	Adaptation and Low Carbon Growth Officer	PNG Forest Authority
Miller Kawanamo	Ecologist REDD	PNG Forest Authority
Elisapecs Tamanisau	Manager Development	Ministry of iTaukei Affairs
Zilpah Yahamano	Project Officer	UNREDD Program PNG
Clara Angela U. Barnes	Local Community Member	IFSA
Mark Jason T. Yebes	Local Community Member	IFSA
Hyo Ju Son		UNCCB
Sung Eun Kim		UNCCB

Mary Anne Then	President	IFSA
Lena Lackner	Forestry Education	IFSA-IUFRO
Jordana Marie L. Argamosa		IFSA
Max Spiegelberg		Kyoto University
Apple Jean Balili	Youth Delegate	AFFS-CMU
Perla Q. Binahm	Manager	BAFF
Maria Vio Bianca Fernandez		Department of Natural Resources - National Capital Region
Cathy A Pauig		FMB - Department of Natural Resources
Henrys Binchan		BAFF
Lee Xiong	REDD+ Project Manager	SNV
Harry Purnomi	Scientist	CIFOR
Sera Noviany	Forest Sustainability Head	APP/Sinarماس Forestry
Grewa Gomoga	Manager - REDD and Climate Change	PNG Forest Authority
Masamichi Haraguchi	UN-REDD/FAO, PNG	Kokusai Kogyo Co. Ltd
John Darren M. Chua	DMO I	DENR-FASPS
Monina M. Cunanan	Chief, PMED	DENR-PMED
Nelson V. Gorospe	ARD	DENR 4B
Hebeng Soviriya	Programme Officer	NTFPEP
Ked Tai	Country Coordinator	NTFPEP
Baw Htan	Media Coordinator	CHRO
Gerrardo O. Kitche	Professor	CSU - Caraga State University
Pey N. Coggid	Associate Professor	CSU - Caraga State University
M Al-Amin	Professor	University of Chittagong
David Neidel	Asia Coordinator	ELTI - Yale University
Jeff Silverman	TA	Wildlife Conservation Society (WCS)
Vu Tan Phuong	Director of ICD, VAFS	VCAFS
Mark Castillo II	AP 1	IRNR - CFNF - UPLB
Van Nguyen	Coordinator	Pan Nature
Nfuyen Duc To Luu	Program Manager	Pan Nature
Chris Martius		CIFOR
Adam Gerrard	Forest Officer, REDD+	FAO
Beni Hocd Hilajleu	TL	G12
Ohilie Mooshops	Principal Advisor	G12
Daniel Plugze	REDD+ Advisor	G12

Agenda

Friday, February 26th, 1:30-3:00pm

1:30-1:45pm Dr. John Innes: Introduction and overview of climate change and policy

1:45-2:00pm Dr. Brad Seely (on behalf of Dr. Rod Keenan): Adaptation to climate change in the Asia-Pacific

2:00-2:15pm Dr. Tongli Wang: Climate modeling for the Asia-Pacific

2:15-2:30pm Dr. Brad Seely: Selecting and applying modelling tools to evaluate forest management strategies in the context of climate change

2:30-2:45pm Dr. Guangyu Wang: Issues and solutions for SFM in a changing climate in the Asia-Pacific region

2:45-3:00pm Question and answer

Post Presentation Survey:

Asia-Pacific Forestry Week 2016

Innovative Tools for Sustainable Forest Management under Climate Change

Post Presentation Survey

The purpose of this survey is to gauge the impact and usefulness of our research outcomes. You may choose to remain anonymous. This information will only be used for internal evaluation of project success and will not be shared with anyone outside of our project team.

Name (optional): _____

Affiliated Institution: _____

Home Country: _____

1. Based on today's presentations, would you use any of the following models/tools for your research or development of management strategies, etc. in the future?

- ☐ ClimateAP
- ☐ Climate Niche Models
- ☐ Google Maps based tools
- ☐ FORECAST Climate
- ☐ Physiological Principles to Predict Growth (3-PG)
- ☐ Statistical Downscaling Model (SDSM)
- ☐ I would not use any of the models/tools presented

1. a) If **you selected any of the models/tools**, please explain your research topics/objectives and how the models/tools would be of use: _____

1. b) If **you would not use any**, please select why:

- ☐ Too complicated
- ☐ Not relevant to my research
- ☐ Not relevant to my region of study
- ☐ There are other models/tools that I prefer to use

☐ Other

Please specify _____

Thank you for your participation!

Dr. John Innes

Dean, Faculty of Forestry, University of British Columbia

Appendix D.3.4: Survey Results

Response Rate:

Surveys distributed	Surveys returned	Response rate
75	38	0.506666667

Responses by Country:

Country	Number of respondents	Percentage of all respondents
Bangladesh	1	2.63
Cambodia	3	7.89
Chinese Taipei/Taiwan	2	5.26
Fiji	1	2.63
India	1	2.63
Indonesia	1	2.63
Laos	2	5.26
Malaysia	1	2.63
Myanmar	1	2.63
Papua New Guinea	2	5.26
Philippines	20	52.63
Thailand	1	2.63
Vietnam	2	5.26

Use of models:

Name of model	Percentage of respondents stating they would use the model
ClimateAP	65.79
Climate niche models	28.95
Google-maps based tools	44.74
FORECAST Climate	10.53
3-PG	10.53
SDSM	7.89
None	7.89*

* 3 respondents indicated that they would not use any of the proposed models, each stating either that the models were too complicated, not relevant to their research, or not relevant to their study area.

Ranking of likelihood of model use:

1. ClimateAP
2. Google-maps based tools
3. Climate niche models
4. FORECAST Climate
5. 3-PG
6. SDSM

Annex D8.2: Summary Report – Phase II Inception Workshop

Adaptation of Asia-Pacific Forests to Climate Change

23-26 February 2016 Pampanga Philippines

The Phase II Inception Workshop took place in two parts on Tuesday, February 23rd and Friday February 26th as a Stream 5 event at Asia-Pacific Forestry Week 2016 in Clark Freeport Zone, Philippines. The event successfully invited 20 participants including the UBC Research Team and local partners/representatives from the five Phase II pilot site locations throughout the Asia-Pacific (Malaysia, Myanmar, Laos, Chinese Taipei and China). During Part I of the event, the UBC Research Team shared presentations to provide background on the research that has been completed as part of Phase I of the *Adaptation of Asia-Pacific Forests to Climate Change* research project, as well as share plans for future research to take place during Phase II. Representatives from each pilot economy then shared presentations on the current research taking place in their pilot site location and the key climate change impacts and research topics of interest to be considered in that location. Part 2 of the event was dedicated to discussion, led by members of the UBC Research Team, on the detailed requirements for implementation of Phase II research activities, as well as discussion of the Phase II work plan, including technical agreements, milestones, communication strategy, and budget allocation.

The event provided a valuable opportunity to bring together the UBC research team and all local partners to lay an important foundation for Phase II of the project. The key outcome of this event was finalization of the species to be analysed and research questions to be addressed in each pilot site. The UBC team left with a better understanding of the economically and ecologically important species in each of the five pilot economies, as well as an understanding of what issues related to climate change are of particular interest in these regions. The UBC team also gained an understanding of the data resources available (either to be gathered, collected or purchased) from these local economies in order to perform the analysis required to answer these research questions. The local partners left with a better understanding of the research project as a whole, and particularly their role within the project. The local partners also left with a list of data they are required to collect and provide by the time they attend the Kunming Training Workshop in June 2016. Other outcomes of this event included a draft technical agreement between UBC and each institution, a confirmed date for the Kunming Training Workshop, a draft schedule of the main responsibilities and deadlines for the UBC research team and each local partner over the next 3 years, and an agreement regarding compensation to be provided by UBC to each partner institution.

A summary of each presentation and discussion is provided below.

PART 1

Opening remarks

Dr. De Lu, Director General of APFNet, represented APFNet (the funding agency of this project) at the event. Dr. De Lu provided brief opening remarks as he welcomed all participants to the meeting, thanked them for their attendance, and stated his expectation of an efficient and productive meeting for the launch of Phase II of this research project.

Presentation 1: Review of Phase I and introduction to Phase II

Dr. John Innes, Dean of the Faculty of Forestry at UBC, provided background information on Phase

I of the project including the objectives, achievements and lessons learned. The achievements highlighted include the review of existing climate science and policy, development of ClimateAP, development and integration of 9 niche-based and process-based ecological models, application of models in four pilot sites in China, Canada and Australia, development of web-based tools, and communication of project findings. Dr. Innes then introduced the research to be completed in Phase II of the project, stating the objectives, 5 target economies (China, Chinese Taipei, Laos, Malaysia and Myanmar), and 5 outputs to be completed to expand and improve upon the achievements of Phase I. This presentation provided necessary background information to all meeting attendees in order to move forward with more detailed discussion of Phase II research activities.

Presentation 2: ClimateAP and niche-based ecological models – Phase II

Dr. Tongli Wang, Assistant Professor in the Faculty of Forestry at UBC, presented on the need for climate-based forest resource management for forest adaptation to climate change. Dr. Wang explained how he developed ClimateAP, a high-resolution, high accuracy climate model, and how it is changing the way researchers in the field design and analyze results. He shared results of climate-niche modeling for the five major forest tree species analyzed in Phase I of the project, and explained how climate niche modeling will be used to project the future climate niche of important tree species and to create ecosystem classifications in the five Phase II pilot economies. This presentation provided a detailed explanation of the climate and climate-niche modeling tools available for Phase II to give local partners a more educated understanding of the potential research questions that can be answered for their economy.

Presentation 3: Application of ecological models to evaluate climate change impacts in Phase II pilot sites

Dr. Brad Seely, Research Specialist in the Faculty of Forestry at UBC, presented his ideas on the key questions related to climate change adaptation to be addressed in each of the five Phase II pilot site locations. He described the key issues related to climate change in each location and suggested a modeling approach that could be used to answer the relevant research questions. He provided an overview of the available process-based ecological modeling tools to be used in these locations including the advantages, limitations and data requirements of each. This presentation provided the local partners with a more educated understanding of process-based ecological modeling and how it can be used to conduct research in their pilot site.

Presentation 4: Chinese Taipei case study

Mr. Huan-Yu Lin, Assistant Researcher at the Taiwan Forestry Research Institute, shared a presentation titled “Assessment of the Impact of Climate Change on Vascular Plants in Taiwan”. Dr. Lin shared information about the topography, climate and vegetation of Taiwan Island, and discussed the research framework currently being used to analyze the impacts of climate change on 4500 vascular species based on temperature data. Mr. Lin also shared the results of a disaster risk assessment of *Fagus hayatae* and identified gaps in the current research and data, as well as future research questions to be addressed through collaboration with this project.

Presentation 5: Bangladesh case study

Dr. M. Al-Amin, Professor in the Institute of Forestry and Environmental Sciences at Chittagong University, shared a presentation titled “Sketching future spatial-temporal distribution of forests applying climate change scenarios and GIS: success stories and way forward”. Dr. Al-Amin shared suitable area maps of important species in Bangladesh based on temperature, rainfall and soil type.

He shared his research goal of developing a model to predict the future local climate scenario and species composition of forests through collaboration with this project. Dr. Al-Amin also presented three possible pilot sites in Bangladesh that could be used for process-based ecological modeling.

Presentation 6: Lao PDR case study

Dr. Sithong Thongmanivong, Associate Professor in the Faculty of Forestry at the National University of Laos, shared a presentation titled “Case study proposal, Lao PDR”. Dr. Thongmanivong provided background information on the state of forests in Lao PDR and details on the pilot site in Nam Kading Protected Area. He shared the main issues related to forest loss and climate change to be addressed in this pilot site and identified potential opportunities for collaboration with this project.

Presentation 7: Malaysia case study

Dr. Siti Nurhidayu Abu Bakar, Senior Lecturer in the Faculty of Forestry at Universiti Putra Malaysia, shared a presentation titled “Malaysian Pilot Site: Danum Valley, Sabah, Malaysia”. Dr. Abu Bakar presented background information on the state of forests and forest management in Malaysia. She then focused on the pilot site location, Danum Valley, and discussed the current research, data collection and forest management being conducted there. Dr. Abu Bakar discussed the key climate change impacts in Danum Valley and proposed numerous potential research questions to be addressed through collaboration with this project. She clearly indicated the support she would need from UBC to complete this research collaboration.

Presentation 8: Myanmar case study

Mr. Thein Saung, Staff Officer in the Forest Research Institute at the Forest Department in Myanmar, shared a presentation titled “Background information & case study of pilot site in Myanmar”. Dr. Saung shared general information about forests and forest management in Myanmar, as well as the main drivers of deforestation and forest degradation in the region. He then discussed the pilot site location in Yedashae Township, Taungoo District, Bagoyoma Region, including the climate, forest and socioeconomic conditions in the pilot location. Dr. Saung also shared findings of the ITTO project that was completed from 2013-2014 in this location.

Conclusion

Dr. John Innes and Dr. Guangyu Wang concluded Part 1 of the meeting by providing their thoughts on the local partner presentations and recapping what had been discussed. Both stated enthusiasm about the interesting research opportunities in each pilot location and about the promising collaboration to take place in Phase II. They closed the meeting by thanking everyone for their attendance and stating a reminder about Part 2 of the meeting to take place later in the week.

PART 2

Presentation 9: China case study

Dr. Shuaifeng Li, Professor in the Research Institute of Resource Insects at the Chinese Academy of Forestry shared a presentation titled “Case presentation of *Pinus kesiya* forest, China”. Dr. Li presented on the location of his current research project in Pu'er city, Yunnan Province in the *Pinus kesiya* forest. He discussed the objective of his research, and the data and methods used to determine the effect of climate factors on the relationship between tree biomass and stand age. Dr. Li also presented limitations of his research and indicated opportunities for improvement through collaboration with this project.

Discussion 1: Climate and ecosystem modeling

Based on the local partner presentations during Part 1 of the meeting and individual discussions with each local partner throughout the week, Dr. Tongli Wang provided a more detailed presentation on ClimateAP and how it is used for climate-niche modeling and ecosystem classification. He provided a list of the data he has currently received and the data that is still required from each local partner to begin Phase II research activities. Dr. Wang then led a discussion about data requirements, local partner compensation, and answered any questions regarding climate-niche modeling and ecosystem classification.

Presentation 10: Work plan for Phase II

Dr. Guangyu Wang, Assistant Dean in the Faculty of Forestry at UBC, shared a presentation outlining the detailed work plan for Phase II of the project. Dr. Wang discussed the roles and responsibilities of the UBC research team and local partners, and provided an overview of the project milestones for years 1-3. He then presented a list of all the important dates and deadlines to be followed for smooth execution of the project, highlighting those relevant and important for the local partners. Dr. Wang provided an overview of the project budget and compensation available for partners, as well as provided a list of immediate actions and responsibilities to be completed by the UBC research team and local partners.

Discussion 2: Ecological modeling and application in each pilot site

Based on the local partner presentations during Part 1 of the meeting and individual discussions with each local partner throughout the week, Dr. Brad Seely presented a summary of pilot project discussions including the study area, forest type, target species and key research questions in each pilot economy. Dr. Seely provided a list of the potential data sources that each local partner indicated they could provide in order to answer the questions of interest in their pilot site. He then facilitated a discussion regarding the data requirements in each site, the research questions of most interest, and answered any questions or concerns posed by the local partners.

Discussion 3: Phase II milestones, communication strategy, technical agreements and budget allocation

Dr. Guangyu Wang and Dr. Brad Seely presented a draft version of a Technical Agreement and Schedule B as an example of the type of agreement that will be signed between UBC and each partner institution. This was also the opportunity for local partners to ask questions regarding the work plan, including milestones, communication and budgeting. All questions and concerns were addressed by Dr. Wang and Dr. Seely, including how compensation will be transferred to each partner institution.

Conclusion

Dr. John Innes concluded the meeting by summarizing what had been discussed and stressed the importance of communication and clarity in completing all research activities smoothly and efficiently over the next 3 years. He stated that he was pleased with the success of the inception meeting and closed the meeting by thanking all attendees for their participation.

Attendance List

Name	Position		Institution
	APFNet		
Dr. De Lu	Director General		APFNet
	UBC Research Team		
Dr. John Innes	Dean, Faculty of Forestry		University of British Columbia
Dr. Guangyu Wang	Assistant Dean, Faculty of Forestry		University of British Columbia
Dr. Tongli Wang	Assistant Professor, Faculty of Forestry		University of British Columbia
Dr. Brad Seely	Research Associate, Faculty of Forestry		University of British Columbia
Ms. Brianne Riehl	Project Coordinator, Faculty of Forestry		University of British Columbia
	Local Partners		
Dr. Mohamed Zakaria Hussin	Professor/Dean, Faculty of Forestry		Universiti Putra Malaysia
Dr. Siti Nurhidayu Abu Bakar	Senior Lecturer, Department of Forest Management, Faculty of Forestry		Universiti Putra Malaysia
Dr. Sithong Thongmanivong	Associate Professor/Director, Research Centre for Natural Resource and Climate Change, Faculty of Forestry		National University of Laos
Mr. Daovorn Thongphanh	Lecturer/Deputy Director, Research Centre for Natural Resource and Climate Change, Faculty of Forestry		National University of Laos
Mr. Thein Saung	Staff Officer, Forest Research Institute		Forest Department, Myanmar
Dr. Chen Tzu-Ying	Professor, Department of Forest and Natural Resources		National Ilan University
Mr. Huan-Yu Lin	Assistant Researcher, Taiwan Forestry Research Institute		Council of Agriculture, Taiwan Island
Dr. Shuaifeng Li	Professor, Research Institute of Resource Insects		Chinese Academy of Forestry
Dr. M. Al-Amin	Professor, Institute of Forestry and Environmental Sciences		Chittagong University, Bangladesh
	Other		
Dr. Jorma Neuvonen	Director, Special Projects, Faculty of Forestry		University of British Columbia
Ms. Michelle Zeng	Manager, Executive Office of APFECM, Faculty of Forestry		University of British Columbia
Dr. Hounghet Chanthavong	Dean, Faculty of Forestry		National University of Laos
Dr. Hsin Yu	Dean, Academic Affairs		National Ilan University
Dr. Nobuya Mizoue	Associate Professor, Lab of Forest Management, Faculty of Agriculture		Kyushu University

Agenda

PART 1: Tuesday, February 23rd, 3:30-6:30pm

3:30-3:40pm Opening remarks by Dr. De Lu from APFNet

3:40-4:00pm Dr. John Innes, Review of Phase I and introduction to Phase II

4:00-4:30pm Dr. Tongli Wang - ClimateAP and niche-based ecological models – Phase II

4:30-4:50pm Dr. Brad Seely – Application of ecological models to evaluate climate change impacts in Phase II pilot sites

4:50-6:30pm Local partners - Pilot site introduction, climate related issues, challenges and further scientific support requirements

4:50-5:10pm Mr. Huan-Yu Lin – Assessment of the Impact of Climate Change on Vascular Plants in Taiwan

5:10-5:30pm Dr. M. Al-Amin – Sketching future spatial-temporal distribution of forests applying climate change scenarios and GIS: success stories and way forward

5:30-5:50pm Dr. Sithong Thongmanivong – Case study proposal, Lao PDR

5:50-6:10pm Dr. Siti Nurhidayu Abu Bakar – Malaysian Pilot Site: Danum Valley, Sabah, Malaysia

6:10-6:20pm Mr. Thein Saung – Background information & case study of pilot site in Myanmar

6:20-6:30 Dr. John Innes and Dr. Guangyu Wang - Conclusion

PART 2: Friday, February 26th, 9:00am-12:00pm

9:00-9:20am Dr. Shuaifeng Li – Case presentation of *Pinus kesiya* forest, China

9:20-9:40am Discussion – led by Dr. Tongli Wang about climate and ecosystem modeling

9:40-10:00am Dr. Guangyu Wang - Work plan for Phase II

10:00-10:30am Discussion – led by Dr. Brad Seely about ecological modeling and application in each pilot site

10:30-11:00am Coffee break

11:00-11:30am Discussion – led by Dr. Guangyu Wang and Dr. Brad Seely about Phase II milestones, communication strategy, technical agreements and budget allocation

11:30am-12:00pm Dr. John Innes - Conclusion

Annex D 8.3: Tackling climate change adaptation in tropical and subtropical forests

IUFRO Asia-Oceania Conference 2016

22-24 October, Beijing China

An open session event titled ‘Tackling climate change adaptation in tropical and subtropical forests’ was held Monday October 24th from 13:30-15:30 at the IUFRO Asia-Oceania Conference in Beijing, China. The event successfully attracted upwards of 30 attendees including academics and industry professionals whose work/research pertains to the Asia-Oceania region. The Principal Investigator (PI) Dean John Innes presented on the project objectives, research, and management implications as a means provide adaptive forest management strategies in light of climate change. Additionally, 6 other research abstracts were accepted into the session, allowing other relevant research and findings to be shared during the 2 hour event. The purpose of organizing this event, similarly to other events held throughout the project year, was to disseminate the purpose and outcomes of this project from Phase I achievements, as well as Phase II progress. The presentation highlighted the need for such technical adaptive research, while successfully promoting this project to stakeholders in the Asia-Pacific region.

This session successfully discussed the crucial need to address a lack of information and tools focused on Asia-Pacific ecosystems to successfully employ adaptive forest management strategies in light of a changing climate. Academics representing a variety of countries gathered to present relevant research. Collectively, presentation topics explored a variety of pertinent issues, including effects of climate change on forest ecosystems, sustainable forest management policies and prospects, climate and ecological modeling tools, and their potential contributions to adaptive forest management strategies.

Abstracts for each presentation are provided below:

Presentation 1: Integration of climate and ecological modeling tools for adaptive management in Asia-Pacific Forests

Climate change is an immense threat to the stability and productivity of forest ecosystems in the Asia-Pacific region. Potential changes to or loss of forests will have drastic environmental impacts on biodiversity, ecosystem function and resilience, as well as immense socio-economic impacts on people and economies dependent on forest resources and ecosystem services. Despite their importance, there is a lack of information and tools focused on Asia-Pacific ecosystems and economies, which are necessary to understand the potential effects of climate change and develop regionally-specific adaptation and mitigation strategies. The project *Adaptation of Asia-Pacific Forests to Climate Change* aims to address this lack of knowledge and tools and to increase the adaptive capacity of Asia-Pacific forest ecosystems. This objective has been achieved through: development of a high-resolution climate model, ClimateAP, applicable to any location in the region; development of ecological models to project how climate change will affect suitable climatic conditions, regeneration, and productivity of forest tree species; development of tools to assess the most effective local management strategy based on management objectives and projected impacts of climate change; evaluation of models to assess forest fire risk and the relationship between forest fire and climate change; assessment of ecosystem carbon storage using LiDAR; and evaluation of how vegetation dynamics respond to climate change using remote sensing technology. All project outputs were developed with ease of communication in

mind, as to ensure that information can be clearly disseminated and easily understood. This is necessary to allow for project findings to be used in the development of effective policy and sustainable forest management strategies related to adaptation and mitigation of forests to climate change.

Presentation 2: Conservation strategies for vascular plants under the impact of climate change in Taiwan

Taiwan is a continental island on the Tropic of Cancer with the highest ridge to 4,000 m. Because of the diverse topography and warm-humid climate, it supports over 4,200 vascular species. In 2013, we established a research framework and compiled a geo-referenced database with 1,432,173 records to assess biodiversity vulnerability caused by climate change.

Based on the upper distribution limit of each vascular species' optimal temperature range, we found 14 areas where more upper-limited individuals aggregated could be highly sensitive to global warming. Half of them are isolated mountain tops occupied by fragmented cool-temperate vegetation. Some of these areas experienced climate change or extreme natural disasters (e.g. weakening northeast monsoon, landslides, typhoons or droughts) during the past 3 decades, and induced an evident recession of small populations, such as *Fagus hayatae*, *Lithocarpus formosanus* and *Rhododendron simsii*. To draw up adequate conservation strategies, we established an evaluation scheme that integrates vegetation characteristics and environmental factors to assess conservation priority among sensitive ecosystems and populations. The conservation strategies of lower cost and greater feasibility, including in-situ conservation, corridor establishment and migration assistance, are suggested for populations that are not endangered critically. Furthermore, we have developed breeding techniques simultaneously to raise capability of seedling cultivation and transplanting because immediate ex-situ conservation is essential for rare species experiencing critical recession.

Presentation 3: Ecosystem goods and services in adaptation to climate changes. Insights from the Panchase Mountain ecological region of Western Nepal

Ecosystem goods and services (EGS) from forests are critical to tackle climate change and improve human well-being especially in developing countries. However, various natural and anthropogenic drivers of environmental and climate changes have posed challenges to the sustainable supply of EGS. Improved understanding of interactions between EGS and these drivers is required to help people cope with the challenges because interaction between multiple drivers and EGS are largely unknown. To better understand the role of EGS in adaptation to environmental and climate change, and enhance human well-being, this study applies IPBES conceptual framework, using a catchment of the Panchase Mountain Ecological Region (PMER) in Western Nepal as a case study. Major natural drivers of change were identified as climate change, drought, and invasive species, whereas anthropogenic drivers included agriculture land abandonment, plantation of new species, and demographic changes. All drivers were found to impact the availability of EGS, and the livelihoods of people reliant on them. Current anthropogenic assets and institutional mechanisms were found to be effective in managing some of the challenges. Similarly, proper governance and adequate financial and technical support seem essential for addressing environmental challenges that influence the sustained flow of EGS in

the region.

Presentation 4: Adapting forest management for climate change in Australia: practices, prospects, and policies

Australia has a highly diverse and variable climate and its forests are well-adapted to climatic variation. However, human-induced changes in climate could exceed historical ranges of variability and have effects on forests well beyond the experience of forest managers. These conditions will require implementation of management practices appropriate to a changing climate. While many management actions to support adaptation to climate change can be considered as part of best practice sustainable forest management arrangements, others are not. These include developing gene management programs and off-site gene banks, ex-situ conservation and increasing wider cooperation in species management, increasing stand and regional species diversity, identification and deployment of more drought or disturbance tolerant species or genotypes, planning for reduced disease losses through monitoring and sanitation harvests, managing stand structure to reduce impacts on water availability and implementing silvicultural techniques to promote stand vigour, as practiced elsewhere in Australia. More intense rainfall and storm events will require changes to infrastructure, such as forest road design and construction specifications. This paper presents an overview of practices to address future climate impacts and a framework for assessing the costs and benefits of prospective new practices. The policy changes required to support their implementation are discussed.

Presentation 5: Effects of imposed drought on carbon storage of moso bamboo ecosystem in southeast China

Drought, a common climatic extreme event, could occur more frequently and more intensely in the context of climate change. Soil water deficit will result in the alteration of cycling of water and carbon in forest ecosystems. In the present work, we assessed imposed drought effect on carbon storage and soil carbon dynamics in a moso bamboo forest ecosystem in a subtropical area of China using a throughfall exclusion experiment during the period between July 2012 and June 2013. The number of bamboo shoots, new bamboo culms, and the height and diameter at breast height were significantly lower in the throughfall exclusion (TE) plots than in the control (CK) plots. The carbon storage in the arborous layer in the TE plots decreased by 13.14% and 58.11%, respectively, while the litterfall increased by 6.19% when compared with the CK plots. A significant decrease in carbon storage occurred in TE plots in all soil layers except for the 10–20 cm layer. The imposed drought significantly decreased the carbon storage by 13.71 t·ha⁻¹, whereas it increased by 4.75 t·ha⁻¹ in the CK plots. This study will provide important information to quantify the potential for carbon sequestration and to understand how future climate change might impact carbon budgets.

Session Program

24 OCT 13:30-15:30

Tackling climate change adaptation in tropical and subtropical forests

<i>Room:</i>	307A
<i>Organizers:</i>	Wang Guangyu (UBC, Canada)
<i>Moderators:</i>	Wang Guangyu
<i>Description:</i>	The objective of this session is to share the knowledge produced over the first four years of the Adaptation of Asia-Pacific Forests to Climate Change project (conducted in the Faculty of Forestry, University of British Columbia). It will include presentations by experts on climate and ecological modeling and sustainable forest management (SFM), as well as presentations by local partners from three of our pilot site economies in SE Asia that will demonstrate the use of the online tools developed by this project and discuss how they can be applied in a local forest for SFM.

Presentations	Presenters	Country
Integration of climate and ecological modeling tools for adaptive management in Asia-Pacific forests	Guangyu Wang	Canada
Conservation Strategies for Vascular Plants Under the Impact of Climate Change in Taiwan	Tze-Ying Chen	Chinese Taipei
Ecosystem Goods and Services in Adaptation to Climate Changes. Insights from the Panchase Mountain Ecological Region of Western Nepal	Shankar Adhikari	Nepal
Adapting forest management for climate change in Australia: practices, prospects and policies	Rodney Keenan	Australia
Effects of imposed drought on carbon storage of moso bamboo ecosystem in southeast China	Benzhi Zhou	China

Annex D 8.4: Bamboo Forest Ecology and Management in Changing Climate

Global Bamboo and Rattan Congress

June 25-27, 2018

National Convention Center, Beijing, China

A parallel session “Bamboo Forest Ecology and Management in Changing Climate” was organized in partnership with International Center for Bamboo and Rattan, China on 26 June 2018 from 15:45 to 18:30 at the Global Bamboo and Rattan Congress (25-27 June, 2018). The main objective of this session was to discuss multifaceted issues of bamboo forest ecology and sustainable management in the changing climate. Academics and practitioners representing different economies presented series of research on current status, gaps and development trends of the international research to address how bamboo ecosystems play a role in alleviating poverty and sustainable development and how to integrate the issues of climate change in sustainable bamboo management. The event successfully attracted more than 30 attendees including academics and industry professionals whose work/research pertains to the Asia-Pacific region. Ten scientific papers were presented, each lasted for 15 minutes and discussion took place thereafter. The Principal Investigator (PI) Dean John Innes presented on the “Sustainable Management of Bamboo Resources and UBC-ICBR New Initiative, while Dr. Guangyu Wang presented “Bamboo Role in the key Plantation Forests” followed by Dr. Tongli Wang who presented “Bamboo Distribution and Prediction under Climate Change”. Additionally, seven papers were presented in the session with focus on bamboo ecology, sustainable management and climate change. Please see table below for detail information. Organizing this event disseminated the outcomes of this project from Phase I achievements, as well as Phase II progress as well as provide opportunity for networking with scholar and practitioners in Asia-Pacific region.

Session Name: <i>Bamboo Forest Ecology and Management in Changing Climate</i> • Time: Day 2, 26 June 2018, 15:45:-18:30 • Venue: Room_407_, <i>China National Convention Center</i> • Co-organizer: Faculty of Forestry, University of British Columbia
Session introduction (100 words) Bamboo is used as a substitute for wood, plastic, steel, and so on. At the same time, bamboo forests have great potential for carbon sequestration. Therefore, bamboo industry is a very potential green low-carbon sustainable industry. As the basis for the development of bamboo industry, the research on bamboo ecosystem is still lagging behind the demand of actual production practice. In view of how bamboo forest ecosystems play a role in alleviating poverty and sustainable development, how to face the problems of climate change in the future, we invite experts from the field of bamboo forest ecology and climate change to explore the current status, deficiency and development trend of the current international research.
Main topics/questions(for panel discussion) The impact of climate change and bamboo forest management.

	<u>Opening: Chaired by Shirong Liu, Prof. and Dr., International Centre for Bamboo and Rattan</u>
First Part	1. Presentation by Shirong Liu, Prof. and Dr. Chinese Academy of Forestry <i>Topic: Climate change drives the redistribution of bamboo in China.</i>
15:45 - 17:00	2. Presentation by Akifumi Makita, Prof. and Dr. Faculty of Bioresource Science Akita Prefectural University <i>Topic: The significance of the mode of clonal growth on the regeneration process after mass flowering of bamboos.</i>
Each speaker 15 minutes	3. Presentation by Xinzhang Song, Prof. and Dr. Agricultural & Forestry University of Zhejiang Province <i>Topic: Effects of simulated nitrogen deposition on moso bamboo forest ecosystem</i>
	4. Presentation by Ping Zhao, Prof. and Dr. South China Botany Garden, Chinese Academy of Science, <i>Topic: Sap flow-based transpiration in Phyllostachys pubescens: Applicability of the TDP methodology, age effect and rhizome role</i>
	5. <i>Topic: Bamboo role in the key plantation forests – Dr. Guangyu Wang, Associate Professor, University of British Columbia, Canada</i>
	6. <i>Topic: Sustainable Management of Bamboo Resources and UBC-ICBR New Initiative – Dr. John Innes, Dean, Faculty of Forestry, University of British Columbia</i>
	7. <i>Topic: Bamboo Distribution and Prediction under Climate Change – Dr. Tongli Wang, Assistant Professor, Faculty of Forestry, University of British Columbia</i>
Second part 17:05-18:20	8. Presentation by Associate Prof. Dr. Junwei Luan, International Centre for Bamboo and Rattan <i>Topic: The coordinated effects of soil biota and litter quality drive the consequences of bamboo expansion on litter decomposition—a dual-transect study</i>
	9. Presentation by Chinese Academy of Forestry, Subtropical Forestry Center, Prof. and Dr. Benzhi Zhou <i>Topic: Litterfall effect on soil respiration and its temperature sensitivity in moso bamboo stand under simulated drought stress</i>
	10. <i>Topic: Bamboo Panel and New Materials – Dr. Greg Smith, Professor, Faculty of Forestry, University of British Columbia</i>

Annex D 9: Published papers in peer review journal.

1. ClimateAP-an application for dynamic local downscaling to historical and future climate data in Asia-Pacific published in Frontiers of Agriculture Science and Engineering <https://doi.org/10.15302/J-FASE-2017172>
2. Simulating the impact of climate change on the Growth of Chinese Fir Plantations in Fujian Province, China published in New Zealand Journal of Forestry Science (2017) 47:20 DOI 10.1186/s40490-017-0102-6
3. Spatial modelling of fire drivers in urban-forest ecosystems in China published in Forests 2017, 8, 180; doi:10.3390/f8060180
4. Understanding fire drivers and relative impacts in different Chinese forest ecosystems published in Science of the Total Environment 2017 411-425 <http://dx.doi.org/10.1016/j.scitotenv.2017.06.219>
5. A dynamic downscaling approach to generate scale-free regional climate data in Taiwan in TAIWANIA 2018 63 (3) 251-266 DOI: 10.6165/tai.2018.63.251
6. Climate change impacts and forest adaptation in the Asia-Pacific region: from regional experts' perspectives in Journal of Forestry Research 2019 30 (1) 277-293

RESEARCH ARTICLE

ClimateAP: an application for dynamic local downscaling of historical and future climate data in Asia Pacific

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Abstract While low-to-moderate resolution gridded climate data are suitable for climate-impact modeling at global and ecosystems levels, spatial analyses conducted at local scales require climate data with increased spatial accuracy. This is particularly true for research focused on the evaluation of adaptive forest management strategies. In this study, we developed an application, ClimateAP, to generate scale-free (i.e., specific to point locations) climate data for historical (1901–2015) and future (2011–2100) years and periods. ClimateAP uses the best available interpolated climate data for the reference period 1961–1990 as baseline data. It downscales the baseline data from a moderate spatial resolution to scale-free point data through dynamic local elevation adjustments. It also integrates and downscales the historical and future climate data using a delta approach. In the case of future climate data, two greenhouse gas representative concentration pathways (RCP 4.5 and 8.5) and 15 general circulation models are included to allow for the assessment of alternative climate scenarios. In addition, ClimateAP generates a large number of biologically relevant climate variables derived from primary monthly variables. The effectiveness of the local downscaling was determined based on the strength of the local linear regression for the estimate of lapse rate. The accuracy of the ClimateAP output was evaluated through comparisons of ClimateAP output against observations from 1805 weather stations in the Asia Pacific region. The local linear regression explained 70%–80% and 0%–50% of the total variation in monthly temperatures and precipitation, respectively, in most cases. ClimateAP reduced prediction error by up to 27% and 60% for monthly temperature and precipitation, respectively, relative to the original baselines data. The improvements for baseline portions of historical and future

were more substantial. Applications and limitations of the software are discussed.

Keywords biologically relevant climate variables, downscaling, dynamic local regression, future climate, historical climate

1 Introduction

High-quality climate data are essential for conducting climate change impact analyses. Accordingly, a large volume of climate data has become available through various sources^[1–4] in recent years. However, these data sets are mostly in grid format with low-to-moderate spatial resolutions. While such data are suitable for climate impact modeling and analyses conducted at global and ecosystems scales, modeling studies are increasingly shifting toward local scales often with the goal of developing practical and effective adaptive management strategies. Considering the high levels of heterogeneity in climate in mountainous areas, such gridded climate data are often not adequate to meet the requirements for such studies. Thus, the demand for high-resolution and high-quality spatial climate data are rapidly increasing^[5].

Historical climate data, often from a specific reference period (e.g., 1961–1990), are widely utilized to support a wide range of research focused on understanding the relationships between climate variables and plant health and productivity. They are also essential for building climate niche models for examining the distribution of specific ecosystems and their components^[6,7] and for testing mechanistic models designed to predict plant growth response to climate^[8,9]. Further, the veracity of analyses of plant-climate relationships is dependent on the degree to which the climate conditions reflected in historical data match the actual climate conditions where the plants or ecosystems reside^[10,11]. For example, when

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conducting research with a climate component, it is desirable that climate data are derived from a nearby weather station(s) as such data would be the most accurate and reliable. However, as the number of weather stations is limited, the locations for research projects are often far away and have considerably different climate conditions from weather stations^[2,12]. Spatial interpolation techniques are often used to predict climate conditions for these locations or for developing spatial climate data sets to cover large areas. Statistical methodologies applied to interpolate climate data, including kriging, bilinear and spline interpolations, are primarily based on distances from nearby weather stations. Yet, considering the degree to which topography variations and other factors can influence local climates over relatively short distances, the accuracy of interpolated climate data obtained through these methods is often not adequate.

A number of algorithms and software packages have been developed to facilitate the spatial interpolation of climate data. The ANUSPLIN software developed at the Australian National University employs thin plate smoothing splines to improve on distance-based interpolation, and has been widely used. For example, WorldClim hosts gridded climate data for the entire globe using this approach^[2]. The algorithm used in ANUSPLIN is a purely statistical approach and its accuracy often limited for the areas with sharp changes in elevation^[1]. Another widely used interpolation method is the Parameter-elevation Regressions on Independent Slopes Model (PRISM)^[13] developed at the Oregon State University. PRISM uses a combination of statistical techniques and knowledge-based methods to make adjustments to account for the effect of factors including rain shadows, coastal proximity, and temperature inversions on climate interpolations. PRISM climate data are generally regarded as the highest quality spatial climate data sets currently available. Interpolated climate data are available for the United States and some other regions, including China, at moderate resolutions.

Spatialized historical climate data sets are essential for supporting research geared toward understanding the response of plants, communities and ecosystems to past and ongoing climate change. The most widely used historical climate data are from the Climate Research Unit in the UK, which provides global time series for monthly climate data at the spatial resolution of 30 arcmin (about 50 km × 50 km) available from 1901 to 2015^[3].

Although the availability of climate data has improved considerably during the last decade, some challenges remain for non-meteorological users. For example, the process required to obtain climate data for locations of interest can be onerous. Specific software and knowledge of geographic information systems are typically required to process the data. This is particularly true when climate data for historical and future periods are derived from different sources and with different formats, variables and resolutions. In addition, climate data generated by meteorologists

often lack climate variables that are relevant for biological applications.

Several climate databases and tools have been developed to address these needs including those created by McKenney et al.^[7] and Rehfeldt et al.^[14] using ANUSPLIN for North America. With these tools, users must submit coordinates files for specific locations to request climate data. The web-based Climate Wizard Tool^[15] covers the entire world and allows users to obtain climate data for a location. However, there is no downscaling involved and it can be time consuming to assemble climate data for multiple locations. ClimateBC represents another tool that has been widely used for its effectiveness in downscaling, inclusion of both historical and future data, and its user-friendly interface^[16]. ClimateBC was initially developed for western Canada and was subsequently expanded to cover the western North America (ClimateWNA)^[17] and finally encompassed the whole of North America (ClimateNA)^[18]. Along with expansion in coverage, its functionality has also been enhanced, particularly by shifting the downscaling algorithm from a partial-derivative-function based approach^[16] to a dynamic-local-regression approach^[18].

Using the dynamic-local-regression approach designed for ClimateNA, we developed a climate model to represent the eastern Asia Pacific region called ClimateAP. While the fundamental approach is similar to that employed in ClimateNA, ClimateAP differs considerably in terms of the baseline data, the fact that it covers distinct terrains and topography, and the fact that it crosses an equatorial region. Considering these differences, the effectiveness of the downscaling algorithms and the accuracy of the output of ClimateAP need to be evaluated to provide confidence for its use in supporting climate change research in the Asia Pacific region. Accordingly, the primary objective of the work presented here is to describe the key algorithms employed in the model and to evaluate the accuracy of its output through comparisons against historical climate data. The evaluation includes detailed assessments of derived biologically relevant climate variables, the performance of regionally specific functions, and the efficacy of methods to incorporate daily weather station data in estimating these climate variables.

2 Data and methods

2.1 Baseline data

Baseline gridded climate data for the reference period 1961–1990 are required to drive the ClimateAP. PRISM data represent the highest quality data but were only available for China and Mongolia. Consequently, it was necessary to use monthly climate data from WorldClim^[2] for other countries within the AP region (Fig. 1). Since the WorldClim data set had a complete coverage for the region,

it was used as the base data set, with the PRISM data substituted for China and Mongolia. To avoid steps at the contact points between the data sets, inverse-distance-weighted averages were applied to a 20 km overlapping zone of the two data sets. The baseline climate data were provided at the resolution of 0.25×0.25 arcmin (about $4 \text{ km} \times 4 \text{ km}$). The climate variables obtained from these data sources included three primary climate variables: monthly minimum temperatures (Tmin01–Tmin12), monthly maximum temperatures (Tmax01–Tmax12) and monthly precipitation (Pre01–Pre12). The mean elevation of each grid cell was also included.

2.2 Historical climate data

Monthly temperature and precipitation data for 1901–2015 (version CRU TS 3.24) generated by the Climatic Research Unit (CRU) at the University of East Anglia^[3,19] were used to represent the historical climate data. According to Mitchell and Jones^[19], the original data

were developed based on anomalies relative to the reference period 1961–1990, although absolute values were delivered for each individual year at the resolution of $0.5^\circ \times 0.5^\circ$. To facilitate the delta downscaling approach (described below) in ClimateAP, the data were converted back to anomalies for each year by subtracting 1961–1990 normals.

2.3 Future climate data

The climate data for future periods and years were derived from a variety of general circulation models (GCM) included in the CMIP5 project in the IPCC Fifth Assessment Report^[20] and downloaded from <http://cmip-pcmdi.llnl.gov/cmip5>. GCM data are available at various spatial resolutions, ranging from $0.75^\circ \times 0.75^\circ$ to $2.85^\circ \times 2.85^\circ$. The GCM data were converted to a resolution of $1^\circ \times 1^\circ$ using bilinear interpolation to simplify the process of integration into ClimateAP. Monthly climate data from two emission scenarios (RCP 4.5 and 8.5) and 15 GCMs^[21]

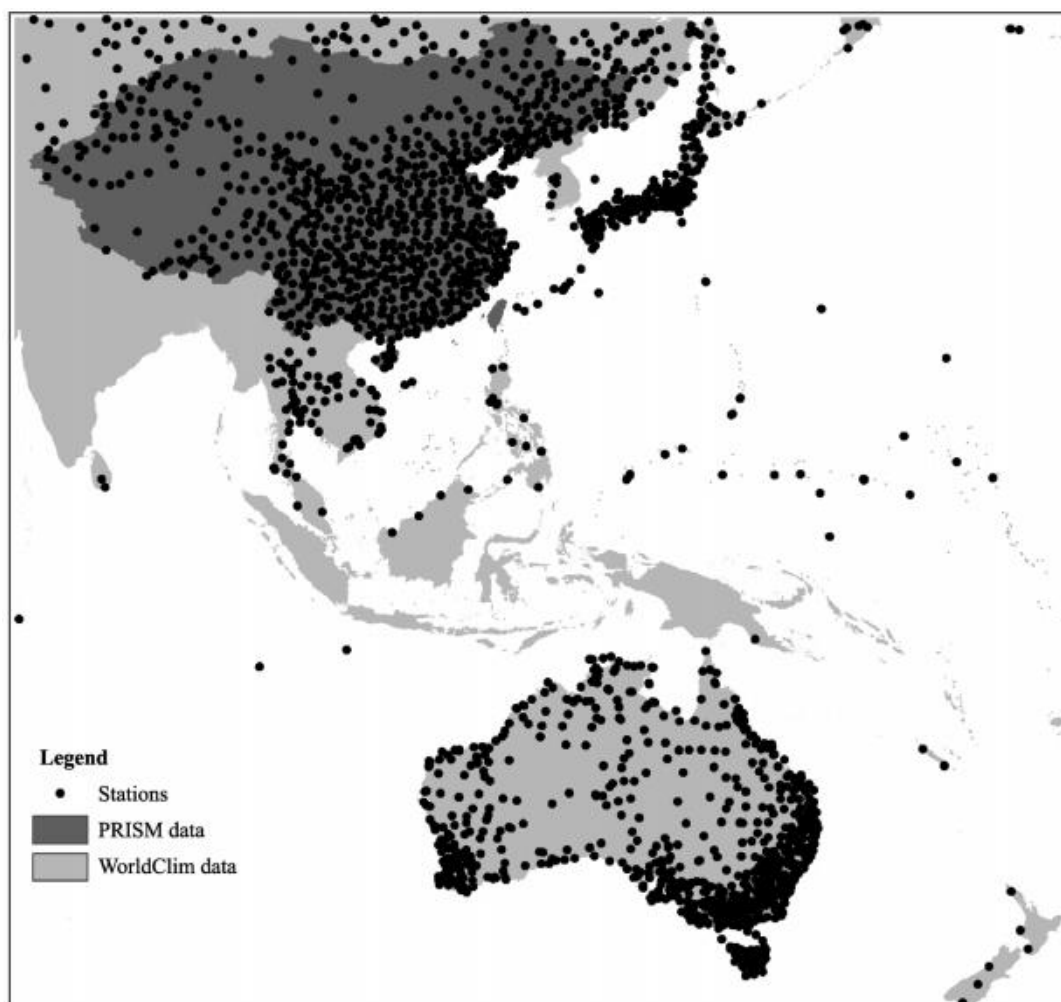


Fig. 1 The distribution of the baseline climate data (from PRISM and WorldClim) and weather stations that were used to derive biologically relevant climate variables and to evaluate the output of ClimateAP.

were included in ClimateAP for three normal periods 2011–2040, 2041–2070 and 2071–2100. An ensemble data set based on all the 15 GCMs was generated for each of the two RCPs and the three periods. In addition, future monthly data were included for individual years 2011–2100 from three GCMs for the two RCPs. As for the historical data, future monthly values were converted into anomalies relative to the 1961–1990 normals for the purpose of downscaling using the delta approach described below.

2.4 Downscaling of the baseline climate data

The downscaling algorithm in ClimateAP was adopted from ClimateNA^[18]. It uses a combination of bilinear interpolation and local regression approaches to downscale the baseline monthly grid data (4 km × 4 km) to scale-free point data. The bilinear interpolation functions to interpolate values for locations between midpoints of the four neighbor grids, while the local linear regression is used to estimate lapse rates for the location of interest to account for elevation effects. In the case of the local regression, ClimateAP retrieves monthly climate data and elevation values from nine closest neighbors of the location of interest and calculates differences in climate variables and elevation between all 36 possible unique pairs of the nine data points. A simple linear regression of the differences in a climate variable on the difference in elevation is performed and the slope of the regression is used as the lapse rate for the climate variable at that specific location. A lapse rate is estimated for each of the 36 monthly primary climate variables at each location of enquiry. Given that the local linear regressions are dynamically performed for every location of interest, the process is called dynamic local regression or dynamic local downscaling. To avoid over-adjustment due to a weak local regression, the adjusted amount is weighted by the R^2 value of the regression.

2.5 Integration and downscaling of historical and future climate data

Both historical and future monthly climate data were integrated and downscaled using a delta method following Wang et al.^[18]. With this approach, the historical data (and future projections) are split into two sections: one section for the reference period (i.e., 1961–1990 normal period) and another section for the anomaly period (e.g., the period between the reference period and 2015). For the anomaly section, historical and future monthly climate anomaly grids are interpolated to continuous surfaces using bilinear interpolation at runtime. For the reference-period section, the scale-free baseline monthly climate normal data generated by ClimateAP are used to replace the original historical and future climate data. After adding the interpolated anomaly section to the scale-free reference

section, ClimateAP produces scale-free climate data for historical and future years or periods. Since the baseline data downscaled by ClimateAP are at much higher accuracy than that of the historical and future projections, this process is designed to improve the prediction accuracies for both historical and future climate data over their original values.

2.6 Calculated and derived climate variables

The baseline data contain 36 primary monthly climate variables including monthly maximum (Tmax01–Tmax12) and minimum (Tmin01–Tmin12) temperatures and precipitation (PPT01–PPT12). ClimateAP generates many additional biologically relevant climate variables based on these primary climate variables (Table 1). Some of these variables, such as mean annual temperature (MAT) and mean annual precipitation, can be directly calculated using the primary monthly climate variables. Others, such as degree-days (DD) above 5°C (DD > 5) and number of frost-free days, require daily climate data. Since daily data are not available in ClimateAP, daily climate data from weather stations in the region were used to calculate these climate variables and then related back to monthly climate data. The functions reflecting such relationships were used in ClimateAP to estimate those climate variables. Specifically, these relationships were modeled using daily climate data from 1805 weather stations located throughout the Asia Pacific region from the Daily Global Historical Climatology Network. The distribution of the weather stations is shown in Fig. 1.

Due to the wide range of variation in climate variables in the Asia Pacific region, no single linear, polynomial or nonlinear function could adequately reflect the relationships between DD and monthly climate variables. Thus, piecewise functions constructed using combinations of linear and nonlinear functions were applied to model these relationships^[18]. The DD variables included DD < 0, > 5, < 18 and > 18. The general form of the DD piecewise functions (DD_m) is:

$$DD_m = \begin{cases} \text{if } T_m > k, \frac{a}{1 + e^{-\left(\frac{T_m - T_0}{b}\right)}} \\ \text{if } T_m \leq k, c + \beta T_m \end{cases} \quad (1)$$

where T_m is the monthly mean temperature for the m month; and k , a , b , T_0 , c and β are the six parameters to be optimized. The annual values of the DD variables were calculated by summing up the monthly values. The same approach was applied to other derived monthly climate variables described below.

For the number of frost-free days (NFFD) and precipitation as snow (PAS), a sigmoid function was used to model the relationship between these monthly variables and monthly temperatures:

Table 1 Climate variables directly calculated (Calculated) using the primary climate variables included in the baseline data and functionally derived (Derived) based on the relationships between the climate variables calculated using daily climate data and monthly climate variables from the 1805 weather stations shown in Fig. 1

Category	Variable short name	Variable long name	Availability at monthly and seasonal levels
Calculated	MAT	Mean annual temperature	Yes
	MWMT	Mean warmest month temperature	Yes
	MCMT	Mean coldest month temperature	Yes
	TD	Continentially, temperature difference between MWMT and MCMT	No
	MAP	Mean annual precipitation	Yes
	AHM	Annual heat-moisture index (MAT + 10)/(MAP/1000))	No
Derived	DD < 0 (°C)	Degree-days below 0°C	Yes
	DD > 5 (°C)	Degree-days above 5°C	Yes
	DD < 18 (°C)	Degree-days below 18°C	Yes
	DD > 18 (°C)	Degree-days above 18°C	Yes
	NFFD (day)	Number of frost-free days	Yes
	EMT (°C)	Extreme minimum temperature over a 30-year period	Yes
	EXT (°C)	Extreme maximum temperature over a 30-year period	Yes
	PAS (mm)	Precipitation as snow	Yes
	Eref	Hargreaves reference evaporation	Yes
	CMD	Climatic moisture deficit	Yes

$$\text{NFFD}_m(\text{or PAS}) = \frac{a}{1 + e^{-\left(\frac{T_m - T_0}{b}\right)}} \quad (2)$$

where T_m is the monthly minimum temperature for the m month; and a , b and T_0 are the three parameters to be optimized.

For extreme minimum (EMT) and maximum (EXT) temperature over a 30-year period, polynomial functions were used as follows:

$$\text{EMT} = a + bT_{\min 01} + cT_{\min 01}^2 + dT_{\min 12}^2 + eTD^2 \quad (3)$$

$$\text{EXT} = a + bT_{\max 07} + cT_{\max 07}^2 + dT_{\max 08} + eT_{\max 08}^2 + fTD \quad (4)$$

where a , b , c , d , e and f are the parameters to be optimized; $T_{\min 01}$ and $T_{\min 12}$ are monthly minimum temperature for January and December; $T_{\max 07}$ and $T_{\max 08}$ are monthly maximum temperature for July and August, respectively; and TD is continentality.

The other two derived climate variables, Hargreaves reference evaporation and a climatic moisture deficit were directly adopted from Wang et al.^[18] due to a lack of observations to evaluate these variables and the fact that the methods used to estimate them are rather generic^[22].

2.7 Statistical evaluations of ClimateAP outputs

The accuracies of the climate variables generated by

ClimateAP were evaluated against observations from weather stations. Observed monthly normals of the primary climate variables for the reference period 1961–1990 were calculated based on the daily climate data from the 1805 weather stations across the entire study area shown in Fig. 1. The amount of variance explained by the ClimateAP outputs and prediction errors, defined as the mean absolute error, were used to evaluate the accuracy of the climate variables generated by ClimateAP for the baseline data.

For the evaluations of the historical data downscaled with the delta approach, we compared the predicted values using CRU, GCMs and ClimateAP against observations for the three primary monthly variables for the baseline normal period 1961–1990. As in the delta approach, the baseline part of the historical and future climate data was replaced by the scale-free baseline data generated by ClimateAP. The amount of improvement in the scale-free baseline data relative to the baseline part of the historical and future climate data provides a conservative evaluation of the predictions of historical and future climate data.

3 Results

3.1 Effectiveness of the local downscaling

The dynamic local linear regressions explained 70%–80% of the total variation in monthly maximum and minimum temperatures, and 0%–50% in monthly precipitation

variables among the nine neighboring pixels in most cases (i.e., medians) (Fig. 2). These results suggest the local downscaling algorithm is effective for temperature and moderate for precipitation variables. An assessment of seasonal results shows that the downscaling was more effective for warmer months than for cooler months. Spatially, the downscaling was more effective in mountainous areas ($R^2 > 0.85$ in most cases), where elevation adjustment is critical, than in flat areas. The seasonal and spatial patterns were similar for areas both north and south of the equator (Fig. 2).

The local regression showed a negative linear relationship between the changes in elevation and the changes in monthly minimum and maximum temperatures in most cases. However, positive relationships were also found in winter months associated with temperature inversions that often occur in mountainous areas during the winter. The relationship between precipitation and elevation was mostly positive. The benefit of downscaling for refining gridded climate data in mountainous regions is illustrated in Fig. 3. When considered for the whole AP region, the effect of downscaling applied in ClimateAP was relatively small in terms of the amount of total variance explained for temperatures (less than 1%) and precipitation (0%–12%) due to the large amount of total variation in the region. However, the improvement was substantial on prediction

errors (Fig. 4). The downscaling reduced prediction errors by 16%–27% for monthly maximum temperatures and up to 60% for monthly precipitation. The improvement on monthly minimum temperatures was relatively small (1%–6%).

The amount of variance in observed climate variables explained by ClimateAP predictions were high, between 97.3% and 99.3% for monthly minimum temperatures, between 97.7% and 99.6% for monthly maximum temperatures, and between 81.6% and 93.9% for monthly precipitation (Table 2). The prediction errors were between 1.0 and 1.4°C for monthly minimum, between 0.7 and 1.0°C for maximum temperatures, and between 22 and 30 mm for monthly precipitation.

3.2 Accuracies of derived climate variables

The fits of the piecewise and nonlinear functions were strong for all derived climate variables. Comparisons between the derived climate variables that were estimated from monthly climate variables and those that were calculated from observed daily climate data indicated that the derived climate variables were highly accurate based on the amount of variance explained (mostly over 99%) and the prediction errors listed in Table 3.

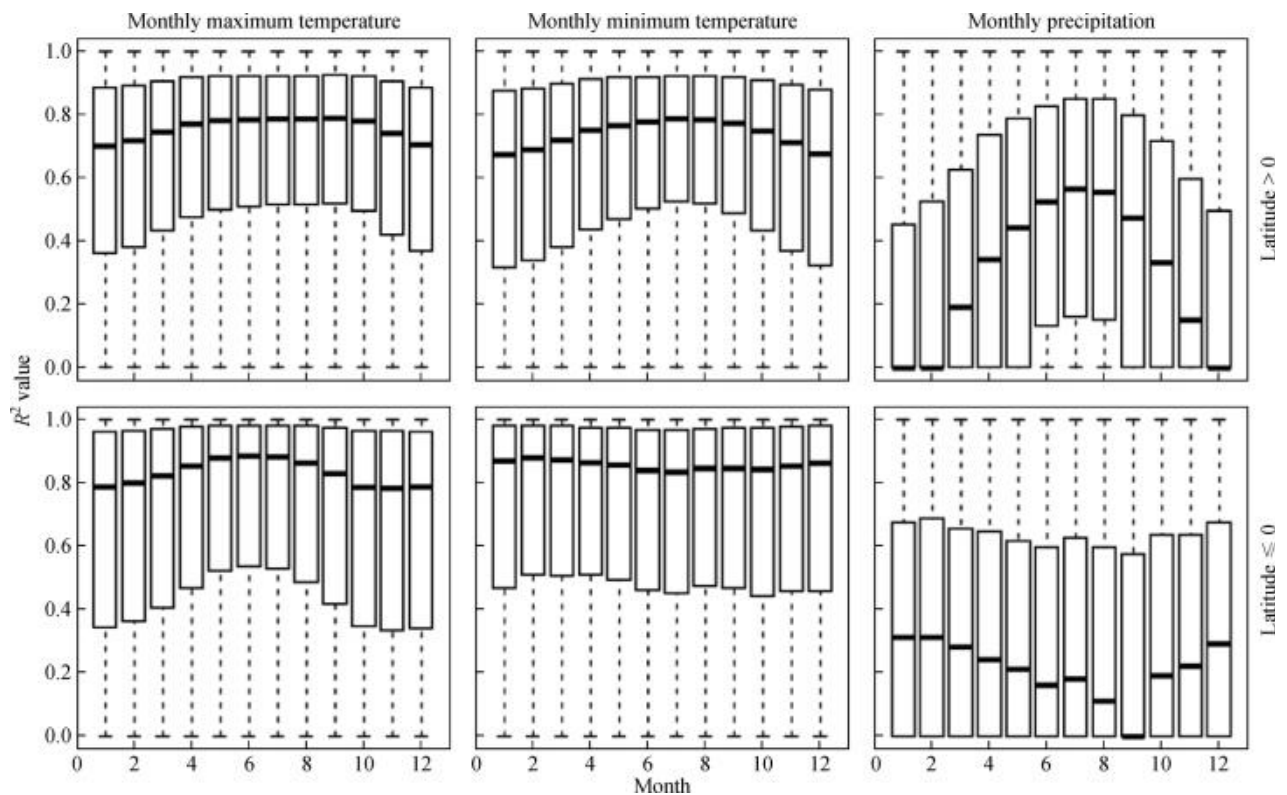


Fig. 2 Proportions of variance explained by local linear regressions in total variation among the nine neighboring pixels for the three primary monthly climate variables separated by the equator. The extent of the box indicates the 25th and 75th percentiles. The horizontal solid lines inside the boxes indicate the medians.



Fig. 3 Illustration of the effectiveness of the local downscaling applied in ClimateAP shown in a mountainous area in Fujian Province (117.50° E and 26.52° N). (a) Mean annual temperature (MAT) of the baseline data at 4 km × 4 km; (b) downscaled MAT (90 m × 90 m) by ClimateAP and overlaid on a satellite geographic image for the reference period; (c) downscaled future MAT for the period of 2041–2070 based on the 15 GCMs' ensemble for the RCP 4.5.

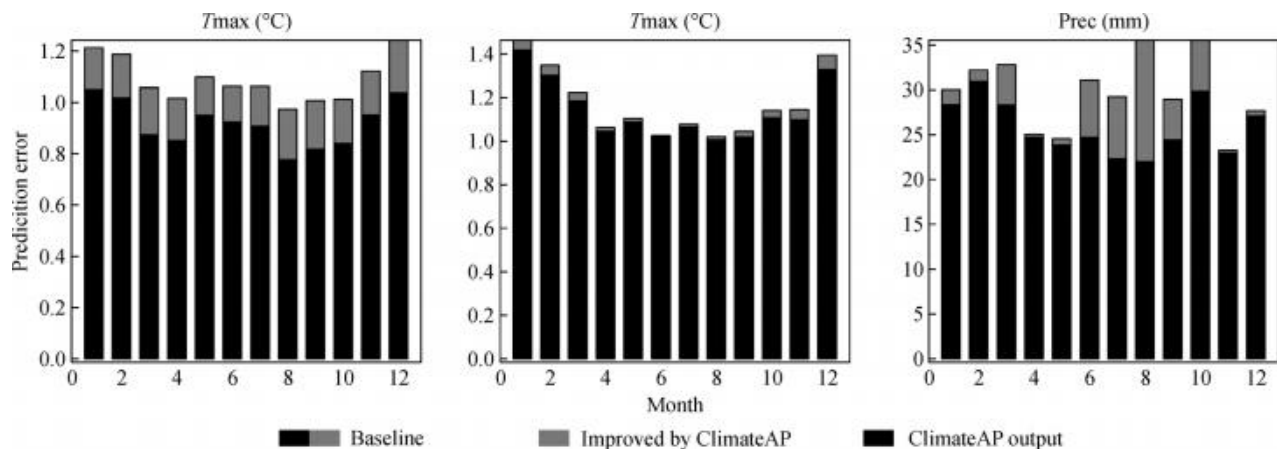


Fig. 4 Comparisons in prediction errors between baseline data (i.e., directly from PRISM and WorldClim) and ClimateAP output for monthly maximum temperature (Tmax01–Tmax12), monthly minimum temperature (Tmin01–Tmin12) and monthly precipitation (Prec01–Prec12).

3.3 Improvements of historical and future climate data

ClimateAP output showed substantial improvements for historical and future climate data relative to the original CRU and GCM data for the baseline period (1961–1990 normal) (Fig. 5). On average, the prediction errors for CRU data were reduced by 0.5°C (31%) for monthly minimum temperatures, 0.8°C (47%) for monthly maximum temperatures, 21 mm (44%) for monthly precipitation. The relative improvement for GCM output was even greater as prediction errors were reduced by 2°C (67%) for monthly temperatures and 35 mm (56%) for monthly precipitation on average.

4 Discussion

High-quality and high-resolution climate data are essential

for facilitating climate impact studies and applications. ClimateAP allows users to extract and downscale gridded climate data to scale-free climate data for specific point locations through a dynamic local downscaling approach. It also generates a diverse series of biologically relevant derived climate variables at monthly, seasonal and annual time steps. Evaluations of the downscaling process and comparisons of output against observations suggest that the dynamic local downscaling approach implemented in ClimateAP is effective for reducing interpolation error in baseline data. The level of improvement in prediction accuracy is comparable to that determined for ClimateNA^[18]. Historical monthly climate data from CRU and future monthly climate data from GCMs for individual years or normal periods can also be effectively downscaled using the delta method by taking advantage of the scale-free climate data for the reference period generated by ClimateAP.

Table 2 The amount of variance in observed climate variables explained by ClimateAP predictions and their prediction errors

Variable	Variance explained/%*	Prediction error/°C	Variable	Variance explained/%	Prediction error/°C	Variable	Variance explained/%	Prediction error/mm
Tmin01	99.2	1.4	Tmax01	99.6	1.0	Pre01	88.2	28
Tmin02	99.3	1.3	Tmax02	99.5	1.0	Pre02	85.2	30
Tmin03	99.0	1.2	Tmax03	99.4	0.9	Pre03	88.4	28
Tmin04	98.3	1.0	Tmax04	98.8	0.8	Pre04	84.8	24
Tmin05	97.3	1.1	Tmax05	97.7	0.9	Pre05	89.1	23
Tmin06	97.9	1.0	Tmax06	98.2	0.9	Pre06	92.4	24
Tmin07	98.2	1.1	Tmax07	98.6	0.9	Pre07	93.7	22
Tmin08	98.3	1.0	Tmax08	98.9	0.7	Pre08	93.9	22
Tmin09	97.8	1.0	Tmax09	98.4	0.8	Pre09	91.9	24
Tmin10	98.0	1.1	Tmax10	98.8	0.8	Pre10	86.5	29
Tmin11	99.0	1.1	Tmax11	99.3	0.9	Pre11	85.6	23
Tmin12	98.6	1.3	Tmax12	99.3	1.0	Pre12	81.6	27

Note: * ClimateAP predictions all exceeded the significance level of $P < 0.0001$.

Table 3 The amount of variance in observed climate variables explained by monthly climate variables and their prediction standard errors

Variable	Variance explained/%		Prediction standard error	
	Monthly	Annual	Monthly	Annual
DD < 0 (°C)	94.4 – 99.9	99.8	0.5 – 8.2	21.7
DD > 5 (°C)	98.7 – 100.0	99.8	3.2 – 27.2	97.9
DD < 18 (°C)	99.3 – 100.0	99.8	5.2 – 13.9	73.4
DD > 18 (°C)	99.2 – 99.8	99.9	5.0 – 10.8	41.5
NFFD (day)	90.5 – 99.8	98.5	0.5 – 1.6	7.1
EMT (°C)		99.3		2.1
EXT (°C)		86.5		1.5

Note: All derived climate variables exceeded the significance level of $P < 0.0001$.

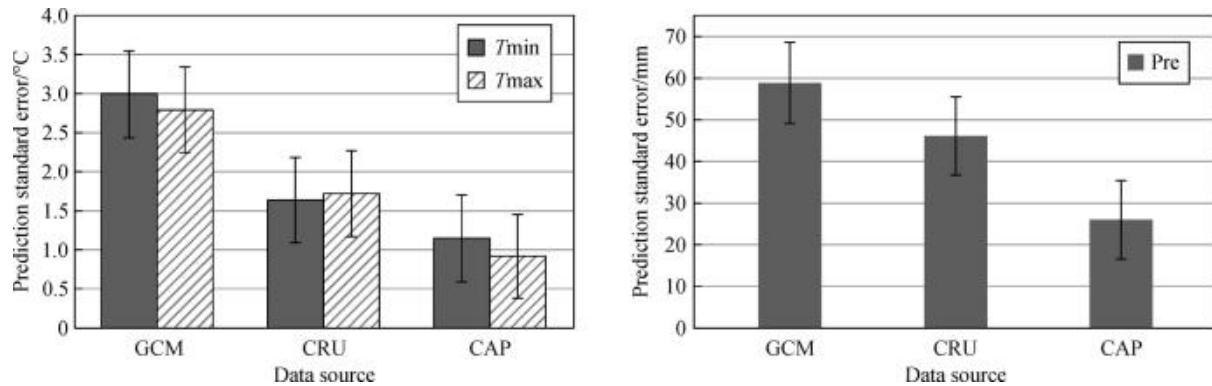


Fig. 5 Comparisons in prediction errors among three data sources for the reference normal period 1961–1990: IPCC GCM predictions (GCM), Climate Research Unit (CRU) and ClimateAP (CAP) output. The error bars are standard errors indicating the variation among the 12 months.

4.1 Downscaling and prediction accuracy for the reference period

The baseline data used in ClimateAP from PRISM^[23] and

WorldClim^[2] are at relatively high spatial resolution (4 km × 4 km) in comparison to historical climate data from CRU^[3] (50 km × 50 km) and projected future climate data from GCMs^[20] (up to 250 km × 250 km). Elevation has

been identified as the dominant factor driving the local variation in climate within each pixel of the baseline climate data^[1]. Results of this study have confirmed this. Thus, the effectiveness of the downscaling depends largely on the accuracy of the estimated lapse rate, which varies with latitude at a large scale and local site factors at a fine scale. Although partial derivative functions have been used successfully for elevation-related temperatures adjustment, they are not feasible for precipitation^[24]. In this study, a dynamic local linear regression approach developed for ClimateNA^[18] was applied to ClimateAP. Results of the analyses show that the lapse rates estimated through local linear regressions were able to capture such variation in monthly temperature and precipitation variables among the neighboring pixels, including temperature inversion in winter months, which is considered difficult to model^[7,25].

The accuracy of ClimateAP predictions for temperatures were high based on the amount of variance explained (97%–99%) and prediction errors (0.7–1.4°C) (Table 2). The prediction accuracy was considerably lower for precipitation than for temperatures in terms of both the amount of variance explained (82%–94%) and prediction errors (22–30 mm). The accuracy of ClimateAP predictions was slightly lower than those observed for ClimateNA^[18], despite the fact that the relative improvement over the baseline data by elevation adjustment was comparable or even greater in ClimateAP. This suggests that the quality of the baseline data in ClimateNA is better, as would be expected. PRISM data have been updated for the USA, but not for China. In addition, the number of weather stations used for developing these baseline data was much greater in North America than in the Asia Pacific region.

4.2 Calculated and derived climate variables

The baseline climate data used in ClimateAP have 36 primary monthly climate variables (Tmin01–Tmin12, Tmax01–Tmax12 and Pre01–Pre12). ClimateAP calculates and derives many additional biologically relevant climate variables at monthly, seasonal and annual time steps (Table 1). These additional climate variables have been widely used in modeling forest ecosystem and species climate niches^[6,10,26], population response to climate^[8,27,28] and evolutionary genomics^[29]. The most frequently used climate variables include MAT, annual heat-moisture index, continentality or temperature difference, cooling and growing DD (< 0 and > 5 , respectively), and precipitation as snow. The ability to generate these biologically relevant climate variables significantly expands the utility of ClimateAP.

4.3 Integration and downscaling of historical and future climate variables

ClimateAP integrates both historical and future climate

data through a delta method. While the delta method is relatively simple, it appears to perform as well as sophisticated downscaling methods in producing mean characteristics^[30]. With this method, the baseline portion of the historical and future climate data are replaced by the scale-free data generated by ClimateAP. As the accuracy of the scale-free baseline data are much higher than that in the historical or future climate data, this replacement not only increase the spatial resolution, but also considerably improves the accuracy of the historical (31%–47% for temperatures and 44% for precipitation) and future climate data (67% for temperatures and 56% for precipitation).

For the anomaly section of the historical and future climate data, ClimateAP bilinearly interpolates the gridded data into point data at runtime. Although this process is not likely to improve the accuracy of the predictions, it smoothens steps across the original grid cells. Moreover, errors associated with the anomalies are typically small as they are less sensitive to topography and their spatial variations are relatively easy to model in comparison to absolute values for historical climate data^[19]. The same applies for projections of future climate data. Through a combination of the replacement of the baseline section and the bilinear interpolation to the anomaly section, ClimateAP is able to generate seamless climate surfaces (Fig. 3c). This makes it possible to develop adaptive forest management strategies at the local scale for a changing climate.

4.4 Applications and limitations

Modeling climate niches for ecosystems and species requires climate data that are consistent with the actual locations of the vegetation in question^[31,32]. The scale-free climate data generated by ClimateAP allows it to meet this requirement. In addition, the availability of a large number of calculated and derived biologically relevant climate variables will considerably increase the flexibility of models to address such objectives. ClimateAP has been used to model the climate niche for four major forest tree species in Asia Pacific^[33].

Due to the difficulty in accessing climate data in the past, scientists have been using geographic variables, such as latitude, longitudes and elevation as substitutes for climate variables in experimental design and data analysis. However, results obtained from such studies are limited to specific locations. In contrast, a relationship between plant performance and specific climate variables should theoretically remain consistent at different locations. ClimateAP significantly improves access to spatially distributed, climate variables for use in a wide range of applications including climate based experimental design, modeling climate niches for ecosystems and species, and population responses to climate. In particular, the time-series function in ClimateAP allows users to generate monthly climate time series for multiple locations and

multiple years for historical and future years between 1901 and 2100. In the absence of such a tool, it may take several months to obtain and process the same amount of data. ClimateAP can be used to generate climate surfaces. ClimateAP produces output in a comma-separated-values format that can be imported easily to ArcGIS to generate maps. The resolution of the map depends on the resolution of the input file. It is particularly useful to generate high-resolution climate maps for specific areas to develop management strategies accounting for locally variable climate conditions.

ClimateAP predictions can account for more than 97% of the total variation in temperatures and more than 82% in precipitation for the 1961–1990 normals. However, the standard prediction errors in term of absolute values are still considerably large, that is 0.7–1.4°C for temperatures and 22–30 mm for monthly precipitation. This can be much greater when it comes to specific locations and specific years (instead of the 30-year normal periods). The prediction errors are expected to be smaller in the regions with more weather stations than the regions where weather stations are lacking. The dynamic local elevation adjustment is effective to downscaling the baseline data. However, it is not able to correct all the errors associated with the baseline data or the anomalies of the historical and future climate data. In addition, although ClimateAP can generate spatial climate surface at very fine resolution or for specific locations, the microclimate affected by aspect, slope and vegetation types at micro-scale are not reflected in the predictions. Therefore, caution is required when interpreting the climate data at very fine spatial resolution.

5 Conclusions

ClimateAP uses the best available climate data as baseline climate data and downscales it to a scale-free format with improved prediction accuracy using a dynamic local downscaling approach. It incorporates historical and future climate data into a single package and improves prediction accuracy using a delta approach by taking advantage of the high-quality scale-free baseline data generated by the application. Additions of calculated and derived biologically relevant climate variables make the application more useful for a variety of applications in forest modeling. In addition, ClimateAP allows users to generate climate data at any spatial resolution, which is particularly important for development of adaptive forest management strategies at local scales. However, it should be noted that errors inherent in the original baseline and anomaly climate data cannot be totally corrected by the application. The desktop version (intensive users) and a Google Map based web version (occasional users) of ClimateAP can be accessed at UBC server (<http://asiapacific.forestry.ubc.ca/research-approaches/climate-modeling>).

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Compliance with ethics guidelines Tongli Wang, Guangyu Wang, John L. Innes, Brad Seely, and Baozhao Chen declare that they have no conflicts of interest or financial conflicts to disclose.

This article does not contain any studies with human or animal subjects performed by any of the authors.

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RESEARCH ARTICLE

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Simulating the impact of climate change on the growth of Chinese fir plantations in Fujian province, China

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Abstract

Background: Climate change represents a considerable source of uncertainty with respect to the long-term health and productivity of Chinese fir (*Cunninghamia lanceolata* (Lamb.) Hook.) plantations in southeastern China.

Methods: We employed the process-based, stand-level model FORECAST Climate to investigate the potential impact of four alternative climate-change scenarios on the long-term growth and development of Chinese fir plantations in Fujian province, China. The capability of the model to project seasonal patterns of productivity related to variation in temperature and moisture availability was evaluated using 11 years of 8-day composite MODIS remote sensing data.

Results: Simulation results suggest climate change will lead to a modest increase in long-term stemwood biomass production (6.1 to 12.1% after 30 to 60 years). The positive impact of climate change was largely attributable to both a lengthening of the growing season and an increase in nutrient-cycling rates. The increase in atmospheric CO₂ concentrations associated with the different emission scenarios led to an increase in water-use efficiency and a small increase in productivity. While the model predicted an overall increase in dry-season moisture stress, it did not predict increased levels of drought-related mortality.

Conclusions: Climate change is expected have positive impact on the growth of Chinese fir in the Fujian region of China. However, the projected increase in plantation productivity associated with climate change may not be realised if the latter also results in enhanced activity of biotic and abiotic disturbance agents.

Keywords: FORECAST Climate, Process simulation, Climate change, *Cunninghamia lanceolata*, Forest productivity, Nutrient cycling, MODIS

Background

Chinese fir (*Cunninghamia lanceolata* (Lamb.) Hook.) is an evergreen conifer species and is one of the most important commercial species in China. Not only is it a valuable timber species useful for construction and furniture manufacturing (Huang 2013; Zhang et al. 2013), but it is also commonly used for pulp and biomass energy production (Nie et al. 1998; Li et al. 2013). Chinese fir has been widely planted throughout subtropical China (Yu 1997; Wu 1984), and according to the results

of the 8th National Forest Inventory, the planting area of Chinese fir is about 11.0 million ha, accounted for 15.8% of all plantations in the country (SFA 2014). In addition to its importance as a source of fibre, Chinese fir plantations also play an important role in water and soil conservation, and in climate regulation through their function as carbon sinks (Tian et al. 2002; Wang et al. 2009). Considering their large area of cultivation, and high potential for atmospheric CO₂ fixation (Yao et al. 2015), Chinese fir plantations represent a key component of China's greenhouse gas mitigation strategy.

There is considerable uncertainty surrounding the possible effects of climate change on the long-term health and productivity of Chinese fir plantations throughout

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China. Deviations from historical temperature and precipitation regimes can influence a wide range of ecological processes associated with forest productivity including decomposition of dead organic matter and nutrient mineralisation rates (Gholz et al. 2000), photosynthetic rates and length of growing season (Boisvenue and Running 2006), and water stress and drought-related mortality (Allen et al. 2010). Moreover, relatively little is known about how climate change may influence the long-term growth and development of Chinese fir plantations in different parts of its range. In general, Chinese fir is adapted to warm and relatively moist climate regimes although it is also considered to be tolerant of periods of moisture stress (Wei et al. 1991). Past studies on the relationship between the growth of Chinese fir and climate factors have primarily focused on the analysis of suitable climate envelopes throughout its distribution (Wei et al. 1991; Guan 1989; Shi 1994; Wu and Hong 1984; Zhang 1995). While such studies are useful, they do not provide adequate information to inform managers how current plantations may respond to shifting climate regimes. Such information is essential to support the development of sustainable and resilient plantation management systems.

Another valuable approach to examining and monitoring the impacts of climate change is through the application of remote-sensing technologies. Satellite imagery and other remotely sensed data have been shown to be effective tools for detecting subtle long-term impacts of climate change on extensive forest areas (e.g. Keenan et al. 2014). Such data, when used in combination with ecosystem models, represent an efficient approach for projecting long-term impacts of climate change and testing model performance.

In this study we employ the process-based, forest management model FORECAST Climate to evaluate the potential impact of alternative climate change scenarios on the long-term growth and development of Chinese fir plantations in Fujian province, China. The FORECAST model (without the climate change component) has been previously applied in subtropical Chinese fir plantations to evaluate the impact of intensive short-rotation management on soil productivity (Bi et al. 2007; Xin et al. 2011). The capability of FORECAST Climate to project seasonal patterns of productivity related to variation in temperature and moisture availability was assessed using 11 years of 8-day composite MODIS remote sensing data. The broader evaluation includes an assessment of the impacts of climate change on key ecosystem processes regulating growth response.

Methods

Study area description

The study area was located in Shunchang County in the north central part of Fujian province (117° 29'–118° 14'

E and 26° 38'–27° 121' N). The terrain in the north and southwest is generally higher than south central areas, which contain the major rivers. Shunchang has a subtropical maritime monsoon climate, but is also influenced by a continental climate. The annual average temperature in the study area is 16.9 °C, the frost-free period lasts 305 days and the average annual rainfall is 1628 mm. With a mild and humid climate and ample sunshine and rainfall, Shunchang is suitable for the growth of Chinese fir. The specific study area includes Shuangxi Town and Yangkou Town with a total area of about 29,361 ha (Fig. 1). Spatial forest resource survey data of Shunchang County in 2007 were used as the principal data source for the analysis. Productive forests within the study area are dominated by stands of Chinese fir of ranging in age from 1 to 52 years and developed on soils with variable fertility.

Soil description

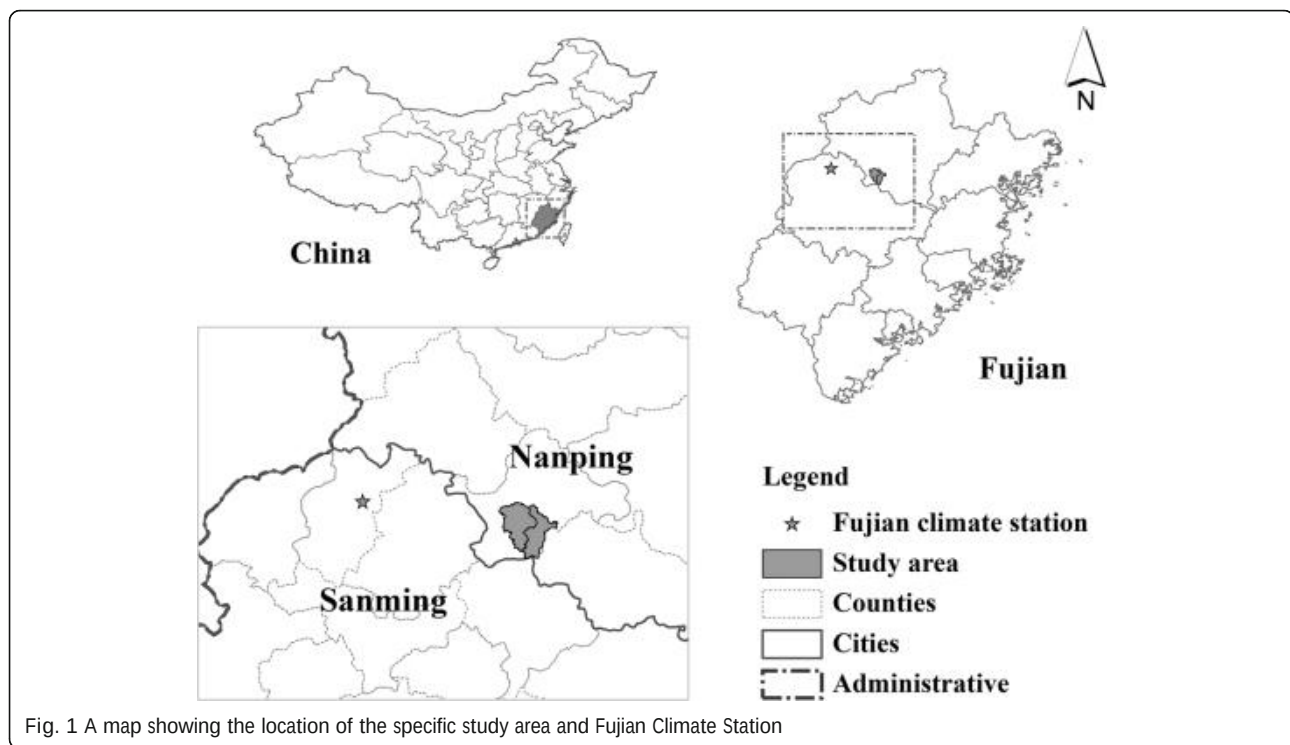
Soils within the study area are largely classified as “red earth” under the Chinese classification system (equivalent to Ultisol under USDA soil taxonomy). Soils in this region tend to be acidic, with depths greater than 1 m. The texture is mostly loam and clay, and they tend to be rich in organic matter.

Model description

The FORECAST Climate model (Seely et al. 2015) was developed as an extension of the hybrid forest growth model FORECAST (Kimmins et al. 1999) created through the dynamic linkage of FORECAST with the stand-level hydrology model ForWaDy (Seely et al. 1997). The linked model is capable of representing the impact of climate and climate change on forest growth dynamics. Specifically, it includes detailed representations of the relationships between temperature and water availability on growth rates and as well as the effect of soil temperature and moisture contents on decomposition and nutrient cycling. The model also includes a function to represent mortality associated with severe drought events. The following sections include descriptions of the two underlying models and their linkage to form FORECAST Climate.

The FORECAST model

The Forestry and Environmental Change Assessment Tool (FORECAST) is an ecosystem-based, stand-level growth and forest ecosystem management simulator. The model was designed to accommodate a wide variety of harvesting and silvicultural systems in order to compare and contrast their effect upon forest productivity, stand dynamics and a series of biophysical indicators of non-timber values. FORECAST employs a hybrid approach whereby local growth and yield data are used to



derive estimates of the rates of key ecosystem processes related to the productivity and resource requirements of selected species. This information is combined with data describing rates of decomposition, nutrient cycling, light competition, and other ecosystem properties to simulate forest growth under changing management conditions.

Decomposition and dead organic matter dynamics are simulated using a method in which specific biomass components are transferred, at the time of litterfall, to one of a series of independent litter types. Decomposition rates used for the main litter types represented in the model are based on the results of extensive field incubation experiments (Camiré et al. 1991; Prescott et al. 2000; Trofymow et al. 2002). Residual litter mass and associated nutrient content is transferred to active and passive humus pools at the end of the litter decomposition period (when mass remaining is approximately 15 to 20% of original litter mass). Mean residence times for active and passive humus types are typically in the range of 50 and 600 years, respectively. In FORECAST Climate, these decomposition rates are modified through the use of annual indices of temperature and moisture.

FORECAST has been widely used in Canada, Scotland, Norway, China and other countries in the world. It has been applied in variety of forest ecosystems including lodgepole pine forest (Wei et al. 2000; Wei et al. 2003), mixed aspen and white spruce forest (Seely et al. 2002; Welham et al. 2002), Scots pine forest (Blanco et al. 2006), coastal Douglas-fir forest (Blanco et al. 2007;

Morris et al. 1997), Korean larch (Sun et al. 2012), and Chinese fir plantations (Bi et al. 2007; Xin et al. 2011). The model has been used in a variety of applications and evaluated against field data for growth, yield, ecophysiological and soil variables. A detailed description of FORECAST is provided in Kimmins et al. (1999).

The forest water dynamics (ForWaDy) model

The ForWaDy model simulates the hydrologic dynamics of a forest stand on a daily time step for a given set of climatic and vegetation conditions. It has been shown to perform well for predicting the effect of forest management on evapotranspiration (Seely et al. 2006) and temporal patterns in soil moisture content under field conditions (Dordel et al. 2011; Titus et al. 2006). The model represents potential evapotranspiration (PET) using an energy balance approach based on a modified version of the Priestley-Taylor equation (Priestley and Taylor 1972). This equation has shown to be effective in predicting evapotranspiration under a wide variety of forest types and conditions (Rao et al. 2011; Stagnitti et al. 1989; Sumner and Jacobs 2005). Net shortwave solar radiation interception is used to drive the PET calculations. It is calculated for each tree and plant species from the light competition submodel built into FORECAST (Kimmins et al. 1999) and surface albedo. ForWaDy includes a representation of the vertical flow of water through canopy and soil layer compartments. Storage and movement of water in and through each soil

layer is regulated by physical properties that dictate moisture holding capacity, permanent wilting point moisture content, and infiltration rate.

Water stress is calculated for each species on a daily time step and expressed as a transpiration deficit index (TDI). The TDI is the relative difference between potential energy-limited transpiration demand and actual transpiration:

$$TDI_{i,d} = (\text{CanT}_{\text{Demand};i,d} - \text{CanT}_{\text{Actual};i,d}) / \text{CanT}_{\text{Demand};i,d} \quad (1)$$

where:

$\text{CanT}_{\text{Demand}, i,d}$ = energy-driven transpiration demand for species i (mm) on day d , as a function of leaf area index (LAI), intercepted short-wave radiation, canopy albedo, and canopy resistance,

$\text{CanT}_{\text{Actual}, i,d}$ = actual tree transpiration for species i (mm) on day d , as a function of $\text{CanT}_{\text{Demand}, i,d}$, root occupancy, and available soil moisture.

A detailed description of the ForWaDy model including its general data requirements are provided in Seely et al. (2015, 1997).

Linking tree growth with hydrology

In the general version of the FORECAST model, forest productivity is simulated based primarily upon light and nutrient availability. FORECAST Climate was designed to incorporate explicit representations of the impact of moisture availability and temperature on forest growth processes to expand the application of the model to address potential climate change. The foundation for the expanded model was established through the creation of a dynamic linkage between the detailed representation of forest biomass growth and structure in FORECAST with the hydrological processes represented in ForWaDy (Seely et al. 2015).

Accounting for climate impacts on ecosystem processes

The impact of climate on tree growth and decomposition processes in FORECAST Climate is focused primarily on their relationship to temperature and water availability. These relationships are represented using curvilinear response functions, simulated on a daily time step and summarised annually. The temperature growth response functions are designed to encapsulate the physiological growth processes governing the response of trees and minor vegetation growth to mean daily temperature. The relative effect of temperature as a limiting factor on tree growth is captured annually through the sum of daily values. The positive effect of a lengthening growing season, for example, may be captured with this approach. The effect of moisture availability on plant growth rates is calculated using daily TDI values, which represent the

degree that a given tree species is able to meet its energy-driven transpiration demands. As TDI increases, plants tend to close stomata to conserve water and there is an associated reduction in photosynthetic production (McDowell et al. 2008). The model also includes a representation of the effect of increasing atmospheric CO_2 concentration on water use efficiency (Seely et al. 2015).

The temperature and moisture response functions are incorporated into FORECAST Climate through their inclusion in a climate growth response index. Specifically, GRI_y is calculated for each climate year (y) as the sum of the daily product of the temperature (T_{Growth}) and water stress (S_{Growth}) indices (Eqs. 2 and 3). A similar approach is used to represent the daily effect of temperature (T_{Decomp}) and moisture content (M_{Decomp}) on dead organic matter decomposition rates through the calculation of an annual climate decomposition response index (DRI_y , Eq. 4).

$$\text{GRI}_d = (T_{\text{Growth};d} \times S_{\text{Growth};d}) \quad (2)$$

$$\text{GRI}_y = \sum_{d=1}^{365} \text{GRI}_d \quad (3)$$

$$\text{DRI}_y = \sum_{d=1}^{365} (T_{\text{Decomp};d} \times M_{\text{Decomp};d}) \quad (4)$$

where:

$T_{\text{Growth},d}$ = The temperature growth index (range 0–1; dimensionless) on day d .

$S_{\text{Growth},d}$ = The water stress growth index (range 0–1; dimensionless) on day d .

$T_{\text{Decomp},d}$ = The temperature decomposition index (range 0–1; dimensionless) on day d .

$M_{\text{Decomp},d}$ = The moisture decomposition index (range 0–1; dimensionless) on day d .

FORECAST climate model calibration

The calibration of FORECAST Climate includes three steps: (1) the calibration of the FORECAST model, (2) the parameterisation of the ForWaDy model and (3) the calibration of the climate response functions in FORECAST Climate. The calibration of the base FORECAST model for Chinese fir in the Fujian region is described in Bi et al. (2007) and Xin et al. (2011) and the main calibration parameters employed in the model are provided in Additional file 1. The calibration of the climate response functions was verified using remotely sensed measures of NPP from the study area.

Parameterisation of the ForWaDy model

The calibration of descriptive soil variables including soil texture, coarse fragment contents and depths of soil layers and the values for key parameters describing soil water extraction and transpiration rates for Chinese fir and minor vegetation are provided in Table 1. The

original version ForWaDy has been modified to facilitate its application for climate change analysis including different CO₂ emissions scenarios (Seely et al. 2015). A detailed description of the representation of the effect of increasing atmospheric CO₂ concentrations on stomatal conductance and water use efficiency (WUE) is provided in Additional file 1. The model does not include a representation of increased atmospheric CO₂ concentrations on photosynthetic rates as there is little evidence to support the long-term effects of CO₂ fertilisation on forest productivity (See Seely et al. 2015 for a detailed discussion).

Calibration of climate response functions

Growth response functions A temperature growth response function for Chinese fir (Fig. 2a) was established based upon reported optimal temperatures from a number of studies (Zhang 1995; Wang 2006; Zhang and Xu 2002). The curve shows a sigmoidal increase in growth rate with increasing temperature up to 20 to 22 °C, representing the optimal temperature range for growth. This is followed by a declining trend as the respiration rate increases with increasing temperature (Wang 2006; Zhang and Xu 2002). Similarly, a water stress response curve was established to represent the relationship between plant growth and daily water stress (Fig. 2b). The shape of the curve is based on the model default.

Climate impacts on decomposition The decomposition of litter and soil organic matter in FORECAST is represented by grouping litter, created through the death of specific biomass components, into different litter types with defined mass loss rates based on litter quality and field studies (Kimmins et al. 1999). In FORECAST

Climate, these base litter decomposition rates and their associated nutrient mineralisation rates are adjusted based on mean air temperature and moisture content. The climate-influenced decomposition functions for the study area are shown in Fig. 2c, d. The shape of the temperature-decomposition response curve was based upon a Q₁₀ relationship of 2 (Zhou et al. 2008).

Drought-related mortality rate

FORECAST Climate includes a drought mortality function to capture the potential impacts of prolonged drought events on tree and plant mortality rates. The function simulates drought mortality using a response curve in which a 2-year running average of species-specific TDI is used as a predictor of the annual mortality rate (Fig. 3). This relationship is based upon the widely held assumption that extended periods of drought will lead to carbon starvation (Hogg et al. 2008). The shape of the curve is based on the model default derived from testing with unpublished data from several tree species in western Canada and is assumed to be relatively consistent across species.

Reference climate data

The FORECAST Climate model requires daily climate data to drive the simulation of climate change. Specifically, 30 years of historical climate data are suggested to provide a baseline against which any climate change scenarios can be evaluated. The Fujian climate station (see Fig. 1), near the study area, was selected for this purpose. It is located at 117.17° E and 26.9° N, with an elevation of 208 m. Daily data from 1961 to 1990 were selected to represent the 30-year reference period, including maximum temperature, minimum temperature, mean temperature and total precipitation. The average monthly

Table 1 Parameter values in the ForWaDy submodel relevant for the simulation of plant available water, transpiration and water stress on a mesic site

Soil variables	Edaphic class	Soil texture class	Coarse fragment (%)		Mineral soil depth (cm)		Field capacity moisture content (θ)
	Mesic site	Silt loam	25		85		0.25
Soil water extraction and transpiration	Species	Maximum LAI ^a	Canopy parameters		Permanent wilting point ^d (%)		Maximum root depth ^e (cm)
			Albedo ^b	Resistance ^c	Humus	Mineral soil	
	Chinese fir	4.5	0.12	0.3	0.07	0.09	100
	Shrubs	NA	0.12	0.25	0.08	0.1	100
	Grass	NA	0.12	0.2	0.07	0.09	75

^aSets the upper limit for LAI by species. LAI is determined as a function of simulated foliage biomass. Not applicable (NA) for understorey vegetation

^bEstimated values

^c"Canopy resistance" represents a general measure of the resistance to water loss from foliage via stomata and cuticle. It is used to adjust the α value in the Priestley-Taylor equation to represent the amount of stomatal control on transpiration from a dry canopy based upon the relationship $R_{Can} = 1 - (\alpha/1.26)$ (Seely et al. 2015). An α value of 1.26 represents a freely evaporating surface, a canopy resistance value of 0.3 would reduce the α value to approximately 0.88. The value 0.3 for Chinese fir was estimated based upon the physical characteristics of its foliage and its known climate niche in comparison to other species for which values of canopy resistance have been measured (dry pine = 0.45, Douglas fir = 0.33, non-sclerophyllic broad leaves 0.13, see Seely et al. (2015))

^dRefers to the volumetric moisture content at which the species can no longer extract moisture from the soil. It is related to the soil texture class

^eIndicates the maximum rooting depth within the total soil profile. Estimated values

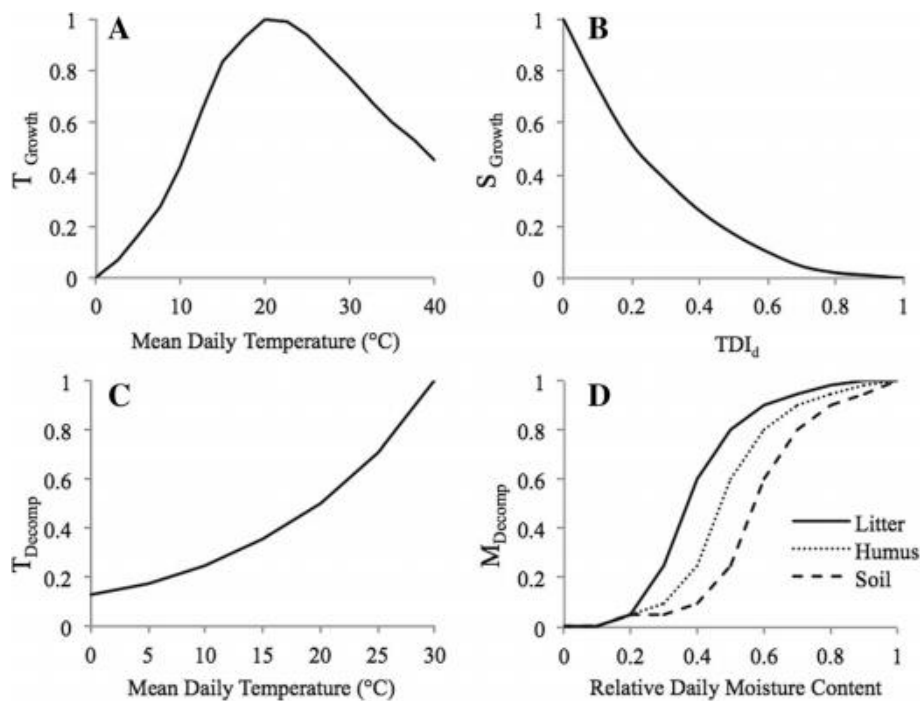


Fig. 2 Climate response functions used in FORECAST Climate related to Chinese fir. These functions illustrate the relationship between daily growth rate for Chinese fir and a mean daily temperature, b daily water stress; and the response of decomposition rates to c mean daily air temperature (based upon a Q_{10} of 2), and d relative daily moisture content, for litter, humus and soil

temperature and monthly total precipitation for the reference period are shown in Fig. 4.

Calculation of climate normals

FORECAST Climate simulates the impact of climate change on growth and decomposition rates using climate normals calculated from reference climate data (Kimmins et al. 1999). Mean values for climate growth and decomposition response indices (GRI_{Normal} and DRI_{Normal}) were calculated by running the model in

climate calibration mode using the 30 years of daily reference climate data to drive the model without climate feedback on growth. The normal climate indices are subsequently stored for use in climate simulation runs where they are compared against simulated future climate indices to determine relative changes in baseline growth and decomposition rates.

Application of the FORECAST climate model

Model validation using MODIS data

Measurements of photosynthesis from the Moderate Resolution Imaging Spectroradiometer (MODIS) on the NASA satellites, Terra and Aqua (Zhao et al. 2006), were used to validate the parameterised model. MODIS data were selected for evaluation as previous studies have demonstrated that MODIS estimates of GPP provide a good approximation for ground-based measures of productivity derived from eddy flux measurements in Chinese fir forests located in neighbouring Jiangxi Province (Wang et al. 2014). The data were collected during an 11-year period (2000–2010) with 8-day composite time steps. The MODIS product (MOD 17A2) provides an estimate of GPP and net photosynthesis (PSNnet) based upon direct measures of the absorption of photosynthetically active radiation (PAR) (Zhao et al. 2005).

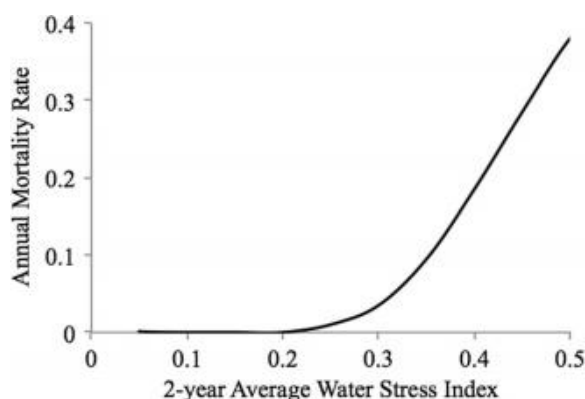


Fig. 3 Annual drought-related mortality rate in relationship to 2-year average water stress

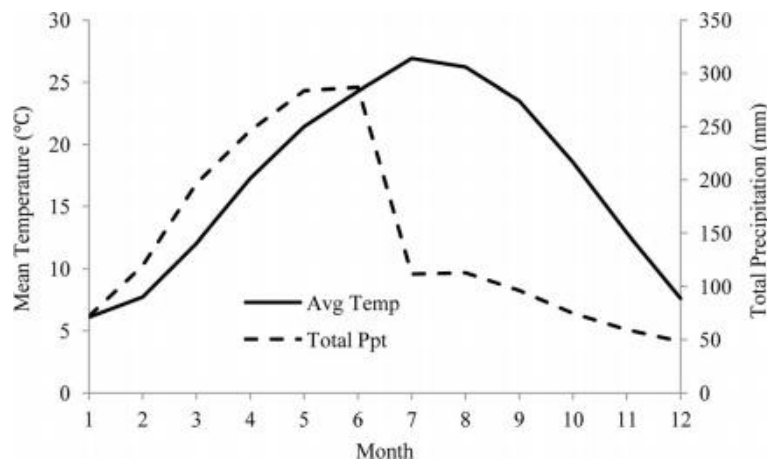


Fig. 4 Average monthly temperature and precipitation calculated with data from the Fujian climate station, years 1961–1990

The MODIS data, available at (<http://modis.gsfc.nasa.gov/data/>), are formatted as a HDF EOS (Hierarchical Data Format – Earth Observing System) tile with a $1\text{ km} \times 1\text{ km}$ grid in a sinusoidal projection. A total of 18 tiles with predominant Chinese fir cover were identified within the Shunchang study region (Fig. 1). A relative PSNnet value was calculated for each 8-day period for each tile and combined to produce a study-area average. Relative 8-day composite values were calculated using annual maxima for each tile. The relative values help to isolate the effects of climate on PSNnet as compared to absolute values, which are subject to differences in forest cover and other factors among tiles. Quality control data, included as part of the MOD 17A2 product (Zhao et al. 2005), were used to exclude periods for which there was excessive cloud cover or other error factors.

Daily climate data from the Fujian climate station (2000–2010) were used to drive the validation simulation of the study area with FORECAST Climate. An initial condition of a medium site quality Chinese fir plantation age 20 was established as a starting condition for the model validation exercise. For the purposes of comparison, daily output of the modelled climate growth response index (GRI_d) was averaged for the equivalent 8-day periods used with the MODIS data.

Development of climate change scenarios

To illustrate the potential impact of climate change on long-term stand growth and development of forests in the study area, it was necessary to develop a set of alternative climate change scenarios. Two general circulation models (HadGEM2 and CNRM-CM5) included as part of the International Panel on Climate Change Fifth Assessment Report (IPCC 2013) were selected in combination with two different emission scenarios to

generate four alternative climate change projections for the study site location. The Climate models were selected to represent a general range in potential change patterns where HadGEM2 = “warm and wet” and CNRM = “cool and dry”. The two emission scenarios selected were RCP4.5 and RCP8.5, derived from the IPCC AR5 analysis (Meinshausen et al. 2011; Peters et al. 2012). Monthly outputs for the 2025, 2055 and 2085 from these models were downscaled to daily data and extrapolated for a 100-year period (2013–2112) using a direct approach linked to the daily reference climate data. In other words, the variability present in the daily reference data was projected forward in the future scenarios with the daily temperatures and precipitation amounts adjusted according to the monthly trends from the GCM models. Time periods after 2080 were assumed to have no further change other than the inherent interannual variation. Projected patterns of change in mean temperature and precipitation for the four climate change scenarios are shown in Fig. 5. Each climate data set also includes projections for annual changes in atmospheric CO_2 concentrations that are consistent with the associated emission scenarios.

Establishment of initial conditions

Prior to conducting a simulation run, it is necessary to establish initial soil conditions that are representative of past management activities. This is achieved by running the model in setup mode to generate an ECOSTATE file that contains values for state variables describing amounts of soil humus, decomposing litter and soil nutrient capital. We created an initial ECOSTATE file to represent a medium site (where top height = 13 m at age 20) within the study area following steps described in Bi et al. (2007).

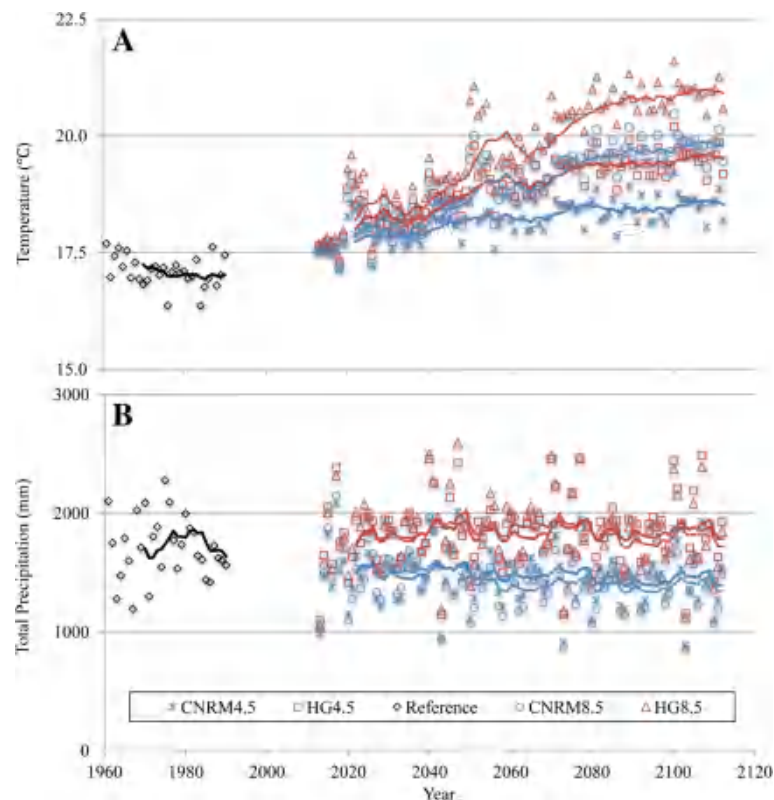


Fig. 5 Historical reference climate data and projected pattern of change. a, b Mean annual air temperature and total annual precipitation for the next 100 years based on four downscaled climate change projections, respectively. Lines represent the 10-year moving average for each series

Simulation of climate change impacts

Following the establishment of an initial ECOSTATE file, the model was used to simulate the long-term impact of climate change on the growth of Chinese fir. The four climate change scenarios described above (HG4.5, HG8.5, CNRM4.5 and CNRM8.5) and a reference climate scenario were used to drive climate simulation runs for three consecutive 30-year rotations starting in 2013. A total of five simulations were conducted.

Sensitivity analysis

A two-part sensitivity analysis was conducted to evaluate the sensitivity of the model response to changes in atmospheric CO₂ concentrations and to potential changes in growing-season rainfall patterns. The impact of changing CO₂ concentrations was assessed by running the climate change scenarios described in the “Development of climate change scenarios” section without the corresponding changes in atmospheric CO₂ concentrations (atmospheric CO₂ was held at 396 ppm). To evaluate the impact of changes in growing season rainfall patterns, a new set of climate change scenarios were generated in which the frequency of growing season (Mar–Oct) precipitation events were reduced by 35% while maintaining the total monthly rainfall amounts.

The scenarios were created using the Statistical Downscaling Model (SDSM v5.2) developed by Wilby and Dawson (2013). These were intended to represent potential increases in rainfall intensity associated with climate warming.

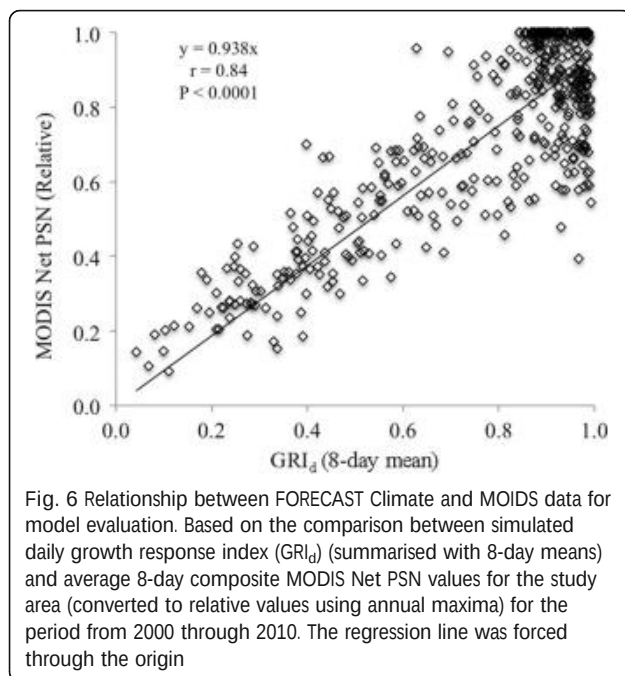
Results

Model evaluation against MODIS data

MODIS 8-day composite Net PSN data, averaged across 18 Chinese fir-dominated 1 km × 1 km tiles within the study area, were used to validate the capability of the model to project temporal patterns in productivity as indicated by simulated GRI_d. As described above, relative values of Net PSN were calculated for each tile to better isolate the impact of climate variations on changes in productivity. There was a good correlation ($r = 0.84$, $p < 0.0001$) between the model and the MODIS data suggesting the model is able to represent the temporal patterns in seasonal productivity associated with temperature and moisture availability with reasonable accuracy (Fig. 6).

Effects of climate change on tree growth

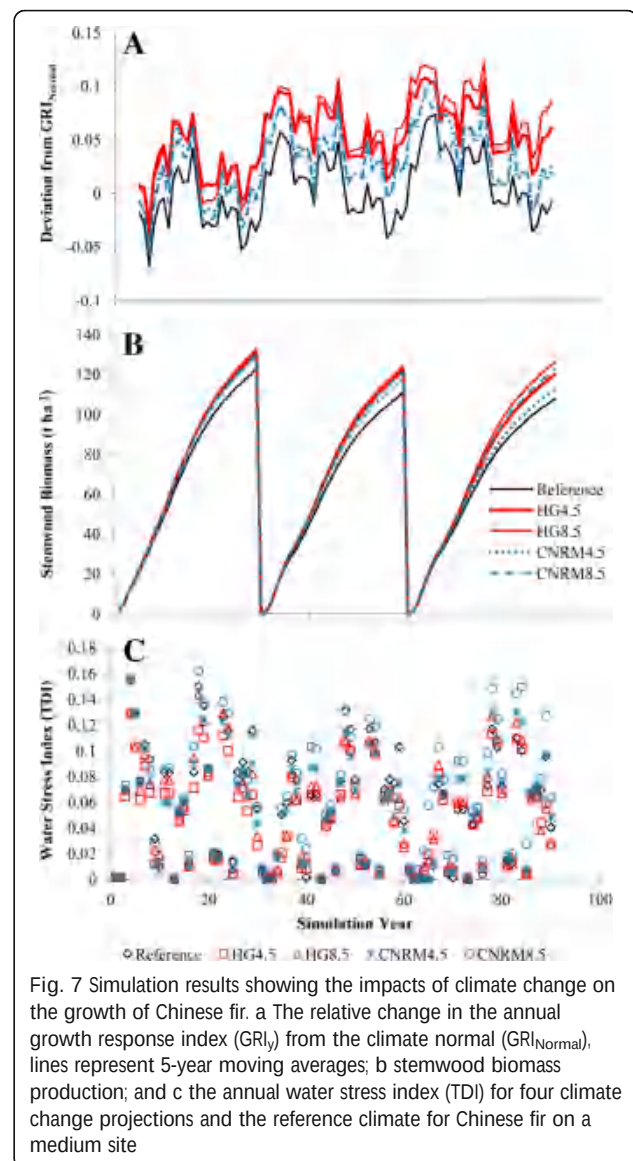
The influence of the alternative projected climate change scenarios on the simulated annual growth response



index for Chinese fir is shown in Fig. 7a. In general, the climate change scenarios showed modest increases in GRI_y relative to the reference scenario. The selection of climate model had a greater impact than the emission scenario with the HadGEM model showing the largest increase. Simulation results for stemwood biomass production followed a similar pattern (Fig. 7b) with increases in productivity of 5.4 to 8.1% by the end of the first rotation (years 1–30), 6.1 to 12.1% for the second rotation (years 31–60), and 4.5 to 17.1% for the third rotation (years 61–90).

The projected impact of the different climate change scenarios on the annual water stress index is illustrated in Fig. 7c. Water stress varies substantially year-to-year in all climate scenarios as a result of interannual variability inherent in the reference data. Scenarios based upon the CNRM-CM5 model show the highest water stress while those based upon the HadGEM2 model tend to be slightly lower than the reference climate. These results are consistent with projected rainfall trends shown in Fig. 5. Consecutive years of elevated water stress were rare in all scenarios (Fig. 7c) and, accordingly, the model projected low levels of drought-related mortality.

Effects of climate change on daily growth response index
To evaluate long-term trends in seasonal climate change impacts on forest growth rates, the 90-year simulations (2013–2102) were divided into three 30-year future periods (coinciding with each rotation) for each climate scenario. Model results showing the average daily growth response index of Chinese fir for the different



periods and climate scenarios are provided in Fig. 8. The daily growth response index (GRI_d) is the product of temperature response index and water stress response index. Increases in average GRI_d were greatest during the spring and fall for all climate change scenarios. In contrast, average GRI_d tended to show modest declines in the future climate periods relative to the reference period during mid- to late summer due to higher-than-optimal temperatures and greater than normal moisture deficits. However, this negative impact was offset by a simulated lengthening of the growing season. For example, compared to reference climate, the average length of the growing season (determined as the number of calendar days in which $T_{Growth} \geq 0.25$) for the period from 2073 to 2102 increased by 26 days and 34 days under the HG4.5 and HG8.5 scenarios, respectively.

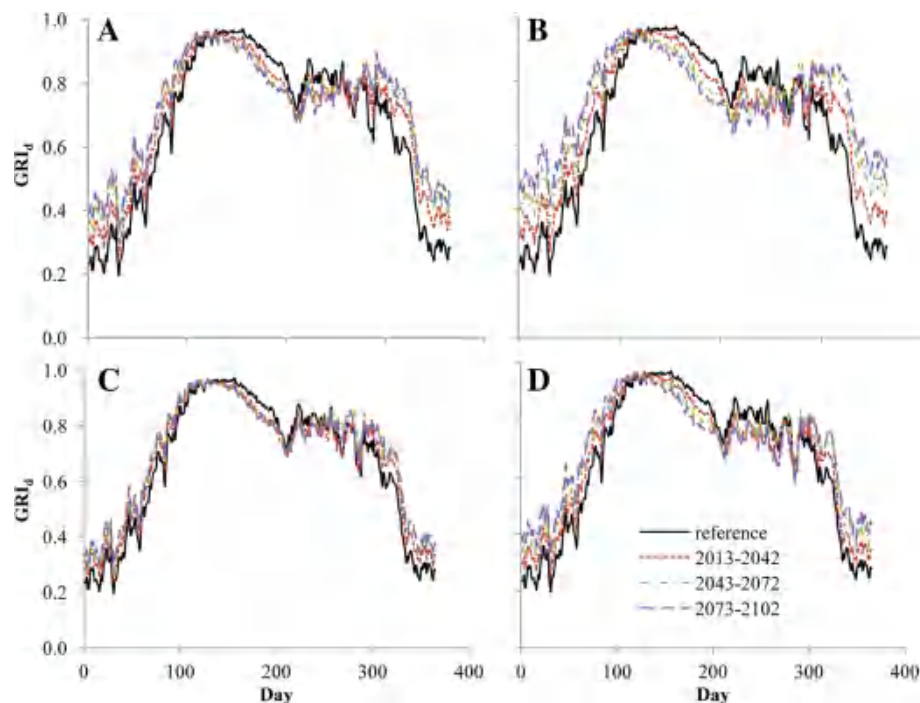


Fig. 8 Simulation results showing the average daily growth response index. Based on three 30-year future time periods (coinciding with each rotation) relative to the reference period for the a HG4.5 scenario, b HG8.5 scenario, c CNRM4.5 scenario and d CNRM8.5 scenario

Effects of climate change on decomposition rates and nutrient cycling

In addition to its impact on tree growth, climate change also had a positive impact on site productivity through its impact on litter decomposition rates. The litter decomposition rate index is a measure of the effect of temperature and moisture content on mass loss rates. Five-year running averages show that the litter decomposition rate increased substantially in all climate change scenarios relative to the reference climate data (Fig. 9a). The increased rates of litter decomposition led to significant increases in the rate of litter N release relative to the reference scenario (Fig. 9b), which had a positive impact on site productivity.

Results of the sensitivity analysis

Results from the sensitivity analysis described above show that the calculation of water stress in the model is sensitive to both changes in atmospheric CO₂ concentration and the frequency and intensity of growing season precipitation events. Removing the effect of CO₂ on water use efficiency (by holding CO₂ constant) led to average increase of water stress of 22% above the levels observed for the original scenarios. Similarly, decreases in the frequency of growing season precipitation events led to an average increase of 24% in the mean annual water stress index (TDI) relative to the original scenarios. However, despite the increase in water stress, biomass

production at rotation only declined slightly (1 to 2%) in the sensitivity analysis runs. The impact of the increased water stress was small because although it increased, water stress was still low enough that it had only a minimal impact on growth and mortality. Detailed results from the sensitivity analysis are provided in Additional file 1.

Discussion

Projections of future climate regimes

The projection of future climate regimes is invariably a source of uncertainty in modelling studies of climate change impacts on forest health and productivity. The approach taken here was to provide a range of potential patterns of change derived from the combination of two reputable climate models and two possible emission scenarios derived as part of the IPCC AR5 analysis. It should be noted that the prediction of future trends of interannual variability is extremely challenging considering most of the output from global climate models only report trends as changes in annual and monthly means and often only for particular time slices. The direct downscaling approach applied here is based upon the assumption that future patterns of interannual variability will reflect past observations. However, there is mounting evidence that this may not be the case (Wilby and Dawson 2013), particularly with respect to precipitation patterns. The sensitivity analysis conducted herein provided some

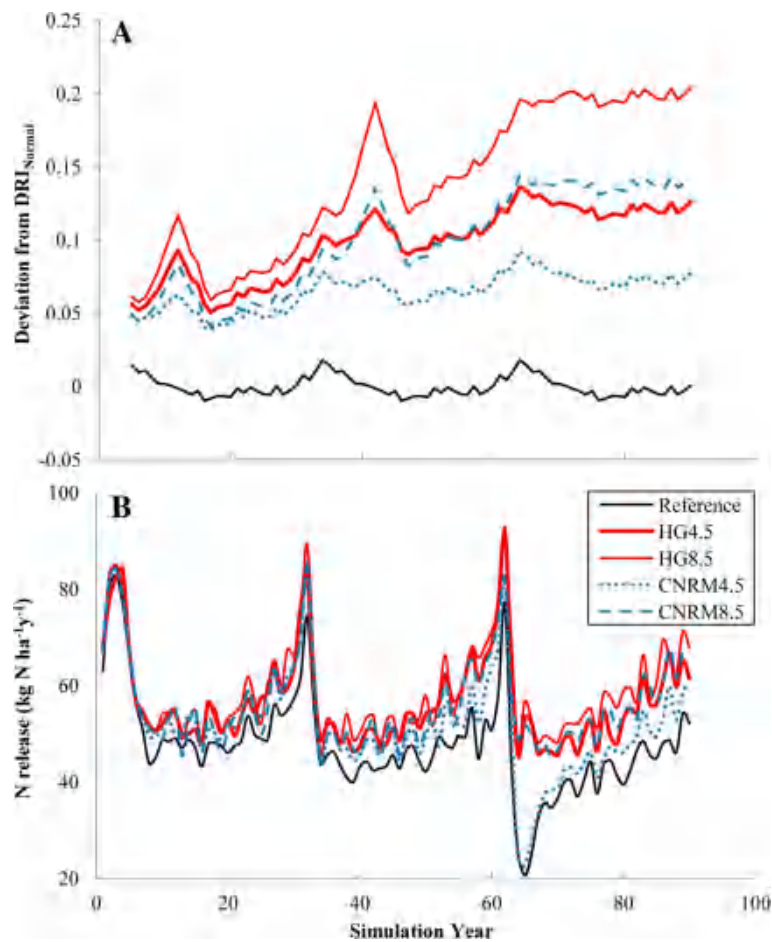


Fig. 9 Simulation results showing the effects of climate change on decomposition rate (a) and litter nitrogen release (b). The lines in a represent 5-year moving averages

insight as to potential impact changes in the frequency of and intensity of growing season precipitation events but more work should be done in this area.

Effects of climate change on Chinese fir productivity

Model results suggest that Chinese fir plantations developed in the subtropical climate of Fujian province will show modest increases in productivity (6.1 to 12.1%) over the next 30 to 60 years due primarily to a lengthening of the growing season. These results are consistent with a recent study by Wang et al. (2014), who observed that productivity of Chinese fir in the Fujian region increased during a 10-year warming trend from 2000 to 2010. They suggested this pattern was linked to a prolonging of the photosynthetically active period. This conclusion is supported by a spatial-temporal climate analysis conducted by Liu et al. (2009), who reported an increase in the growing season in southeastern China of 6.9–8.7 days during the period from 1955 to 2000.

While net annual growth rates are projected to increase, FORECAST Climate predicts variably reduced

growth during the dry season as a result of increased water stress and greater-than-optimal daytime temperatures depending on the climate model selected (see Fig. 5). Predicted elevations in peak summer temperatures will exceed optimal levels causing reductions in growth during these periods, but the net positive impacts of increased growing season length were greater. Wang (2006) found that the optimal temperature and humidity required during the main period of the Chinese fir growing season were 18–20 °C and 80%, respectively. In addition, he observed that growth of Chinese fir was limited when daily temperature exceeded 28 °C and/or monthly precipitation was less than 50 mm.

Our modelling results suggest that warming associated with climate change will also benefit productivity by increasing rates of litter decomposition and associated nutrient cycling. These results are consistent with those reported by Moore et al. (1999), in a study of litter decomposition rates in Canadian forests in which litter decomposition rates were projected to increase by 4 to 7% above contemporary levels because of warming

trends expected with climate change. Evidence of the positive influence of climate enhanced decomposition and nutrient mineralisation rates on productivity has been observed by several authors. For example, Kirwan and Blum (2011) found that organic matter decomposition rates increased by about 20% per degree of warming in salt marsh experiments, which led to the enhanced productivity of marsh vegetation. Further, Melillo et al. (2011), in a 7-year soil warming study, pointed out that the plant carbon storage increased with the support of the additional inorganic nitrogen released by the warming-enhanced decay of soil organic matter.

Projected impacts on mortality rates

While the model predicts an increase in the negative impact of dry season moisture stress on growth rates in some climate change scenarios, simulated stress levels were not high enough in consecutive years to cause increases in drought-related mortality. Several studies have observed increases in drought-related tree mortality attributed to prolonged periods of moisture stress associated with climate change (Breshears et al. 2005; Gitlin et al. 2006; van Mantgem et al. 2009; Allen et al. 2010; O'Grady et al. 2013). The reader should be reminded that the direct downscaling approach employed in the analysis presented here limits the interannual variability of future precipitation as it forces the data to follow historic patterns of variation. If interannual variation were to increase as a result of climate change, it could lead to a significant increase in drought-related mortality, which would, in turn, have a negative impact on estimates of future productivity in Chinese fir plantations. Further research is required to assess the potential of such events.

It also is important to note that FORECAST Climate does not account for the potential impacts of climate change on the activity of other disturbance agents. There is evidence that both biotic (insects and pathogens) and abiotic (fire and wind) disturbance are influenced by climate change (van Mantgem and Stephenson 2007; Mutch and Parsons 1998). O'Grady et al. (2013) pointed out that trees suffering from soil-water deficits are more susceptible to biotic disturbance agents due to significant changes in the energy and carbon balance of the plants. Thus, the predicted increases in Chinese fir plantations associated with climate change may not be realised if changes in climate regime lead to increased mortality from biotic and abiotic disturbance agents.

Conclusions

The process-based, stand-level model FORECAST Climate was applied to examine the potential impacts of alternative climate change scenarios on the long-term growth and development of Chinese fir plantations in Fujian province. Climate change is projected to have a

modest positive impact on plantation productivity due to a gradual lengthening of the growing season and an associated increase in nutrient cycling rates. While the model predicted an increase in dry-season water stress under climate change, it did not project an increase in drought-related mortality. Moreover, the model predicted that the increases in atmospheric CO₂ concentrations associated with climate change would lead to increases in WUE thereby reducing the development of water stress. However, additional research should be conducted to examine the potential sensitivity of Chinese fir forests in this region to significant changes in the interannual variability in precipitation patterns associated with climate change. It is also important to note that the predicted increases in Chinese fir plantations associated with climate change may not be realised if changes in climate regime also lead to increased mortality from biotic and abiotic disturbance agents. The work presented here demonstrates the value of employing a process-based model with relatively minor calibration requirements to evaluate the potential impacts of climate change on key ecosystem processes and long-term productivity.

Additional file

Additional file 1: Additional information describing the FORECAST Climate model. (DOCX 57 kb)

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Authors' contributions

BS, GW and DZ conceived and designed the study; HK and BS analysed the data; BS, JI, TW and PC contributed reagents/materials/analysis tools; HK and BS wrote the paper. All authors contributed to preparing the manuscript. All authors read and approved the final manuscript.

Competing interests

The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

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Article

Spatial Modelling of Fire Drivers in Urban-Forest Ecosystems in China

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Abstract: Fires in urban-forest ecosystems (UFEs) are frequent with complex causes, posing a serious hazard to human lives and infrastructure. Thus, quantifying wildfire risks in UFEs and their spatial pattern is quintessential to develop appropriate fire management strategies. The aim of this study was to explore spatial (geographically weighted logistic regression, GWLR) versus non-spatial (logistic regression, LR) modelling approaches to determine the relationship between forest fire occurrence and driving factors in Yichun, a typical urban-forest ecosystem in China. As drivers of fire, 13 factors related to topographic, vegetation, infrastructure, meteorological and socio-economy were considered and regressed against fire occurrence data from 1980 to 2010. Results demonstrate the superiority of GWLR models over LR in terms of prediction accuracy, goodness of fit and model residuals. The GWLR model further captured the spatial variability of driving factors over a broad study area, and the fire likelihood maps identified areas with different zones of fire risk in the study area. In conclusion, the study demonstrates quantitatively and spatially the importance of accounting for local variation in drivers of fires, thereby improving fire management and prevention strategies. The findings also contribute to the emerged field of fire management and fire risk assessment in UFEs.

Keywords: spatial heterogeneity; geographically weighted logistic regression; fire risk; wildfire management

1. Introduction

Uncontrolled forest fire results in loss of forest resources and land degradation, while affecting air quality and posing a threat to human life and property [1–3]. Urban-forest ecosystems (UFEs) are zones that consist of urban areas and surrounding forests. In China, the UFEs usually refer to the forested city or urban area with high forest coverage. Compared to natural forests or remote forested regions, more forest fires occur in UFEs due to the high frequency of human activities and density of infrastructure [4]. Although these fires are generally small due to early detection, intense suppression efforts and better firefighter accessibility [5], every ignition source has the potential to grow into a large fire. The large and increasing number of lives and infrastructures being exposed to wildfire hazard highlights the need to quantify wildfire risks and understand the fire drivers in UFEs. However, the causes of UFE fires are usually more complex than those in pure forested areas due mainly to various human activities, thus a fire prediction tool, which can fully account for the complexity between fire occurrence and its driving factors, is urgently needed.

Fire prediction modelling has become an important tool for forest managers to recognize the timing and location of fire events and to optimize the allocation of resources for firefighting [6]. In the past decade, many different statistical methods have been applied to identify fire driving factors and establish fire prediction models by considering all possible environmental, topographic, climatic and infrastructure factors. These include the artificial neural network [7], the maxent algorithm [8], the autoregressive model [9], classification trees [10], global logistic regression [11–19], multiple linear regression and random forest [20–22], of which logistic regression is the most commonly used tool.

On the other hand, improved 3S technology (Remote Sensing, RS; Geographical Information System, GIS; Global Position System, GPS) enable the application of large spatial information of factors such as topography, vegetation, and climate for fire modeling [17–19,21,23,24], which provides a valuable contribution to the improvement of fire management and prevention strategies. However, the most commonly used methods mentioned above have not fully considered the spatial heterogeneity of the relationship between fire occurrence and its potential drivers, but have instead assumed that model parameters are valid and homogeneous for the entire study area, or assumed that the models are spatially stationary or non-spatial. In reality, however, the relationship between fire ignitions and driving factors are spatially non-stationary, and the coefficients of model parameters vary with spatial location [4].

Geographically weighted regression (GWR) is a useful analytical tool that can provide information on spatial non-stationarity in relationships between variables [25]. Geographically weighted logistic regression (GWLR) is an extension of GWR; currently being applied in the fields of fire occurrence prediction and fire risk mapping, and its superiority over general logistic regression (LR) has started to manifest [4,26,27]. However, to date, comprehensive analyses of the application of GWLR to understand specific relationships between variables and forest fire in China are limited [28]; in particular, whether GWLR is a proper method for fire risk evaluation in UFEs is still a critical question that needs to be answered.

Thus, the aims of this study were to (1) evaluate the applicability of GWLR to identifying the spatial-informative driving factors of fire occurrence prediction in Yichun, China; (2) explore the importance of considering spatial interaction between factors and fire occurrence on fire risk analysis; and (3) map the likelihood of fire occurrence based on selected fire driving factors and propose relevant fire management perspectives for the study area. The study will provide valuable insights to better understand drivers of fire in UFEs in China by accounting for spatial variation of potential driving factors.

2. Materials and Methods

2.1. Study Area

The study was conducted in Yichun city, which is located in the Chinese boreal forest ecosystem (127°37'–130°46' E, 46°28'–49°26' N) with an administrative area of 32,759 square km and average altitude about 600 m (Figure 1). Yichun has the world's largest plantation area of *Pinus koraiensis*. The average annual air temperature is 1 °C; average annual precipitation is between 750 and 820 mm. Yichun is a typical forest resource-based urban city and ecological garden city, which make it a famous destination for tourism. Because of its geographic location, Yichun exhibits some common characteristics of boreal forest ecosystems and is threatened by fire [29,30]. The fire season extends from April to October and ignitions are mainly caused by human activities [31]. According to Forest Fire Prevention Office of Yichun, China, the majority of reported fires during the period 1980–2010 occurred due to human activity (31.78%), railways (29.2%), electrical wires (4.5%), lighting (5.47%), and other unknown reasons (29.05%) (Figure 1). There is an utmost need in this area for investigation of fire driving factors and mapping of fire risk for forest managers.

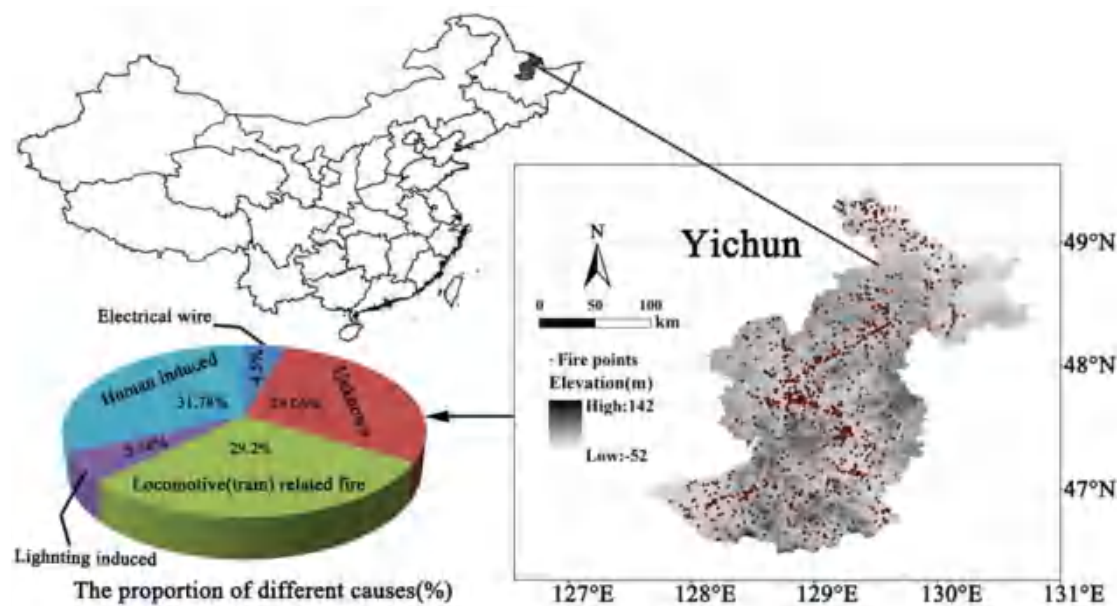


Figure 1. Maps of the study area, fire locations and fire cause distribution. “Human induced” cause in the pie chart represents both intentional and unintentional fires due to various human activities.

2.2. Data Acquisition

Forest fire data from 1980 to 2010 were collected from the Forest Fire Prevention Office of Yichun, China. This dataset included fire location, size, cause, and date of occurrence. Since both LR and GWLR models require binary target variables, we randomly generated non-fire points as control points (1:1.5 as the fire ignition number) [15,32]. To avoid creating control points that would be on the same or nearby location to fire ignition points, a buffer zone of 1000 m around fire points was considered as a barrier, excluding the control points that fell into the buffer [33]. The double random principle of time and space was adopted during the random generation process; i.e., the space coordinates were randomly generated, while the time points were selected from 360 months from 1980 to 2010 (repeatable), then the space and time points were randomly combined together. Our dependent variables consisted of real fire points ($n = 479$) and the generated control points ($n = 720$). For the purpose of analysis, we assigned a value of 1 to fire points and 0 to control points.

The independent variables used in this study consist of five categories, including topography, vegetation type, infrastructure, meteorology, and socio-economic factors, with a total of 13 explanatory variables. The meteorological dataset was composed of average monthly precipitation, average monthly relative humidity, and average monthly temperature. Elevation, slope and aspect were used as topographic variables while distance to rivers, railways, roads and settlement were used as proxies of infrastructure, and forest types as a descriptor of vegetation. For socio-economic drivers, per capita GDP and population density were used as descriptors. Data sources and extraction methods are presented in Table 1.

Table 1. Variables included as predictors in the model.

Variable Name	Code	Data Type/Resolution	Data Description and Extraction	Source
Climate				
Average monthly precipitation	Preci_m_avg	Raster/1 km	The climate factors of each fire point and control point were retrieved from the HADCM2 climate model. The HADCM2 climate model, developed by the Hadley Centre for Climate Research and Prediction, was used in coupled mode. The original dataset was collected from the Intergovernmental Panel on Climate Change (IPCC) and rescaled. The corresponding monthly climate factors for each fire and control point were retrieved from ArcGIS19.0 environment.	Earth System Science Data Sharing Platform, China
Average monthly relative humidity	RH_m_avg			
Average monthly temperature	Temp_m_avg			
Topographic		Raster/25 m	Elevation, slope and aspect values were retrieved from the Digital Elevation Model (DEM) data with resolution of 25 m. Elevation and slope values for each fire and control point were used directly in the modelling process. The aspect was categorised as flat, North (315–45°), East (45–135°), South (135–225°) and West (225–315°). The proportion of each variant in the study area was calculated and the corresponding value for each fire and control point was used to develop the model.	National Administration of Surveying, Mapping and Geoinformation of China, 2002
Elevation	Elev			
Slope	Slope			
Aspect	Aspect			
Vegetation		Raster/1 km	Forest vegetation types for each fire and non-fire point were extracted from the vegetation map (1 km resolution). Accordingly, four categories were identified: (1) needle leaf deciduous and needle leaf evergreen trees; (2) broadleaf deciduous trees and broadleaf deciduous shrubs; (3) grass and agricultural crops; and (4) urban construction land, permanent wetland and barren or sparsely vegetated land. These vegetation types were extracted from the vegetation map layer for each fire point and control point in ArcGIS 10.0; and the proportion of each vegetation type located in a fire or control point was used during modelling.	The Cold and Arid Regions Science Data Center, China, 2000
Forest type	Forest type			
Infrastructure		Vector/1:250,000	Basic geographic information was obtained from the National Administration of Surveying, Mapping and Geoinformation of China. The data were collected in 2000. The variables were retrieved based on a 1:250,000 Digital Line Graphic (DLG) map and included: distance to nearest railway, distance to nearest road and distance to nearest river.	National Administration of Surveying, Mapping and Geoinformation of China, 2002
Distance to river	Dis_river			
Distance to railway	Dis_railway			
Distance to road	Dis_road			
Distance to settlement	Dis_sett			
Socio-economic		Raster/1 km	Two variables represent the Per Capita GDP and annual population density of the study area. This data was then correlated with fire points and control points using the ArcGIS Raster Extraction tool.	The Road of Revitalization—Thirty Years of Reform, Heilongjiang, 2009 Statistical Yearbook of China 2000, 2001
Per Capita GDP	CGDP			
Density of population	Den_Pop			

The codes chosen may not include the whole description of the variable for simplicity purposes.

2.3. Modeling Approaches

Both LR and GWLR modelling approaches were applied to predict fire occurrence in the UFEs. The LR, a non-spatial model, is a generalized linear model with a binomial distribution for the response variable. It has been widely used on forest fire-related studies and the model has been described in detail elsewhere [11,28,32,34]. The GWLR model assumes that the relationship between the dependent variable and independent variables is spatially dependent and varies with location [35]. It is an expansion of the global (non-spatial) LR model that takes into account geographic location factors and carries out LR for each location. Therefore, the estimation of parameter coefficients in a GWLR model is spatially variable. The GWLR model can be written as follows:

$$\log it(P) = \log\left(\frac{P}{1-P}\right) = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)x_1 + \beta_2(u_i, v_i)x_2 + \dots + \beta_n(u_i, v_i)x_n \quad (1)$$

where (u_i, v_i) are geographic coordinates for location i , and $\beta_0(u_i, v_i)$, $\beta_1(u_i, v_i)$, $\beta_2(u_i, v_i)$, ..., $\beta_n(u_i, v_i)$ are the regression coefficients for location i . The calculation of estimated coefficients for location i uses weighted least-squares regression, namely:

$$\hat{\beta}(u, v) = \left(X^T W(u, v) X \right)^{-1} X^T W(u, v) \log it(P) \quad (2)$$

where $\hat{\beta}(u, v)$ is the estimated value of β , $W(u, v)$ is the weighting matrix, and X is the independent variable matrix [28,36,37].

To fit the model, Adaptive Gaussian function was employed, as it has shown strong performance in previous studies [28]:

$$W_{ij} = \exp(-d_{ij}^2 / \theta_{i(k)}^2) \quad (3)$$

where W_{ij} is the weight value of an observation at location j for estimating the coefficient at location i , d_{ij} is the Euclidean distance between locations i and j , θ is the bandwidth size, and $\theta_{i(k)}$ is the kernel bandwidth size defined as the k th nearest neighbor distance.

In a GWLR model, estimation of parameters is related to the bandwidth used by the kernel function; thus, the optimal kernel bandwidth was determined by corrected Akaike's Information Criterion (AICc) [38,39].

2.4. Model Fitting and Evaluation

Prior to model fitting, multicollinearity analysis was conducted, and no correlation between independent variables and dependent variables was detected. Therefore, all predictor variables were included during model fitting. Two types of tests (i.e., the full variables test and significant variables test) were set up to compare the fitting effect of LR and GWLR models. To avoid the influence of sample distribution on test results, the complete dataset was divided into 60% training and 40% validation sets [21]. This procedure was iterated five times, resulting in five data sub-sets and a complete dataset. Procedures for the two test types were as follows: (1) in the all variables test, 13 independent variables were used to fit the five data sub-sets and the complete dataset; (2) in the significant variables test, the forward Wald method was used in the LR model to select significant variables. In the GWLR model, we used an approach applied by previous researchers to determine whether local parameter estimates were significantly stationary or not [28,35]. That is to say, the variables might exhibit non-stationarity if the inter-quartile range (25% and 75% quartiles) of the GWLR parameters was greater than ± 1 standard deviations (SD) of the equivalent global LR parameters. This approach was applied in the GWLR model to fit five data sub-sets, and variables that appeared to be significant in space in at least three out of five intermediate models were included in the final model. In order to model the entire study area, we applied local polynomial interpolation using ArcGIS 10.2 to estimate coefficients for the non-observed values [3]. The LR model was computed using SPSS 19.0 software (IBM, New York, NY, USA) while GWR4.0 software (Department of Geography, Ritsumeikan University, Kyoto, Japan, updated 7 May 2012) was used for fitting the GWLR model.

To assess the predictive performance of LR and GWLR, AIC, AICc, and sum of squared errors (SSE) were employed. The smaller the AIC, AICc, and SSE values are, the better the performance of the model fitting will be. Additionally, Receiver Operating Characteristic (ROC) curve analysis [40] was used to evaluate the prediction accuracy of these two models. The area under the curve (AUC) was the measurement criterion of model prediction accuracy [41,42], where the larger the AUC value is, the better the performance of the model fitting will be [43]. In addition, the Youden criterion (i.e., Youden criterion = sensitivity + specificity – 1) was used to determine the cut-off point derived from ROC curve analysis. If the predicted probability of fire occurrence is greater than the cut-off point, there is a considerable chance of forest fire occurrence; otherwise, there is no forest fire occurrence [11,15]. Based on this, the correct classification rate of both models was computed, and the classification accuracy of the two models compared.

The total residuals of LR and GWLR models in the full variables and significant variables tests were calculated. We also performed interpolation using the Kriging method on the residuals of LR and GWLR models, respectively in ArcGIS 10.0. Besides, the spatial autocorrelation pattern in residuals of both models was compared using correlograms [44,45]. The smaller the value of Moran's I, the better

the performance of the model fitting, taking into account spatial structure [46]. Correlograms and Moran's I values were calculated using the Rookcase software package in Microsoft Excel [47,48].

2.5. Classification of Fire Risk Zones

Likelihood maps of fire occurrence were created based on the LR and GWLR models. The mapping process was conducted using Kriging interpolation in an ArcGIS 10.2 environment. Furthermore, cut-off values of each model (the average cut-off value of the five data sub-sets and complete dataset) were used to divide the study area into three fire risk zones following Changet al. [19] as: (1) low fire risk zone (cutoff = 0), (2) medium fire risk zone (cutoff = 0.5) and (3) high fire risk zone (cutoff > 0.5). Spatial distribution characteristics of the likelihood of forest fire occurrence were analyzed and high fire risk zones within the study area were identified.

3. Results

3.1. Overview of LR and GWLR Models

3.1.1. Model Fitting

The contribution of each explanatory variable and significant variable in the LR and GWLR models, as well as the respective estimated coefficients are given in Table 2. For both modeling approaches, negative correlations were found between fire occurrence and distance to railway, distance to settlement, slope, elevation, monthly average relative humidity, and per capita GDP; while a positive correlation was observed between fire occurrence and distance to the road and average monthly temperature. While population density negatively correlated with fire occurrence in the LR model, distance to river and monthly average precipitation correlated positively and negatively with fire occurrence, respectively in GWLR. Explanatory variables that had no significant correlation with fire occurrence for both modeling approaches were vegetation type and aspect. In addition, population density in the GWLR model and monthly average precipitation in the LR model had no significant correlation with fire occurrence. Evaluation of model performance revealed that the GWLR model had smaller AIC, AICc and SSE values; but a slightly higher AUC and prediction accuracy for each data sub-set and the complete dataset than the LR model (Table 3). The average prediction accuracy of the LR model was 76.69% and 65.62% for training and validation sets, respectively, whereas the GWLR model predicted the likelihood of fire occurrence with 82.04% and 81.48% accuracies for the training and validation sets, respectively.

3.1.2. Residual Analysis

Both total residuals and spatial pattern of residuals for the LR and GWLR model were produced for the all variables test and significant variables test. The distribution of residual for both models appeared to be more or less symmetrical, with no serious bias; and the median residuals of the GWLR model were closer to 0 compared to the LR model (Figure 2). With regard to the spatial pattern of residuals, the GWLR model had the best fit; i.e., overall smaller residuals across the study area (Figure 3). In contrast, the overall residual of the LR final model was higher than that of GWLR and spatially uneven. The positive (under-prediction) and negative (over-prediction) residuals of the LR model were also clustered within the study area. The Moran's I values were smaller for the GWLR than the LR model at different lag classes (Figure 4), indicating that the GWLR modelling had minimized residuals that might be caused by spatial autocorrelation.

Table 2. Coefficient estimates of all variables and significant variables tests for the logistic regression (LR) and geographically weighted logistic regression (GWLR) models.

Statistics	$\beta_{\text{intercept}}$	$\beta_{\text{Dis\_railway}}$	$\beta_{\text{Dis\_road}}$	$\beta_{\text{Dis\_sett}}$	$\beta_{\text{Dis\_river}}$	$\beta_{\text{Veg\_type}}$	β_{Slop}	β_{Aspect}	β_{Elev}	β_{RH}	β_{Temp}	β_{Preci}	β_{CGDP}	$\beta_{\text{Den\_pop}}$
All variables														
LR model														
Estimate	9.931	−0.013	0.147	−0.211	0.026	0.098	−0.029	4.268	−0.004	−0.019	0.036	0.011	−0.0002	−0.219
S.D.	1.101	0.005	0.031	0.027	0.012	0.279	0.017	3.204	0.0006	0.012	0.015	0.075	0.00003	0.030
Estimate − 1s.d.	8.830	−0.018	0.116	−0.238	0.014	−0.181	−0.046	1.064	−0.0046	−0.031	0.021	−0.064	−0.00023	−0.249
Estimate + 1s.d.	11.032	−0.008	0.178	−0.184	0.038	0.377	−0.012	7.472	−0.0034	−0.007	0.051	0.086	−0.00017	−0.189
GWLR model														
Minimum	7.335	−0.064	−0.147	−0.240	−0.006	−0.446	−0.033	0.041	−0.00583	−0.064	−0.0003	−0.188	−0.0003	−0.233
25% quartile	8.518	−0.056	0.056	−0.202	−0.0003	−0.277	−0.024	1.514	−0.0043	−0.035	0.031	−0.132	−0.0003	−0.211
Mean	9.817	−0.038	0.078	−0.184	0.013	−0.120	−0.019	2.451	−0.00358	−0.019	0.045	−0.065	−0.0002	−0.202
Median	9.745	−0.039	0.089	−0.179	0.005	−0.132	−0.020	2.403	−0.0034	−0.014	0.050	−0.062	−0.0002	−0.201
75% quartile	11.268	−0.020	0.136	−0.164	0.029	0.059	−0.016	3.484	−0.00278	−0.002	0.064	−0.001	−0.00008	−0.192
Maximum	12.449	−0.014	0.173	−0.145	0.044	0.143	−0.002	4.580	−0.00212	0.004	0.071	0.063	−0.00002	−0.176
Significant variables														
LR model														
Estimate	0.047	−0.015	-	-	−0.033	-	−0.063	-	−0.004	0.018	-	0.099	-	-
<i>p</i> -value	0.969	<0.001	-	-	<0.0001	-	<0.001	-	<0.001	0.005	-	0.03	-	-
S.D.	0.308	0.004	-	-	0.007	-	0.011	-	0.0002	0.006	-	0.034	-	-
GWLR model														
Minimum	4.740	−0.068	−0.159	−0.241	−0.003	-	−0.036	-	−0.006	−0.058	-	0.037	−0.0004	-
25% quartile	5.333	−0.061	0.055	−0.206	0.002	-	−0.028	-	−0.004	−0.048	-	0.045	−0.0004	-
Mean	5.824	−0.043	0.080	−0.190	0.015	-	−0.023	-	−0.004	−0.041	-	0.069	−0.0003	-
Median	5.965	−0.044	0.089	−0.187	0.006	-	−0.024	-	−0.003	−0.039	-	0.061	−0.0004	-
75% quartile	6.341	−0.024	0.142	−0.171	0.030	-	−0.018	-	−0.003	−0.035	-	0.086	−0.0002	-
Maximum	6.707	−0.018	0.178	−0.150	0.049	-	−0.005	-	−0.002	−0.030	-	0.116	−0.0001	-

The abbreviated variable names are the same as in Table 1.

Table 3. Comparison of goodness of fit and prediction accuracy of LR and GWLR models in all variables (A.V.) and significant variables (S.V.) tests.

Dataset	Model	AIC		AICc		SSE		AUC		Cut-Off		Prediction Accuracy (%)			
		A.V.	S.V.	A.V.	S.V.	A.V.	S.V.	A.V.	S.V.	A.V.	S.V.	Training Set (60% Data)		Validation (40% Data)	
												A.V.	S.V.	A.V.	S.V.
Sample 1	LR	1603.59	1665.92	1603.85	1666.05	257.14	339.09	0.827	0.683	0.438	0.381	77.8	68.1	76.3	68.1
	GWLR	1504.49	1542.29	1507.32	1543.80	227.32	238.54	0.865	0.853	0.433	0.415	79.7	77.4	85.2	83.8
Sample 2	LR	1615.02	1637.89	1615.28	1638.03	258.97	336.73	0.814	0.669	0.400	0.384	78.0	67.9	75.1	63.9
	GWLR	1516.63	1486.21	1519.49	1496.31	229.27	210.74	0.854	0.879	0.336	0.385	77.2	80.1	83.9	86.6
Sample 3	LR	1599.73	1626.39	1599.99	1626.50	256.66	332.46	0.823	0.693	0.395	0.414	77.3	69.2	75.3	69.8
	GWLR	1491.39	1471.72	1496.36	1480.67	220.07	210.39	0.870	0.883	0.395	0.364	79.8	80.4	85.8	86.1
Sample 4	LR	1567.02	1615.77	1567.28	1615.91	251.37	339.67	0.833	0.686	0.444	0.395	78.3	68.0	75.7	67.7
	GWLR	1451.52	1516.59	1469.29	1518.07	224.21	234.06	0.866	0.855	0.419	0.431	80.0	77.9	85.9	83.6
Sample 5	LR	1560.97	1819.49	1561.23	1819.56	248.80	355.93	0.833	0.596	0.424	0.338	77.9	65.3	75.2	48.2
	GWLR	1478.60	1664.90	1480.13	1665.16	226.20	267.36	0.863	0.814	0.383	0.422	78.0	75.1	84.9	83.8
Complete dataset	LR	2670.82	3331.48	2670.97	3331.53	431.58	568.22	0.820	0.676	0.429	0.410	77.5	67.8	-	-
	GWLR	2534.87	2616.65	2535.87	2617.27	398.32	415.33	0.847	0.835	0.440	0.355	78.5	73.7	-	-

AIC = Akaike's information criterion; AICc = AIC with a correction for finite sample sizes; SSE = sum of squared errors of prediction; AUC = area under the curve. For the complete dataset, the data were not divided into training or validation datasets, so we only calculated one prediction accuracy for the all variables and significant variables tests.

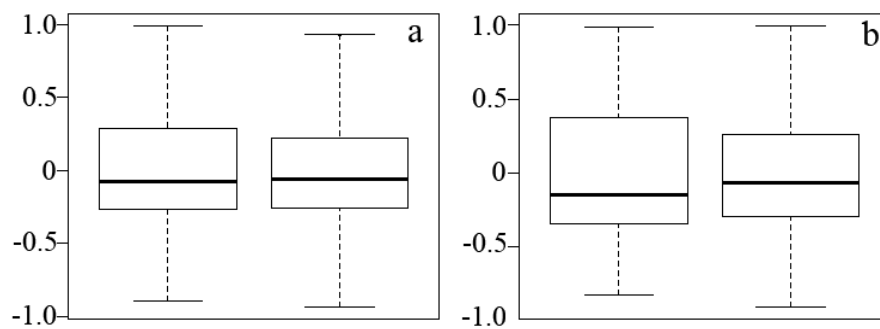


Figure 2. Residual box plots of the LR and GWLR models in the all variable test (a) and significant variable test (b). The left box in both panels represents the LR model, and the right box represents the GWLR model.

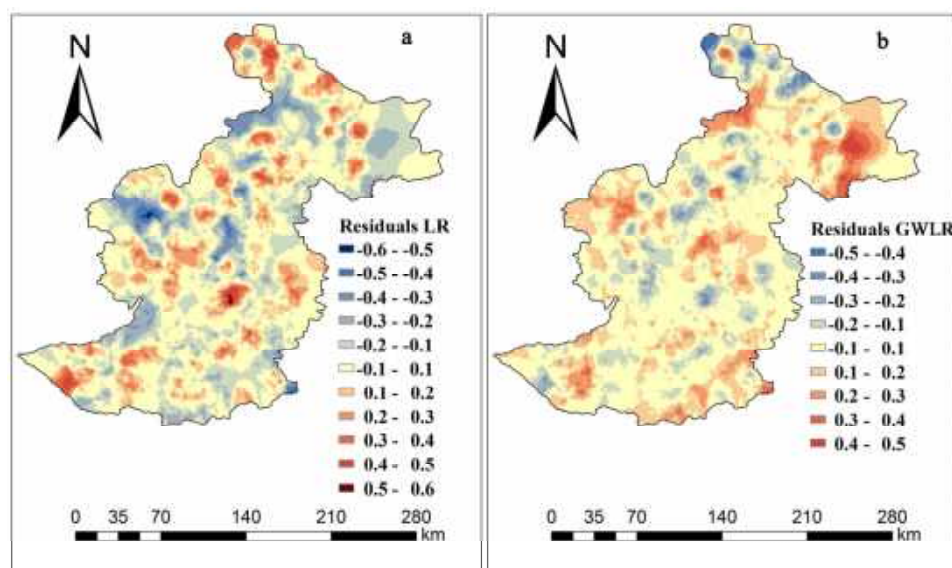


Figure 3. Spatial distribution of model residuals of LR (a) and GWLR (b) models.

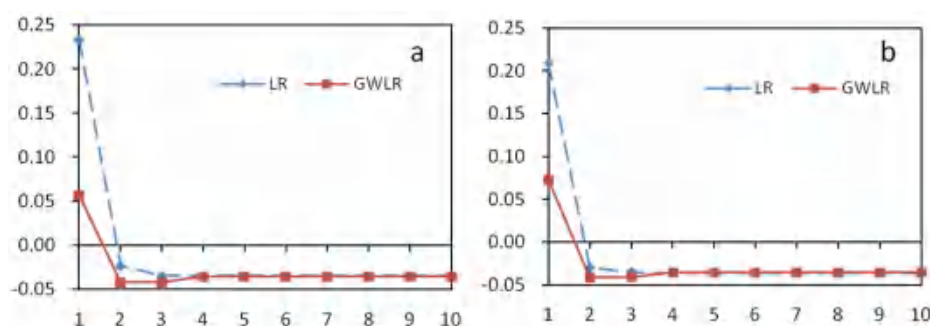


Figure 4. Correlograms for residuals of LR and GWLR models in the all variable test (a) and significant variable test (b).

3.2. Spatial Distribution of Fire-Drivers

Spatial interpolation of the estimated coefficient of explanatory variables included in the GWLR model was performed using the complete dataset to better understand their spatial pattern. The estimated coefficients of the GWLR model showed that distance to railway, distance to settlement, elevation, slope, population density and per capita GDP were negatively correlated with fire occurrence

over the entire study area, while aspect and average monthly temperature correlated positively with fire occurrence in the majority of the study area. Other variables, including distance to road, forest type, distance to river, average relative humidity, and precipitation showed both positive and negative relationships over the study area (Figure 5).

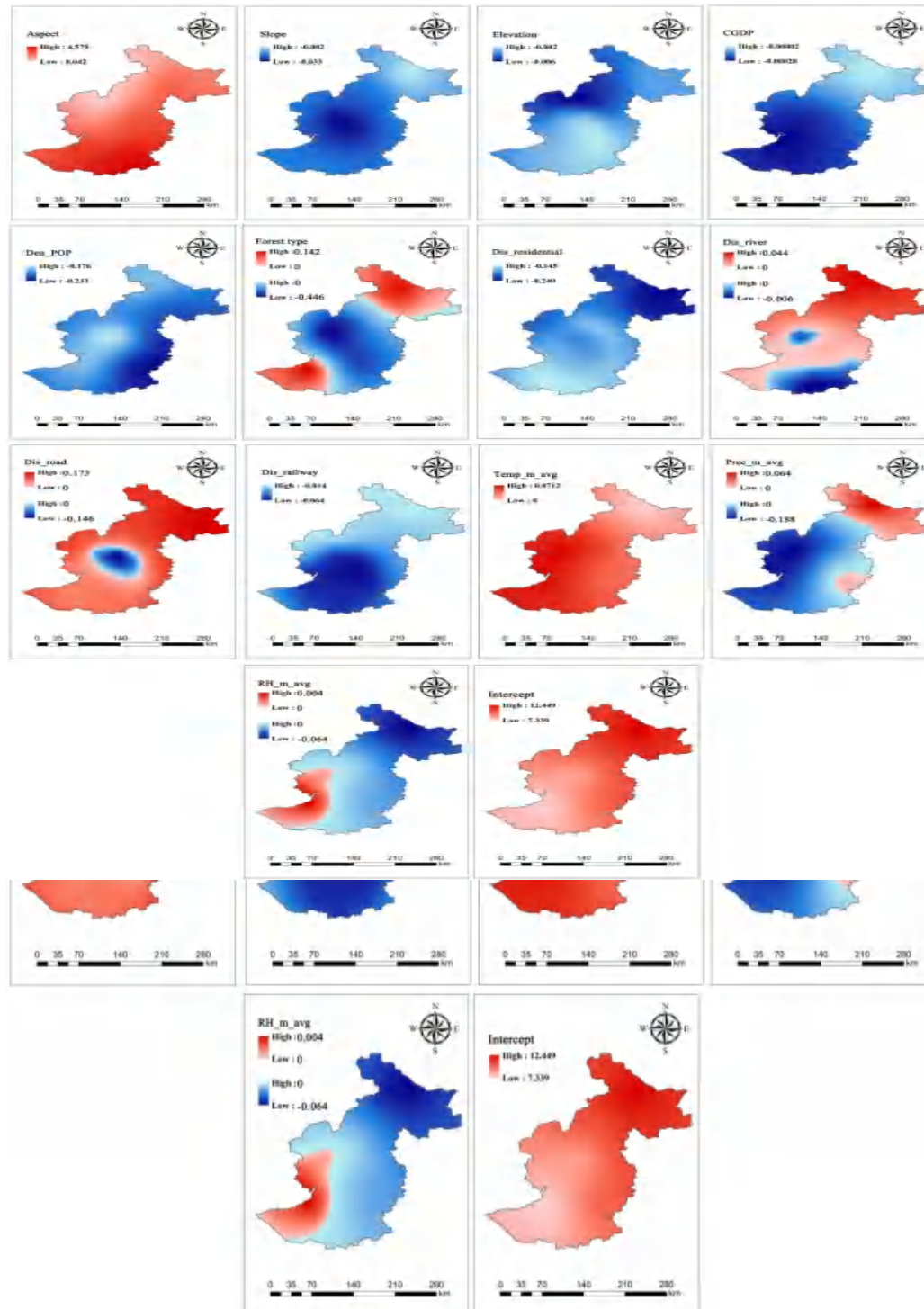


Figure 5. Spatial patterns of regression coefficients for explanatory variables in the GWLR model. The abbreviated variable names are the same as in Table 1. The estimated coefficient was displayed with a warm color (orange to red) when positive and with a cold color (blue) when the coefficient was negative.

The spatial heterogeneity of coefficients of selected significant variables, such as distance to railway, distance to residential area, average relative humidity, elevation and per capita GDP showed a negative correlation with forest fire occurrence across the study area (Figure 6). However, the influence area of other variables on fire occurrence concentrated in some specific parts of Yichun. The average monthly precipitation and distance to river only showed a significant positive relationship with forest fires in the south and north of Yichun, respectively. Both slope and distance to road have a strong negative correlation with fire occurrence at the center of the study area; distance to road also positively correlated to fire occurrence in the south and north of Yichun.

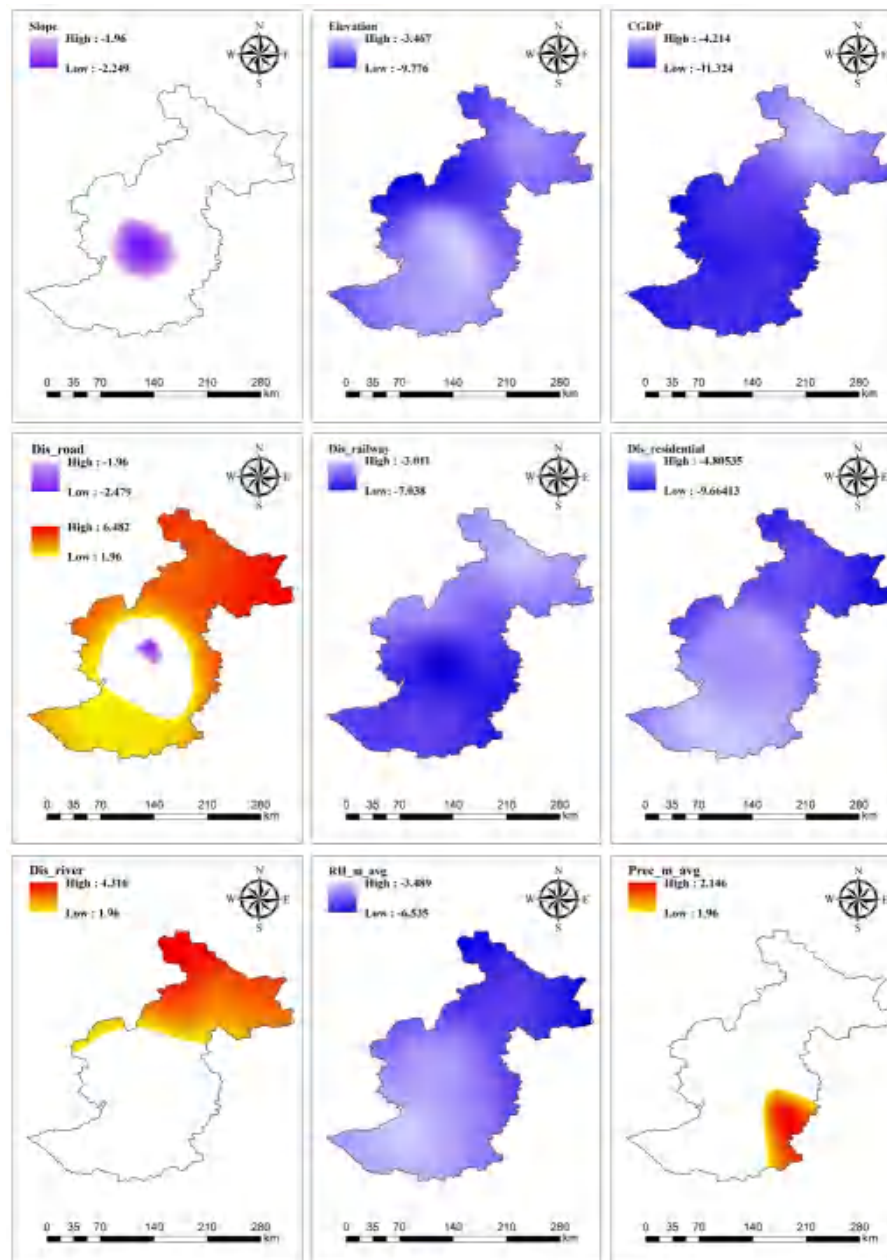


Figure 6. Spatial patterns of estimated GWLR coefficient for selected significant variables. If the t-value of the estimated coefficient for a particular variable is <-1.96 or >1.96 , then the variable had a significant effect on fire occurrence; otherwise the variable was considered as insignificant. Negative coefficients are mapped with cold colors (blue), and positive coefficients are mapped with warm colors (orange to red). The abbreviated variable names are the same as in Table 1.

3.3. Fire Risk Classification

Maps of the likelihood of fire occurrence show that fire ignition was more likely to occur in the central region of Yichun, where the majority of forest-related human activities have taken place, with low possibility of fire detected around the peripheral regions (Figure 7A1,A2). In addition, fire risk zone maps derived from the cut-off values of LR and GWLR models showed more or less similar fire risk distribution in the study area; however, the GWLR model classified more high and moderate fire risk zones than the LR model (Figure 7B1,B2). The map obtained from both models shows that high fire risk zones were concentrated in the central region of Yichun; moderate risk zones surrounded the high risk zones, covering only minor regions of the study area; the low fire risk category covered the majority of the study area.

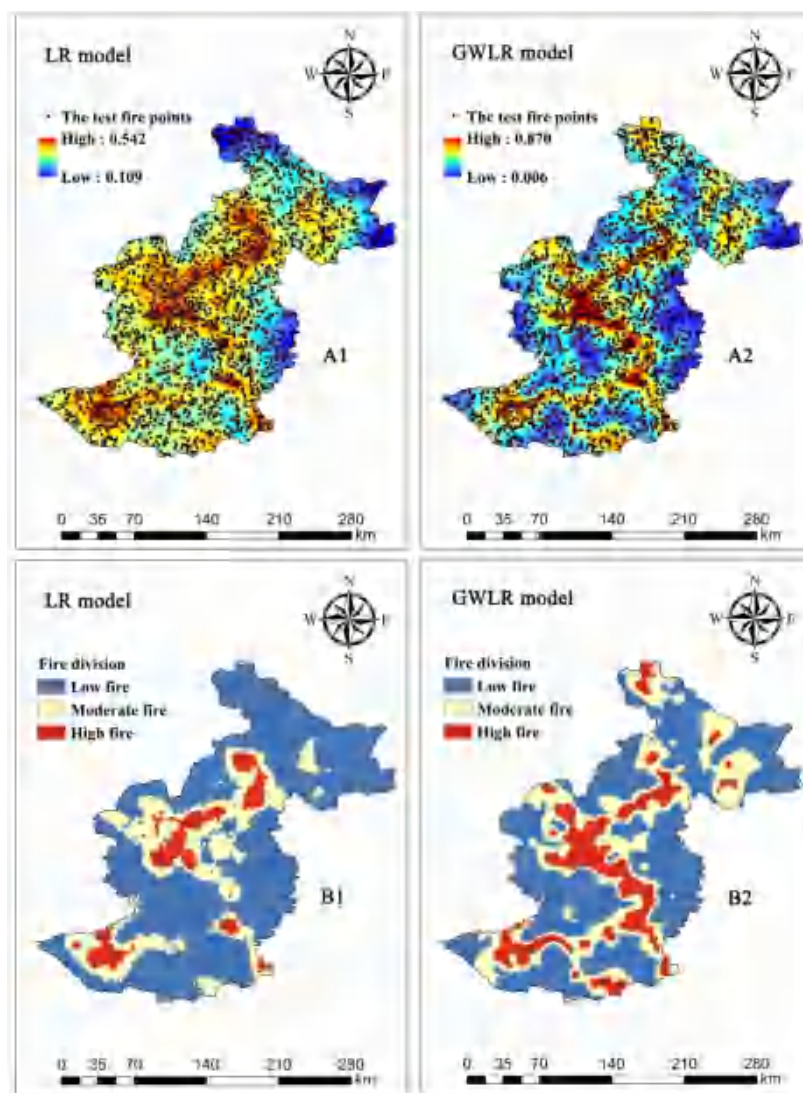


Figure 7. Maps of the likelihood of fire occurrence (A1,A2) and fire risk classes (B1,B2) from LR and GWLR models. The cut-off values for fire risk zone classification are 0.39 and 0.35 for the LR and GWLR models, respectively.

4. Discussion

The study demonstrates spatial variability in fire occurrence and its drivers in the UFEs, and the GWLR modelling approach captures this variability better than the LR. The GWLR model has better classification accuracy than non-spatial LR models (Table 2), with small spatial residuals (Figures 2–4).

This is attributed to the fact that the GWLR model is not designed to model spatial autocorrelation; but rather estimates local parameters explicitly at each data point, which can account for spatial heterogeneity [37]. Our result is consistent with previous studies that demonstrated higher classification accuracy with GWLR than a non-spatial logistic regression modelling approach [3,4]. The results also show that the causes of spatial variability in fire occurrence in UFEs are related to few anthropic and natural factors, notably infrastructure development, topography and weather variables. When studying factors that influence significantly the likelihood of fire occurrence, it is essential to consider regional variation in environmental and social conditions, as the same variables may function differently depending on the location and scale of analysis [49].

In the present study, the most important fire drivers in the UFEs were distance to railway, distance to river, slope, elevation and monthly average relative humidity. However, some variables such as distance to road, distance to settlement, precipitation, and per capita GDP are only identified as main fire drivers in the GWLR model. Fire occurrence was negatively correlated to distance to railway, distance to settlement, elevation, relative humidity and per capita GDP (Figures 5 and 6). Railways reflect a transportation corridor in Yichun, and national fire records reveal that the majority of fire occurrences during this study period were accidental and negligent fires caused by human activities in and around railways, fire accidents by machinery, or lack of controlled burning activities near the tracks and railway infrastructure. Similar negative correlation between distance to railway and fire frequency was reported in the Upper Midwest states and Missouri and boreal forest in China [50–52]. On the contrary, Guo et al. [53] reported a positive relationship between fire and distance to railway in subtropical forest in China and Rodrigues et al. (2014) [3] reported both positive and negative relationships with spatial distribution in the study area. This discrepancy reflects that the effects of distance to railway on fire occurrences are site-specific. The negative relationship between distance to settlements and fire occurrence in the GWLR model suggests that ignition is most likely to occur near settlements, since most fires are caused by various human activities, such as slash burning and clearing agricultural residue. Our findings agree with previous studies that demonstrated significant negative correlations between fire occurrence and human settlement and activities [32,54–57].

Distance to road showed both significant positive (in the north and south of Yichun) and negative (in the central parts) influence on the likelihood of fire occurrence, revealing strong spatial variation in the influence of roads on fire occurrence. Distance to road has often been found to be related to human caused accidental or negligent fires [46,58,59]. Specifically, this risk appears to be higher in Wildland-Urban Interface (WUI) zones [15,60] where population and human infrastructure facilities are close to forested zones [61]. The positive relationship between road and fire occurrence in northern and southern Yichun is a surprising result and difficult to explain, as these areas are relatively far away from urban areas and road density is low. More fires occur in the forests in these areas and may correlate statistically with greater distance from roads.

Results from the present study show that some topographic and weather variables were found to be important drivers of fire in UFEs. It has been shown that lower elevation and flatter areas correlate positively with fire occurrence [62,63]. This is the case in many regions of China [30], as the majority of people reside at lower elevations in the Chinese boreal forest, and the same findings have been reported elsewhere [64–66]. Elevation likely influences fire frequency through surfacemoisture [67], species composition [68], and fuel moisture [69], which have been shown to increase with elevation. In addition, fire ignitions preferentially occur at lower elevations and at less steep slopes due to easy access by humans. Generally, steep slopes imply greater topographic roughness and are more difficult for humans to access [70]. As expected, average monthly relative humidity showed a significant negative correlation with fire occurrence over the whole of Yichun (Figure 6). High relative humidity induces an increase in moisture content of the fuel, thereby reducing the likelihood of fire. The GWLR model also identified a positive correlation between precipitation and fire occurrence, meaning high precipitation will increase the possibility of fire ignition. This might be related with increased growth

of the herbaceous layer, which in turn increases the amount of fuel load. Similar findings were reported in other studies [71,72].

Socio-economic factors, population density and per capita GDP were negatively correlated with the likelihood of fire occurrence. Particularly, the probability of fire occurrence is lower in the northern part of the study area where per capita GDP is higher than the rural parts of the study area. One possible explanation would be a shift from traditional use of fire for heating and cooking to the use of modern fuels in a controlled environment. Similarly, as population density increases, availability of land resources decreases, which in turn reduces the likelihood of fire. Previous studies on the relationship between fire and GDP [36,73] have found similar results. As a whole, GDP is an important factor to consider at a regional scale, as the probability of fire occurrence is always greater when the per capita GDP is low. Among explanatory variables considered in the present study, vegetation type and aspect appeared to play no role in predicting the likelihood of fire occurrence in the study area. The relatively simple spatial composition of vegetation type in Yichun might be the cause of the weak relationship between vegetation type and fire occurrence, which is consistent with other studies [74,75]. Aspect is regarded as a critical factor of fire behavior, through its influence on wind speed, but was found to be poorly related to fire occurrence [76]. It is not surprising that aspect did not exhibit spatial variability as it is a pre-determined position in the landscape.

5. Conclusions and Management Perspectives

This study provides an improved understanding of the spatial variability of fire occurrence in Yichun, China, a typical UFE, as well as the relative importance of various underlying factors. Non-spatial global (LR) and spatial (GWLRL) models were used to explore wildfire occurrence patterns and the main drivers. Compared to the LR model, the GWLRL model demonstrated better performance, evidencing that spatially varying relationships improve the explanatory power of global LR models. The results show that both environmental and human factors influence the likelihood of fire occurrence in Yichun but the specific influence is spatially variable. The likelihood of fire occurrence was also mapped based on the two models, which in turn provided valuable information for improving fire prevention activities for local forest managers. This assessment contributes to the field of fire management and fire risk assessment in UFEs in China, as it quantitatively and spatially revealed the importance of accounting for local variation when modeling fire drivers.

Forest fire managers are often uncertain about the spatial locations where fire is likely to occur, thus linking fire ecology and management is paramount [77]. In this regard, the results of this study provide evidence about the importance of infrastructure and climate parameters as drivers of fire occurrence in the UFEs. From forest fire management perspectives, the findings have the following implications: (1) fire management policies should be developed based on spatial patterns of factors that will drive the maximum likelihood of fire occurrence; (2) allocation of resources for intensive fire prevention should be made based on the level of fire risk; (3) forest fire managers should implement fire prevention and fire suppression practices in high fire risk zones (such as railway tracks); and (4) planned burning would be a good option to reduce fuel loads and suppress unintended large fire, particularly around infrastructure facilities and settlements.

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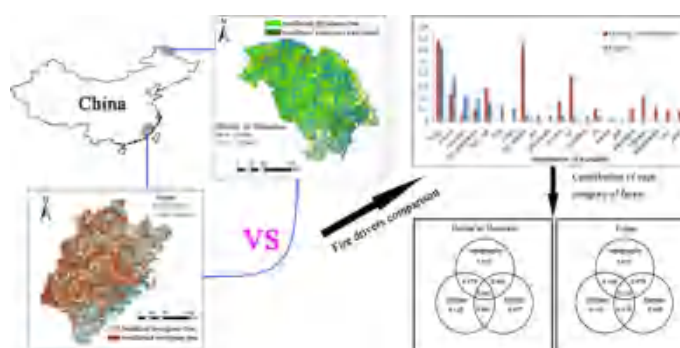
Understanding fire drivers and relative impacts in different Chinese forest ecosystems

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HIGHLIGHTS

- Fire occurrence drivers vary in different forest ecosystems of China.
- Fire occurrence drivers in boreal and subtropical forests were compared.
- Logistic regression model and standardized coefficients method were applied.
- Various fire management strategies are required in Chinese forest ecosystems.
- A strong correlation between socio-economic development and fire regimes was revealed.

GRAPHICAL ABSTRACT



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In this study, spatial patterns and driving factors of fires were identified from 2000 to 2010 using Ripley's K (d) function and logistic regression (LR) model in two different forest ecosystems of China: the boreal forest (Daxing'an Mountains) and sub-tropical forest (Fujian province). Relative effects of each driving factor on fire occurrence were identified based on standardized coefficients in the LR model. Results revealed that fires were spatially clustered and that fire drivers vary amongst differing forest ecosystems in China. Fires in the Daxing'an Mountains respond primarily to human factors, of which infrastructure is recognized as the most influential. In contrast, climate factors played a critical role in fire occurrence in Fujian, of which the temperature of fire season was found to be of greater importance than other climate factors. Selected factors can predict nearly 80% of the total fire occurrence in the Daxing'an Mountains and 66% in Fujian, wherein human and climate factors contributed the greatest impact in the two study areas, respectively. This study suggests that different fire prevention and management strategies are required in the areas of study, as significant variations of the main fire-driving exist. Rapid socio-economic development has produced similar effects in different forest ecosystems within China, implying a strong correlation between socio-economic development and fire regimes. It can be concluded that the influence of human factors will increase in the future as China's economy continues to grow - an issue of concern that should be further addressed in future national fire management.

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1. Introduction

Fire is a critical aspect of ecosystem dynamics, and plays a crucial role in certain forest ecosystems and species evolution (Chandra and

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Bhardwaj, 2015). A better understanding of spatial distribution and drivers of forest fire occurrence is critical for effective fire management, such that fire prevention and suppression resources can be optimally allocated (Hering et al., 2009).

Considerable studies have therefore been carried out to identify the spatial distribution and drivers behind forest fire occurrences in various ecosystems globally (Archibald et al., 2009; Miranda et al., 2012; Oliveira et al., 2012; Guo et al., 2015; Nunes et al., 2016). Previous research has indicated that fire regimes are variable in both space and time (Pereira et al., 2005; Syphard et al., 2008; Parisien et al., 2012; Collins et al., 2015) as a consequence of the interaction of a multitude of factors, which are generally divided into four broad categories, including: climate, vegetation, topography and human activities (Ganteaume et al., 2013; Guo et al., 2016b). Factors such as climate and weather determine the availability and moisture content of fuels, while the fuel load will directly reflect the fuel condition and fire activity - which can be strongly controlled by topography that influences winds, water balance and heat transfer (Rollins et al., 2002; Sharples, 2009). Additionally, human intervention may trigger both fire ignition and suppression, as well as alter the frequency, intensity, severity and distribution of fires (Archibald et al., 2009; Mundo et al., 2013; Penman et al., 2013; Hantson et al., 2015; Guo et al., 2016a, 2016b). Complexity is a prominent feature of forest ecosystems due to diverse internal factors, including climate, terrain, forest composition, human activity and other socio-economic conditions. Interactions amongst influencing factors in an ecosystem have multiple, dynamic effects on forest fires that may change with time due to the inconsistent development of specific factors such as human activity, micro-climate or infrastructure in different ecosystems (Sturtevant and Cleland, 2007; Miranda et al., 2012; Wu et al., 2014). The drivers of fire, therefore, vary amongst different ecosystems, which influence the consistency of future fire prediction and fire management resource allocation.

China's national borders span over a great variation in latitude, and subsequently vegetation can generally be divided into eight vegetation types, including: (1) temperate desert; (2) alpine vegetation of the Tibetan Plateau (very low forest coverage and forest fire are rare to occur); (3) cold temperate needle-leaf forest (boreal forest); (4) temperate coniferous and broad-leaved mixed forest; (5) temperate grassland (low fire frequency but high average burned area); (6) warm temperate broad-leaved forest (low forest coverage, large population, developed industrialization and low forest fire frequency); (7) subtropical broad-leaved forest (occupied nearly one-fourth of China's total area with high forest coverage, high fire frequency but low average burned area); and (8) tropical rainforest (high forest coverage but low fire frequency) (Hu, 2005). Since cold temperate needle-leaf forest and subtropical broad-leaved forest are two typical ecosystems with dominant forest fire regimes, the Daxing'an Mountains and Fujian province were selected as study sites for fire drive and occurrence analysis, as they reside in these two ecosystems respectively. Previous studies regarding fire spatial patterns and drivers in China, however, are unbalanced and primarily focus on Chinese boreal forest with less frequent and less detailed information available regarding fires in sub-tropical forests (Liu et al., 2012; Guo et al., 2016a, 2016b). A comprehensive understanding of the variations of fire drivers in different forest ecosystems in China is the basis for future forest fire risk assessment and the development of regional and national forest fire management policy; however, the lack of comparative analysis limits contributions and implications of the previous studies. Direct comparison of fire drivers in previous studies may lead to uncertainty due to the inconsistency in data extraction, analysis methodology and study span, as studies have been independently conducted in different regions of China.

Taking all aforementioned factors into consideration, two regions - the Daxing'an Mountains and Fujian province - were selected to conduct this study, as they represent Chinese boreal forest and sub-tropical forest ecosystems. The main objectives of this study were: (1) to analyze and compare the spatial patterns of fire ignition in boreal and sub-

tropical forest ecosystems; (2) to identify the most influential fire drivers and their relative importance on fire occurrence, and compare differences amongst drivers in different ecosystems; and (3) to discuss the future trend of forest fire occurrence and the corresponding forest management strategies in various forest ecosystems in China. This study aims to provide insight and aid in promoting the implementation of regionally-specific fire management strategies in various forest ecosystems in China, particularly in the given context of a general national forest fire management policy.

2. Materials and methods

2.1. Study area

The Daxing'an Mountains study site is located in northeastern China, while the Fujian Province study site is located in southeastern China. Both study sites have significant differences in forest composition, climate, topographic and socio-economic conditions, while regional fire regimes also vary. In Fujian, dominant forest types include temperate needleleaf evergreen and temperate broadleaf deciduous shrub (Fig. 1), as the region is located in a humid subtropical environment (Table 1). In the northeastern Daxing'an Mountain region, needleleaf deciduous trees and broadleaf deciduous trees dominant the landscape (Fig. 1) due to its location in a cool temperate zone (Table 1). Fujian has a considerably more mountainous topography than the Daxing'an Mountains, and experiences approximately 3.34–4.77 times more annual average rainfall than the northeastern study site (Table 1). Currently, fire occurrence in Fujian is also considerably higher than that of the Daxing'an Mountains at a frequency of nearly 15,000 forest fires occurring from 2000 to 2010, while the Daxing'an Mountains experienced 4000 fires in the same duration (Table 1). The mean annual density for fires occurring in Fujian, similarly is greater than twice as dense of mean annual forest fire density in the Daxing'an Mountains, which measure $10.9 \times 10^{-3}/\text{km}^2$ and $4.31 \times 10^{-3}/\text{km}^2$, respectively (Table 1). Detailed information about the two regions of study are shown in Fig. 1 and Table 1 below:

2.2. Data preparation

2.2.1. Fire data extraction and control point generation

Historically, information regarding forest fires events in China (the location, time and burnt area of each fire ignition) was recorded and coordinated by government at various levels in "bottom-up" approach, and was eventually reported to the State Forestry Administration (SFA). Errors and uncertainties gradually increase in the process of "bottom-up" reporting systems, which is adverse for the comparative analysis of wildfire characteristics in different forest ecological zones of China. In order to address the above issues, Moderate Resolution Imaging Spectrometer (MODIS) fire products were consistently used for the two study regions to avoid any inconsistencies and discrepancies in the historical reporting approach. The spatial distribution of fire pixels was recorded by MODIS for the Daxing'an Mountains and Fujian province from 2000 to 2010. Remote sensing data obtained by the MODIS radiometer Terra and Aqua satellites have been identified as a suitable and reliable source for monitoring vegetation fires (Justice et al., 2002; Amraoui et al., 2015). Fire products used in this study include daily timescales with 1 km resolution (MOD14A1), which is also a rapid-response fire product for operational near-real time fire data users (Justice et al., 2002). Although MODIS fire products have many advantages for forest fire-related studies, the disturbances from other fire sources such as refuse burning or fires close to forest urban interfaces occur frequently. In the present study, fire pixels for the 2000–2010 fire seasons in the Daxing'an Mountains (March to November) and in Fujian (September to April) were extracted to conduct the analysis as 95% forest fires occur in fire seasons. Strict fire-ignition source investigation was taken, which will improve the accuracy of forest fire

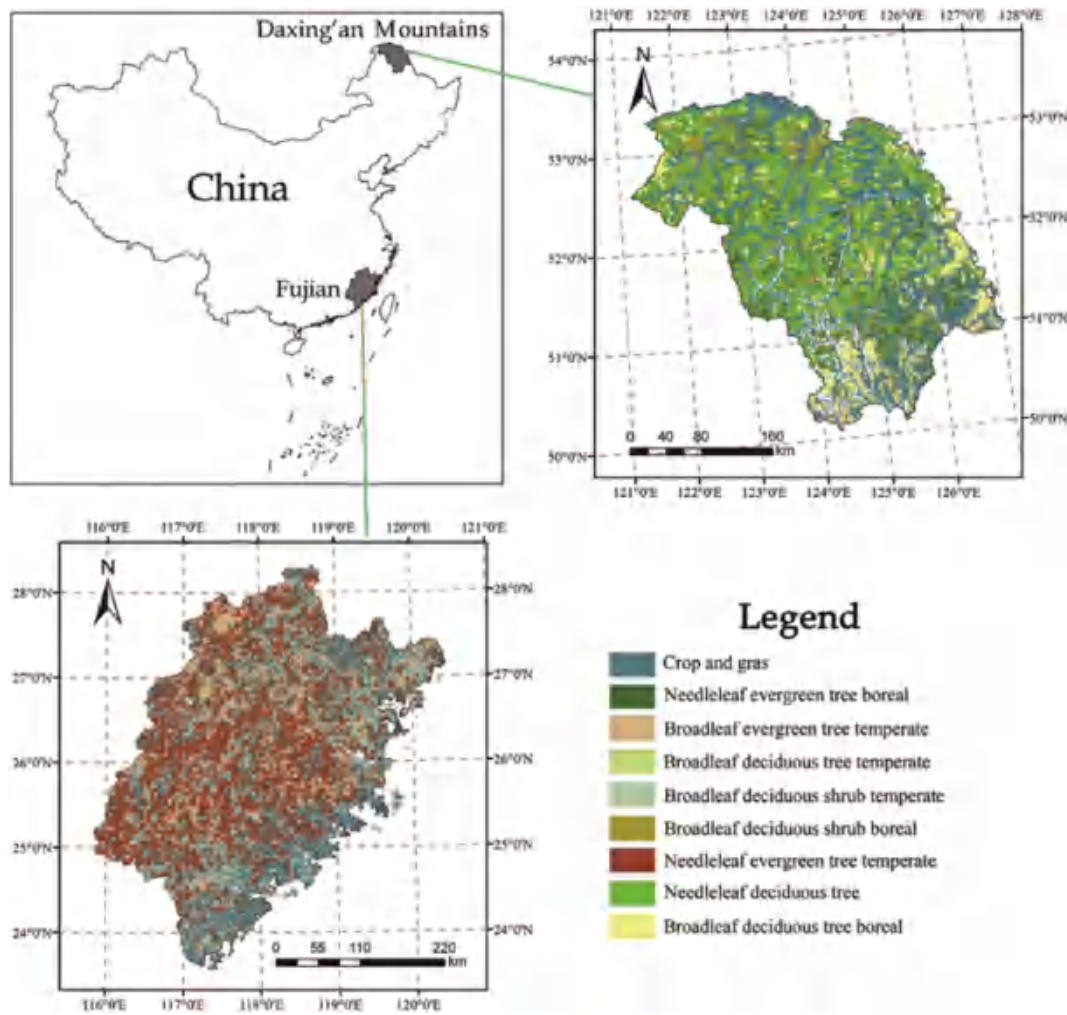


Fig. 1. Study areas and distribution of forest type.

identification. As the release date of MOD14A1 was November 2000, the fire pixels of two months (September and October 2000) are missing. The datasets provide information such as geographic coordinates and timing of 4419 forest fires that occurred in the Daxing'an Mountains and 15,300 in Fujian from 2000 to 2010. Each fire pixel represents a fire point in this study.

A logistic regression model (LR) was used to identify and compare fire drivers between two forest ecosystems (a more detailed description about the LR model to be discussed in Section 2.3.2). Since LR requires binary target variables, we randomly generated non-fire points as control points (1:1.5 as the fire ignition number) (Catry et al., 2009; Chang et al., 2013). To avoid creating control points that would be on the same or nearby location to fire ignition points, a buffer zone of 1000 m around fire points was placed as a barrier, excluding the control points that fell into the buffer zone (Kalabokidis et al., 2007 and Guo et al., 2017). The double random principle of time and space was adopted during the random generation process (i.e., the space coordinates were randomly generated, while the time points were selected from fire seasons during 2000 to 2010, then the space and time points were randomly combined together).

2.2.2. Driving factors

The influence factors in this study were grouped into four categories, namely (1) climate, (2) topography, (3) vegetation, and (4) human

factors, involving nineteen variables in total. The process of fire drivers analysis in the Daxing'an Mountains and Fujian were performed firstly based upon individual factor categories, and then upon the combined factors. A detailed description for each variable is shown in Table 2.

2.2.2.1. Climatic factors. Climate factors are known to affect fuel conditions and have an effect on the probability of fire occurrence (Pereira et al., 2005; Syphard et al., 2008; Oliveira et al., 2012) indicating the critical influence of average temperature, relative humidity, and precipitation on fire occurrence. As climate factors in a previous fire season can significantly influence future fire occurrence (Littell et al., 2009), average temperature, relative humidity and precipitation of the fire season one year prior to the year of fire incidents for the two regions during the period of 2000–2010 were also taken into consideration. The climate dataset for the fire seasons for the two areas of study was generated by the Geographical Sciences and Resources Research Institute, Chinese Academy of Sciences. The data generating process was based on the combination of reanalysis of National Centre for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) Modis Normalized Differential Vegetation Index (NDVI) and Digital Elevation Model (GLS DEM) data (Yang, 2014). The spatial resolution of NDVI data is 1 km × 1 km and the validation results (the final predicted values were compared with observed records at 380 meteorological stations in China) show that the data quality is high, with an R^2 value

Table 1
Basic description of study regions.

Study area	Location	Topography and climate conditions	Human and economic conditions	Dominate species	Fire regime
Daxing'an Mountains	Northeast of China, in Chinese boreal forest	Total area is 83,500 km ² . Terrain is low mountains and hills and slope is between 15°–30°. It belongs cool temperate zone with mean annual temperatures between −2 °C and 4 °C, and a range extending from −52.3 °C to 39.0 °C and annual precipitation of 350–500 mm.	The total population is about 500 thousand. GDP is around \$ 1.5 billion dollars, and Per capita GDP is around \$ 3000 dollars in 2010 (China statistical yearbook, 2011).	Natural forest is abundant in this area and its important forest base in China. Dominant tree species are Dahurian larch (<i>Larix gmelinii</i> Rupr.), Mongolian pine (<i>Pinus sylvestris</i> L. var. <i>mongolica</i> Litv.), and Mongolian oak (<i>Quercus mongolica</i> Fischer ex Ledeb.).	The current fire regime is less frequent but more severe than the historical fire regime (Chang et al., 2008). Lightning-ignited fires account for nearly 30% of total fire ignitions (Zhang and Hu, 2008). MOD14A1 detected nearly 4000 fire ignitions in forest area during 2000–2010, and the annual density of fire ignitions is $4.31 \times 10^{-3}/\text{km}^2$.
Fujian	Southeast of China, in sub-tropical forest ecosystem.	Total area is 124,000 km ² . Terrain is high mountains and hills, account for nearly 80% of the total area of Fujian. Its humid subtropical climate. Annual average rainfall is 1670 mm and annual average temperature is 17–20 °C.	The total population is about 37 million. GDP is around \$ 220 billion dollars, and Per capita GDP is around \$ 6000 dollars in 2010 (China statistical yearbook, 2011).	Forest plantation dominated in this area and its important commercial forest base in China. Dominant tree species are <i>Pinus massoniana</i> Lamb., <i>Cunninghamia lanceolata</i> , <i>Casuarina equisetifolia</i> L. and <i>Phyllostachys heterocycla</i> .	Relatively high forest fire frequency as compared to boreal forest areas in China. Wild fires occurred 1000 times per year on average and nearly 95% of fires were caused by human activities (Zheng et al., 2001). MOD14A1 detected nearly 15,000 fire ignitions in forest area during 2000–2010, and the annual density of fire ignitions is $10.9 \times 10^{-3}/\text{km}^2$.

between 0.86 and 0.95 (Jing et al., 2013). This data is available on the Earth System Science Data Sharing Platform, China (<http://geodata.nju.edu.cn/>).

2.2.2.2. Topographic and vegetation factors

2.2.2.2.1. Topography.

High resolution (25 m) Digital Elevation Model (DEM) data was collected from the National Administration of Surveying, Mapping and Geoinformation of China. Elevation, slope and aspect values were retrieved from the dataset. Elevation and slope values for each fire and control point were used directly in the modelling process. The DEM-based aspect was transformed into cosine aspect (Cos_as) using ArcGIS 10.0 by applying a trigonometric function such that Cos_as will be close to 1 when the aspect is generally northward, close to −1 when the aspect is southward, and close to 0 when the aspect is eastward or westward (Zhang et al., 2014).

2.2.2.2.2. Vegetation cover.

Fractional vegetation cover (FVC) was used to represent the corresponding fuel amount at each fire or control point. FVC is the vertical projection of the crown or shoot region of vegetation to the ground surface within a unit area, expressed as a fraction or percentage (Purevdorj et al., 1998). The FVC was calculated based on the NDVI, which is a simple graphical indicator that can be used to assess whether the observed target contains live or deceased vegetation (Gutman and Ignatov, 1998). The proposed relationship model between NDVI and FVC are:

$$FVC = \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}} \quad (1)$$

where $NDVI_{veg}$ and $NDVI_{soil}$ are the NDVI of dense vegetation canopy and bare soil. For the purpose of this study, the NDVI dataset has a spatial resolution of 1 km and includes data for years 2000 to 2010. The NDVI data was provided by the International Scientific and Technical Data Mirror Site, Computer Network Information Center, Chinese Academy of Sciences (<http://www.gscloud.cn>).

2.2.2.3. Human factors.

Anthropogenic influences on fire regimes are associated with human presence and activities. The proxies considered were Euclidean distance to roads, railways, settlement. Socio-economic developments in recent decades have led to changes in human behaviour, with the increasing mobility of people, spread of tourism and recreational activities and the subsequent increase in the number of visitors to forest ecosystems. Socio-economic factors involved in this study include population density, GDP, railway mileage, length of highways and length of classified roads, which collectively can reflect the accessibility of the forest. Variables that can represent the local forest managers' management level and the willingness of people to travel to the forest for recreational purposes were also considered, including: the education level of local forest managers represented by the ratio of the education level (higher than middle school); and area of urban public recreation lawn, as these green spaces may decrease the frequency of people accessing into the forest for recreation, which may lower the fire risk caused by human activities. Additionally, the local electricity consumption and net income of rural residents were taken into account as they can represent the dependency degree of people who rely upon forest resources for their livelihood.

Gridded demographic and socioeconomic data was obtained from the Data Sharing Infrastructure of Earth System Science (<http://www.geodata.cn/Portal/index.jsp>). Data included grid population density and per capita GDP for the years 1995, 2000, 2003, 2005 and 2010 at 1-km resolution. Based on the years 2000, 2003, 2005 and 2010 raster population and GDP data, the Raster Calculator tool in ArcGIS10.0 was used to calculate average annual population and GDP growth rates in from 2000 to 2010. This data was then correlated with fire points and control points using the ArcGIS Raster Extraction tool. Other socio-economic factors were collected based on the 2001–2011 National Statistical Yearbook.

Table 2
Independent variables included in forest fire model development for the Daxing'an Mountains and Fujian province.

Variable type	Variable name	Code	Resolution/scale	Source	Reference
Climatic	Average precipitation of fire season (the year of fire)	Pre0_avg	1 km/mm	Earth System Science Data Sharing Platform, China (http://geodata.nju.edu.cn/) (Jing et al., 2013)	Pew and Larsen (2001); Prasad et al. (2008); Oliveira et al. (2012); Chas-Amil et al. (2015)
	Average relative humidity of fire season (the year of fire)	RH0_avg	1 km/%		
	Average temperature of fire season (the year of fire)	Temp0_avg	1 km/°C		
	Prior average precipitation of fire season (the year of fire)	Pre-1_avg	1 km/mm	Earth System Science Data Sharing Platform, China (http://geodata.nju.edu.cn/) (Jing et al., 2013)	Pew and Larsen (2001); Prasad et al. (2008); Oliveira et al. (2012)
	Prior average relative humidity of fire season (the year of fire)	RH-1_avg	1 km/%		
	Prior average temperature of fire season (the year of fire)	Temp-1_avg	1 km/°C		
Topographic	Elevation	Elev.	25 m/m	National Administration of Surveying, Mapping and Geo-information of China, 2002	Catry et al. (2009); Prasad et al. (2008), Syphard et al. (2008); Vilar et al. (2010); Chang et al. (2013); Guo et al. (2015)
	Slope	Slope	25 m/degree		
	Aspect	Aspect	25 m/%		
Vegetation	Fractional vegetation cover	FVC	1 km/%	International Scientific and Technical Data Mirror Site, Computer Network Information Center, Chinese Academy of Sciences (http://www.gscloud.cn)	Che'ret and Denux (2011); De Angelis et al. (2012); Li et al. (2014)
Human	Distance to nearest railway	Dis_railway	1:250,000/km	National Administration of Surveying, Mapping and Geo-information of China, 2000	Syphard et al. (2008); Romero-Calcerrada et al. (2010); Miranda et al. (2012); Narayanaraj and Wimberly (2012); Chang et al. (2013); Guo et al. (2015)
	Distance to nearest road	Dis_road			
	Distance to nearest settlement	Dis_sett			
	Per Capita GDP	CGDP	1 km/RMB	Data Sharing Infrastructure of Earth System Science (http://www.geodata.cn/Portal/index.jsp), 2010	Guo et al. (2015)
	Density of population	Den_Pop	1 km/number/km	Data Sharing Infrastructure of Earth System Science (http://www.geodata.cn/Portal/index.jsp), 2010	Catry et al. (2009); Prasad et al. (2008); Sturtevant and Cleland (2007); Syphard et al. (2007); Narayanaraj and Wimberly (2012)
	Proportion of education level of local forest managers higher than middle school		%	China statistical yearbook (2000–2011) (http://www.stats.gov.cn/)	
	local electricity consumption		100 million kwh		
	Net income of rural residents		yuan		
	Area of urban public recreation lawn		ha		
	Railway mileage		km		
	Length of classified roads		km		
	Length of highway		km		

2.3. Statistical analysis

2.3.1. Spatial patterns of fire density

Ripley's K (d) function is a statistical method used to calculate nearest neighbor distance, and has been widely used to describe relationships between two or more point patterns (Peterson and Squiers, 1995; Stoyan and Penttinen, 2000; Guo et al., 2015). The definition of Ripley's K (d) function is:

$$K(d) = \frac{A}{n^2} \sum_{i \neq j} I(d_{ij} \leq d)$$

where d_{ij} is the distance between point i and point j , A is the area of the study area, n is the number of observation points, d is the distance to any point, and $I(d_{ij} \leq d)$ is the indicator function. If $d_{ij} \leq d$ then $I(d_{ij} \leq d) = 1$, otherwise $I(d_{ij} \leq d) = 0$ (Dixon 2002). Theoretically, for a homogeneous Poisson process, known as “complete spatial randomness” (CSR), $K(d) = \pi d^2$. For $d \geq 0$, Ripley's K-function can be used to test the null hypothesis of CSR. Values of $K(d)$ less than πd^2 indicate regularity, whereas aggregation is indicated when $K(d)$ values are greater than πd^2 . “Guard area correction”, a basic edge correction method, was used in Ripley's K-function in this study. SpPack 1.38 software was used to perform the K-function (Perry, 2004), and confidence envelopes were set to 95%, based on 499 replicates.

Additionally, two parameters are required prior to running the Ripley's K (d) function, namely “maximum distance” and “enter step length”, which indicate the gradient distance entered for each model fitting. A suggested maximum distance value is 1/2 the length of the shortest dimension of the plot (Haase, 1995). “Maximum distance” was set at 1.5 degrees (~150 km) and “enter step length” at 0.1 degrees (~10 km). These values were held constant in both study regions.

Spatial patterns of fire ignitions annually and collectively were separately identified for years 2000 to 2010 in the Daxing'an Mountains and Fujian province, and comparisons were conducted accordingly.

2.3.2. Identification of fire drivers

2.3.2.1. Logistic regression model. LR describes the relationship between a binary response variable (Y , coded as 0 [= No] and 1 [= Yes]) and one or more predictor variables (X) by the means of a link function. It has been widely used for fire occurrence prediction and the examination of driving factors in different regions of the World at various scales (Martell et al., 1987; Vega Garcia et al., 1995; Martínez et al., 2009). Logistic regression is commonly expressed as follows:

$$\ln \frac{P_i}{1 - P_i} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p \quad (2)$$

where P_i is the probability of fire occurrence; Z is the linear combination of the independent variables ($X_1 - X_p$), and $\beta_1 - \beta_p$ are the coefficients for each independent variable to be estimated from data using maximum likelihood method.

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p \quad (3)$$

The logistic function (Eq. (1)) lies between zero and one and takes on a curve of S-shape.

2.3.2.2. Modelling procedures. The identification of significant variables was completed using climatic, topographic, human factors and combined factors. The factors identified as significant variables in any category of factors were then combined together (combined factors) to determine their comprehensive influence on fire occurrence in the two different forest ecosystems. A logistic regression model (LR) was used to assess different categories of factors. The multicollinearity

tests were performed prior to LR model fitting. The VIF (variance inflation factor) was used to test for multicollinearity, and variables with significant collinearity were gradually removed. In this study, VIF values equal to 10 were considered the benchmark. If the VIF was ≥ 10 , this indicated significant collinearity between variables which were gradually removed (Wu and Zhang, 2013).

The process of model fitting began by randomly dividing the original dataset into training (60% of data) and validation (40% of data) samples. This procedure was performed five times, resulting in five random sub-samples of data, each one containing a training and validation dataset. LR was then applied to the training data of each sub-sample, and validated using its corresponding validation sample. The variables that were significant ($\alpha = 0.05$) in at least three of the five intermediate models were included in the final LR model, which was applied to the complete dataset. The process of identification of fire drivers and relative importance measurement of factors in the two study regions were all carried out based on climatic, topographic, human factors and combined factors, separately. The comparative analysis between the Daxing'an Mountains and Fujian were also conducted accordingly.

2.3.2.3. Measuring the relative importance of explanatory variables. A frequently asked question in fire-driver studies is which explanatory variables in the predictor set are most strongly associated with fire occurrence. To answer this question, it is necessary to rank the predictors; however, there is little consensus on how best to rank predictors in the logistic regression. In this study, the “standardized coefficients” method was used to test the relative importance of variables to fire occurrence. Standardized coefficients are coefficients adjusted so that they may be interpreted as having the same, standardized scale and the magnitude of the coefficients can be directly compared or ranked. The greater the absolute value of the standardized coefficient, the greater the predicted change in the probability of the outcome given a 1-standard deviation change in the corresponding predictor variable, holding constant the other predictors in the model (Menard, 2004). Standardized logistic regression coefficients can be computed in SAS by using the STB option in the MODEL statement of PROC LOGISTIC.

2.3.3. Prediction accuracy of models

Receiver Operating Characteristic (ROC) analysis was applied to compare the model predictive ability based on climatic, topographic, human factors and combined factors in the two study areas. ROC analysis was performed to quantify the area under the curve (AUC) – a measure of the predictive capability of models (Catry et al., 2009; Jiménez-Valverde, 2012; Chang et al., 2013). AUC values ranging from 0.5–1, where an AUC value of 0.8 generally indicates good predictive capability (Vilar del Hoyo et al., 2011). Yueden criteria calculated based on the sensitivity and specificity of ROC (Catry et al., 2009; Martínez et al., 2009) were used to determine the “cut-off” value which was applied as a threshold to determine the prediction accuracy of LR. According to the coefficients of each variable in LR, the predicted probability of fire occurrence can be calculated for each fire and control point. If the predicted probability of the model is higher than the cut-off value, it is assumed that a forest fire has occurred; if it is less than the cut-off value, it means there is likely no forest fire. The probability of fire occurrence of each point can then be classified as “fire” and “no-fire”, while the prediction accuracy can then be calculated accordingly comparing with the real value of each point. The prediction accuracy for both the training dataset and validation dataset were computed.

3. Results

3.1. Comparison of spatial patterns between the Daxing'an Mountains and Fujian

A K-function for 2000 to 2010 and the combined fire ignitions of eleven years for both study areas was then computed. Results indicate, overall,

that there is a clear departure from CSR towards clustering, in most individual years or across the eleven years of the dataset in the Daxing'an Mountains. For the years 2001, 2004 and 2009, the fire ignitions indicated a cluster pattern b 0.5 degrees (~50 km) and a regularity pattern appeared

at distance scales of N 0.5 degrees (~50 km) in the Daxing'an Mountains (Fig. 2). In contrast, forest fire clustered in Fujian in both individual years and throughout the duration of the study period, while the degree of clustering appears to increase with distance (Fig. 3).

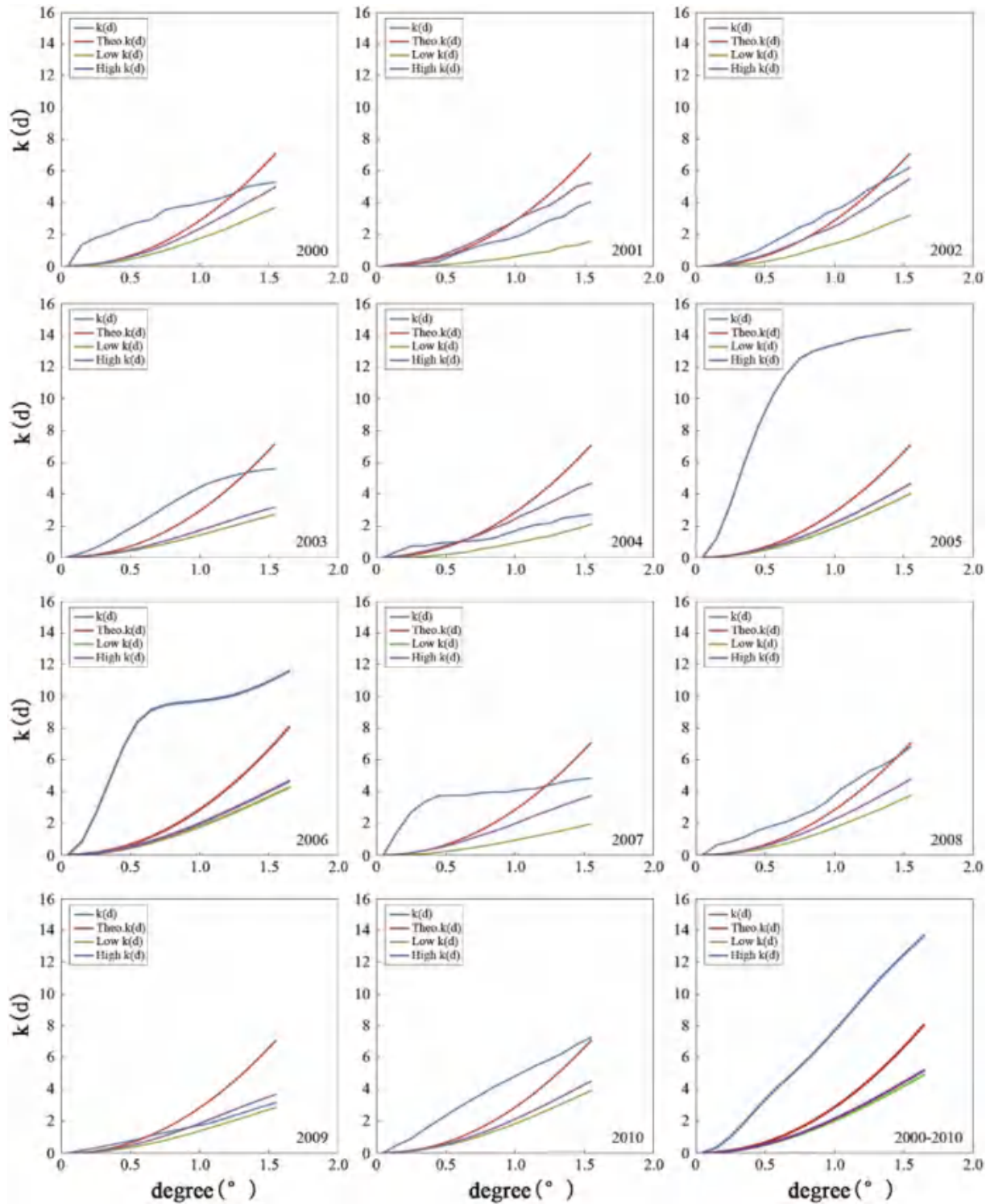


Fig. 2. Calculated Ripley's K functions for the density of fire ignitions each year from 2000 to 2010 and the whole period of elevation years in the Daxing'an Mountains compared with the theoretical Ripley's K function, which represents complete spatial randomness. The red line represents the empirical K-function under CSR with green and purple lines, which are 95% confidence envelopes. X-axis represents the distance to the nearest ignition from a given ignition.

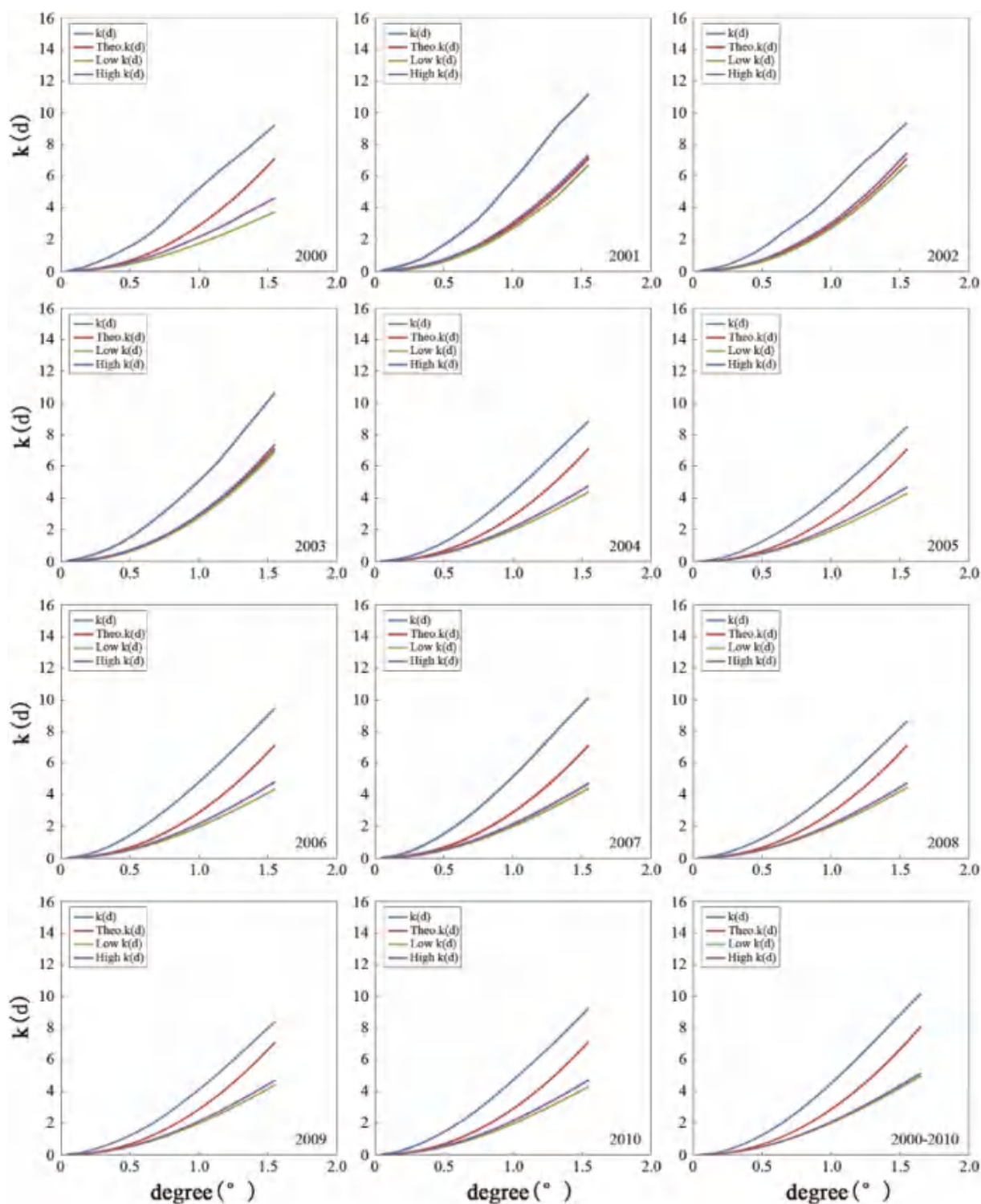


Fig. 3. Calculated Ripley's K functions for the density of fire ignitions each year from 2000 to 2010 and the whole period of elevation years in Fujian compared with the theoretical Ripley's K function, which represents complete spatial randomness. The red line represents the empirical K-function under CSR with green and purple lines, which are 95% confidence envelopes. X-axis represents the distance to the nearest ignition from a given ignition.

3.2. Comparison of influence of climate factors on fire occurrence between the Daxing'an Mountains and Fujian

No collinearity between climate factors was found, and therefore all variables can be used in model fitting. Five intermediate models were created based on sub-samples of the dataset and intermediate models for both study areas. The models that were based on the complete

dataset of both study areas were also fitted. According to the prediction accuracy of LR models in sub-samples and complete dataset (Table 3), the climate factors have the similar influence in both forest ecosystems. The range of prediction accuracy based on all sub-samples and complete dataset is 55.5%–64.8% in the Daxing'an Mountains and 59.3%–64.5% in Fujian province. In addition, AUC values of each sub-sample and complete dataset were also calculated in both areas, wherein little variation

Table 3

Comparison of prediction accuracy and goodness of fit of LR model in the Daxing'an Mountains and Fujian based on climate factors.

Sample	Study area	Cut-off	AUC value	Prediction accuracy (%)	
				Training data	Validation
Sample1	Daxing'an	0.323	0.667	57.6	63.9
	Fujian	0.359	0.686	64.5	59.3
Sample2	Daxing'an	0.346	0.672	57.2	62.1
	Fujian	0.370	0.683	64.4	61.0
Sample3	Daxing'an	0.333	0.667	55.5	62.3
	Fujian	0.348	0.685	64.1	59.0
Sample4	Daxing'an	0.335	0.665	57.0	64.8
	Fujian	0.366	0.684	64.4	60.7
Sample5	Daxing'an	0.343	0.676	57.9	62.1
	Fujian	0.369	0.680	63.8	61.2
Complete dataset	Daxing'an	0.336	0.675	64.1	
	Fujian	0.370	0.684	64.2	

Note: The first column represents the intermediate (sample 1–5) and final model (complete dataset); cut-off values were used to determine the prediction accuracy of each model. The complete dataset was not divided into training and validation subsets.

exists. Additionally, six variables in Fujian and four variables in the Daxing'an Mountains were found to be significant in at least three of these five sub-samples, which were included in the subsequent analysis of the final model with the complete dataset (Table 4). Table 4 shows parameter estimation of the final LR models of two study areas. All variables included in the final model were significant at $\alpha = 0.05$ level. Statistically significant variables include; average temperature during the fire season (one year before and the year of fire), average precipitation during the fire season (the year of fire) and relative humidity of the fire season (one year before) in both areas, other variables including the relative humidity of the fire season (the year of fire), and the average precipitation of the fire season (one year before) only in Fujian province.

Fig. 4 shows the variable importance measurement of two study areas using the standardized coefficients method in the process of LR model fitting. In comparison to other climate factors, temperature was proved to be the most important variable impacting fire occurrence in both forest ecosystems. Precipitation and relative humidity showed equal contributions to fire ignition, but a much lower impact than temperature in Fujian. In the Daxing'an Mountains, average relative humidity of the fire season (one year before) ranked the third most important variable, followed by the average precipitation of the fire season.

Table 4

Climate factors identified by intermediate models using LR model and parameter estimation using the selected variables.

Variable	Study area	# variables significant in samples	Parameter estimation			
			Coefficients	Standard error	Wald test	p-Values
temp	Daxing'an	5	0.046	0.0025	339.114	b0.0001
	Fujian	5	−0.231	0.0032	5190.237	b0.0001
rh	Daxing'an	/	/	/	/	/
	Fujian	5	−0.011	0.0023	22.723	b0.0001
Prec	Daxing'an	4	−0.072	0.0198	13.211	0.0003
	Fujian	4	−0.009	0.0035	7.305	0.0069
Prec1	Daxing'an	/	/	/	/	/
	Fujian	4	0.012	0.0037	9.774	0.0018
rh1	Daxing'an	5	0.205	0.0116	315.043	b0.0001
	Fujian	5	0.012	0.0030	14.783	0.0001
temp1	Daxing'an	5	0.302	0.0208	212.212	b0.0001
	Fujian	5	0.195	0.0042	2139.659	b0.0001

Note: # variables significant in samples represents the total number of times that the variable is tested as significant in the five intermediate models. The four columns on the right of the table show the parameter estimation of each variable in the final model that was fitted based on the complete dataset. The abbreviated variable names are the same as in the Table 2.

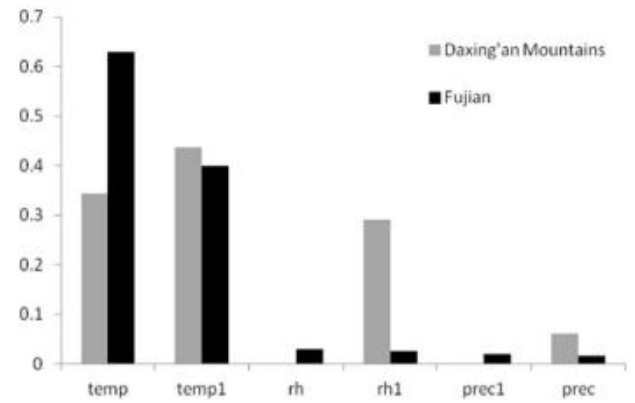


Fig. 4. The comparison of variable importance of climate factors from the final model using the LR model according to the standardized coefficients method. The abbreviated variable names are the same as in Table 2.

3.3. Comparison of influence of topography and vegetation factors on fire occurrence between the Daxing'an Mountains and Fujian

No collinearity between topographic factors was found, and therefore all variables can be used in model fitting. According to the prediction accuracy and the AUC values of LR models in sub-samples and the complete dataset (Table 5), topographic and vegetation factors have a similar effect on fire occurrence in both areas. Based on the sub-samples and complete dataset, the range of predictive accuracy is 55.1%–60.6% in the Daxing'an Mountains and 49.9%–60.0% in Fujian province. In addition, all four variables (elevation, slope, aspect and FVC) in Fujian and three variables (except for aspect) in the Daxing'an Mountains were found to be significant in at least three of these five sub-samples and were included in the subsequent analysis of the final model using the complete dataset (Table 6).

According to Fig. 5, the degree of influence of each variable in each forest ecosystem is similar to one another, and elevation has the most important impact in both study areas, followed by slope and FVC. Aspect was not selected as a significant variable in the Daxing'an Mountains but exhibits relatively lower importance than other variables in Fujian.

3.4. Comparison of influence of human factors on fire occurrence between the Daxing'an Mountains and Fujian

After the multicollinearity test, local electricity consumption, net income of rural residents and classified highway were removed and were

Table 5

Comparison of prediction accuracy and goodness of fit of LR model in the Daxing'an Mountains and Fujian based on topography factors.

Sample	Study area	Cut-off	AUC value	Prediction accuracy (%)	
				Training data	Validation
Sample1	Daxing'an	0.405	0.568	59.8	57.7
	Fujian	0.373	0.557	59.2	50.5
Sample2	Daxing'an	0.389	0.570	60.6	55.9
	Fujian	0.380	0.553	59.3	51.9
Sample3	Daxing'an	0.402	0.577	59.4	57.5
	Fujian	0.373	0.553	60.0	49.9
Sample4	Daxing'an	0.408	0.575	59.5	56.1
	Fujian	0.377	0.553	59.7	51.1
Sample5	Daxing'an	0.393	0.566	60.2	55.1
	Fujian	0.384	0.556	58.9	52.4
Complete dataset	Daxing'an	0.397	0.568	57.4	
	Fujian	0.377	0.554	51.1	

Note: The first column represents the intermediate (sample 1–5) and final model (complete dataset); cut-off values were used to determine the prediction accuracy of each model. The complete dataset was not divided into training and validation subsets.

Table 6

Topography factors identified by intermediate models using LR model and parameter estimation using the selected variables.

Variable	Study area	# variables significant in samples	Parameter estimation			
			Coefficients	Standard error	Wald test	p-Values
Elevation	Daxing'an	5	−0.001	0.0001	48.249	b0.0001
	Fujian	5	−0.0004	b0.0001	159.635	b0.0001
Slope	Daxing'an	5	−0.031	0.0061	25.865	b0.0001
	Fujian	5	−0.011	0.0009	155.600	b0.0001
Aspect	Daxing'an	\	\	\	\	\
	Fujian	5	−0.075	0.0120	38.694	b0.0001
FVC	Daxing'an	5	0.425	0.0742	32.764	b0.0001
	Fujian	5	0.396	0.0484	66.870	b0.0001

Note: # variables significant in samples represents the total number of times that the variable is tested as significant in the five intermediate models. The four columns on the right of the table show the parameter estimation of each variable in the final model that was fitted based on the complete dataset. The abbreviated variable names are the same as in the Table 2.

not used in the model fitting. The prediction accuracy and AUC values of LR models in sub-samples and complete dataset are shown in Table 7, which indicate that human factors have much greater influence on fire occurrence in the Daxing'an Mountains than that in Fujian. The AUC values in sub-samples and complete dataset of the Daxing'an Mountain is around 0.82 and only 0.59 in Fujian. The range of prediction accuracy based on all sub-samples and complete dataset is 75.0%–76.7% in the Daxing'an Mountains and 58.4%–62.1% in Fujian (Table 7). Additionally, with the exception of education which is not selected as a fire driver in Fujian, all other selected human factors were proved to hold important influence on fire occurrence in both areas. According to the coefficients of each factor, human factors have the same influence on the fire occurrence in two areas (Table 8).

The measurement of variable influence revealed that distance to railways is the most important fire driver in the Daxing'an Mountains, followed by distance to road and settlement, while GDP and education levels have relative lower influence on fire occurrence (Fig. 6). In contrast, distance to roads, distance to settlement, and population density were identified as the three most critical variables in Fujian, followed by distance to railways and GDP.

3.5. Comparison of influence of combined factors on fire occurrence between the Daxing'an Mountains and Fujian

LR models were fitted using combined factors for the Daxing'an Mountains and Fujian, respectively. Table 9 shows the prediction accuracy and AUC values of LR models in sub-samples and complete dataset based on all factors. Results indicate that the AUC values in sub-samples and complete dataset in the Daxing'an Mountains and Fujian are

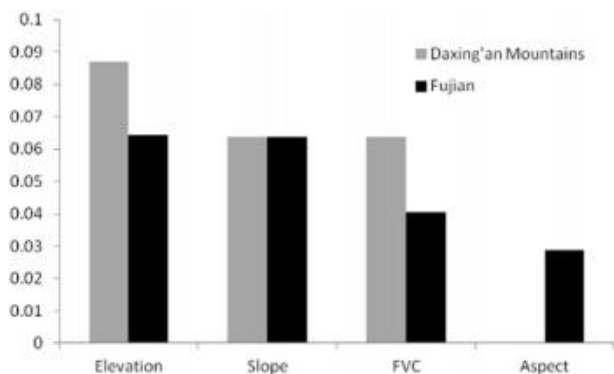


Fig. 5. The comparison of variable importance of topography and vegetation factors from the final model using the LR model according to the standardized coefficients method. The abbreviated variable names are the same as in Table 2.

Table 7

Comparison of prediction accuracy and goodness of fit of LR model in the Daxing'an Mountains and Fujian based on human factors.

Sample	Study area	Cut-off	AUC value	Prediction accuracy (%)	
				Training data	Validation
Sample1	Daxing'an	0.345	0.824	75.8	76.3
	Fujian	0.408	0.597	61.7	58.9
Sample2	Daxing'an	0.293	0.824	75.9	75.0
	Fujian	0.410	0.600	61.6	58.7
Sample3	Daxing'an	0.333	0.821	76.0	76.5
	Fujian	0.408	0.597	61.7	58.7
Sample4	Daxing'an	0.327	0.827	76.7	75.3
	Fujian	0.416	0.595	61.7	59.1
Sample5	Daxing'an	0.373	0.829	76.4	76.1
	Fujian	0.415	0.598	62.1	58.4
Complete dataset	Daxing'an	0.329	0.827	75.8	
	Fujian	0.414	0.598	58.9	

Note: The first column represents the intermediate (sample 1–5) and final model (complete dataset); cut-off values were used to determine the prediction accuracy of each model. The complete dataset was not divided into training and validation subsets.

approximately 0.86 and 0.73, respectively (Table 9). The range of prediction accuracy measures 79.0%–80.3% in the Daxing'an Mountains and 65.0%–68.2% in Fujian province (Table 9). Some variables were identified as fire drivers in both study areas, including average temperature of the fire season (one year before and the year of fire), elevation, distance to settlement, distance to roads, distance to railways, vegetation cover, average relative humidity of fire season and railway operation mileage (Fig. 7). Highway distributions only exhibited its importance in the Daxing'an Mountains and, in contrast, urban lawn area only significant in Fujian.

3.6. Contribution of each category of factor

With respect to logistic regression, there is at present no widely accepted measure of explained variation with which one could judge the fit of a given model (Wade and Inderjit, 2011). ROC analysis has been widely used to compare the model predictive ability and AUC enable to quantify the goodness of fit of the LR model, which may also be used to reflect the explanation power of the variables in LR models (Jiménez-Valverde, 2012; Chang et al., 2013; Guo et al., 2016a).

In this study, climate, topography and human factors and their contribution to the fire occurrence in the two study areas were analyzed based on the AUC values and prediction accuracy of LR models. The AUC value and prediction accuracy for each group or combined groups were calculated based on the complete dataset and corresponding variables. Fig. 8a indicates that all factors explained 86.5% of variances of the fire occurrence in the Daxing'an Mountains, in which the climate, topography and human factors contributed 67.5%, 56.8% and 82.7% of variance, respectively. In contrast, all factors explained 73.3% of the variance of the fire occurrence in Fujian, and climate, topography and human factors contributed 68.4%, 55.4% and 59.8%, respectively. According to the Fig. 8a/b, topography factors were less important to fire occurrence in the two forest ecosystems than other types of factors. Human factors were identified as the important drivers on fire occurrence in the Daxing'an Mountains; however, climate factors were identified as critical to fire ignitions in Fujian. Additionally, the prediction accuracy of the LR model using all factors in the Daxing'an Mountains reached 79.5%, roughly 15% higher than that of Fujian (Fig. 8b).

4. Discussion

4.1. Comparison of influence of variables on fire occurrence in different forest ecosystems

Fires in the Daxing'an Mountains and Fujian exhibit differences in the response of fire occurrence to the explanatory variables. Fires in

Table 8

Human factors identified by intermediate models using LR model and parameter estimation using the selected variables.

Variable	Study area	# variables significant in samples	Parameter estimation			
			Coefficients	Standard error	Wald test	p-Values
Dis_railway	Daxing'an	5	0.026	0.0012	487.094	b0.0001
	Fujian	5	0.002	0.0003	65.187	b0.0001
Dis_road	Daxing'an	5	0.080	0.0038	450.653	b0.0001
	Fujian	5	0.302	0.0121	623.753	b0.0001
Dis_settlement	Daxing'an	5	0.012	0.0016	53.360	b0.0001
	Fujian	5	0.030	0.0013	579.345	b0.0001
Education	Daxing'an	5	−0.090	0.0202	19.773	b0.0001
	Fujian	\	\	\	\	\
GDP	Daxing'an	5	0.001	0.0003	8.222	0.0041
	Fujian	4	0.00001	b0.0001	6.374	0.0116
POP	Daxing'an	3	−0.00001	b0.0001	0.039	0.8428
	Fujian	5	−0.0002	b0.0001	58.698	b0.0001

Note: p-Value min and p-value max in the table represent the minimum and maximum significance level of each variable in the five intermediate model; # significant samples represents the total number of times that the variable is tested as significant in the five intermediate models. The four columns on the right of the table show the parameter estimation of each variable in the final model that was fitted based on the complete dataset. The abbreviated variable names are the same as in the Table 2.

the Daxing'an Mountains respond primarily to human factors, of which infrastructure (distance to railways, distance to roads and distance to settlements) are recognized as the most influential, in accordance with other studies (Wu et al., 2014; Guo et al., 2015). Climate factors were identified as most important drivers of fire ignitions in Fujian, however, of these climatic factors the temperature of fire season was found to be more influential than other climate factors such as precipitation and humidity. It is worth noting that spatial scale may also influence the fire driver analysis. Climate factors were generally pointed out as the dominate factors in the large scale studies (Wotton et al., 2003; Zumbunnen et al., 2011; Tian et al., 2013) and more local factors were involved as important fire drivers as the study scale decreases (Sturtevant and Cleland, 2007; Syphard et al., 2008; Vilar et al., 2010). In this study, dominant factors vary when we conduct the study in two ecosystems, separately; however, if the two study sites are considered collectively, the conclusion regarding dominate factors may change, which, from another side, also highlights the spatial applicability of our study.

4.1.1. Influence of climate variables on fire occurrence

Climate factors, including average temperature of the fire season, average precipitation of the fire season and the average relative humidity of the fire season were all selected as important drivers to fire occurrence in the Daxing'an Mountains, in which temperature and relative humidity contributed equally to fire occurrence and were more influential than precipitation. Precipitation and relative humidity affect the moisture content of fuel in the forest. High precipitation and relative humidity contribute to fuel moisture, which in turn decreases the possibility of fire ignition (Zumbunnen et al., 2011). Our findings are aligned

with previous studies (Wotton et al., 2003; Maingi and Henry, 2007), including those conducted in the boreal forest of China (Chang et al., 2013; Wu et al., 2014). It is worth noting that although the temperature was selected as important factors in both study areas, it influences fire occurrence in an opposing manner (Table 4). Temperature directly influences fuel moisture content. High temperatures can contribute to increased evaporation from plants, as well as decreased moisture content of potential fire fuels, leading to increased probability of fire occurrence (Chuvieco et al., 2004). High temperatures, however, seem to dampen the fire occurrence in Fujian. One possible reason may be that unanticipated or subtle thresholds may be present between some climate variables and fire occurrence (Castro et al., 2003; Wu et al., 2015), such that the linear regression model may not reveal the relationship between temperature and fire occurrence. Another possible explanation may be because high temperatures are usually a signal of high fire risk which may cause increased awareness from local forest managers regarding fire prevention and will indirectly decrease the number of fire occurrences, which is also supported by other researcher (Hu and Zhou, 2014).

4.1.2. Influence of topography and vegetation variables on fire occurrence

Elevation has been identified as an important forest fire driver by many researchers (e.g. Syphard et al., 2008; Miranda et al., 2012; Pereira et al., 2015; Guo et al., 2016a, 2016b). According to Table 6, fire is more likely to occur in low elevation areas in both the Daxing'an Mountains and Fujian. It is well known that elevation diminishes fire occurrence, as human activity is reduced in high-altitude areas and the

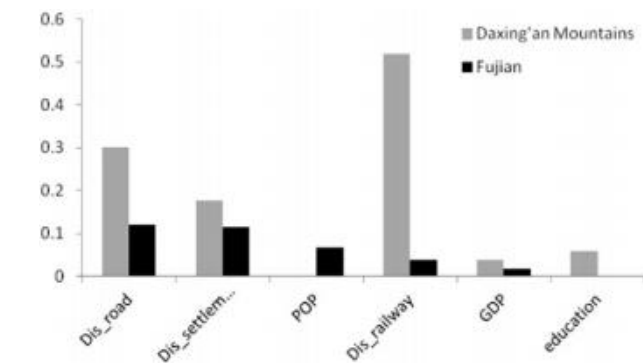


Fig. 6. The comparison of variable importance of human factors from the final model using the LR model according to the standardized coefficients method. The abbreviated variable names are the same as in Table 2.

Table 9

Comparison of prediction accuracy and goodness of fit of LR model in the Daxing'an Mountains and Fujian based on human factors.

Sample	Study area	Cut-off	AUC value	Prediction accuracy (%)	
				Training data	Validation
Sample1	Daxing'an	0.349	0.863	79.2	79.7
	Fujian	0.385	0.732	67.9	65.8
Sample2	Daxing'an	0.361	0.864	79.0	79.8
	Fujian	0.379	0.734	68.2	65.4
Sample3	Daxing'an	0.351	0.865	79.5	79.3
	Fujian	0.387	0.734	68.1	65.7
Sample4	Daxing'an	0.386	0.859	79.0	80.3
	Fujian	0.365	0.733	67.8	65.0
Sample5	Daxing'an	0.375	0.866	79.5	79.8
	Fujian	0.389	0.735	68.2	65.8
Complete sample	Daxing'an	0.350	0.865	79.5	
	Fujian	0.388	0.733	65.9	

Note: The first column represents the intermediate (sample 1–5) and final model (complete dataset); cut-off values were used to determine the prediction accuracy of each model. The complete dataset was not divided into training and validation subsets.

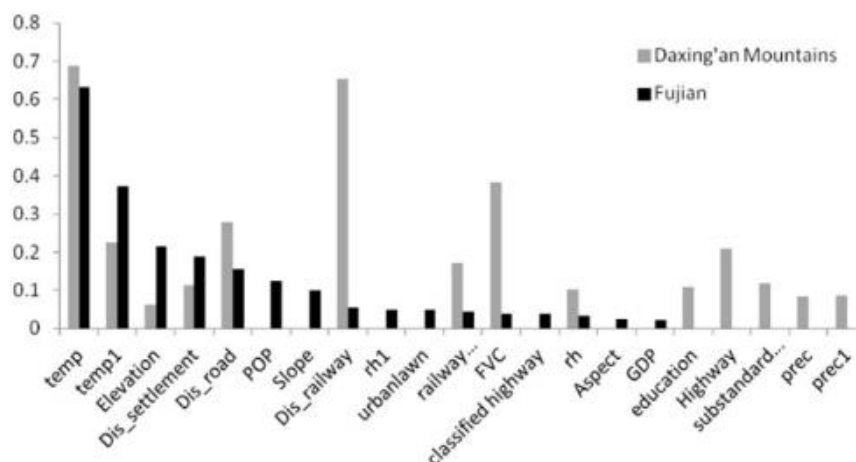


Fig. 7. The comparison of variable importance of combined factors from the final model using the LR model according to the standardized coefficients method. The abbreviated variable names are the same as in Table 2.

likelihood of human-caused ignitions decreases. Fig. 5, however, revealed a much higher relative importance of elevation on fire occurrence in Fujian (ranking third) than that in the Daxing'an Mountains. Undulating terrain in Fujian accounts for this variation, meanwhile elevation is relatively uniform in the Daxing'an Mountains, which may also create variation in the importance of aspect in the two study areas - an important fire driver in Fujian but a factor that contributes no influence to fire in the Daxing'an Mountains. Gentle terrain where solar radiation differs little amongst facets (Heyerdahl et al., 2001) will cause light influence on micro-conditions between slopes, which may lead to little

impact on fire ignitions. Vegetation cover exhibits a significant influence on fire occurrence in both study areas (Fig. 5), and signifies the amount of available fuel, which has been identified as an important indicator of forest fire ignition in previous studies (Chuvieco et al., 2004).

4.1.3. Influence of human variables on fire occurrence

Previous studies suggests that population density is commonly expected to exhibit a positive correlation with fire occurrence, as occurrence may be related to human activities (Sturtevant and Cleland, 2007; Syphard et al., 2007; Pereira et al., 2011); however, population

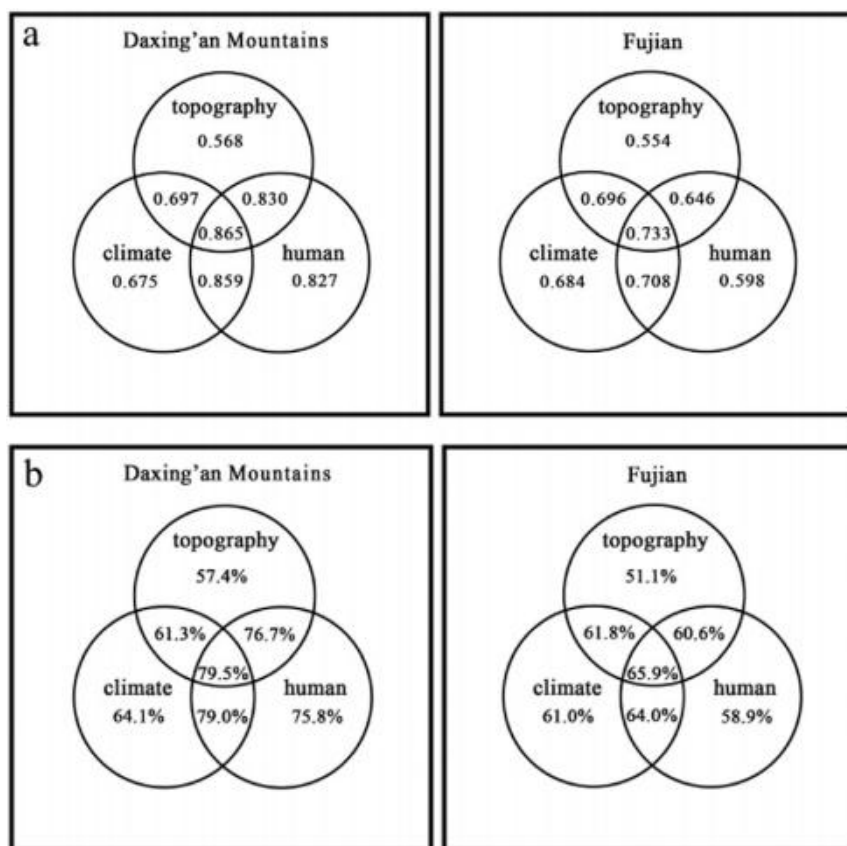


Fig. 8. Contribution (a) and prediction accuracy (b) of climate, topography, human factors and all factors to fire occurrence in the Daxing'an Mountains and Fujian, respectively. The calculations were based on complete datasets of two study areas.

density was not a significant variable in the Daxing'an Mountains, and in fact negatively influences the fire occurrence in Fujian, which may be due to the dramatic urbanization processes in Fujian over the past few decades. High population density is concentrated in cities or developed areas that have advanced industry and characteristically low forest cover, and therefore a lower percentage of human-induced forest fires. Distance to infrastructure has also been identified as a main driver of fire ignition in previous research (Vega Garcia et al., 1995; Maingi and Henry, 2007; Miranda et al., 2012; Guo et al., 2016a, 2016b). Distance to railways, distance to roads and distance to settlements, however, were identified as positive drivers in the two study areas. Penman et al. (2013) attributed an increase in fire ignitions with greater distance from human infrastructure, as typically more continuous vegetation exists in these comparatively remote areas and therefore, fires would not be interrupted by fragmented fuels that characterize urban areas. China, especially after 2000, underwent rapid development of high-speed railway and modern highway construction. Modern transportation isolates the forest via transportation corridors and residential areas. On the other hand, confined train carriages have successfully prevented fire ignitions caused by the disposal of cigarette butts or other fire triggers tossed from trains - previously a major fire cause in the fire history of the Daxing'an Mountains (Guo et al., 2015). Per capita GDP, which can reflect socio-economic activity, was found to increase fire occurrence in the Daxing'an Mountains and Fujian. Prestemon and Butry (2005) concluded that low wages and poverty increased wildland arson. Aldersley et al. (2011) stated that GDP can negatively influence burned area at the regional scale. Our study was inconsistent with the above findings. Although GDP showed positive influence on both ecosystems, the possible explanation may vary. In Daxing'an Mountains, forest related activities occupy an important position in the regional economy, which may increase the possibility of fire occurrence. In contrast, the industrial and commercial development of Fujian went through a high speed increase phase, which accelerated the forest fragmentation. The regular forest related human activities became fragmented accordingly, which consequently led to an increase in the number of forest fires. The education level of local forest staff was proven to be negatively related to fire occurrence in the Daxing'an Mountains, indicating a higher education level of forest managers will decrease the likelihood of fire occurrence. This phenomenon may be explained by two aspects. On one hand, a higher education level may facilitate greater fire safety awareness, which can lead to safer forestry production and management activities. On the other hand, higher education levels of local forest managers may indicate their fire management skill level, wherein they can effectively conduct fire prevention and forecast. Fires in Fujian, however, were unrelated to the education level of local forest managers. The main reason may be because of the low efficiency of fire prevention efforts in Fujian due to the high proportion of forest fragments. Nearly 95% forest fires were caused by human activities, however these fires primarily occurred in fragmented forest and are very hard to prevent, potentially eliminating the importance of education level of local forest managers in this given region.

4.2. Implications for forest fire management

According this study, main fire-driving factors vary amongst the two study areas. Fires in the Daxing'an Mountains respond primarily to human factors whereas fires in Fujian are driven by climate factors (Fig. 8a, b). As the primary drivers of fire occurrence differ, differing and locally-specific fire prevention and management strategies are required for sufficient management in various forest ecosystems. Most predictions of future fire regimes only consider changes in meteorological factors (Stocks et al., 1998; Fried et al., 2004), which will not be appropriate for the Daxing'an Mountains or the regions where other factors exhibited the most driving power on fire occurrence. Results suggest that China's fire management policies should be targeted for different forest ecosystems and specific fire prevention measurements

need to be implemented accordingly, which will benefit the efficiency of forest fire management.

Several human factors such as infrastructure, per capita GDP, population density etc. were selected to reflect the influence of socio-economic development on fire occurrence in different forest ecosystems. Similar relationships between fire occurrence and each human factor in two study areas were identified, indicating that rapid socio-economic development may lead to similar influence on fire occurrence in different forest ecosystems in China. This also implies a strong influence of socio-economic development on fire regimes in China. It is reasonable to infer that the influence of human factors will increase in the future along continuous growth of China's economy, which consequently should require further attention in regards to fire management, although human factors are not main fire drivers in some forest ecosystems.

4.3. Limitations

A major limitation in this study is that, although the applicability of the LR model in the fire related study has been widely proved in the past decades, its limitation on testing non-linearity between dependent and independent variables is not negligible. Several previous studies have found non-linear relationships between fire weather conditions and burned size, and have also indicated the existence of thresholds. When weather conditions cross certain thresholds, the relationship between weather factors and fire regimes may change (Castro et al., 2003; Wu et al., 2015; Fang et al., 2015). Consequently, a comprehensive analysis, combining theoretical knowledge and practical experience is required to explain the relative importance of each variable to fire occurrence.

5. Conclusions

In this study, spatial patterns of fire in two different forest ecosystems in China using Ripley's K (d) function were identified. In addition, logistic regression models and standardized coefficients were applied to identify the fire drivers and the relative effects of each factor on fire occurrence, in two different forest ecosystems present in the Daxing'an Mountains and Fujian.

Results revealed that fires were spatially clustered and that the fire-drivers varied in the Daxing'an Mountains and Fujian from 2000 to 2010. Fires in the Daxing'an Mountains respond primarily to human factors, of which infrastructure is recognized as the most critical. In contrast, climate factors were identified as most influential drivers in Fujian, of which temperature of the fire season was more important than other climate factors. The combined factors can predict nearly 80% of the total fire occurrence in the Daxing'an Mountains; however, human factors can independently predict 76%. In contrast, the combined factors can predict nearly 66% in Fujian and climate factors can independently predict 61%. Fires were more likely to occur at lower elevation and vegetation cover areas in both study regions.

As the most influential factors driving fire ignition varied amongst the two study areas and their respective ecosystems, different fire prevention and management strategies are required to provide more suitable, locally-specific management plans and strategies. Rapid socio-economic development has had a similar influence on the fire occurrence in different forest ecosystems in China, implying a strong relationship between socio-economic development and fire regimes. It can be concluded that the influence of human factors will continue to grow in the future as China continues to undergo rapid socio-economic development, requiring greater attention in future fire management.

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A dynamic downscaling approach to generate scale-free regional climate data in Taiwan

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ABSTRACT: Plenty of climate data from various sources have become available in recent years. However, to obtain climate data adequately meeting the requirement of ecological studies remains a challenge in some cases due to the difficulty of data integration and the complexity of downscaling, especially for mountainous regions. Lapse rate is one of the most important factors that influence the change of climatic variables in the mountains, and it should be incorporated into climatic models. In this study, we applied a synthetic approach combining bilinear interpolation (to produce seamless surfaces) and dynamic local regression (to obtain local lapse rates) to develop a scale-free and topography-correspondent downscaling model in R environment for Taiwan, called *clim.regression*. This model can generate 73 climatic variable estimates specific to the user-defined points of interest, including primary climatic variables and additional biologically relevant derivatives for historical (1960–2009) and future periods (2016–2035, 2046–2065 and 2081–2100). Results of our evaluation indicated that *clim.regression* reduced prediction error by 54.6%–66.7% relative to the original gridded climate data for temperatures. In addition, we demonstrated the spatiotemporal patterns of lapse rate for different climate variables.

KEY WORDS: Climate change, Downscaling model, Dynamic local regression, Historical and future climate scenarios, TCCIP.

INTRODUCTION

Climate variables, particularly temperature and precipitation, are the most well-known key factors related to vegetation zonation. A high-quality and accessible climate dataset is essential for ecological studies and applications, especially in regions with diverse topography and high climatic heterogeneity. However, to obtain and to process substantial climate data were difficult for ecologists in the past, and scientists often use statistically interpolated climate data from a few existing stations as substitutes for the continuous climate surface (Su, 1984a; Tang and Ohsawa, 1997).

Over the last decade, a large volume of climate data has become available through various sources; most of them were represented in grid format with the finest resolution of arc-seconds or kilometers in global or regional scale (Hannaway *et al.*, 2005; Hijmans *et al.*, 2005; Harris *et al.*, 2014). Although such gridded data are suitable for modeling general patterns and trends at global and regional scales, they are still too coarse to provide detailed climatic information in mountainous and topographically diverse areas to facilitate local ecological studies and resources management. To overcome this limitation, several downscaling methods

have been developed to generate high-resolution spatial climate data, such as Ordinary Kriging (Chiu and Lin, 2004), a combination of Kriging and polynomial linear regression (Chiou *et al.*, 2004), a combination of bilinear interpolation and partial derivative functions for elevational adjustment (Wang *et al.*, 2006; 2012), and an approach of dynamic local regression (Wang *et al.*, 2016; 2017). ClimateAP, a scale-free climate downscaling model based on dynamic local regression approach, was recently developed and covered Asia-Pacific (AP) region (Wang *et al.*, 2017). The baseline data of this model used a 4-km gridded climate data from PRISM (Daly *et al.* 2002) for China and Mongolia, and WorldClim (Hijmans *et al.* 2005) for the rest of the Asia-Pacific. The model reduces prediction error by up to 27% and 60% for monthly temperature and precipitation, respectively, relative to the original baseline data. However, the prediction accuracy for a specific region varies depending on the quality of the baseline data, which is affected by the density of weather stations used for developing the baseline data for the region. Unfortunately, historical climate data from weather stations in Taiwan were not included in the climate mapping project of PRISM (Hannaway *et al.*, 2005). Thus, it could adversely impact the prediction accuracy of ClimateAP in Taiwan.



Taiwan is a subtropical island on the west edge of the Pacific Ocean with diverse and complicated topography. The climate of Taiwan is mainly affected by the northeast monsoon during winter and by the southwest monsoon and typhoons in the summer. The Central Range occupying more than 70% of the area of Taiwan, runs through the whole island from northeast to southwest with the highest peak of 3,952 meters a.s.l., and creates an obvious altitudinal temperature zonation (Su, 1984a), as well as the seasonal allocation of precipitation (Su, 1985). Many studies have revealed a strong relationship between the natural vegetation and the large-scale altitudinal climate zonation (Su, 1984b; Chiu, 2004; Chiou *et al.*, 2010; Lin *et al.*, 2012; Li *et al.*, 2013). Furthermore, the local climate is induced by the co-effects of monsoon and topography (Sun, 1993; Sun *et al.*, 1998; Chao *et al.*, 2007; Chao *et al.*, 2010; Li *et al.*, 2013). Ecologists have a strong demand on fine-scale climate data to depict the ecological and environmental correlations in detail. However, most studies can only utilize indirect variables such as elevation and topography as substitutes to climatic variables due to the lack of a high-quality and high-resolution spatial climate dataset for the island.

Meteorologists in Taiwan have accomplished a framework called Taiwan Climate Change Projection and Information Platform (TCCIP) and generated a 5km×5km gridded climate surface based on historical observations from thousands of weather stations and provided future projections based on different AR5 General Circulation Models (GCMs) and scenarios (Hsu *et al.*, 2011; Weng and Yang, 2012). TCCIP's datasets are powerful supplements to the remote and observation-sparse mountains, but its resolution is not fine enough to represent the diverse climate situation due to the steep topography within a 5km×5km grid.

In this study, our main objectives were to: (1) establish a statistical downscaling model named as *clim.regression* in R environment to downscale the 5km×5km gridded climate data of TCCIP to a scale-free format based on the algorithm of bilinear interpolation and dynamic local regression from ClimateNA (Wang *et al.*, 2016) and ClimateAP (Wang *et al.*, 2017); (2) generate additional biologically relevant derivatives for ecological studies; (3) analyze the spatiotemporal patterns of variation in lapse rate; and (4) evaluate the prediction accuracy of *clim.regression* in comparison to the original TCCIP data.

MATERIALS AND METHODS

Source of historical and future climate data

The 5km×5km gridded surfaces of historical meteorological data used in this study were developed by TCCIP (Weng and Yang, 2012). The dataset covers the main island of Taiwan and spans the period from

1960 to 2009. TCCIP incorporated historical records of air temperature from 1,152 weather stations and precipitation from 1,497 rainfall stations to construct the gridded dataset through a conventional spatial interpolation process. There are four sets of primary climate variables including monthly precipitation (precip01 to precip12), monthly minimum temperature (Tmin01 to Tmin12), monthly mean temperature (Tmean01 to Tmean12) and monthly maximum temperature (Tmax01 to Tmax12). The values of these variables were obtained and united with the coordinate (latitude, longitude and elevation) of the center of each grid. There were 48 primary monthly climate variables in total. TCCIP has also provided future climate projections in the same resolution of 5km×5km, which were downscaled from GCMs of CMIP5 and rectified by observations of Aphrodite (Asia Precipitation Highly-Resolved Observational Data Integration Towards Evaluation of the Water Resources) and historical climate data of Taiwan (Lin *et al.* 2016). Projections of 49 GCMs (Table 1) covering different RCPs (RCP 2.5, RCP 4.6, RCP 6.0 and RCP 8.5) and periods (2016–2035, 2046–2065, 2081–2100).

The downscaling process of historical and future climate data

To obtain smooth and continuous climate surface estimates, *clim.regression* utilized the combination of bilinear interpolation and dynamic local regression approach to downscale the original 5km×5km gridded climate dataset to scale-free point estimates, which is the same as in ClimateNA (Wang *et al.* 2016) and ClimateAP (Wang *et al.* 2017). The downscaling process included four steps for each of the 48 primary monthly climate variables as illustrated in Figure 1:

- (1). Extraction of a primary climate variable and elevation from the grid covering the point of interest and eight neighboring grids (Fig. 1A);
- (2). Calculation of the bilinear interpolated estimate of the primary monthly climate variable (t'_p) and elevation (Z'_p) of the location of interest from the nearest four grids (Fig. 1B, Formula 1 & 2);
- (3). Calculation of the differences in the primary monthly climate variable (Δt) and in elevation (Δz) between each of the 36 unique pairs among the nine neighbor grids (Fig. 1C, Formula 3);
- (4). Construction of a simple linear regression based on the 36 pairs to represent the local relationship between Δt and Δz with the slope of the regression line, m , representing the local lapse rate of the cell where the interest point is located. Elevation adjustment was based on the lapse rate (m) and the difference between actual elevation (Z_p) and the bilinear interpolate (Z'_p) of the interest point (Fig. 1D, Formula 4).

**Table 1.** All the 49 GCMs and emission scenarios provided by TCCIP available for *clim.regression*.

GCM	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	GCM	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
10th-percentile	✓	✓	✓	✓	GFDL-ESM2M		✓	✓	✓
25th-percentile	✓	✓	✓	✓	GISS-E2-H	✓	✓	✓	✓
75th-percentile	✓	✓	✓	✓	GISS-E2-H-CC		✓		✓
90th-percentile	✓	✓	✓	✓	GISS-E2-R	✓	✓	✓	✓
ACCESS1-0		✓		✓	GISS-E2-R-CC		✓		✓
ACCESS1-3		✓		✓	HadGEM2-AO	✓	✓	✓	✓
bcc-csm1-1	✓	✓	✓	✓	HadGEM2-CC		✓		✓
bcc-csm1-1-m	✓	✓	✓	✓	HadGEM2-ES	✓	✓	✓	✓
BNU-ESM	✓	✓		✓	inmcm4		✓		✓
CanESM2	✓	✓		✓	IPSL-CM5A-LR	✓	✓	✓	✓
CCSM4	✓	✓	✓	✓	IPSL-CM5A-MR	✓	✓	✓	✓
CESM1-BGC		✓		✓	IPSL-CM5B-LR		✓		✓
CESM1-CAM5	✓	✓	✓	✓	maximum	✓	✓	✓	✓
CESM1-CAM5-1-FV2		✓		✓	media	✓	✓	✓	✓
CMCC-CESM				✓	minimum	✓	✓	✓	✓
CMCC-CM		✓		✓	MIROC5	✓	✓	✓	✓
CMCC-CMS		✓		✓	MIROC-ESM	✓	✓	✓	✓
CNRM-CM5	✓	✓		✓	MIROC-ESM-CHEM	✓	✓	✓	✓
CSIRO-Mk3-6-0	✓	✓	✓	✓	MPI-ESM-LR	✓	✓		✓
EC-EARTH				✓	MPI-ESM-MR	✓	✓		✓
ensemble	✓	✓	✓	✓	MRI-CGCM3	✓	✓	✓	✓
FGOALS-g2	✓	✓		✓	MRI-ESM1				✓
FIO-ESM	✓	✓	✓	✓	NorESM1-M	✓	✓	✓	✓
GFDL-CM3	✓	✓	✓	✓	NorESM1-ME	✓	✓	✓	✓
GFDL-ESM2G	✓	✓	✓	✓					

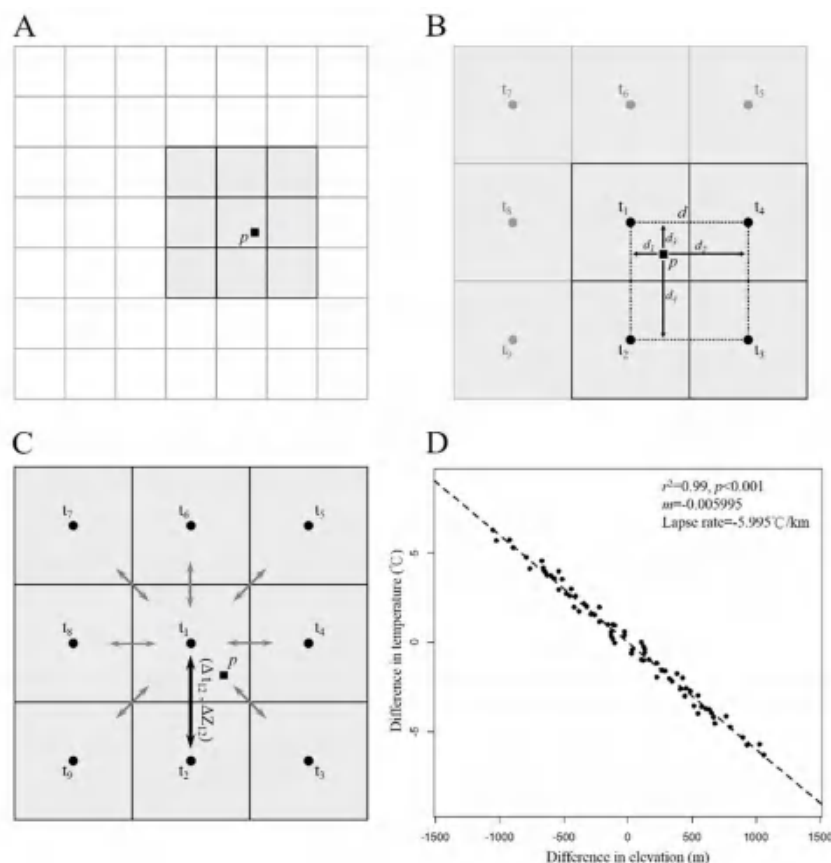


Fig. 1. Four steps of the downscaling process. **(A)** The grid tiles covering the point of interest p and its eight neighbors were extracted from the original climate dataset. **(B)** Bilinear interpolated estimates of temperature, precipitation and elevation of the point p were calculated by the weighting of distance to the center of the four nearest grid tiles. **(C)** A total of 36 unique pairs were subset to calculate the paired differences for temperature, precipitation (Δt) and elevation (Δz), respectively. **(D)** A simple linear regression of $\Delta t_{mn} \sim \Delta z_{mn}$ was conducted to obtain the slope m , representing the local lapse rate of the nine grids surround point of interest for each of the climate variables.



Clim.regression generated 73 climate variable estimates (Table 2) for either a single point location or a continuous surface. These climate variables were either directly calculated from the four primary climate variables or derived as indicated in Table 2.

The formula for the downscaling process included:

- (1) $t'_p = \frac{t_1 d_2 d_4 + t_2 d_2 d_3 + t_3 d_1 d_3 + t_4 d_1 d_4}{d^2}$
- (2) $Z'_p = \frac{Z_1 d_2 d_4 + Z_2 d_2 d_3 + Z_3 d_1 d_3 + Z_4 d_1 d_4}{d^2}$
- (3) $\Delta t_{mn} \sim \Delta Z_{mn}$, $m = \{1, 2, 3, \dots, 9\}$, $n = \{1, 2, 3, \dots, 9\}$, $m \neq n$
- (4) $t_p = t'_p + m|Z_p - Z'_p|$

Future climate projections of TCCIP were presented as anomalies relative to the baseline of 1986–2005 at the same spatial resolution of historical climate data. The anomalies of 5km×5km gridded future climate projections were added to the baseline portion (1986–2005) to create a ‘gridded future climate data’ prior to the downscaling procedure.

Table 2. Primary climate variables and the biologically relevant derivatives generated by *clim.regression*.

(1) Primary climate variable estimates. (Category/Climate variables)
Precipitation
Monthly precipitation (precip01 to precip12)
Seasonal precipitation (PPT_DJF, PPT_MAM, PPT_JJA, PPT_SON)
Mean annual precipitation (MAP)
Mean annual summer precipitation (MSP)
Temperature
Minimum
Mean monthly minimum temperature (Tmin01 to Tmin12)
Mean seasonal minimum temperature (Tmin_DJF, Tmin_MAM, Tmin_JJA, Tmin_SON)
Average
Mean monthly temperature (Tmean01 to Tmean12)
Mean seasonal temperature (Tave_DJF, Tave_MAM, Tave_JJA, Tave_SON)
Mean annual temperature (MAT)
Maximum
Mean monthly maximum temperature (Tmax01 to Tmax12)
Mean seasonal maximum temperature (Tmax_DJF, Tmax_MAM, Tmax_JJA, Tmax_SON)
(2) Derivative estimates. (Derivative variable/Definition)
Temperature difference (TD): Tmean07 minus Tmean01
Summer heat:moisture index (SHM): (Tmean07)/(MSP/1000)
Annual heat:moisture index (AHM): (MAT+10)/(MAP/1000)
Ratio of winter precipitation (WPR): PPT_DJF/MAP (Li et al., 2013)
Warmth index (WI): Annual summation of mean monthly temperature higher than 5°C. (Su, 1984b)
Precipitation deficiency (PD): Difference between annual potential evapotranspiration and MAP. (Su, 1985)
Dry month (DM): The month with rainfall less than 2X mean monthly temperature. DM is a factor variable in 0/1. (Su, 1985)

Evaluations of climate variable estimates

We collected historical records covering the period of 1961 to 2009 from 15 weather stations to evaluate the accuracies of *clim.regression* model. Ten of the 15 stations are subordinate to the Central Weather Bureau (CWB), which is the main corporation agency of TCCIP. The remaining five stations belong to the Taiwan Forestry Research Institute (TFRI), which is independent of the samples of TCCIP network. The observations from the 15 weather stations were also used to evaluate the magnitude of improvement over the original TCCIP gridded surfaces. Four sets of climate variable estimates generated by *clim.regression*, including monthly precipitation, monthly minimum temperature, monthly mean temperature and monthly maximum temperature, were evaluated against observations from the 15 weather stations (Table 3, Fig. 2). Prediction errors of *clim.regression* were assessed and compared using the following three statistical measures:

Mean error (ME):

where n is the number of samples, f_i is the predicted value of the i -th sample and y_i its real value.

Mean absolute error (MAE):

Root mean squared error (RMSE):

Table 3. Localities of 15 weather stations and the period of observed data that available for model evaluation.

Subordination/ Station	Longitude	Latitude	Altitude (m)	Observation period
Central Weather Bureau (CWB) Incorporated by TCCIP				
Kaohsiung	120.32	22.57	2	1961–2009
Taitung	121.15	22.75	9	
Hualien	121.61	23.98	16	
Hengchun	120.75	22.00	22	
Keelung	121.74	25.13	27	
Taichung	120.68	24.15	84	
Anbu	121.53	25.18	826	
Sunmoon Lake	120.91	23.88	1018	
Alishan	120.81	23.51	2413	
Yushan	120.96	23.49	3845	
Taiwan Forestry Research Institute (TFRI) independent from TCCIP				
Taimali	120.98	22.60	120	1980–2009
Liukuei	120.63	23.00	230	1999–2009
Fushan	121.60	24.76	634	1992–2003
Lienhuachih	120.90	23.93	666	1999–2009
Piluhsi	121.31	24.23	2150	1991–2009



Fig. 2. Long-term observation data from fifteen weather stations were incorporated to evaluate the downscaling model. Solid stars demonstrate stations subordinate to the Central Weather Bureau of Taiwan (CWB). Open stars represent stations belonging to the Taiwan Forestry Research Institute (TFRI), which were independent from TCCIP system.

**Table 4.** The R-square values of the local linear regressions for different monthly climate variables.

Monthly variable	R ² value / Month												Average
	1	2	3	4	5	6	7	8	9	10	11	12	
Tmean	0.82	0.82	0.81	0.84	0.86	0.87	0.88	0.88	0.88	0.87	0.86	0.84	0.85
Tmin	0.79	0.80	0.81	0.83	0.85	0.85	0.85	0.85	0.86	0.84	0.83	0.80	0.83
Tmax	0.79	0.79	0.78	0.81	0.84	0.85	0.85	0.86	0.85	0.82	0.81	0.79	0.82
Precipitation	0.20	0.21	0.24	0.23	0.25	0.26	0.23	0.25	0.22	0.21	0.22	0.22	0.23

RESULTS

Scale-free climate surfaces from the downscaling model
Clim.regression is a scale-free and topography-correspondent downscaling model, which attributes to the continuous and smooth characteristics of bilinear interpolation and the elevational adjustment by lapse rate from a dynamic local regression. Regular grids for MAT (mean annual temperature) and MAP (mean annual precipitation) surfaces were generated by the model at the spatial resolution of the original baseline data (5km×5km) and a downscaled spatial resolution (250m×250m) (Fig. 3). The results showed that MAT in Taiwan ranges from 1 °C to 28 °C and exhibits a trend of decline from lowland to alpine and from south to north. A more detailed spatial distribution of temperature due to geographical effect, such as warm basin of Puli and cool tablelands of Linkou and Pagua, could also be revealed by the downscaled surface (Fig. 3A–B). The spatial distribution of MAP demonstrated a different pattern from that of MAT; it exhibited two-ended humid regions in the northeast and the southwest of Taiwan. The northeastern mountains in Taipei and Ilan and the southwestern edge of the Central Mountain Range in Kaohsiung and Pingtung are the moistest regions of Taiwan, and the downscaled surface more clearly revealed some precipitation hotspots with annual rainfall up to 6,000 mm (Fig. 3C–D).

In comparison with the original climate dataset at the resolution of 5km×5km, the downscaled one offers a detail depiction on the climatic alternation with topographies as the examples showed in Fig. 3. The scale-free modeling approach not only has the advantage in providing continuous and seamless climatic surface for large-scale studies (e.g., the classification of ecological-climatic regions, climatic niche modeling, and projections, etc.), but also generates accurate and point-specific climatic estimates as environmental correlates for plot-based researches (e.g., vegetation survey and plotting, etc.).

Lapse rate and effectiveness of the elevational adjustment

The dynamic local linear regression among the nine neighboring cells explained, on average, 85.3% of the total variation in monthly mean temperature. The amount of variance explained for monthly minimum temperature (83.1%) and monthly maximum temperature (81.9%) were slightly lower (Table 4). The

average temperature lapse rate in the mountain areas was -5.65 °C/km but displayed an obvious seasonal variation. Fig. 4A–C illustrate the same pattern in three primary temperature variables with a higher variation of lapse rate in winter (from Nov. to Apr.) than in summer (from May to Sep.). The relationships revealed in the local regressions were weaker for precipitation than for temperatures. Only 20.3–25.7% of precipitation's variation can be explained by the local regressions (Fig. 4D, Table 4).

We compared the relationships between the changes in temperature and the elevation between two mountains, Alishan and Taipingshan. Such a relationship was stronger for Alishan with a steady lapse rate from -6.00 to -6.44 °C/km from winter to summer. In contrast, a higher seasonal variation and a weaker relationship between temperature and elevation were observed in Taipingshan (Fig. 5).

The spatial distributions of the estimated lapse rates varied among seasons and regions. In winter, lower lapse rates for monthly average temperature (from -2 to -5 °C/km) were exhibited in the central and western parts of the Central Mountain Range, especially in the hills from Hsinchu, Miaoli, Nantou, Chiayi to Kaohsiung. In contrast, very steep lapse rates (from -6 to -9 °C/km) were demonstrated in the northeastern mountains and Hengchun peninsula (Fig. 6A). The spatial differentiation in lapse rate in most areas mitigated in summer, and demonstrated a mild geographical divergence with a range from -4 to -7 °C/km (Fig. 6C). In some regions, such as the northeastern mountains in Taipei and Ilan, Hengchun peninsula, Tawu Mountain and the Coastal Mountain Range, the steep lapse rates (<-6 °C/km) could be found across all seasons of the year. Our dynamic local regression approach revealed the variation in the lapse rate both spatially and temporally over the island, and thus produced accurate adjustment for elevation.

Statistical evaluations of the downscaling model and its improvement over TCCIP dataset

The prediction accuracy of *clim.regression* was evaluated by comparing to historical observations from the 15 weather stations (Table 5). *Clim.regression* demonstrated a high prediction accuracy for monthly mean temperature with a low prediction error (0.56 °C in MAE) and a high percent of variance explained (99.1%). The prediction accuracy and variance explanation were slightly lower for monthly minimum temperature and

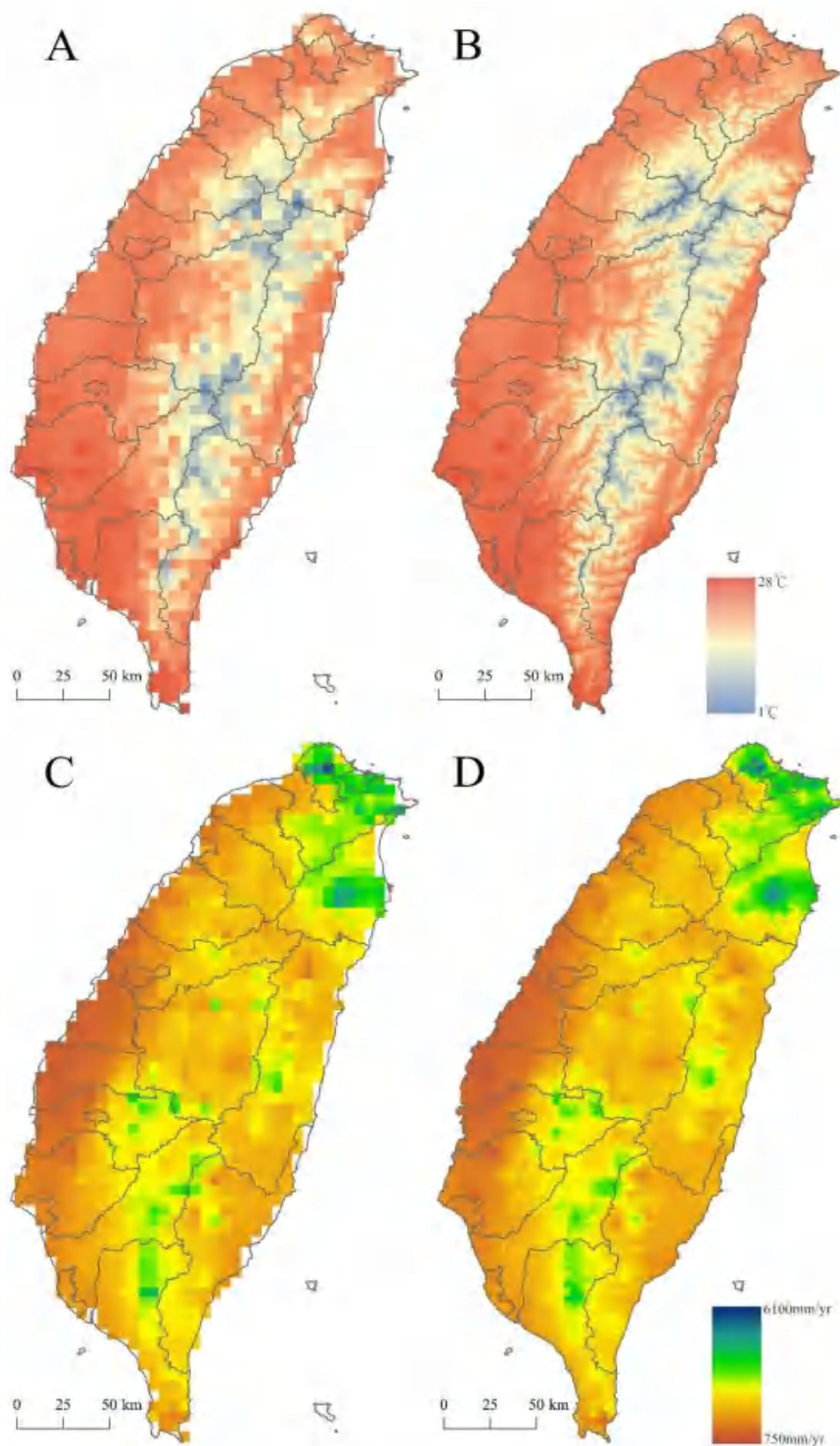
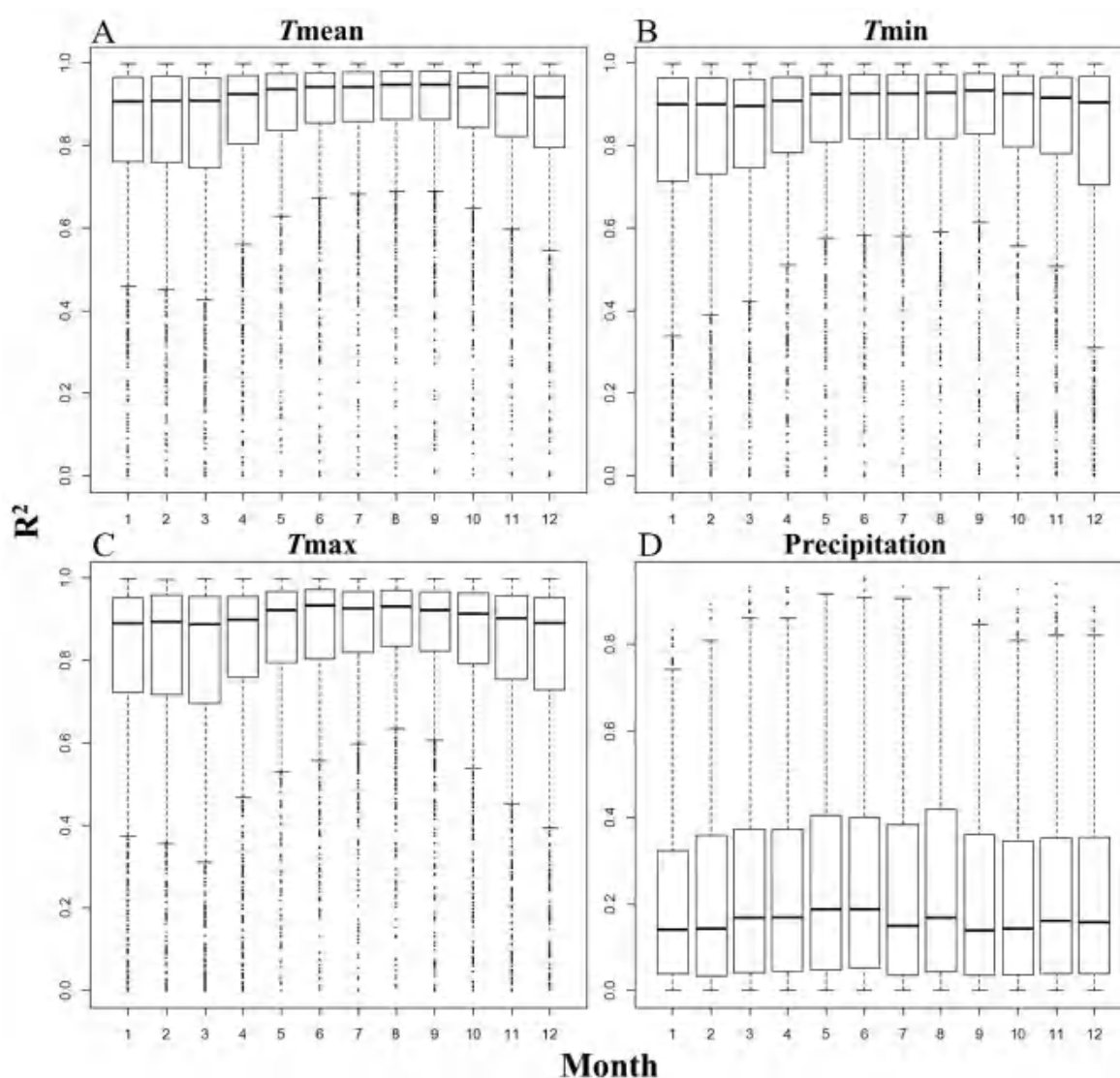


Fig. 3. Spatial distributions of mean annual temperature (MAT) and mean annual precipitation (MAP) for original climate data at the resolution of 5 km and downscaled to the resolution of 250 m. (A) Original and (B) downscaled MAT; (C) Original (D) and downscaled MAP. Data period: 1986–2005.

**Table 5.** Summaries of statistical evaluations of *clim.regression* against historical observed data from Central Weather Bureau (CWB) and Taiwan Forestry Research Institute (TFRI).

Subordination	Climate variable	<i>Clim.regression</i>			TCCIP		
		MAE	RMSE	Variance explained (%)	MAE	RMSE	Variance explained (%)
CWB (10 stations)	Tmean (°C)	0.56	0.73	99.10	1.73	3.40	87.83
	Tmin (°C)	0.79	0.98	98.72	1.92	3.51	87.04
	Tmax (°C)	0.71	1.00	98.22	1.67	3.25	88.29
	Precipitation (mm)	34.65	64.63	94.39	31.10	67.08	93.75
TFRI (5 stations)	Tmean (°C)	0.58	0.74	98.56	1.34	1.56	96.75
	Tmin (°C)	0.82	1.17	97.27	1.24	1.49	96.51
	Tmax (°C)	1.52	1.85	95.61	2.53	2.78	92.27
	Precipitation (mm)	49.56	105.39	79.77	46.39	106.14	79.62
Average (15 stations)	Tmean (°C)	0.56	0.73	99.06	1.68	3.25	86.71
	Tmin (°C)	0.79	1.00	98.52	1.85	3.35	86.61
	Tmax (°C)	0.80	1.13	97.61	1.76	3.21	84.76
	Precipitation (mm)	36.26	70.16	93.00	32.74	72.30	92.43

**Fig. 4.** Proportions of variance explained by local linear regressions in total variation among the nine neighboring cells for the four primary climate variables: (A) monthly mean temperature (Tmean), (B) monthly minimum temperature (Tmin), (C) monthly maximum temperature (Tmax) and (D) monthly precipitation, by month. The black horizontal solid lines inside the boxes indicate the medium. For temperature variables, a similar trend of higher variation in winter and lower variation in summer can be observed. Data period: 1961–2009.

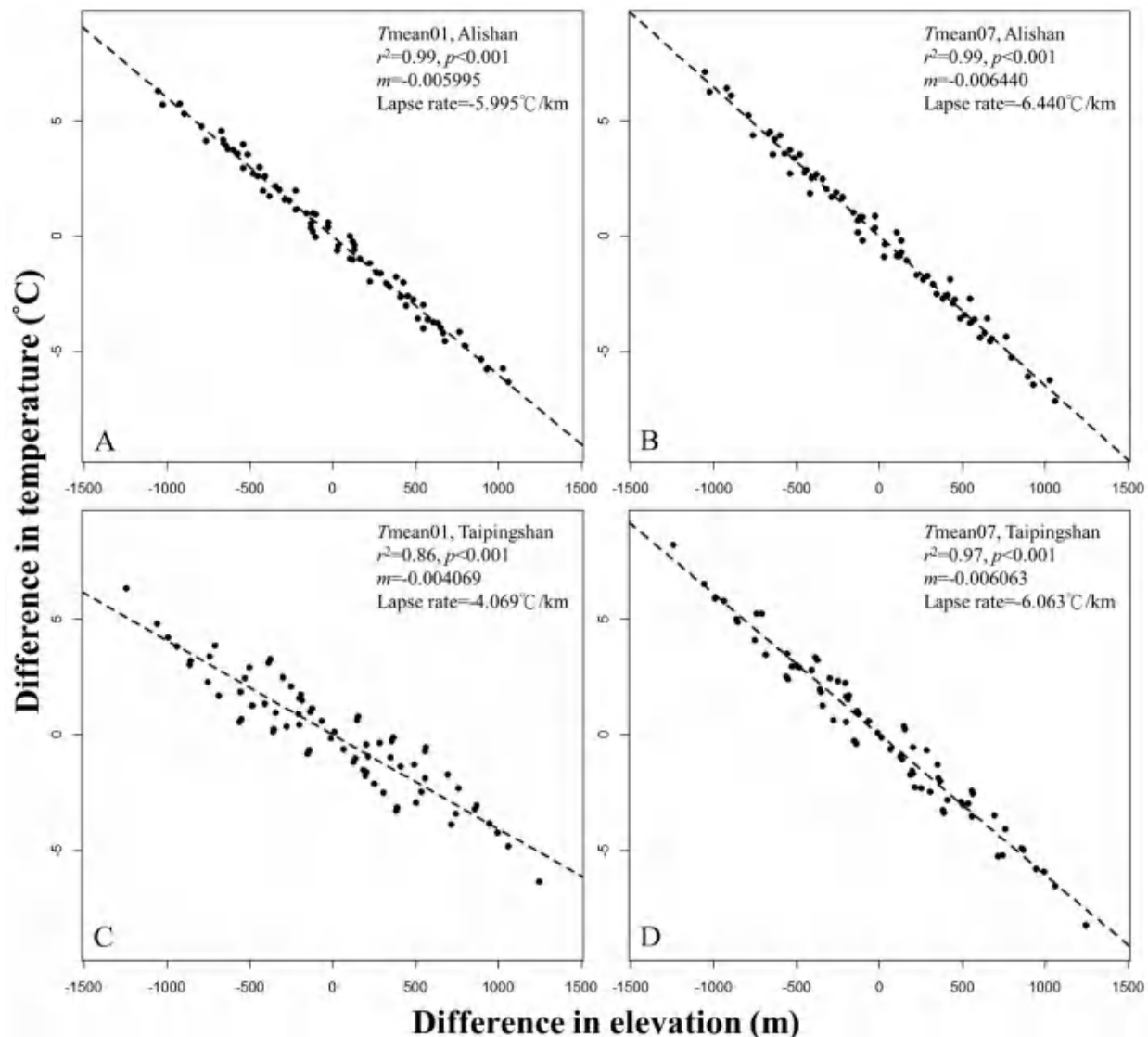


Fig. 5. Comparisons in lapse rates for winter and summer between two mountains, Alishan (A, B) and Taipingshan (C, D). Alishan (120.81E, 23.51N) is a mountain located in the south-west Taiwan, while Taipingshan (121.53E, 24.49N) is located in the north-east part. The two mountains have a similar elevation around 2000 m. Data period: 1961–2009.

monthly maximum temperature in terms of the prediction error (0.79 °C and 0.80 °C) and the percent of variance explained (98.5% and 97.6%, respectively). However, the prediction accuracy was considerably lower for precipitation. The precipitation estimates explained 93.0% of the total variance of observations with a prediction error of 36.26 mm in MAE.

Monthly mean temperature was the most predictable climate variable. The prediction accuracy of monthly mean temperature in regions lower than 2,500 m a.s.l. could reach the level of 0.3–0.6 °C in MAE. However, we found that the prediction error increased with elevation ($r^2=0.55$, $p=0.0015$). For example, in the subalpine area of Taiwan, *clim.regression* had a comparatively weak predict ability with the MAE of 1.02 °C. Interestingly, such a relationship was not

observed for monthly minimum temperature and monthly maximum temperature ($r^2=0.07$ and 0.35 , $p=0.3252$ and 0.0209). The prediction accuracy for precipitation was lower and accompanied with a higher variation and a less amount of variance explained (92.1%). In addition, there was no obvious trend found between prediction error in precipitation and altitude ($r^2=0.01$, $p=0.7612$). It suggests that the pattern of precipitation could be dominantly influenced by regional terrains rather than a local elevational gradient within the 5km×5km grids.

In comparisons to TCCIP original dataset, *clim.regression* reduced prediction errors by 1.12°C (66.7%), 1.06°C (52.3%) and 0.96 °C (54.6%) for Tmean, Tmin and Tmax, respectively (Fig. 7A–C, Table 5). These results demonstrated that *clim.regression*

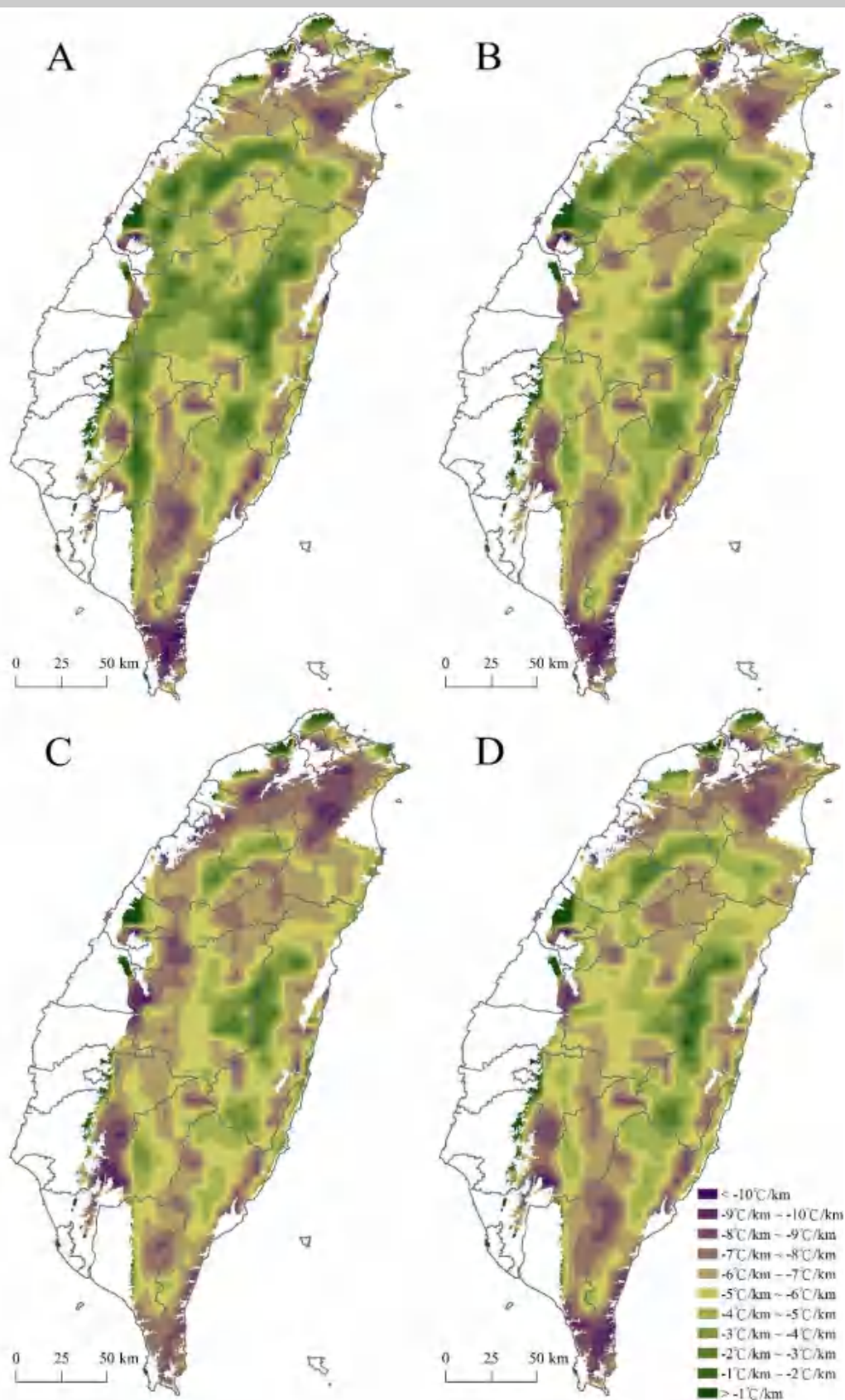


Fig. 6. Spatial distributions of estimated lapse rate for monthly mean temperature in the mountain areas (regions higher than 100 m a.s.l.) in Taiwan: (A) January, (B) April, (C) July and (D) October. Data period: 1961–2009; resolution: 250 m.

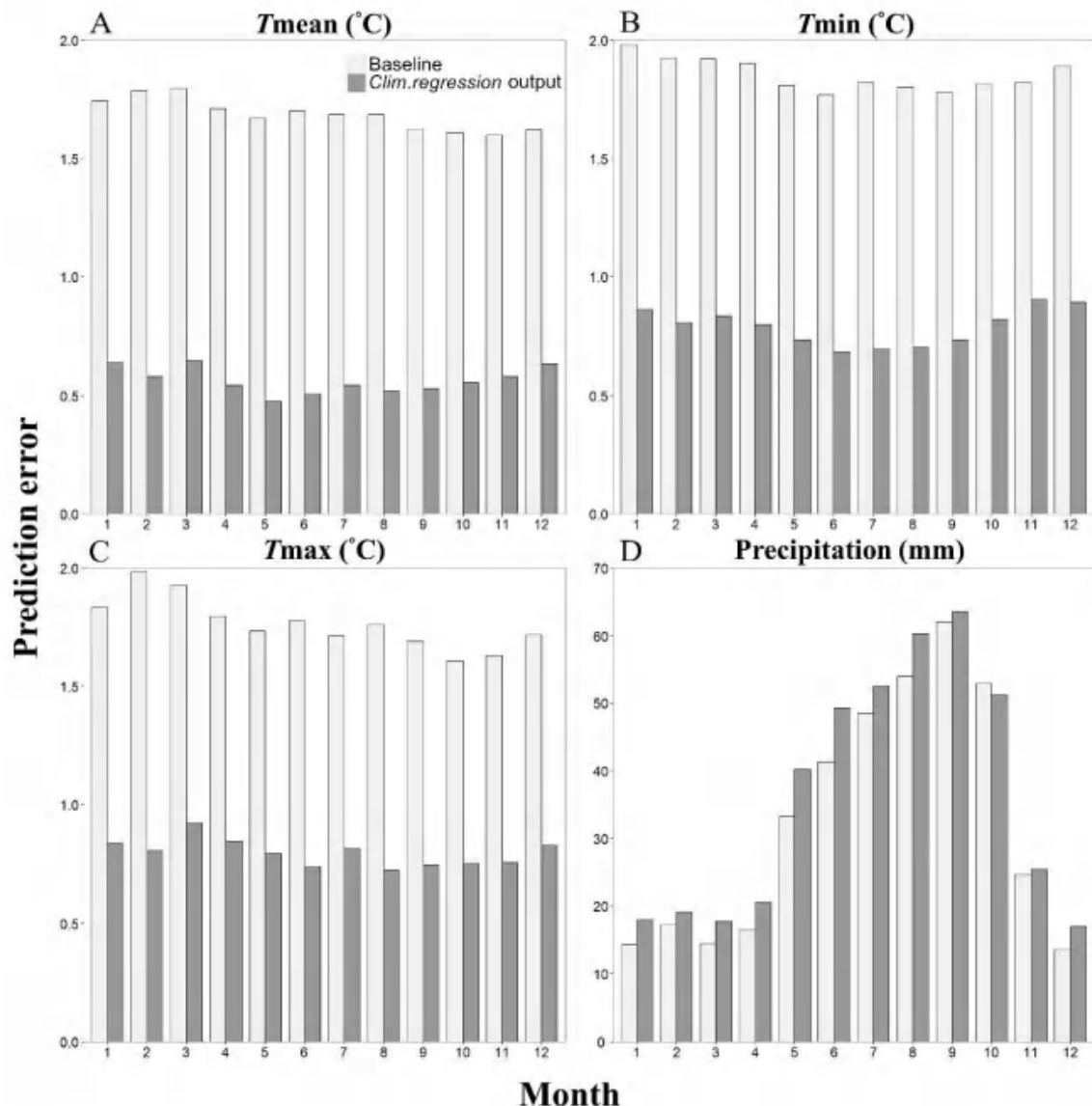


Fig. 7. Comparison in prediction error between baseline data (directly from TCCIP) and *Clim.regression* output of 15 weather stations for: (A) monthly mean temperature (Tmean), (B) monthly minimum temperature (Tmin), (C) monthly maximum temperature (Tmax) and (D) monthly precipitation.

effectively improved the accuracy and refined the spatial resolution of temperature estimates relative to the original dataset from TCCIP, especially with advantages in temperature projection for mountains with diverse topography. However, the improvement in precipitation is limited (Fig. 7D). Both TCCIP baseline and *clim.regression* had a higher prediction error for precipitation during summer months (May to Oct.). As illustrated in Fig. 8, the magnitude of the improvement was more substantial at higher elevations (the lower end of the temperatures), especially in the alpine area of Yushan (3,952m) and Alishan (2,413m). The downscaled temperatures followed a 1:1 relationship with observations much closer than the TCCIP predictions.

Downscaling for future climate projections

Based on the estimated lapse rate of future scenarios, *clim.regression* was also effective to downscale the ‘gridded future climate data’ to a scale-free and continuous surface with the same 73 climate variables as for the historical period. Downscaled MAT by *clim.regression* for the reference period and future scenario in the mountainous area of Taiwan were illustrated in Fig. 9. The benefit of the downscaled MAT is clearly shown in this example in term of fine spatial resolution and high topographical correspondence. Based on the comparison among current and future climate under the RCP 4.5 scenario, not only an evident warming can be found in the valleys and plains but also demonstrate an obvious retreat of isothermals to the

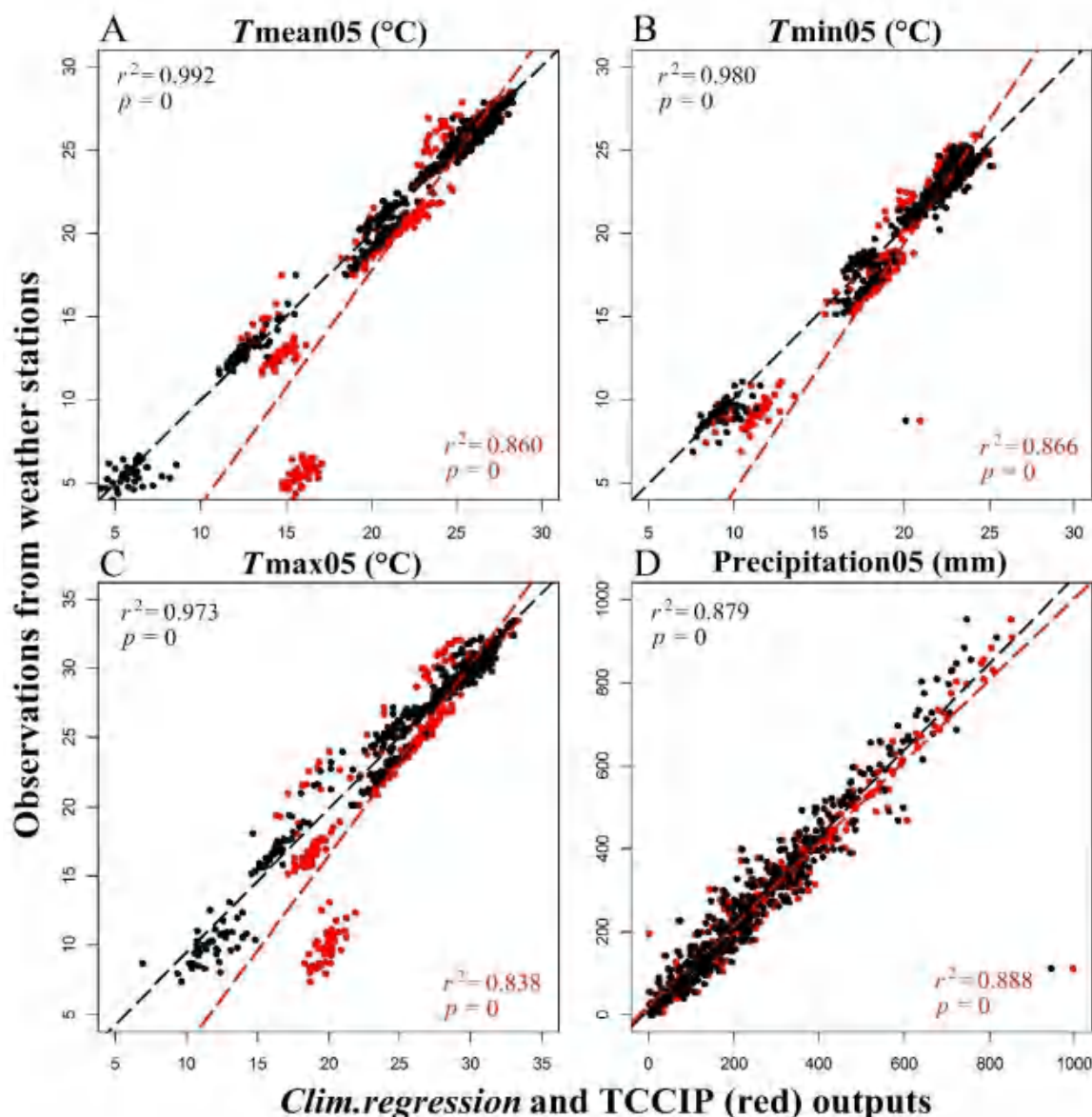


Fig. 8. An illustration to demonstrate the difference between observations from 15 weather stations and its corresponding climatic estimates from TCCIP outputs (red) and *clim. regression* in May for (A) monthly mean temperature (Tmean05), (B) monthly minimum temperature (Tmin05), (C) monthly maximum temperature (Tmax05) and (D) monthly precipitation (Precipitation05). It was clearly revealed that TCCIP outputs are biased as the decreasing of observed temperature, which is highly correspond to the raise of altitude.

subalpine area (Fig.9). *Clim. regression* has a solid advantage in generating current and future climate data with the same and desirable spatial resolution, which is a convenient for modeling biological response to climate change and for advanced comparative studies.

DISCUSSION

Spatio-temporal heterogeneity of temperature lapse rate in Taiwan

Temperature lapse rate, the rate of change in temperature with elevation in the troposphere, is widely used as the most important predictor in mountain climate

(Su, 1984a; Tang, 2006; Chiu *et al.*, 2014). Many authors have revealed the spatio-temporal variation of lapse rate caused by atmospheric processes, interaction of prevailing monsoon, geographical and topographical positions, etc. (Su, 1984a; Tang and Ohsawa, 1997; Pepin, 2001; Chiu *et al.*, 2014), thus suggested using regional observed data to derive the lapse rate as a local climate predictor rather than the commonly used global constant (-6.5 °C/km in Barry and Chorely, 2009; or -6.0 °C/km in Willmott and Matsuura, 2009). In Taiwan, a high spatio-temporal variation of lapse rate has been reported. Su (1984a) mentioned that temperature in the mountain area is highly correlated to elevations, and

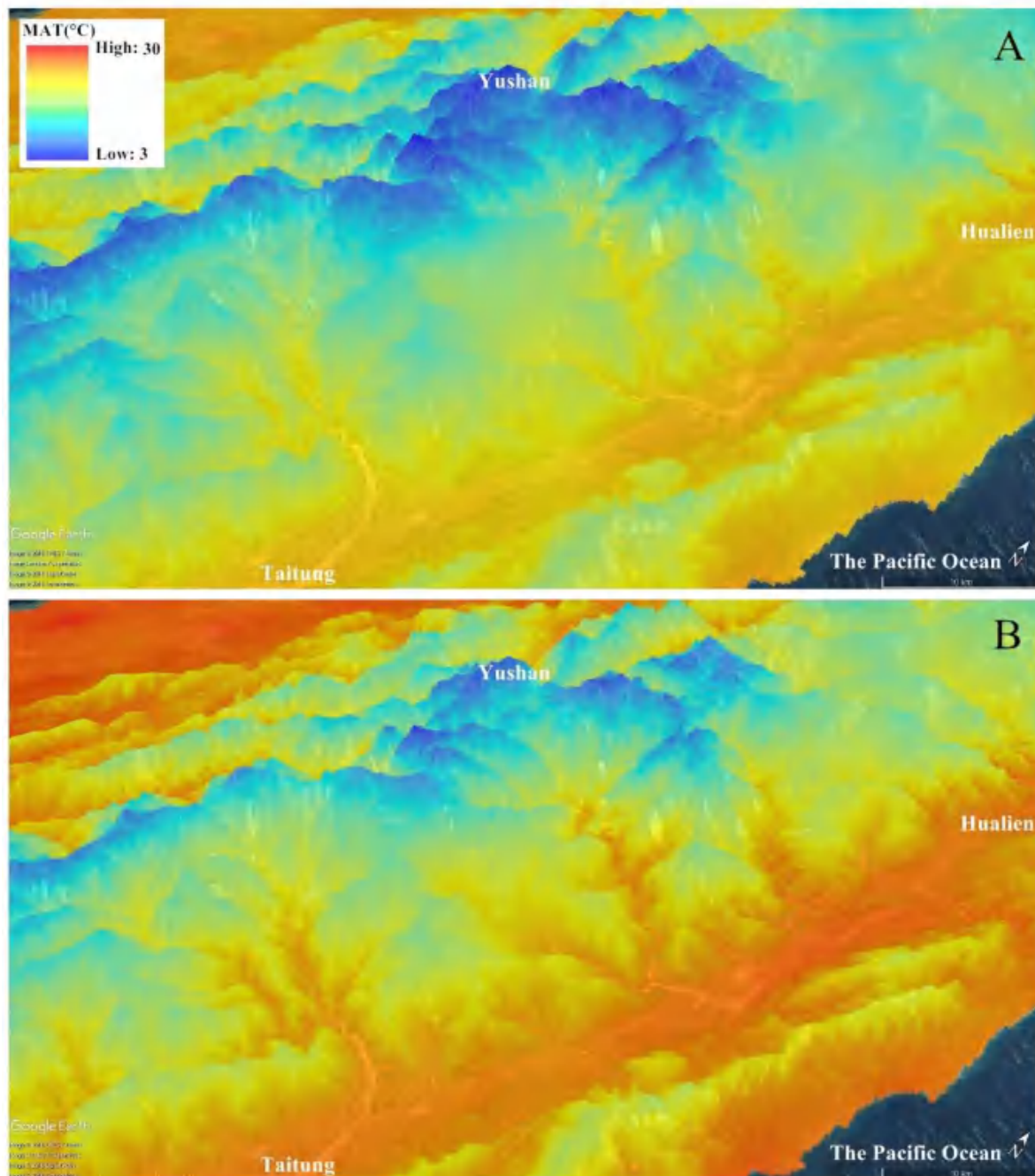


Fig. 9. Illustration of the effectiveness of downscaled climatic surface in the mountainous area of Taiwan, stretching from the coast of the Pacific Ocean up to the highest peak, Yushan, at 3,952 m a.s.l. (A) Downscaled mean annual temperature (MAT) by *clim.regression* in the resolution of 250 m for the reference period of 1986–2005; (B) downscaled future MAT for the period of 2090–2100 based on the GCM of CSIRO-Mk3-6-0 in RCP 4.5 scenario.

represented a lapse rate ranges from -3.08 to -6.98 $^{\circ}\text{C}/\text{km}$ but varies among regions and seasons. Guan *et al.* (2009) has modeled a steeper temperature lapse rate from April to December with a range between -4.93 and -5.62 $^{\circ}\text{C}/\text{km}$, and a shallower rate from -3.22 to -3.61 $^{\circ}\text{C}/\text{km}$ during January to March according to historical observation data from 43 meteorological stations, mostly located in the west of the Central Mountain Range and

Snow Mountain. A full exploration of the spatio-temporal variation of lapse rate was accomplished by Chiu *et al.* (2014). Based on historical records from 219 weather stations, Chiu *et al.* (2014) depicted that the average temperature lapse rate for all of Taiwan is -5.17 $^{\circ}\text{C}/\text{km}$ with a general tendency to be steeper in summer and shallower in winter. They also found that the lapse rate exhibits a pronounced contrast between the

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windward side (steeper, $-5.97\text{ }^{\circ}\text{C/km}$) and the leeward side of the Central Mountain Range (shallower, $-4.51\text{ }^{\circ}\text{C/km}$) due to the atmospheric effect of prevailing winter monsoon. However, to obtain a lapse rate for specific locations remained a challenge.

Through the approach of dynamic local regression, we have delineated a fine scale of lapse rate and used it as the key adjustment for the downscaling procedure. The distribution maps of lapse rate for the monthly temperature (Fig. 6) have shown a similar spatio-temporal pattern to that of Chiu *et al.* (2014), which exhibited a steeper lapse rate in regions exposed to the northeast monsoon (e.g., The northeast mountains, the Coastal Mountain Range from Hualien to Taitung, and Hengchun peninsula) and shallower in the leeward side (e.g., The west of the Central Mountain Range) during winter, and became obscure in summer. In the context of high spatio-temporal variation of lapse rate in Taiwan, *clim.regression* shows an excellent performance by using the local lapse rate to facilitate a high-resolution downscaling. Our evaluations have proved that this model considerably improves prediction accuracy relative to the original TCCIP climate data and it is suitable for the steep and mountainous areas and provides accurate and topography-corresponded climate variable estimates.

In addition, Lenoir *et al.* (2008) have pointed out that temperature lapse rate is the most important predictor of temperature variability in mountains, and can be one of the key contributions to predict the response of plants to climate change. In this study, steep lapse rates ($<-6\text{ }^{\circ}\text{C/km}$) are found all year round in several areas, such as the northeast mountains, Hengchun peninsula, Tawu Mountain and Coastal Mountain Range. Some studies have reported the compression of vegetation zones in these areas due to a dramatic change in temperature along the altitudinal gradient (Su 1984a; Su, 1984b; Chiou *et al.*, 2010). In consequence of the feature of local regression, *clim.regression* can provide a deep insight into the entire spatial and temporal distribution of lapse rate in Taiwan, and our results show a great promise for providing high quality scale-free climate variables for a wide spectrum of research and application activities in biology, ecology, and adaptation to climate change.

Benefits of the dynamic local downscaling model

Dynamic local regression is a simple but effective method to achieve a scale-free downscaling. This method has been utilized to develop ClimateNA for North America (Wang *et al.*, 2016) and ClimateAP for Asia-Pacific region (Wang *et al.*, 2017) to downscale WorldClim and PRISM gridded datasets to scale-free climate estimates. The model evaluation demonstrated that the prediction error of ClimateNA and ClimateAP are $0.77\text{ }^{\circ}\text{C}$ and $1\text{ }^{\circ}\text{C}$ (in MAE). *Clim.regression* is a R script based on the same algorithm of ClimateNA and

ClimateAP but use TCCIP $5\text{km}\times 5\text{km}$ gridded climate surface, an interpolation based on historical data from thousands of weather stations of Taiwan, as the data source. Our statistical evaluations revealed that the prediction error of *clim.regression* is $0.56\text{ }^{\circ}\text{C}$ in monthly mean temperature and 36.26 mm in monthly precipitation, which are substantially smaller than that for the original TCCIP data (in MAE, Table 5). These results suggest that the dynamic local regression approach is effective in downscaling climate variables to meet the requirement for ecological studies in mountain areas in Taiwan.

Chiu and Lin (2004) utilized regression and Ordinary Kriging to develop a scale-free model based on 219 meteorological stations and 877 rainfall stations to interpolate the distribution of monthly temperature and monthly precipitation. A cross validation revealed that the prediction errors of monthly temperature ranged from $1.57\text{--}1.74\text{ }^{\circ}\text{C}$ and monthly precipitation ranged from $17.51\text{--}53.07\text{ mm}$ (in RMSE). In addition, some authors applied polynomial regression to model the distribution of monthly temperature based on historical observations from 156 weather stations, but exhibited a lower prediction accuracy ranging from $-5.15\text{ }^{\circ}\text{C}$ to $4.68\text{ }^{\circ}\text{C}$ (in ME) due to the inflexibility of universal regression coefficient (Chiou *et al.*, 2004). In contrast, *clim.regression* provides more accurate temperature estimates ($0.73\text{--}1.13\text{ }^{\circ}\text{C}$ in RMSE) than using Kriging and polynomial regression, due to its flexibility of local lapse rate and the effectiveness of elevational adjustment. However the rainfall prediction error of our model is 70.16 mm in RMSE, it does not meet the level shown in Chiu and Lin (2004).

We found that *clim.regression* is not effective in downscaling precipitation (Fig. 7D). In Taiwan, the co-effect of humid monsoons and strong typhoons with diverse topography creates dramatic changes of precipitation in the mountains. For a windward slope at the middle elevation, the monthly precipitation during wet seasons can reach $2,000\text{ mm/month}$ but decrease to less than 800 mm/month as the change of aspect in a short distance of kilometers at the same elevation. Bilinear interpolation with a sampling window of 2 by 2 cells ($10\text{km}\times 10\text{km}$) and the dynamic local regression within a sampling unit of 3 by 3 cells ($15\text{km}\times 15\text{km}$) are the kernel of *clim.regression* to produce climatic estimates for the point of interest, however, the severe change of precipitation in mountains may neither linearly correlate with the change of elevation nor correspondently fit with the coverage of sampling windows to lead to a poor performance in precipitation prediction than temperature. It is worthy of advanced researches to explore the spatial pattern and its statistical correlates of precipitation to achieve an accurate predict model in the future.

The results of validation by weather stations of CWB



and TFRI demonstrated that the estimates of *clim.regression* were more approximate to observations from CWB rather than TFRI. It could be partly attributed to the reason that most historical observation data of CWB stations were the main component of TCCIP system, so that it might not be an independent validation and could lead to an over estimation of both TCCIP and *clim.regression* model performances, but it would not affect the evaluation of the improvement in prediction accuracy relative to TCCIP. Historical observation data from TFRI was not included by TCCIP, so that an independent validation could be achieved theoretically. However, due to the lack of sustainable maintenance and long-term financial support, data quality of these independent weather stations could be harsher than CWB. It could be another effect leading to an under estimation of the downscaling model.

CONCLUSION

Ecologists have accumulated a large amount of field investigation data in Taiwan. Many studies exploring vegetation-climate relationship have also been published. However, due to the difficulty in accessing climate data in the past, researchers usually used geographical variables, such as elevation, longitude, latitude, aspect, the distance to seashore and exposure to prevailing monsoon as substitutions for climate variables in data analysis. Results of these studies based on indirect variables could lead to a biased result of ecological-climate relationships. The scale-free climate variables generated by *clim.regression* offer a solution to this problem. Users cannot only generate a continuous and seamless surface for climate niche modeling but is also possible to estimate historical and future climate condition for specific locations such as numerous vegetation survey plots. It provides a large number of climate variables for scientists to explore, delineate and quantify the relationships between climate and vegetation.

However, some limitations still exist in our downscaling approach. *Clim.regression* downscales gridded source climate variables through a combination of bilinear interpolation and concise elevational adjustment. Therefore, the performance of *clim.regression* is mostly determined by two factors in addition to the effectiveness of the downscaling algorithm: the quality of the original climate dataset and the accuracy of the imported digital elevation surface. The quality of baseline data strongly depends on the number of historical observations and the number of weather stations being incorporated. Therefore, we regard both of the robust meteorological observation network and the effective interpolation approaches are the critical issues to provide a high-quality gridded dataset for downscaling. TCCIP has an ongoing project to improve the accuracy and the coverage of periods for

gridded climate data of Taiwan, which serves as an ideal baseline data to be used in *clim.regression* to generate high-resolution and high-quality climate data for ecological studies for ecosystem adaptation to climate change.

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Climate change impacts and forest adaptation in the Asia–Pacific region: from regional experts’ perspectives

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Abstract Expert opinions have been used in a variety of fields to identify relevant issues and courses of action. This study surveys experts in forestry and climate change from the Asia–Pacific region to gauge their perspectives on the impacts of climate change and on the challenges faced by forest adaptation in the region, and explores recommendations and initiatives for adapting forests to climate change. There was consensus regarding the impacts of climate change on forest ecosystems and on economic sectors such as agriculture and forestry. Respondents also indicated a lack of public awareness and policy and legislation as challenges to addressing climate change. However, the results indicate differences in opinion between regions on the negative impacts of climate change and in satisfaction with actions taken to address climate change,

highlighting the need for locally specific policies and research. The study presents specific recommendations to address issues of most concern, based on subregion and professional affiliation throughout the Asia–Pacific region. The results can be used to improve policy and forest management throughout the region. This research will also provide valuable suggestions on how to apply research findings and management recommendations outside of the AP region. The conclusions should be communicated relative to the level of the research and the target audience, ensuring that scientific findings and management recommendations are effectively communicated to ensure successful implementation of forest adaptation strategies.

Keywords Adaptation · Asia–Pacific · Climate change · Expert opinion · Forest management · Questionnaire

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Introduction

The Asia–Pacific region is particularly vulnerable to climate change given its large population, high biodiversity, and large number of forest-dependent communities. Effects of climate change have already impacted freshwater resources, coastal systems, food production, and human livelihoods (IPCC 2014). Forest ecosystems are particularly sensitive to changes in temperature and precipitation (FAO 2015), and climate change, therefore, has the potential to alter future composition of forests in the Asia–Pacific region and the nature and extent of the services they provide may become uncertain. Forests also present a major opportunity for climate change adaptation and mitigation, as they have the potential to act either as a carbon source and accelerate climate change (through deforestation and forest degradation), or as a carbon sink and an

adaptation strategy (through afforestation and sustainable management) (IPCC 2014). Recognizing the important role of forests as they relate to climate change and wisely managing their potential capacity is crucial for future climate change mitigation and adaptation.

Many forest-related initiatives and strategies have been developed to utilize the potential of forests for climate change mitigation and adaptation. The Kyoto Protocol indicated that forests could contribute to meeting carbon emission reduction targets, and REDD++ (Reducing emissions from deforestation and forest degradation and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries) has become an important means of achieving these targets (Mollicone et al. 2007). Carbon management has become a standard component of sustainable forest management (SFM), as illustrated by the criteria and indicators developed by the International Tropical Timber Organization (ITTO 2005). Despite many available initiatives and strategies, the extent to which forests contribute to climate change mitigation and adaptation remains limited. Many studies have suggested that this low level of achievement is the result of insufficient institutional effort and a failure to effectively implement policy (Jantarasami et al. 2010; Moser and Ekstrom 2010).

This lack of political structure and guidance has led to the limited success of policies, strategies, and action plans to address climate change in the Asia-Pacific region. Development and implementation of effective forest management plans and policy is hindered by the complexity of social, political, and economic issues, as well as highly diversified local, regional, and national contexts. The capacity for climate change research and understanding of its impacts on forest ecosystems is highly variable across the region, leading to a disparity among countries regarding government and management capacities to adapt to climate change (FAO 2010). As a result, the local context, including specific location and knowledge of the stakeholders, becomes an important factor when making management decisions and communicating forest management recommendations in this region.

As part of the larger research project, *Adaptation of Asia-Pacific Forests to Climate Change*, this study examines current knowledge about climate change in the Asia-Pacific region, including the impacts, tools available for management and decision-making, and opportunities for forest adaptation. The goal of this research is to first identify expert perspectives on the impacts of climate change and on the current challenges faced by forest adaptation in the region, and secondly, to explore recommendations and initiatives for adapting forests to climate change. Experts' opinions have been used successfully in the past to conduct meaningful research (Vaughan and

Spouge 2002; Morgan et al. 2006; O'Neill et al. 2008), and a similar approach was therefore adopted for this study in order to gain an understanding of climate change adaptation in forestry from local stakeholders with an educated interest in the topic.

The results of this research will have strong implications for forest management and policy in the Asia-Pacific region, as this study aims to help determine the most important climate change impacts to be addressed and the type of management practices to be applied in different sub-regions. The results will highlight differences in opinions between different professional affiliations and may lead to insightful explanations for the ineffectiveness of current adaptation policies, as well as recommendations for improvement. This research will also provide valuable suggestions for how research findings and management recommendations could be communicated, depending on the location of the research and the professional affiliation of the reader/listener. This will help to ensure that scientific findings and management recommendations are communicated in the most relevant, effective way and lead to successful implementation of forest adaptation strategies.

Methods

Study area

For the purposes of this study, the Asia-Pacific region includes five subregions: North America, East Asia, Oceania, South Asia, and Southeast Asia (Fig. 1).

The climate in North America ranges from the tropics to frozen tundra in the north, and this subregion hosts a variety of forest types, including boreal forest, temperate rainforest, and deciduous forest. The main climate change impacts include decreases in snowpack causing water resource stress, increases in coastal flooding, pest and forest fire outbreaks, and crop damage and yield losses due to increases in extreme weather (Hijioka et al. 2014). East Asia is characterized mainly by a subtropical climate with both winter and summer monsoons. This subregion contains temperate deciduous, subtropical evergreen, and boreal forests, and the main climate change impacts include increased flooding, vulnerability of coastal zones to sea level rise, reduced yields due to drought and water shortages, and increases in intensity of summer monsoons and heat waves (Westphal et al. 2013; Hijioka et al. 2014). Oceania exhibits a range of climates from moist tropical monsoon to arid, moist temperate and is affected by tropical cyclones. This subregion has tropical and subtropical forests, and the main climate change impacts are changes in rainfall intensity, increases in tropical cyclone intensity, sea level rise, and increases in forest fire frequency

Fig. 1 Study area: the Asia–Pacific region



(Hijioka et al. 2014; IPCC 2014). South Asia ranges from a tropical monsoon climate in the south to temperate in the north, with tropical forests in the south and semi-desert and alpine ecosystems in the north. The main climate change impacts are increases in heavy precipitation and flooding, and extreme temperatures and drought leading to food and water shortages (Hijioka et al. 2014; IPCC 2014). South-east Asia has a mainly humid tropical climate and this sub-region is largely covered in tropical forests. Climate change concerns include increases in events such as fire, landslides, floods, and droughts, as well as sea level rise threatening coastal and marine resources (Asia Development Bank 2009; Hijioka et al. 2014).

Questionnaire design

The questionnaire consisted of 15 qualitative and quantitative questions derived from four overarching research questions: (1) What are the main impacts of climate change in the Asia–Pacific region?; (2) What climate change-related actions/policies are available in the Asia–Pacific region?; (3) What are the challenges of adapting forestry to

climate change in the region?; and, (4) How can current actions to adapt forestry to climate change be improved?

All respondents completed the questionnaire voluntarily and all responses were confidential and anonymous. The first section asked the respondents general information about themselves, including their current country, city, and professional position. The second section examined respondents' perceptions of climate change, including their opinion about possible negative and positive consequences and economic sectors that might be affected. Respondents were then asked whether they were satisfied with adaptation measures taken to address climate change and to indicate their subregion's involvement in international initiatives addressing climate change.

The third section focused on forest adaptation. Respondents were asked if there are initiatives in place to help adapt the forestry sector to climate change, and if so, to rank their satisfaction with these initiatives. This section also examined the impacts of climate change on forestry and challenges in adapting the forestry sector to climate change. Additionally, respondents indicated if and what forest planning tools and climate models were available, if there are policies to promote sustainable forest

management, and what areas lack scientific support in their subregion. In the final section, respondents were asked to rank various actions for addressing climate change, from least to most important.

Sampling method

Survey participants consisted of forestry and climate change experts from various disciplines and countries throughout the Asia–Pacific region. Paper-based questionnaires were distributed and collected from attendees at three international conferences, namely the Workshop of Sustainable Forestry Management in a Changing Climate in Kunming, China, July 2013; the 25th session of the FAO Asia–Pacific Forestry Commission in New Zealand, November 2013; and the Asia Forestry Summit in Indonesia, May 2014 (Table 1). Paper-based questionnaires were also distributed in September 2015 at a seminar of visiting Chinese scholars at the University of British Columbia in Vancouver, Canada. The remaining participants were contacted through an email containing the link to an online survey that was identical to the paper questionnaire. In total, 1250 questionnaires were distributed starting in July 2013, and 206 questionnaires were collected by October 2015 across 31 countries, giving a response rate of 16.5%. Over 200 questionnaires were valid (had complete answers) and were used for this analysis.

Data analysis

A questionnaire pretest was conducted with 15 individuals prior to its distribution to ensure questions were effective, clearly worded, and accurately reflected the desired information. Questionnaire respondents were grouped into the five subregions based on FAOSTAT guidelines ([http://](http://faostat.fao.org/site/371/default.aspx)

faostat.fao.org/site/371/default.aspx). Respondents were also grouped by profession—government, academic (including professor, student or researcher), and private sector (including community/non-governmental organizations (NGOs) or business person).

Questionnaire responses were input into the software Statistical Package for the Social Science (SPSS), version 23. Data entry was checked for accuracy every five questionnaires to ensure reliability. Responses were analyzed using descriptive and frequency analyses, and the significance of key variables was tested using several nonparametric tests. The methods used here assume independence of observations, meaning that the answers of one respondent do not impact the answers of another. The Chi squared test was used for questions where respondents could select multiple response variables to determine if there were differences among groups in the proportion of people that selected a given variable. When a Chi squared test was significant, we analyzed the adjusted standardized residuals of response proportions to identify the relationship yielding the significant difference. Since this analysis was performed many times, there is a greater risk of false positives (type 1 error). Therefore, statistical significance was determined as follows: for overall analyses, a significance level of $p \leq 0.05$ was used; for analyses by subregion, an adjusted significance level of $p_{\text{bonf}} \leq 0.05/5 = 0.01$ was used; and for analysis by profession, an adjusted significance level of $p_{\text{bonf}} \leq 0.05/3 = 0.017$ was used.

This type of analysis may generate cases where the initial Chi squared test is significant, indicating group differences, but none of the subsequent adjusted residual statistics are significant. Groups can be significantly different because of one large difference or several smaller differences, and in the latter case, it may not be possible to conclusively identify the source of the difference. This can

Table 1 Summary of distribution and response rate of the questionnaire

Means	Distribution	Date	Location	N distributed	N collected	Response rate (%)
Paper-based	Workshop of Sustainable Forestry Management in a Changing Climate	July 2013	Kunming, China	135	48	35.6
	25th Session of the FAO Asia–Pacific Forestry Commission	Nov. 2013	New Zealand			
	Asia Forestry Summit	May 2014	Jakarta, Indonesia			
	Faculty of Forestry Visiting Chinese Scholar Seminar	Sept. 2015	UBC, Vancouver, Canada			
Electronic	Email & online survey	Nov. 2013–Aug. 2014 June 2015–Sept. 2015	N/A	1115	158	14.2
Total				1250	206	16.5

explain the results (provided below) that indicate a significant Chi squared test but a non-significant residual analysis. We used the Kruskal–Wallis test for questions where multiple response variables could be selected. This test was chosen based on its advantages of establishing statistical significance of a sample that does not follow a distribution with unspecified parameters. In one analysis, we followed the Kruskal–Wallis analysis with a Mann–Whitney U-test to investigate if there was a significant difference between pairs of subregions and professions; these pairwise tests used an adjusted p value.

Results

Description of respondents

Responses are summarized in Table 2 by subregion and professional position. The largest proportion of respondents were from Southeast Asia, and when grouped by profession, the largest proportion of respondents were academics.

Climate change in the Asia–Pacific

The survey included several general questions about climate change concerns and policies/initiatives in the region in order to better understand varying regional contexts. Respondents ranked their level of concern from ‘1—not

concerned’ to ‘5—very concerned’ for various impacts of climate change. There was variability among subregions in the level of concern for a given impact (Table 3). ‘Drought’ had the highest mean ranking overall ($M = 4.02$, $SD = 1.12$) and among South Asian ($M = 4.54$, $SD = 0.83$) and Southeast Asian ($M = 4.40$, $SD = 0.89$) respondents, followed closely by ‘flooding’ ($M = 4.00$, $SD = 1.16$), which was ranked highest in Oceania ($M = 4.15$, $SD = 1.20$) and East Asia ($M = 4.07$, $SD = 1.12$). North American respondents differed in that, on average, they ranked ‘forest disturbance’ to be their main concern ($M = 3.60$, $SD = 0.94$).

Regarding the positive impacts of climate change, the highest percent of responses overall was for “I don’t know” (25.6%) followed by “improving growth of forests” (22.6%) (Fig. 2). There was a significant relationship between subregion and selection of ‘improving growth of forests’ (Chi squared test; $\chi^2 = 18.28$, $df = 4$, $p = 0.001$) (Fig. 3a) and ‘less need for energy consumption’ ($\chi^2 = 15.64$, $df = 4$, $p = 0.004$) as positive consequences (Fig. 3b). North America had a significantly higher percentage of respondents select ‘improving growth of forests’ (47.9%; $\chi^2 = 8.41$, $p_{\text{Bonf}} = 0.004$) and ‘less need for energy consumption’ (38.1%; $\chi^2 = 9.06$, $p_{\text{Bonf}} = 0.003$) compared to other subregions. The average number of positive consequences differed significantly by region (Kruskal–Wallis test; $H = 11.42$, $df = 4$, $p = 0.022$), with the greatest difference being between North America ($M = 1.48$, $SD = 0.98$) and Oceania ($M = 0.88$, $SD = 0.76$).

Agriculture (92.5%) and forestry (79.1%) were considered the two economic sectors most directly affected by climate change overall (Fig. 4), as well as regionally and professionally (Table 4). Regionally, there were significant differences in the percent of respondents who indicated that ‘agriculture’ (OC = 100%, SA = 95.8%, SEA = 95.3%, NA = 95.2%, EA = 79.5%) ($\chi^2 = 14.47$, $df = 4$, $p = 0.006$) and ‘fisheries’ (NA = 66.7%, SEA = 63.5%, OC = 59.3%, SA = 54.2%, EA = 31.8%) ($\chi^2 = 13.42$, $df = 4$, $p = 0.009$) would be directly affected by climate change (Fig. 4), with East Asia having a significantly lower level of concern for both economic sectors ($\chi^2 = 13.77$, $p_{\text{Bonf}} = 0.0002$; $\chi^2 = 12.48$, $p_{\text{Bonf}} = 0.0004$, respectively) (Table 4). There was also a significant difference in the average number of affected sectors selected among regions ($H = 15.565$, $p = 0.004$) and among professions ($H = 9.95$, $p = 0.007$). The greatest average number selected were for North America ($M = 3.90$, $SD = 1.41$) and private sectors ($M = 4.16$, $SD = 1.36$), with the lowest occurring for East Asia ($M = 2.82$, $SD = 1.43$) and academics ($M = 3.26$, $SD = 1.47$).

The Kyoto Protocol was the international initiative indicated to have the most involvement across all responses (81.2%). Involvement in the Protocol ranked highest

Table 2 Percentage of respondents by region and professional position

Region	Respondents (%)
South Asia (SA)	11.9
Southeast Asia (SEA)	42.3
Eastern Asia (EA)	21.9
Oceania (OC)	13.4
North America (NA)	10.4
Professional position	
Government	22.4
Academic	62.2
Professor	29.9
Researcher	29.9
Student	2.5
Private sector	15.4
NGO	7.0
Business person	3.0
Other	5.4

Table 3 Ranking for various climate change impacts based on average level of concern—overall and by subregion

Impact	Overall	NA*	EA	OC	SA	SEA
Drought	1	6	1	1	3	2
Flooding	2	4	5	2	1	1
Freshwater shortage	3	10	2	5	2	3
Forest disturbance	4	1	3	6	4	4
Fire hazard	5	2	6	3	8	5
Spread of insects	6	3	4	8	6	8
Spread of disease	7	5	7	9	5	7
Rising sea level	8	8	10	4	10	6
Storms and tornadoes	9	7	8	7	9	9
Melting of ice, snow and avalanches	10	9	9	10	7	10

*Subregion abbreviations are the same as in Table 2. Units are ranked from 1 (of most concern) to 10 (of least concern), based on sub-regionally organized responses

Fig. 2 Overall percent of responses for each option associated with the question ‘Any positive consequences of climate change in your region? (Check all that apply)’

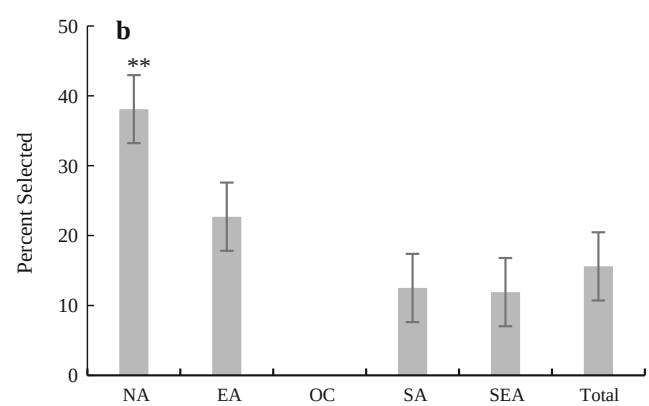
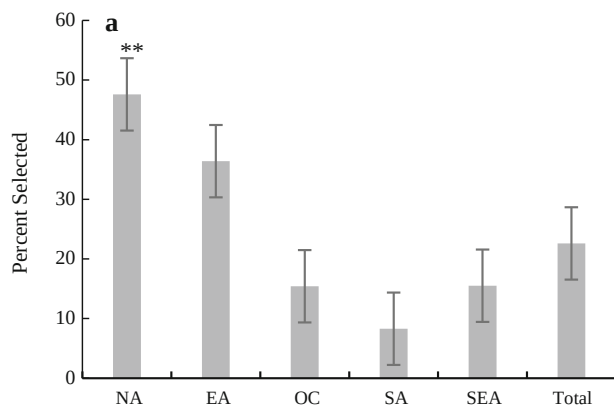
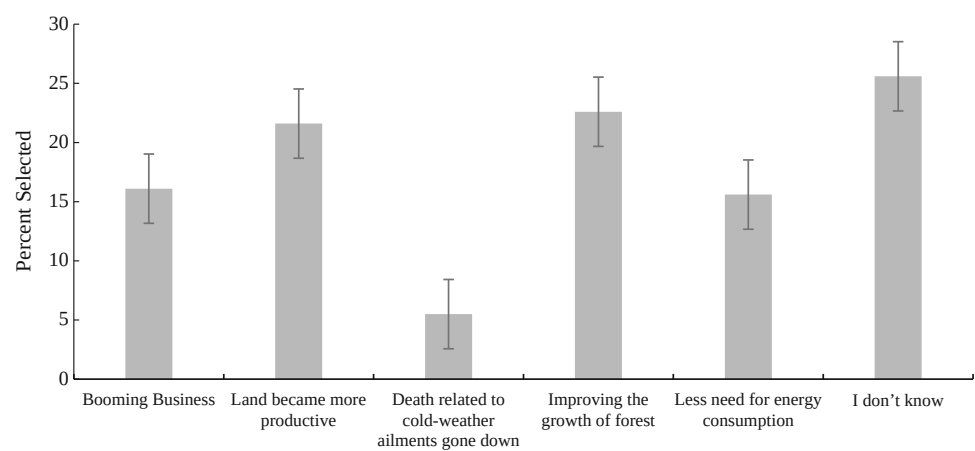


Fig. 3 Percent of responses by subregion associated with the selection of the variables (a) ‘improving growth of forests’ and (b) ‘less need for energy consumption’ for the question ‘Any positive consequences of climate change in your region?’. A significant ($p \leq 0.005^{**}$) relationship was found between subregion and selection of ‘improving growth of forests’ and ‘less energy consumption’

among all subregions except East Asia (63.6%), which had significantly less involvement ($\chi^2 = 16.72$, $df = 4$, $p = 0.002$) ($\chi^2 = 13.05$, $p_{\text{bonf}} = 0.0003$). Subregions also

as positive consequences of climate change. In the case of both variables, North America contributed most significantly ($p_{\text{Bonf}} \leq 0.01^*$) to the relationship, implying that North American respondents indicated these variables as positive consequences more often than other subregions. Subregion abbreviations are the same as in Table 2

differed significantly in their involvement in International Strategies for Disaster Reduction (UNISDR) ($\chi^2 = 20.90$, $df = 4$, $p \leq 0.001$). No North American respondents

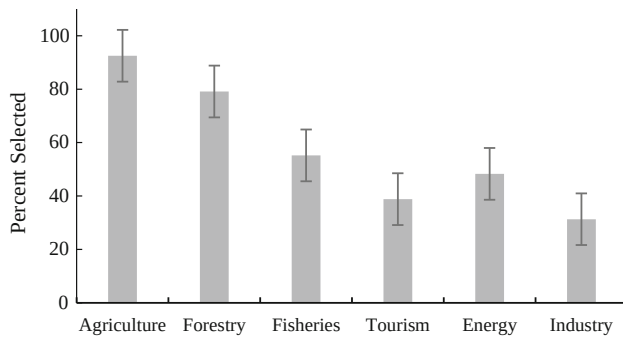


Fig. 4 Overall percent of responses for each option associated with the question ‘Which economic sectors do you think would be directly affected most by climate change? (Check all that apply)’

Table 4 Ranking of economic sectors most directly affected by climate change according to the average percent of responses—overall and by subregion

Economic sectors	Overall	NA	EA	OC	SA	SEA
Agriculture*	1	1	1	1	1	1
Forestry	2	2	2	2	2	2
Fisheries*	3	3	4	3	4	3
Energy	4	5	3	4	5	4
Tourism	5	4a	6	5	3	5
Industry	6	4a	5	6	6	6

There is a significant ($p \leq 0.05^*$) relationship between subregion and respondents selecting ‘agriculture’ and ‘fisheries’ as the sectors affected most by climate change. East Asia is the subregion contributing most significantly ($p_{\text{bonf}} \leq 0.001^{**}$) to this relationship, implying that respondents from this subregion are less likely to indicate these two sectors as being affected by climate change

Note: Subregion abbreviations are the same as in Table 2

a indicates a tie in the percent of respondents that selected the sector

selected UNISDR (0.0%; $v^2 = 9.98$, $p_{\text{bonf}} = 0.0016$), while South Asia had significantly higher selection than the other subregions (54.2%; $v^2 = 7.70$, $p_{\text{bonf}} = 0.0055$). The subregions differed significantly in the average number of selected initiatives that they were involved in ($H = 15.68$, $p = 0.003$), with North America averaging the least ($M = 1.85$, $SD = 0.85$) and South Asia the most ($M = 2.79$, $SD = 0.83$).

Climate change and forest adaptation in the Asia-Pacific

‘Changes in forest fire/drought’ was most frequently indicated as the major impact of climate change on forest ecosystems overall and by respondents in Oceania, Southeast Asia, and East Asia (Table 5). This was followed closely by ‘biodiversity changes’, which differed

significantly between subregions ($v^2 = 12.94$, $df = 4$, $p = 0.012$) (Fig. 5a), with the significance being due to a higher response by respondents from South Asia ($v^2 = 8.33$, $p_{\text{bonf}} = 0.0039$). Subregions differed significantly in their opinion of pest outbreaks ($v^2 = 27.88$, $df = 4$, $p \leq 0.001$), with North American respondents selecting this as an impact significantly more frequently ($v^2 = 17.56$, $p_{\text{bonf}} = 0.00003$) and Southeast Asian respondents significantly less frequently ($v^2 = 16.43$, $p_{\text{bonf}} = 0.00005$) (Fig. 5b). Although ‘disease spread’ had the lowest frequency overall, there was a significant difference between subregions in the percent of responses indicating it as a major impact ($v^2 = 13.75$, $df = 4$, $p = 0.008$), with the highest percent of responses from East Asia ($v^2 = 8.27$, $p_{\text{bonf}} = 0.0040$) and lowest from Southeast Asia ($v^2 = 7.26$, $p_{\text{bonf}} = 0.0071$) (Fig. 5c).

When analyzed by profession, there was a significant relationship between respondents’ profession and their view that ‘forest productivity changes’ ($v^2 = 7.055$, $df = 2$, $p = 0.029$), ‘changes in forest fires/droughts’ ($v^2 = 8.98$, $df = 2$, $p = 0.011$), and ‘biodiversity changes’ ($v^2 = 6.94$, $df = 2$, $p = 0.031$) are the major impacts of climate change in forest ecosystems (Table 6). The significance of ‘changes in forest fires/droughts’ was associated with a lower percent of responses from the government group than from other professions ($v^2 = 8.96$, $p_{\text{bonf}} = 0.0028$), while the significance of ‘forest productivity changes’ and ‘biodiversity changes’ was due to the higher percent of responses by private sector respondents ($v^2 = 7.00$, $p_{\text{bonf}} = 0.0082$; $v^2 = 6.84$, $p_{\text{bonf}} = 0.0089$, respectively).

The majority of respondents indicated that ‘yes’ actions or initiatives have been taken to address climate change in their subregion (Fig. 6a), and ‘yes’ there are specific policies or regulations available in their subregion that promote sustainable forest management (SFM) (Fig. 6b). Satisfaction with actions to address climate change were gauged among those who selected ‘yes’ from “1—very satisfied” to “5—not satisfied at all”, yielding an overall mean satisfaction of $M = 2.70$ ($SD = 0.937$), between ‘2—somewhat satisfied’ and ‘3—neither satisfied nor unsatisfied’. The indication that ‘yes’, policies and regulations that promote SFM are present was highest in North American and Southeast Asian respondents and among government respondents (Fig. 7). Although the majority indicated that policies specific to SFM exist in their subregion, 6% who specified a policy indicated that it exists only on paper and not in practice.

Satisfaction with actions to address climate change adaptation in respondents’ countries as well as in the forestry sector was gauged from ‘1—very satisfied’ to ‘5—not satisfied at all’. With regards to overall satisfaction with action to address climate change, there was a significant difference in the level of satisfaction among subregions

Table 5 Average ranking of responses by subregion for options to the question ‘What are the major impacts of climate change on forest ecosystems in your region? (Check all that apply)’

Impacts	Overall	NA	EA	OC	SA	SEA
Changes in forest fires/droughts	1	2	1	1	4	1
Biodiversity changes*	2	3	2a	2a	1	2
Forest productivity changes	3	4	5a	5	3	3
Land suitability changes	4	6	5a	2a	2	4
Changes in pest outbreak**	5	1	4	4	5	5
Disease spread*	6	5	2a	6	6	6
Other	7	7	7	7	7	7

There is a significant relationship between ‘biodiversity change’ ($p \leq 0.05^*$), ‘pest outbreaks’ ($p \leq 0.005^{**}$) and ‘disease spread’ ($p \leq 0.05^*$) with subregion

Note: Subregion abbreviations are the same as in Table 2

Units are rankings of responses, organized from 1 (of most concern) to 7 (of least concern), based on sub-regionally organized responses

* indicates a significant relationship ($p \leq 0.05^*$) when evaluated by subregion

a indicates a tie in the percent of respondents that selected the impact

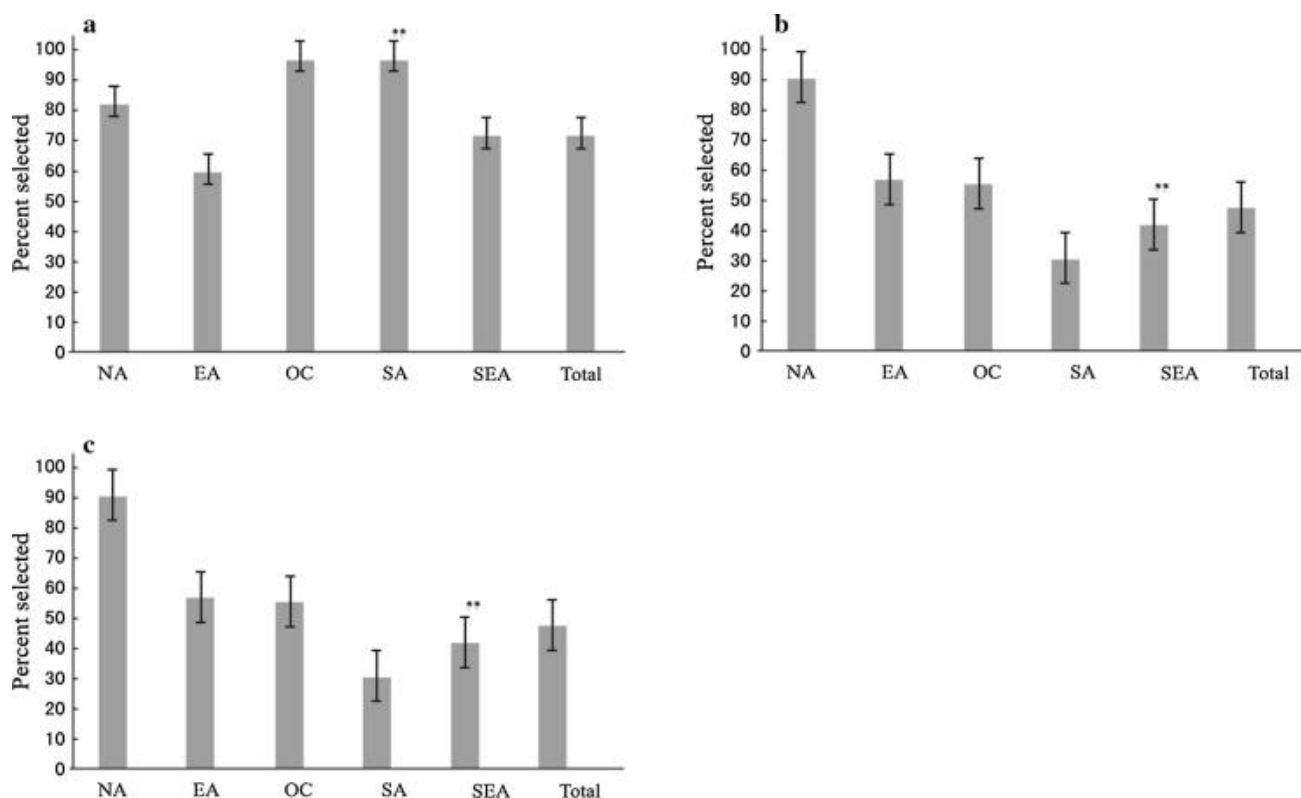


Fig. 5 Percent of responses by subregion associated with the selection of the variables (a) biodiversity change, (b) changes in pest outbreak, and (c) disease spread for the question ‘What are the major impacts of climate change on forest ecosystems in your region? (Check all that apply)’. The subregion contributing most significantly ($p_{\text{bonf}} \leq 0.001^{**}$) to the relationship with the variable is indicated

($H = 18.49$, $p = 0.001$) (Fig. 8); no respondents from North America, Southeast Asia, government, or the private sector selected ‘1—very satisfied’ for this question. However, mean satisfaction with actions to address climate

above. This implies that South Asian respondents are more likely than other subregions to select ‘biodiversity change’, North American respondents are more likely to select ‘pest outbreaks’, and Southeast Asian respondents are less likely to select ‘pest outbreaks’ and ‘disease spread’ as a major impact of climate change. Subregion abbreviations are the same as in Table 2

change specific to the forestry sector was fairly similar among subregions (Fig. 8a) and among professions (Fig. 8b). There was a slightly more positive mean satisfaction with regards to initiatives in the forestry sector

Table 6 Percent of responses by profession to the question ‘What are the major impacts of climate change on forest ecosystems in your region? (Check all that apply)’

Challenges	Overall (%)	Government (%)	Academic (%)	Private sector (%)
Changes in forest fires/droughts*	71.1	53.3	76.0	77.4
Biodiversity changes*	70.6	68.9	66.4	90.3
Forest productivity changes*	55.7	53.3	51.2	76.4
Land suitability changes	55.2	60	52.8	58.1
Changes in pest outbreak	47.3	35.6	48.0	61.3
Disease spread	40.3	33.3	38.4	58.1

Three of the impacts show a significant ($p \leq 0.05^*$) relationship with profession. In the case of ‘forest fires/drought’, government respondents contributed most significantly ($p_{\text{bonf}} \leq 0.017^*$) to the relationship, implying that they are less likely to indicate this as an impact of climate change. For ‘forest productivity changes’ and ‘biodiversity changes’, private sector respondents contributed most significantly ($p_{\text{bonf}} \leq 0.017^*$)

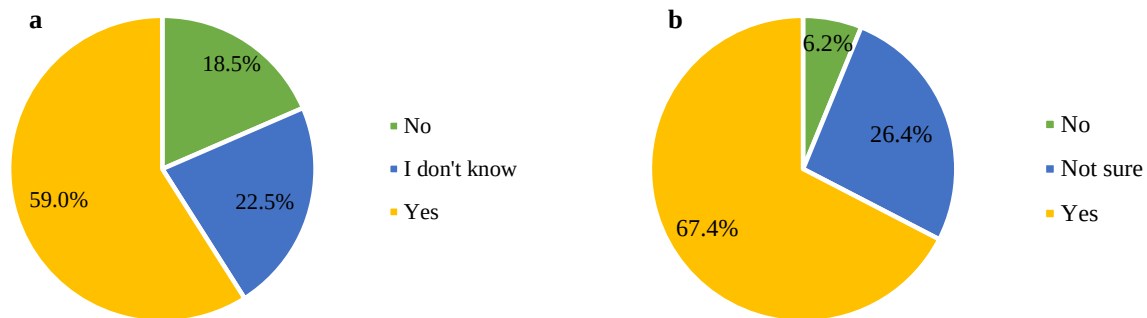


Fig. 6 Distribution of responses to the questions, a Are there any actions or initiatives that have been taken to adapt to climate change in the forestry sector in your subregion?, and b Are there any specific

policies or regulations in your subregion that promote sustainable forest management?

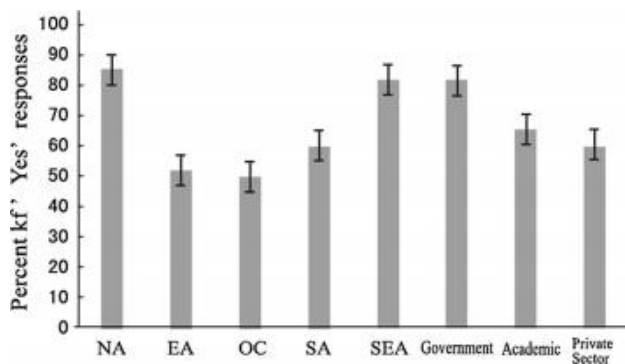


Fig. 7 Percent of respondents from each subregion and profession that indicated ‘yes’ there are specific policies or regulations in their subregion that promote sustainable forest management. Subregion abbreviations are the same as in Table 2

($M = 2.70$, $SD = 0.937$), with the mean lying between ‘2 – somewhat satisfied’ and ‘3 – neither satisfied nor unsatisfied’, as compared to climate adaptation action at the country level ($M = 3.28$, $SD = 1.8$), with the mean lying between ‘3 – neither satisfied nor unsatisfied’ and ‘4 – somewhat unsatisfied’.

The most frequently selected challenge for the forestry sector to adapt to climate change was ‘public awareness’ (63.7%), followed by a ‘lack of scientific guidance’

(59.2%) (Table 7). Among subregions, ‘public awareness’ was the most frequently selected challenge, except for North America and Oceania where ‘actions plans’ (76.2%) and ‘legislation’ (63.0%) were the most frequent, whereas all professions differed in the most frequently selected challenge for the sector to adapt to climate change (Table 7). There was a significant difference among subregions in the percent of responses for ‘public awareness’ ($\chi^2 = 14.50$, $df = 4$, $p = 0.006$), with the significance being due to a low selection of this variable among Oceania respondents ($\chi^2 = 9.57$, $p_{\text{bonf}} = 0.002$) (Fig. 9a). The challenge of ‘stakeholders’ participation’ differed significantly among professions ($\chi^2 = 6.76$, $df = 2$, $p = 0.034$) (Fig. 9b). Although the profession associated with this difference was not discernable based on adjusted residual analysis, the concern tended to be higher for the private sector (71.0%) and lower for academics (48.8%). Furthermore, there was a significant difference in the number of challenges selected by each subregion ($H = 12.42$, $p = 0.014$), with North America on average selecting the most ($M = 3.43$, $SD = 1.12$) and Oceania on average selecting the least ($M = 2.37$, $SD = 1.08$).

Respondents were asked to select areas that lack scientific support that could help address climate change

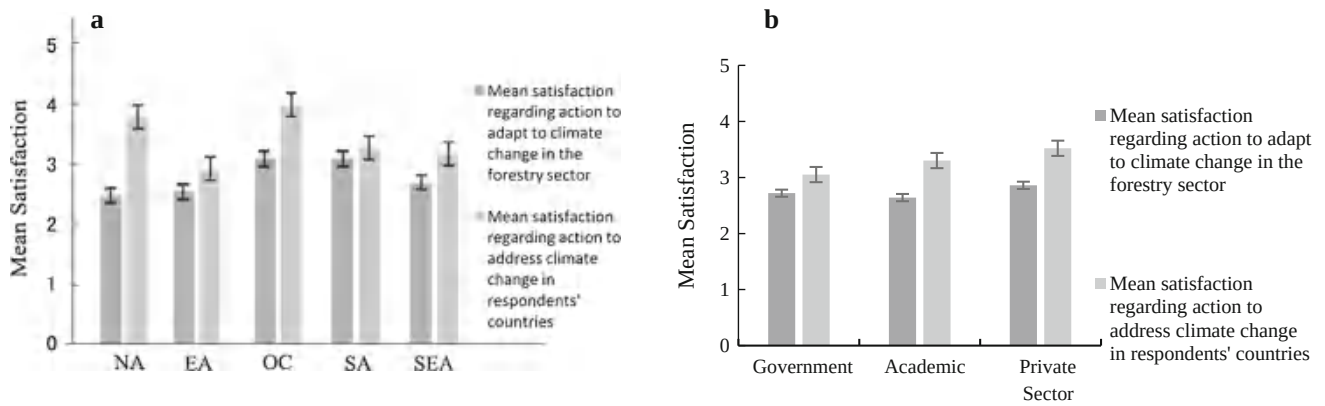


Fig. 8 Mean satisfaction by a subregion and b profession regarding action taken to adapt to climate change in the forestry sector (dark grey), and in the respondents' countries (light grey). Subregion abbreviations are the same as in Table 2

Table 7 Challenges for the forestry sector to adapt to climate change ranked according to percent of responses—overall, by subregion, and by profession

Challenges	Overall	NA	EA	OC	SA	SEA	Government	Academic	Private sector
Public awareness*	1	2a	1	4	1	1	1	2	3
Lack of scientific guidance	2	3	2	3a	2	2	3	3	1
Legislation	3	2a	3a	1	4	5	5	1	5
Action plans	4a	1	3a	2	5	4	4	4	4
Stakeholders participation*	4a	3	4	3a	3	3	2	5	2

There is a significant ($p \leq 0.05^*$) relationship between selection of public awareness and subregion, and a significant relationship ($p \leq 0.017^*$) between selection of stakeholders' participation and profession

Note: Subregion abbreviations are the same as in Table 2

Units are rankings of responses, organized from 1 (of most concern) to 5 (of least concern) based on sub-regionally organized responses

a indicates a tie in the percent of respondents that selected the challenge

* indicates a significant relationship ($p \leq 0.05^*$) when evaluated by subregion

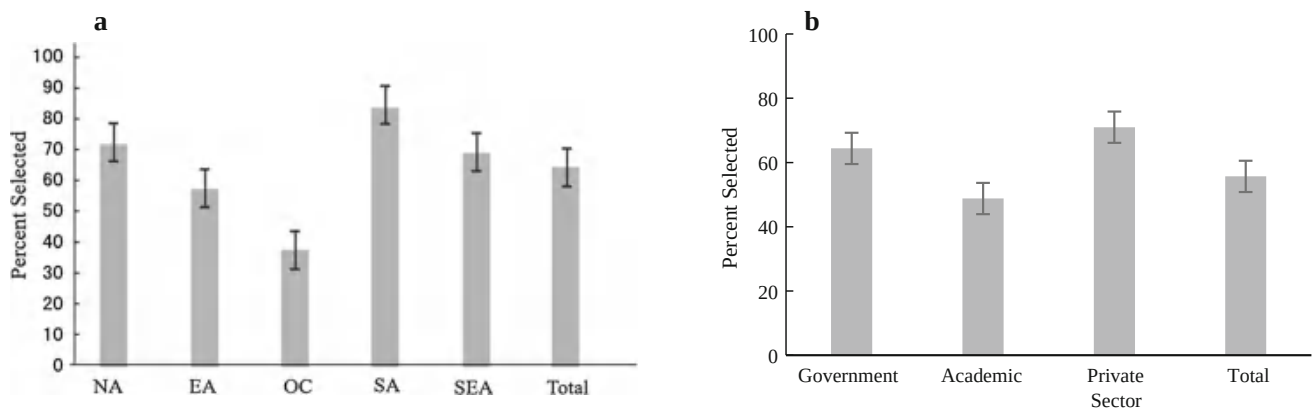


Fig. 9 Percent of respondents from: a each subregion that selected 'public awareness' and from b each profession that selected 'stakeholders' participation' in response to the question 'What are the most important challenges for the forestry sector to adapt to climate change in your subregion (check all that apply)?'. In the case of 'public awareness', Oceania contributed most significantly

($p_{\text{bonf}} \leq 0.017^*$) to the relationship, implying that these subregional respondents were less likely to select 'public awareness' as a challenge for forest adaptation. In the case of 'stakeholders' participation', no single profession was responsible for the relationship. Subregion abbreviations are the same as in Table 2

adaptation. ‘Understanding of local predicted climate change scenarios’ received the highest response percent (69.2%) (Table 8) among all professions (government = 71.1%, academic = 63.2%, private sector = 83.9%), and subregions, with the exception of Oceania (South Asia = 87.5%, North America = 71.4%, Southeast Asia = 69.4%, East Asia = 63.6%, Oceania = 51.9%). ‘Understanding ecosystem dynamics’ was the most frequently selected response among Oceania respondents (63.0%). There was a significant difference in the average number of responses selected among subregions ($H = 17.27$, $p = 0.002$) and professions ($H = 10.24$, $p = 0.006$); SA ($M = 3.58$, $SD = 1.25$) [on average selected significantly more variables] compared to Oceania ($M = 2.15$, $SD = 1.32$), and the private sector selected on average ($M = 3.34$, $SD = 1.38$) significantly more variables than academics ($M = 2.49$, $SD = 1.43$). There was a significant relationship between subregion and selection of ‘knowledge on climate change’ ($\chi^2 = 14.36$, $df = 4$, $p = 0.006$). South Asia (58.3%) had the highest response percent while Oceania (22.2%) had the lowest; however, the specific subregion or subregions contributing to the significant relationship is unclear as the adjusted residual analysis was inconclusive.

When inquiring if climate change models and planning tools for developing forest management plans that address climate change were available in the subregion, ‘I don’t know’ was the most common overall response (41.2% and 45.7%, respectively) (Fig. 10). This was also true subregionally, with two exceptions regarding model development; the majority of Oceania respondents indicated ‘Yes’ (65.4%), and there were equal responses between ‘I don’t know’ and ‘Yes’ (47.6%) for North America. Regarding the availability of climate change models, 65.7% of respondents indicated that only ‘some’ or ‘no’ models were publically available; 41.2% of respondents did not know the suitability of these models for forest management planning. With regards to forest management planning tool

availability, no respondents from North America indicated that ‘high resolution climate models of the region’ were available.

Suggestions for addressing climate change

Respondents were asked to rank the importance of 5 different actions for addressing climate change on a scale from ‘1—least important’ to ‘5—most important’. Out of 201 responses, 178 respondents answered this question completely. When analyzed by subregion, there were significant differences regarding the rankings for ‘governance and institutions’ ($H = 17.34$, $p = 0.002$, $df = 4$) and ‘climate change expert networks and cooperation’ ($H = 14.57$, $p = 0.006$, $df = 4$), which had overall means of $M = 4.19$ ($SD = 1.08$) and $M = 3.58$ ($SD = 1.23$), respectively. Southeast Asian respondents showed significantly higher concern for ‘governance and institutions’ than East Asian respondents (Mann–Whitney U-test; $U = 35.33$, $p = 0.001$) (Fig. 11a). North American respondents had a significantly higher average concern regarding ‘climate change expert networks’ than South Asia ($U = 52.54$, $p = 0.012$), Southeast Asia ($U = 49.56$, $p = 0.003$), and East Asia ($U = 44.15$, $p = 0.026$) (Fig. 11b).

There was a significant difference in overall mean ranking by action ($H = 40.68$, $df = 4$, $p \leq 0.001$) (Fig. 12), as ‘climate change expert networks and cooperation’ was ranked significantly lower than all other variables: ‘scientific support’ ($U = 94.26$, $p = 0.006$), ‘management guidance’ ($U = 117.02$, $p \leq 0.001$), ‘legislation and policies’ ($U = 144.04$, $p \leq 0.001$), and ‘governance and institutions’ ($U = 151.23$, $p \leq 0.001$).

Table 8 Ranking of areas lacking scientific support to address climate change adaptation based on average response percent—overall and by subregion

Scientific area	Overall	NA	EA	OC	SA	SEA
Understanding of local predicted climate change scenarios	1	1	1	2a	1	1
Forest adaptation and/or rehabilitation techniques	2	2	2	2a	3	2
Understanding of ecosystem dynamics	3	3	3	1	2	3
Knowledge on climate change*	4	4	5	4	4a	4
Sophisticated climate models	5	5	4	3	4a	4

There is a significant ($p \leq 0.05^*$) relationship between subregion and selection of ‘knowledge on climate change’ as an area lacking scientific support

Units are rankings of responses to question from 1 (of most concern) to 5 (of least concern), based on subregionally organized responses

Note: Subregion abbreviations are the same as in Table 2

a indicates a tie in the percent of responses

* indicates a significant relationship ($p \leq 0.05^*$) when evaluated by subregion

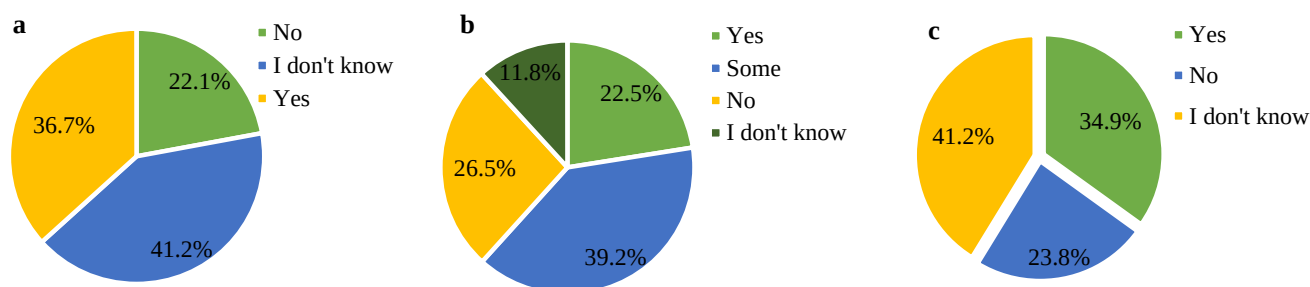


Fig. 10 Distribution of responses to the questions a Have any climate change models been developed in your region? b If yes to the previous question, does the public have access to the climate change

models? and c If yes to the first question, are the models suitable for forest management planning?

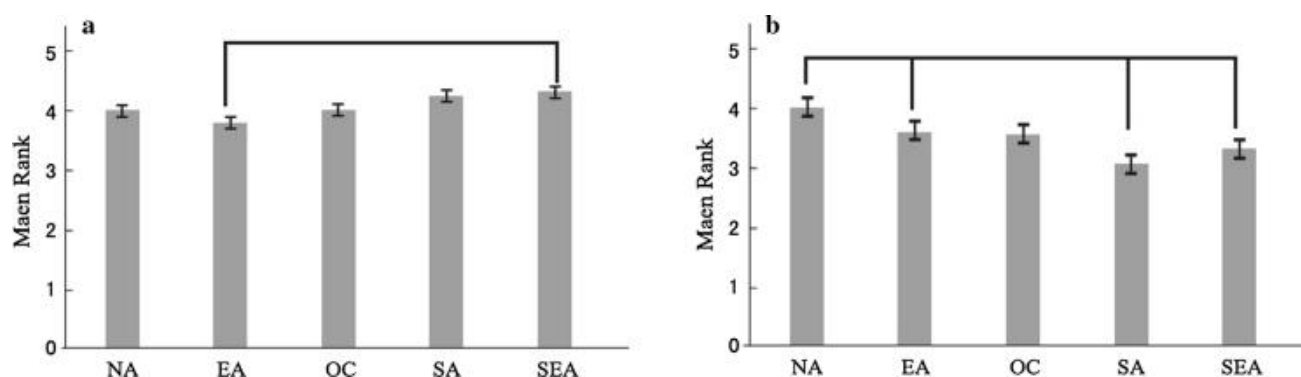


Fig. 11 Mean rank of importance by subregion for (a) 'governance and institutions' to address climate change, and (b) 'climate change expert networks and cooperation' to address climate change. SEA respondents ranked governance and institutions significantly

($p < 0.005^{**}$) higher than EA, and NA ranked expert networks significantly ($p < 0.05^{*}$) higher than SA, SEA, and EA. Subregion abbreviations are the same as in Table 2

Discussion

Main impacts of climate change

The objective of this survey was to identify expert perspectives on the impacts of climate change in the Asia-Pacific region, and to explore current challenges, recommendations and initiatives for adapting regional forests to climate change. As expected, there are subregional and professional differences in opinion regarding the impacts of climate change related to economic and forestry activities, as well as different challenges faced by groups regarding the availability of research and technology and their ability to move forward with adaptation and mitigation activities. However, there are also similarities present among subregions and professions, indicating that similar steps can be taken to resolve these issues across regional and professional sectors.

Although specific concerns about climate change varied by subregion, there was a common concern regarding hydrological related issues such as drought, flooding, and freshwater shortages. The Asia-Pacific is a region adapted to, and reliant on, seasonal rainfall patterns driven by

monsoons, with cyclic variability driven primarily by the El-Nino-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) (IFAD 2009; Christensen et al. 2013). Climate change is expected to alter these climate systems, causing shifts in their arrival times and intensities, leading to variable impacts in the region such as flooding, drought, and greater intensity and frequency of extreme weather events such as tropical cyclones (FAO 2010; Ahmed and Suphachalasai 2014). Although flooding was of highest concern in South Asia and Southeast Asia, the literature suggests that these subregions are also vulnerable to drought and water-stress as a result of climate change (IFAD 2009; Loo et al. 2015). The selection of 'flooding' as more of a concern than 'drought' by these subregions highlights that broad-scale projections and patterns may not match local circumstances and concerns. The respondents may be located in areas within the region more prone to flooding, while other areas will experience drought. Variability within subregions is expected, as the impacts of climate change will differ seasonally and among river basins (Westphal et al. 2013; Hijioka et al. 2014), and shifting rainfall patterns may leave some areas inundated with water and some in extreme drought (The World Bank 2013). As such, forest management efforts across the

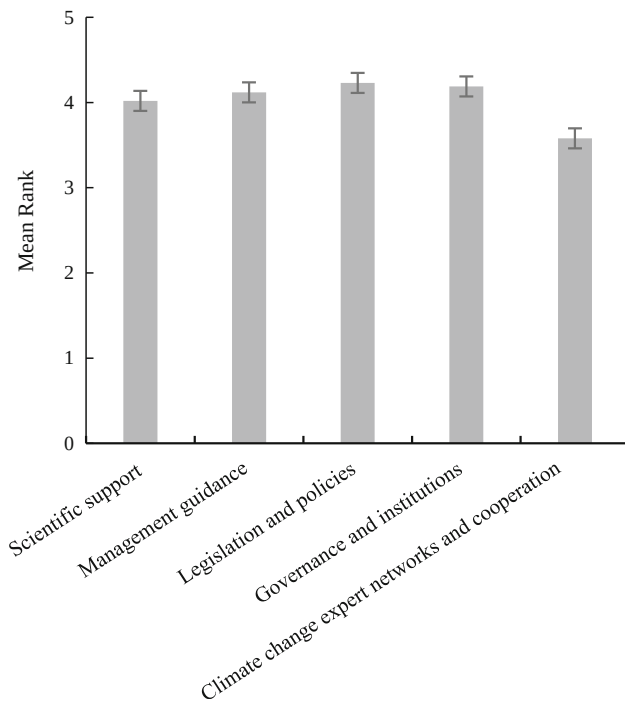


Fig. 12 Mean rank of importance of actions to address climate change. ‘Climate change expert networks and cooperation’ was ranked significantly lower than ‘scientific support’ ($p \leq 0.05^*$), ‘management guidance’ ($p \leq 0.005^{**}$), ‘legislation and policies’ ($p \leq 0.005^{**}$), and ‘government and institutions’ ($p \leq 0.005^{**}$)

region may benefit from research into locally specific climate change impacts such as changes in rainfall patterns. The application of locally specific, high accuracy climate and ecological models (e.g., those used by Wang et al. 2016a, b) are essential to generate accurate predictions that can be used to tailor future management strategies to address ecosystem vulnerability.

The generally positive impact of climate change on forest productivity (Boisvenue and Running 2006) was recognized by respondents. Acknowledgement of this potential benefit creates an opportunity for forest managers and researchers to explore ways to maximize it. For instance, niche modelling in China has shown how the niches of ecologically and economically important tree species will shift spatially and temporally with climate change (Wang et al. 2016a, b). The use of ecological models, such as FORECAST Climate (Seely et al. 2015), can be used to evaluate the long-term impacts of climate change and forest management strategies on forest productivity (Kang et al. 2016), and trade-offs between economic and ecosystem-related factors [e.g., using the Landscape Summary Tool (LST)] can be analyzed to determine the best possible management strategies under climate change (Kang et al. 2016). This type of locally specific analysis can be used to develop long-term management strategies such as plantation development and

reforestation projects in accordance with habitat suitability for species that capitalize on changes in climate to maximize productivity and maintain ecosystem vitality.

Agricultural production and forest ecosystem stability are particularly vulnerable to changes in climate (FAO 2012b; Hijioka et al. 2014), and this was reflected in the respondents’ comments that these sectors will be most affected by climate change. Although some crops in certain locations may be expected to see an increase in productivity [e.g., winter wheat in China (Hijioka et al. 2014)], increases in temperature and changes in precipitation patterns are expected to have an overall negative impact on agriculture and forestry in the Asia–Pacific region, resulting in lower crop yields, increased pest outbreaks, crop damage, changes in the length of the growing season, increased frequency of fires, and greater soil erosion (Asia Development Bank 2009; Hijioka et al. 2014). This in turn will impact the economic stability of these sectors which currently play a key role in sustaining the Asia–Pacific economy (Asia Development Bank 2009; FAO 2010). The populations of several subregions rely heavily on agriculture and forestry for their livelihoods; for instance, approximately 200 million people depend on non-timber forest products for income and subsistence needs (FAO 2010), and SEA’s agriculture industry employed 52.78% of the population and contributed to 12.57% of GDP in 2015 (OCED/FAO 2017). Agriculture and forestry are key areas of concern and importance across the Asia–Pacific region, and effort should be made to better understand the consequences of climate change on these sectors. Research regarding ecological, social, and economic impacts, as well as the interaction between these sectors under climate change, is necessary, particularly regarding the potential of agroforestry in maintaining more resilient and sustainable land-use systems (Verchot et al. 2007; Ong et al. 2015).

Results of this analysis show some consistency between subregions regarding the major impacts of climate change, with the most frequent responses concerning forest fires, drought, flooding, and biodiversity changes. The main disparity among subregions is a higher concern for pest outbreaks among North American respondents, which may be due to the Mountain Pine Beetle outbreak in western North America over the past two decades, making this a prominent concern. The outbreak has impacted over 18 million ha of Canadian pine forest (Natural Resources Canada 2016), while other Asia–Pacific subregions have not experienced the same recent, large-scale pest outbreaks. The high concern for biodiversity changes as an impact of climate change is expected, as the Asia–Pacific region contains some of the world’s most diverse ecosystems (CEPF 2016), including 13 of 34 biodiversity hotspots (UNEP 2010). However, the perceived severity of changes in biodiversity differed between regions, with South Asia

indicating the greatest concern. Although more biodiversity conservation research is conducted in South Asia than in Southeast Asia, there is substantially less literature on the subject from South Asia compared to East Asia, Oceania, and North America (Wilson et al. 2016). Given the high degree of concern for biodiversity, effort should be made to increase research focused on biodiversity conservation in South Asia. This, in conjunction with improved knowledge of the expected changes in climate in the subregion, will enable better understanding of the impacts of climate change on biodiversity, which may improve implementation of mitigation measures.

Tools for climate change adaptation and mitigation

High public awareness of the impacts of climate change is related positively to risk perception (Schulte and Miller 2010), which is critical for climate change adaptation and successful implementation of adaptation and mitigation strategies. Insufficient awareness about ecological requirements and sustainable management practices among forest-dependent communities may constrain their adaptive capacity for future climate change (FAO 2012a). In South Asia, education and awareness were great concerns, as ‘public awareness’ was the most frequently selected challenge and ‘knowledge on climate change’ was selected as most lacking scientific support. Research suggests that awareness of the existence of climate change in South Asian countries occurs in 30–39% of the population, while in Australia (the country having the majority of OC respondents), 97% of the population is aware of climate change (Lee et al. 2015). However, of the people who are aware of climate change in South Asia, the percentage of people who view climate change as a serious threat is between 80 and 89% (Lee et al. 2015). This is consistent with our findings that the challenge of public awareness related to climate change adaptation was lowest for Oceania and greatest for South Asia; although public awareness is low in South Asia, people who are aware of the issue such as this survey’s respondents elicit high levels of concern regarding the economic and environmental implications of climate change. Programs to educate the public, employees of vulnerable economic sectors, and government officials are needed to reduce the challenges posed by uninformed (or misinformed) people. One such program was developed by the Climate and Development Knowledge Network in partnership with Panos South Asia (Panos South Asia 2014). It focuses on increasing climate change awareness in South Asian media through increased capacity and knowledge of the reporters themselves, ultimately leading to improved coverage of climate change issues and increased public awareness. The priority respondents placed on the lack of public awareness overall

in the Asia–Pacific region suggests gaps in knowledge and understanding of the role of forests in climate change. More initiatives are needed across the region to reduce the hindrance that an uninformed public places on forest adaptation to climate change, particularly in South Asia where public awareness is of greatest concern.

Another important challenge for the forestry sector is to respond to a lack of scientific support, particularly a lack of understanding of locally predicted climate change scenarios. Variable adaptive capacities across the Asia–Pacific region (Wang et al. 2015) are highlighted by the differences in the number of areas lacking scientific support by subregions. However, a lack of scientific knowledge is a constraint on climate change adaptation for developed countries (Ford et al. 2011; Milfont 2012) and for developing countries (Begum and Pereira 2013). A lack of accessibility and understanding of the tools available for climate change adaptation may also contribute to a perceived lack of scientific support. From a professional standpoint, academics may be better able to access scientific tools due to resources provided by their employers as compared to respondents working in the private sector. This may account for the greater average number of selections for areas that lack scientific support by private sector respondents. Additionally, nearly half of the respondents indicated that they did not know what forest planning tools were available in their subregion. For instance, no respondents from North America indicated that high-resolution climate models were available, when these specific tools do exist for their subregion, e.g., ClimateWNA (Wang et al. 2012) and Climate Wizard (Girvetz et al. 2009). Improvements in the accessibility and dissemination of research findings, models, and management tools are necessary to enable researchers and resource managers to address areas where true knowledge gaps exist (Sterrett 2011).

Recent development of the climate model, ClimateAP, can address this lack of scientific support and help increase understanding of locally predicted climate change scenarios, as it is a locally specific, high-resolution model that is freely available and can be applied to any location in the Asia–Pacific region (Wang et al. 2016a, b). Furthermore, models such as ClimateAP (Wang et al. 2016a, b), FORECAST Climate (Seely et al. 2015), and LST (Kang et al. 2016), can address this gap in knowledge and scientific support, as they are applicable to species, ecosystems, and management plans in any location. These tools have been applied to several areas in the Asia–Pacific region (Kang 2015; Wang et al. 2015; Kang et al. 2017). However, further work using these tools and similar resources is needed to increase the support available in this region and to provide decision-makers and resource managers with better information to make well-informed

decisions regarding policy implementation and the development of management strategies to cope with climate change (IPCC 2014).

Knowledge and strategies to adapt forests to climate change are not enough if there are insufficient quality action plans and legislation to transform this knowledge into action. Legislation and actions plans were identified as the most important issues for addressing climate change; however, they pose the greatest challenge to adaptation in North America and Oceania. This is reflected in the low levels of satisfaction regarding actions and initiatives taken to address climate change in these subregions. The indication that legislation is the main challenge in addressing climate change adaption may be a result of the low representation of government officials in Oceania and North America, as academics were the most highly represented group in these subregions. As a result, academic respondents may have less knowledge about the state and process of implementing legislation compared to other challenges such as scientific guidance. However, particular attention should be paid in these regions to developing effective and practical legislation for adaptation to climate change.

The results indicate an overall low level of satisfaction regarding actions taken to address climate change. Diverse goals, objectives, and scope of the available actions or initiatives often make it difficult for decision-makers to choose the appropriate strategy (Preston et al. 2011), potentially leading to outcomes that do not meet desired expectations. Action plans are often fragmented, lacking comprehensive solutions, focus on specified sectors, and fail to address long-term mitigation and adaptation to climate change (Preston et al. 2011; Dannevig et al. 2012; Runhaar et al. 2012). However, satisfaction does appear to be higher across all subregions when the focus shifts to actions and initiatives specific to climate change adaptation in forestry. This may reflect the importance of the forestry sector in the Asia–Pacific economy as forest-based industries are rapidly growing and make significant economic contributions in much of the region (Lebedys 2004; Agrawal et al. 2013). This may lead to more adaptation strategies focused on maintaining this important and lucrative industry, and may also be due to the bias of respondents, as respondents were forestry experts more likely to be aware of legislation and action plans focused on their particular area of expertise. This leads to a false sense of awareness that more action is being taken to address forestry adaption than on other climate issues.

Limitations

Although the questionnaire was distributed to residents of several countries, there was not an equal representation of experts from each country within the subregions. Since the

effects of climate change are expected to vary within each subregion and since each country is unique in its vulnerability and adaptive capacity, the analysis for each subregion may not represent the views and conditions of each country within that subregion. Future research may benefit from analysis at the country level or lower, as this might generate more targeted and specific information to account for the nuances in climate change impacts and ecological, social, and economic conditions across the Asia–Pacific region.

It is evident that experts' opinions do not always agree with information in the published literature. It is difficult to determine whether this is due to the respondent associating their answers with an ecosystem or a situation that differs from the regional pattern, or whether it is simply due to the bias of a person's perception of a situation not always reflecting reality. To address this concern, future surveys could include questions designed to gauge the respondents' expertise on the subject, and respondents should be asked to provide further context so that information about their background and reasoning can be obtained from the survey.

Conclusion

Overall, this study identified consensus regarding the major impacts of climate change on forests, and the potential for increased forest productivity to be a positive outcome of a changing climate. This potential benefit should be capitalized on by developing management strategies that account for climate change and the responses of local ecosystems to environmental changes. It is also evident from this study that there are unique risks and challenges related to climate change adaption between subregions. As such, the same policies and management strategies cannot be applied to all locations, even within the same subregion, and locally based research is important to facilitate the development of strategies and policies specific to local needs and objectives. Furthermore, effort should be made by all levels of government, education institutions, and relevant organizations to increase public awareness of climate change impacts on forests, as knowledge is essential for developing socio-economic and ecological resilience to climate change. Greater understanding of climate change impacts may improve policy and legislation through an increased public demand for action. It is evident that actions, policies, and technologies have low accessibility and suitability in the Asia–Pacific region. Limited accessibility in some countries constrains the ability to generate coping strategies for specific problems, to implement national or local policies, and to further adaptive capacity. Without accessible information, assessments about climate change may be biased, limiting the suitability of policies or

technologies. To address this, the research community should increase development and accessibility of climate and ecosystem models, and support research to reduce this knowledge gap and increase adaptive capacity across the region. This will enable better informed policy and management decisions and may help address the lack of action taken towards climate change adaption and the dissatisfaction with current policies and legislation in this region.

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Annex 9.2: Training Handbook on Adaptation of Asia-Pacific Forest to Changing Climate: Modeling Climate and Forest Ecosystem.

1. Training handbook Kunming Workshop, China
2. Training handbook Guangzhou Workshop, China



HANDBOOK: TRAINING WORKSHOP ON MODELLING CLIMATE AND FOREST ECOSYSTEMS IN A CHANGING CLIMATE

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*APFNet
2016*

Introduction: Training Workshop on Modelling Climate and Forest Ecosystems in a Changing Climate

The objective of the workshop is to introduce the models and tools developed during the project *Adaptation of Asia-Pacific Forests to Climate Change – Phase I* to partners of the project's second phase so that they will be able to effectively and accurately implement the research for their respective pilot sites and economies. This workshop will focus on technical applications and management and decision-making methods in order to increase the capacity of participants to conduct research on forest adaptation to climate change in their own economies.

The training will focus on the use of the models FORECAST Climate and ClimateAP. As well, participants will be introduced to using remote sensing and LiDAR technology and fire frequency and risk modeling. The training will be conducted through presentations and activities in which participants will address research questions related to their local economies by selecting appropriate analysis tools, running analysis, and interpreting results.

This handbook serves as a guide to topics and models to be presented during the training workshop. Each chapter covers a different focus topics of the workshop, with appendices providing supplementary published literature to these topics. Thank you to the authors and editors for their contributions to the handbook and the workshop and to APFNet and the Research Institute of Resources Insects, Chinese Academy of Forestry for supporting the organization and development of the workshop.



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CHAPTER 1

Chapter 1: Overview of Issues and Challenges for Forestry in the Asia-Pacific Region

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AN OVERVIEW OF THE ASIA-PACIFIC REGION

There are 4 subregions including 49 countries in the Asia-Pacific Region (FAO 2011) (Figure 1.1 and Table 1.1). This region extends from Pakistan in the west to the small island states in the Pacific in the east, and from the north of Mongolia to the southern borders of Australia and New Zealand (Waggener & Lane 1997), covering nearly 2.8 billion hectares of land area (roughly 22 percent of world's land area). The Asia-Pacific region holds approximately 60 percent of the world population, including 70 percent of the world's poor (UNEP 2011).

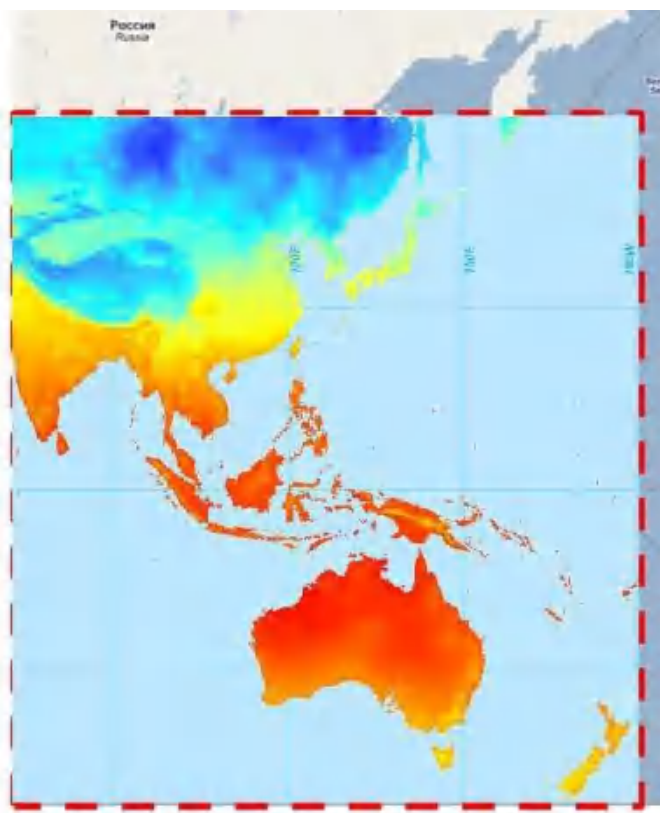


Figure 1.1 The Asia-Pacific Region (Source: <http://asiapacific.forestry.ubc.ca/>)

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Table 1.1 Sub-regions and countries in each sub-region (adapted from FAO (2010a))

Sub-regions	Countries
<i>East Asia</i>	China, Democratic People's Republic of Korea, Japan, Mongolia, Republic of Korea
<i>Oceania</i>	American Samoa, Australia, Cook Islands, Federated States of Micronesia, Fiji, French Polynesia, Guam, Kiribati, Marshall Islands, Nauru, New Caledonia, New Zealand, Niue, Norfolk Island, Northern Mariana Islands, Palau, Papua New Guinea, Pitcairn, Samoa, Solomon Islands, Tokelau, Tonga, Tuvalu, Vanuatu, Wallis and Futuna Islands
<i>South Asia</i>	Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka
<i>Southeast Asia</i>	Brunei, Cambodia, Indonesia, Lao People's Democratic Republic, Malaysia, Myanmar, Philippines, Singapore, Thailand, Timor-Leste, Viet Nam

FOREST RESOURCES IN THE ASIA-PACIFIC REGION

Forest Area and Types

The total forest area in the Asia-Pacific region is estimated at 740.38 million hectares, representing nearly 18.4 percent of the global forest area and accounting for slightly less than one-third of the regional land area (FAO 2011) (Figure 1.2). Due to the relatively high population, this region is the least forested region in the world on a per capita basis, measuring approximately 0.2 hectares per person. In addition to forest area, the Asia-Pacific region holds roughly 312 million hectares of other wooded land of which Australia and China account for 76 percent. Furthermore, 42.5% of forest area in the Asia-Pacific region is designated for conservation of biodiversity (FAO 2010b).



Figure 1.2 Distribution of forests and woodlands in Asia-Pacific region (adapted from FAO 2010a)

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The distribution of forest area is disproportionate within the region, wherein 71 percent of forests are found in the following 4 countries: China, Australia, Indonesia and India (Figure 1.3, Table 1.2). Six countries in the Asia-Pacific region reported a forest cover measuring less than 10 percent of their total land area and among these, two countries (Nauru and Tokelau) reported no forest cover at all (FAO 2011). There is a significant differentiation between the Asian and the Pacific subregions in terms of forest area per capita. In Asian countries, there are 0.15 hectares of forest per capita on average, while the Pacific subregion averages 6.3 hectares of forest per capita (FAO 2011).

Due to the wide geographical range, forest types found in this region exhibit great variety. The Asia-Pacific region covers 4 climatic zones: boreal, arid and semi-arid, tropical and temperate (UNFCCC 2007), producing a combination of temperate, boreal, subtropical and tropical forests.

Asian-Pacific forest area can be further divided into primary, planted, and modified naturally regenerating forests based on the severity and nature of human intervention. Modified naturally regenerating forest occupies the large majority of forest cover within the region, while primary and planted forests comprise the remainder (FAO 2011) (Figure 1.4).

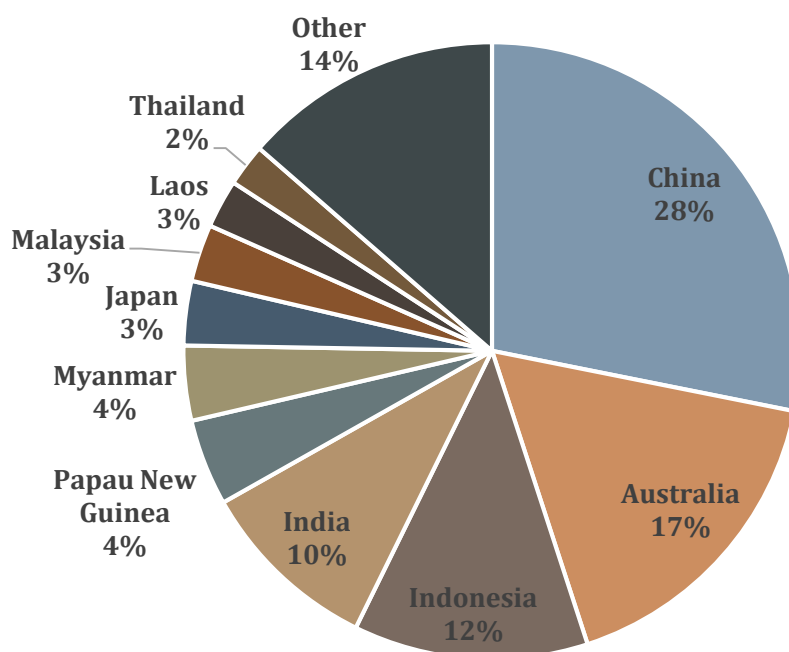


Figure 1.3 Distribution of forest area in the Asia-Pacific Region, based on countries (FAO 2015)

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Table 1.2 Distribution of forest area in the Asia-Pacific Region, based on sub-regions (modified from FAO 2010a)

Sub-regions	Forest area 2010 (million area)	Share of the Asia-Pacific forests (%)	Share of the global forest (%)	Share of the global population (%)
<i>East Asia</i>	255	18.3	6.3	22.6
<i>Oceania</i>	191	13.7	4.7	0.5
<i>South Asia</i>	80	5.7	2.0	23.4
<i>Southeast Asia</i>	214	15.3	5.3	8.5
<i>Asia-Pacific</i>	740	100	18.4	55.1

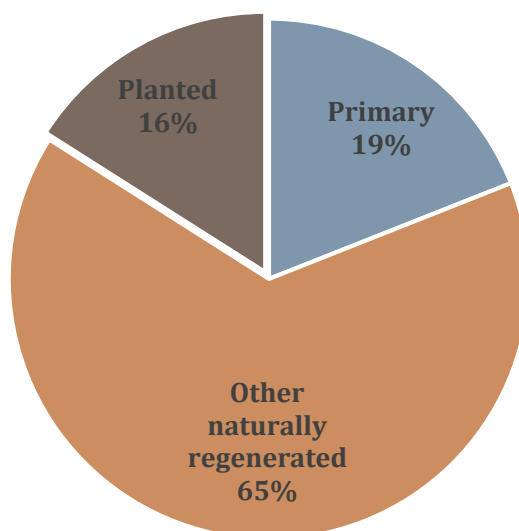


Figure 1.4 Characteristics of Asia-Pacific forests based on human intervention (modified from FAO 2010a)

Change in Forest Area

From 1990 to 2000 total forest area declined by 0.7 million hectares per year, but began to increase at a rate of 0.5 million hectares annually from 2000 to 2010 (Figure 1.5) (FAO 2010a). This change, however, is unevenly distributed amongst countries. Deforestation still persists at a high rate in many nations, particularly those in Southeast Asia where an annual net loss of 0.9 million forested hectares occurred from 2000 to 2010 (FAO 2011), with substantial losses in forest area in namely Cambodia, Indonesia, Myanmar, and Papua New Guinea (FAO 2010a). During this period China became the primary contributor to forest cover in the region after implementing a large scale afforestation program in 2000 that significantly increased its forest area. Additionally, Bhutan, India, the Philippines and Vietnam made substantial contributions to increasing forest area (FAO 2011).

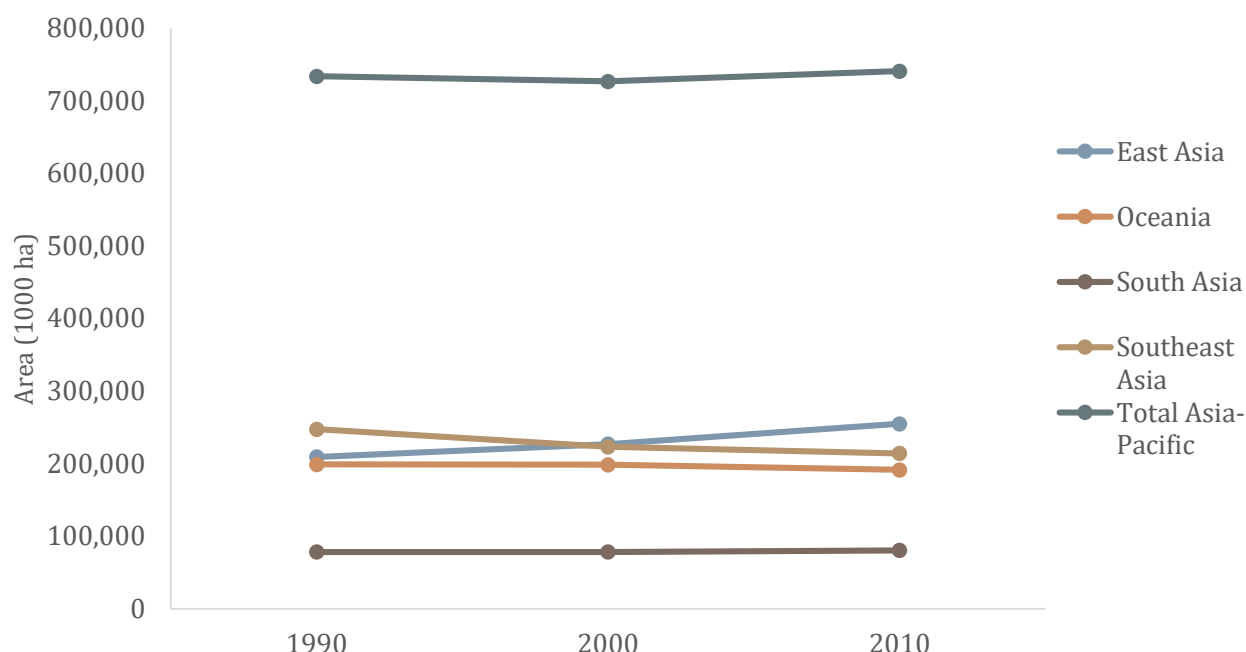


Figure 1.5 Changes of forest areas in Asia-Pacific region from 1990 to 2010 (FAO 2011)

Countries in the Asia-Pacific region can be divided into 3 groups with respect to changes in forest cover over time (FAO 2010c): (1) in countries where agriculture is highly important and the pressure for forest conversion is high; (2) in developing countries where industrialization is considered a priority, and mining, urbanization, and infrastructure construction are the main causes of deforestation; and (3) in developed countries where strong policy incentive is provided for forest conservation to enhance ecosystem services and forest resources, improving forest productivity.

FOREST MANAGEMENT IN THE ASIA-PACIFIC REGION

As previously mentioned, forests in the Asia-Pacific region can be divided into primary forests, modified natural forests, and planted forests. Primary forests account for 19 percent of the total forest area, while modified natural forests comprise 65 percent of the total, reflecting intense human pressure. Planted forests compose the remaining 16 percent of the forest area, with a focus mainly on wood and non-timber products (FAO 2010b) (Figure 1.4). Forest management is much more intensive in the Asia-Pacific region compared with the world average.

Natural Forest

Natural forests can be divided into protection forests and production forests. Relatively easily accessible areas with a high proportion of marketable species are more likely to be managed for wood production. Although the dependence on natural forests as a source of wood supply is declining, wood production remains an important source of revenue for several countries. Overall, the extent of natural forests managed sustainably remains very low (FAO 2010b). In general, there are three approaches to utilizing natural forests in the Asia-Pacific region (Table 1.3): intensive logging; sustained yield management; and banning logging.

Table 1.3 Different forest management approaches to natural forest in Asia-Pacific region (FAO 2010a)

Approaches	Explanations
Intensive logging	Logging activities which give very little attention to the long-term sustainability of wood production and provision of ecosystem services.
Sustained yield management	Forest management which adopts a selective felling system (or variants) aiming to balance production and protection objectives.
Banning logging	Outright bans on logging in response to growing demand for ecosystem services.

To achieve better management in the natural forest sector, several steps have been taken including:

Reduced impact logging (RIL) has been promoted for the last two decades. Although RIL is economically viable in the long term, its adoption is very limited. Conventional logging is easier and commercially more profitable in the short term; hence, most concession holders and logging crews are less willing to adopt RIL. It requires substantial investments in planning, including training of logging crews. In particular, subcontracting various tasks usually discourages the adoption of RIL, with maximizing short-term profits as the main consideration.

Certification aims to create a separate market for products from sustainably managed areas, providing an incentive to move away from unsustainable production. However, obtaining certification often entails significant costs to fulfill the stipulated criteria, as well as the costs associated with third party verification. While certification enhances market access, to date, price premiums have not been commensurate with the additional costs involved. For countries applying only rudimentary formal management to their forests, reaching a level that will make them eligible for certification will require significant changes in management practices entailing substantial expenditure and, often, significant reductions in volumes of wood extracted and potential revenues. Consequently, the extent of certification adoption remains extremely low. The Asia-Pacific region holds approximately 5 percent of the 306 million hectares of certified forests in the world, mainly occurring in Australia, New Zealand, Malaysia and Indonesia (ITTO 2008). Two principal international programmes for certifying sustainable forest management are operational in the region. These are the Forest Stewardship Council (FSC) system and the Programme for Endorsement of Forest Certification (PEFC). In addition, several countries have developed their own certification systems, often drawing on the principles outlined by the FSC and PEFC. The most notable of these national certification systems are those of Indonesia, Malaysia, Myanmar, New Zealand and Australia.

In 2008, 4.4 million hectares of forest were certified under the Forest Stewardship Council (FSC) scheme in the Asia-Pacific region. The area is divided relatively evenly between natural forests (28 percent), semi-natural and mixed plantation and natural forests (34 percent) and plantation forests (37 percent). Sixty-nine percent of the total area is divided between three countries: China, New Zealand and Indonesia. Smaller areas exist in Australia, Japan and Malaysia. Growth rates in areas certified have been high in recent years in China and Indonesia, whereas in the Pacific, rates of increase have been much lower and in South Asia the area certified remains negligible (Figure 1.6).

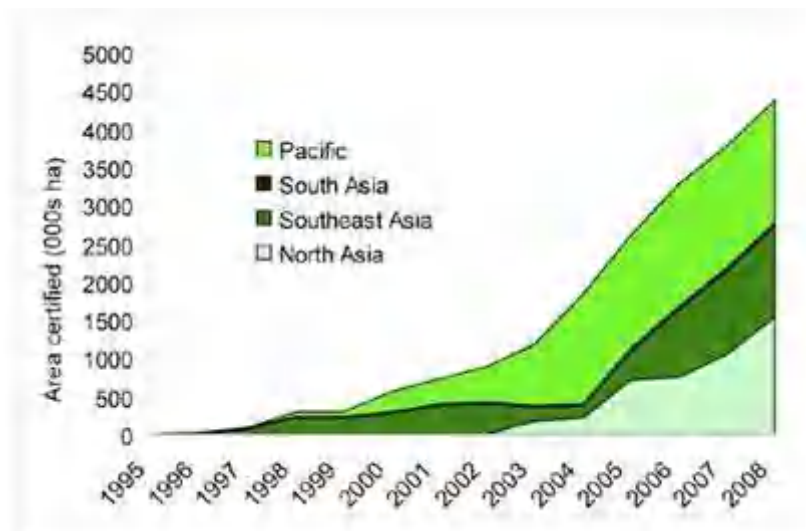


Figure 1.6 Area of FSC-certified forest in each sub-region (Adapted from FAO (2010a))

Partial or total bans on wood production from natural forests have been adopted in several countries. Often natural calamities, such as floods and landslides have triggered such actions (for example, in China and Thailand). Even in countries where natural forests remain important sources of wood supply, large portions of forests have been excluded from wood production, giving them protected status.

Several countries in the Asia-Pacific region have significantly reduced their dependence on natural forests as a source of wood supply. For example, New Zealand obtains almost all of its wood supply from plantations and all natural forests are set aside exclusively for provision of ecosystem services. In the case of Sri Lanka, no logging is allowed in natural forests. Partial or total bans on logging exist in other countries, including China, India, Pakistan, Philippines, Thailand and Viet Nam.

As management of natural forests has become technically and economically more challenging, wood production has shifted towards planted forests.

Planted Forest

Planted forests in the Asia-Pacific region make up approximately 45 percent of global planted forests, with a total area of 120 million hectares. The annual growth rate in the region for planted forests has averaged 2.2 percent from 2005 to 2010 (Table 1.4).

Table 1.4 Change of planted forest area in the Asia-Pacific region (FAO 2010b)

	Area of planted forests (millions hectares)				Annual change (%)		
	1900	2000	2005	2010	1990-2000	2000-2005	2005-2010
Asia-Pacific	68.8	90.6	107.5	119.9	2.79	3.50	2.20
World	171.3	214.6	243.0	264.0	2.28	2.51	1.67

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Key features of planted forests in the Asia-Pacific region (FAO 2010a) include:

- **A few countries (China, Viet Nam, Thailand, India, Indonesia, Japan and Australia) account for most of the increase of planted forest in the region.** Among these countries, China is the dominant force in planted forests. In 2010, China accounted for 64 percent of planted forests in the Asia-Pacific region and, over the preceding five years, 80 percent of the regional expansion in planted forests was in China. China's rapid expansion of plantations is based on highly focused, state-supported programmes.
- Most of the early efforts in forest plantation establishment focused on slow growing, long rotation species aimed to produce saw and veneer logs. Since 1980, there has been a **significant shift to short rotation fast-growing species**, mainly intended to produce pulp and other fiber products. Changes in wood-processing technologies enabling the use of small dimension logs have particularly influenced the choice of species and management practices, including rotation age.
- Historically, most plantations were under public ownership and management. However, this is changing in view of the **increasing involvement of corporate investors, local communities and smallholders**. In particular, there was a significant expansion of the area of planted forests under smallholder ownership between 1990 and 2005, with East Asia accounting for a large part of the increase (Figure 1.7).
- Stagnation in planted forest areas under public sector management is indicative of larger institutional and environmental challenges. The replacement of natural forests with plantations is slowing down as a result of increasing emphasis on environmental protection. Future expansion of plantations will be largely driven by the private sector, including smallholders, with commercial viability being a major consideration.

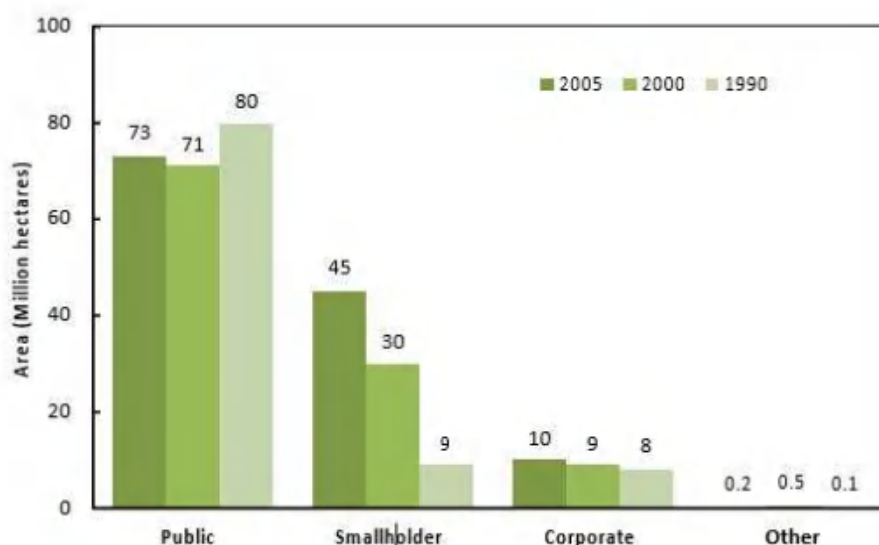


Figure 1.7 Change of planted forest ownership in Asia-Pacific region (modified from FAO (2010a))

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Forest Policies Changes

Forest policies in the Asia-Pacific region have undergone major changes, involving a shift from timber-focused management to multiple-use management that grants due attention to a wide range of goods and services. In many cases, the provisioning of ecosystem services has become a major thrust. Economic growth, globalization, trade liberalization and UNCED-related attention on sustainable development have all directly and indirectly influenced forest policies. Some key trends in forest policies include:

- Increased thrust on ecological aspects with provision of ecosystem services gaining primacy.
- Emphasis on increased involvement of stakeholders in forest management, including in forest policy formulation.

A number of internal and external factors have contributed to these changes. Increased pressure from growing populations has undermined the efficacy of traditional approaches to resource management, compelling public sector forest agencies to involve local communities and other players. Major policy changes have often been made in response to natural disasters, as in the case of logging bans in the context of floods and landslides.

Almost all countries in the Asia-Pacific region have adopted sustainable forest management as the main objective of their forest policies, giving due consideration to social, economic and environmental dimensions. Several countries have shifted their orientation from timber production to broader sustainable forest management. In China, for example, one of the main policy objectives is environmental protection and restoration. Chinese Taipei, Laos, Malaysia, and Myanmar have implemented major reforestation and afforestation projects, focusing on environmental improvement, reflecting a shift in policy objectives. However, establishing trade-offs between competing objectives remains challenging. In the quest for rapid economic growth, extraction of minerals, energy production and infrastructure development have become major threats to forests; however, forest policies seldom provide a robust framework to deal with the changing situation (Table 1.5).

In many countries actual implementation of policies based on sustainable forest management has been weak because of field-level issues including high demand for forest land and forest resources, limited sources of alternative employment and low human resources capacity. Poor governance and low demand for alternative outcomes, for example greater production of environmental services, has also played a part. Similarly, permanent forest estates have often not been demarcated, agricultural frontiers have continued to advance and uncontrolled logging has often remained widespread.

In addition to forest policies, a plethora of extra-sectoral policies impinge on forests and forestry. For example, policies dealing with biodiversity, climate change mitigation, protection of wildlife and desertification control all transcend traditional sectoral boundaries. To some extent this has fragmented forestry agendas all the more so when several institutions are involved in policy implementation. Often such overlap mirrors the international situation, where almost every new convention also entails the creation of a new institution.

More importantly, policies in other sectors (agriculture, industry, energy, rural development, trade, etc.) heavily influence the forest sector, although these policies are usually primarily directed at issues far outside

the forest sector. While there is considerable awareness with regards to the impact of extra-sectoral policies on forests and forestry (and vice versa), difficulties persist in resolving intra-sectoral issues. In the event of conflicting objectives, forest policy objectives are often superseded by other policies that may appear to more directly and immediately affect human welfare.

ISSUES AND CHALLENGES OF A CHANGING CLIMATE IN THE ASIA-PACIFIC REGION

Climate change may produce many detrimental impacts including the increased frequency and severity of wind and fire events, as well as pest and pathogen invasions, finally reducing forest productivity (Pawson et al. 2013; Grimm et al. 2013). There is already a large body of evidence presented in published reports that climate change has negatively affected forest ecosystems, causing decline in tree growth and dieback, invasive species problems, species distributions and migrations, seasonal patterns in ecosystem processes, demographics and even extinctions (IPCC 2007). Table 1.6 summarizes recent changes, future scenarios and potential impacts of climate change in each region.

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Table 1.5 Examples of current forest policies and their respective objectives in the Asia-Pacific region
(Adapted from APEC 2015; UNFCCC 2015; Zhang et al. 2000)

Country	Current policy	Policy objectives	Remarks
<i>China</i>	National Forest Conservation Program	Restore natural forests in ecologically sensitive areas	Forest policies recently include values beyond timber production, promoting preservation.
		Increase timber production in forest plantations	
		Protect existing natural forests from excessive harvesting practices	
<i>Chinese Taipei</i>	Green Forestation Plan	Encourage reforestation	Forest policies prioritize the rehabilitation of nationally significant areas.
		Regenerate degraded state-owned forest	
		Rehabilitate coastal forests	
<i>Laos</i>	National Forest Strategy	Increase forest cover and maintain future forest health	Forest policies promote general forest health, more recently including climate change adaptation components.
		Enhance forest carbon sinks	
		Protect biodiversity and ecosystem services	
	National Adaptation Programme of Action	Promote technical capacity in the forestry sector Promote ecosystem resilience	
<i>Malaysia</i>	National Forestry Policy	Conserve forests through sustainable forest management (SFM)	Forest policies examine demand-side management while also addressing SFM concepts.
		Maintain economic benefits from forestry sector	
	National Policy on the Environment	Achieve a healthy and productive environment Promote sustainable lifestyles and patterns of consumption and production	
<i>Myanmar</i>	National Forestry Master Plan	Decrease rate of deforestation	Forest policies focus on general preservation while increasing the national capacity to sustainably manage forests.
		Preserve natural forest cover to maintain biodiversity and thriving ecosystems	
		Increase capacity of sustainable forest management (SFM)	
	National Biodiversity Strategy and Action Plan	Increase coastal community and mangrove resilience	

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Table 1.6 Recent changes, future scenarios and impacts of climate change

	Asia	Australia and New Zealand	Pacific
<i>Recent Changes</i>	Surface temperature: rose 1- 3 °C over a century; Longer heat waves Precipitation: increased intense rainfall events; decreased total rainfall amount. Extreme events: increased frequency and intensity (tropical cyclones, droughts, etc.). Sea-level: rose 1-3 ml/year.	Surface temperature: rose 0.4 – 0.7 °C since 1950; more heat waves (northwest Australia and southwest New Zealand); hotter droughts. Precipitation: more rainfall in northwest Australia and southwest New Zealand; less rainfall in southern and eastern Australia and north eastern New Zealand. Extreme events: increased extreme rainfall events in north western and central Australia; decreased in the southeast, southwest and central east coast.	Surface temperature: increased faster than 0.6 °C in twentieth century; Increased number of hot days and warm night in the South Pacific. Sea-level: rose about 2 ml/year. Extreme events: increased frequency and intensity of tropical cyclones originated in the Pacific.
<i>Future Scenarios</i>	Increasing extreme events (heat waves and intense rainfall) in South Asia, East Asia and Southeast Asia; sea surface temperature will rise 2 – 4 °C; increasing intensity of tropical cyclones.	Increasing frequency of heavy rainfall events; temperature will rise about 0.1 – 1.3 °C by 2020 within 800 kilometres of Australian coast; 0.1 – 1.4 °C by 2030s in New Zealand; sea-level will rise 0.18 – 0.59 meters by 2100 (±25 percent modification).	Surface temperature will rise greater than 2.5 °C in South Pacific.
<i>Potential Impacts</i>	Rising risk of species extinction; increasing coastal erosion and floods.	Declining productivity of forests.	More frequent and intense floods, storm surge and coastal erosion.

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Forest management for climate change adaptation

Adaptation needs in the Asia-Pacific region

The adaptation needs provided below are based on IUFRO's global assessment report on forest and human adaptation to climate change (Seppälä et al. 2009).

1. Combine traditional forest-related knowledge and formal forest science

Traditional forest-related knowledge (TFRK), practices, and institutions have developed over generations by forest-dependent people. Traditional forest and water management practices are very important to climate change adaptation. Expanding markets have weakened traditional cultures and TFRK. TFRK should be recorded, translated and synergized with formal forest science, before it is lost.

2. Increase participatory reform and flexibility in forest-related bureaucracies

Standard operating procedures in forest bureaucracies need to change. Locatelli et al. (2008) stress two key changes that are required:

- Forest-dependent people need to be recognized, to be drawn into the discourse and to contribute to official decision-making.
- Changing attitudes among forestry personnel and strengthening feedback mechanisms within forestry-related bureaucracies.

3. Maintain/enhance biodiversity as a key ecosystem service

Management for maintaining biodiversity includes the prevention of disturbances such as fire (managing fuel load, prescribed burning) and maintaining natural cycles, particularly in arid and semi-arid forest areas. The prevention of invasive species and diseases is also crucial for maintaining biodiversity, through quarantine regimes and phytosanitary procedures. Another option is to assist forests to adapt after a perturbation by establishing priority species according to planned ecological succession (Locatelli et al. 2008).

Increasing landscape connectivity through the establishment and preservation of corridors and reducing forest fragmentation is important to facilitate natural progression and succession within ecosystems. Connectivity and corridors increase the ability of species to adapt through migration and the maintenance of genetic diversity.

In managed natural forests, for example, logging gaps may be planted with a variety of seedlings to maximize genetic diversity. Tree plantations may be established with a range of genotypes, seed sources and age classes to increase their capacity to adapt to expected future climate conditions. Plantation management strategies that mimic natural conditions and avoid monocultures are advocated to take into account climate change adaptation requirements (Roberts 2009). Throughout the region, traditional home gardens have increased the use of drought-tolerant varieties to minimize crop failure in years with severe drought (Altieri & Koohafkan 2008).

4. Create/enhance robust management strategies and extensive communication networks

Because of the uncertainty of climate change impacts, robust, sustainable forest management strategies are needed. Community-based management strategies are an important tool for ensuring responsiveness. These management strategies must also consider the projected increase of forest disturbance regimes in the form of fire, pests and diseases and must be flexible enough to incorporate and respond to new information. Effective adaptation requires the formation of extensive communication networks for monitoring the effectiveness of strategies at local, national and regional levels.

5. Improve inter-sectoral coordination

Policies from agriculture, transportation and land-use sectors will exert significant influence on the forest sector. Forest adaptation should not ignore the many anthropogenic drivers of forest change that originate in other sectors; developments in agriculture, energy, transportation, conservation and macroeconomic policies can have dramatic effects on the incentives to destroy or degrade forests.

6. Mainstream forest adaptation into policy

In order to mainstream forest-based climate change adaptation strategies at the country level, National Forest Programmes (NFPs) must explicitly address both the role of forests for reducing vulnerability to climate change at the national level and the importance of increasing the adaptive capacity of forests themselves.

7. Incorporate new actors and new modes of governance

Many institutions and sectors are becoming increasingly concerned about forest-based climate change adaptation strategies from the local to the global scale. They include local forest-dependent communities, commercial or industrial forest stakeholders, ecotourism ventures, conservation and development NGOs, national agencies concerned with forests, power generation agencies and industries, agriculture and food sectors, disaster risk reduction organizations, intergovernmental organizations, international research/development organizations and funding agencies. Adaptation policies should aim at linking these diverse actors with those engaged in forest conservation and management.

Adaptive forest management

Adaptive forest management for climate change is consistent with SFM (IUFRO 2009). Adaptive management involves design, management and monitoring processes and requires constant learning from the past to plan for the future (FAO 2010c).

The major goal of adaptive management is to enhance and assist resiliency, stress resistance, and dynamic response such that forests can survive under a changing climate (Bottle et al. 2009). Biodiversity conservation is an important measure to achieve this goal as more diverse ecosystem tend to be more resilient to disturbance events, such as insect outbreak. Tree species should be conserved with dispersed and viable populations in order to reduce the risk of extinction (Fischlin et al. 2007). Planting forests with mixed species rather than single species can also lead to greater biodiversity in the ecosystem (Spittlehouse & Stewart 2003).

Other adaptation strategies and practices include: changing rotation periods, salvaging dead timber, shifting to species more productive in altered climatic conditions, taking action to minimize fire and pest damage, connecting corridors and adjusting production objectives to altered wood size and quality (Spittlehouse & Stewart 2003), reducing damage to remaining trees, practicing reduced-impact logging, and employing soil conservation.

From the administrative point of view, forest managers should be allowed “freedom to fail” within an allowable extent when implementing their forest practices, as it is difficult to achieve goals in a first trial given variable environmental factors (Locatelli et al. 2008). Although there are models that can be used to predict the impacts of climate change, results are often limited to a general trend rather than detailed impacts (FAO 2010c). Therefore, forest management strategies need to be robust and diverse considering such uncertainty and the increasing disturbances under climate change. Community-based management can help to ensure the responsiveness of management plans, while monitoring can help to secure the activeness (FAO 2010c).

For example in Nepal and many Indian states, local communities have sole control over forest management and the power in policy-making processes. Community-based management has resulted in more efficient feedback from the direct stakeholders in the community and has also led to improved policies benefited from field experience (Poffenberger 2000).

Estimation of adaptation costs

Adapting to climate change involves a significant transition with far-reaching economic implications. Full economic assessments of the costs associated with adaptation allow countries to prioritize strategic measures and anticipate the associated development impacts. To date, knowledge of anticipated adaptation costs, particularly those costs specific to the forestry sector, remains highly limited and imprecise.

Since 2006, there have been only five global studies estimating climate change adaptation costs for developing countries. The estimated cost is summarized in Table 1.7.

Table 1.7 Estimate of adaptation cost (FAO (2010c))

Estimate year	Estimate by	Cost (US billion/annually)
2006	World Bank	9-41
2006	Stern Review	4-37
2007	Oxfam	50
2007	UNDP	86-109
2007	UNFCCC	27-66

Mitigation options and issues

1. Reduced emissions from deforestation

Between 1850 and 1995, 75 percent of the total carbon emissions in South and Southeast Asia were due to the clearing of forests for permanent crops. This trend is set to continue, even though deforestation rates in tropical Asia have declined since the 1990s (Houghton & Hackler 1999).

Strategies for avoiding deforestation depend upon the drivers of deforestation in each context. However, there appear to be four clear categories of mitigation strategies for avoiding deforestation (see Peskett & Harkin 2007):

- Strengthening existing policy and legislation for forest protection.
- Reclassification of land-use zones or renegotiating concessions.
- Modification of agriculture or infrastructure programmes to reduce pressure on forests.
- Implementation of economic incentives through PES, or disincentives such as taxes or fines.

2. Enhanced carbon sequestration from afforestation, reforestation and other strategies

There is a suite of strategies to create carbon sinks through forestry. Some of these strategies are:

- Afforestation: Establishment of planted forests on lands that historically have not been forested
- Reforestation: Planting of new forests on land that had tree cover recently
- Forest restoration: Restoring degraded forests through assisted or natural regeneration; protecting secondary and other degraded forests to allow them to regenerate naturally; or mechanical/infrastructural means, such as damming canals that drain peatlands.
- Modification of forest management practices to increase sequestration: Including prevention of fires, changing harvesting rotations and practices (e.g. reduced impact logging).
- Adoption of agroforestry practices: Increasing tree cover on agricultural or pasture lands.
- Urban forestry: Planting trees in 'vacant areas' for urban green space.
- Increasing soil carbon: Soil restoration and woodland regeneration, no-till farming, introduction of cover crops and set-asides (Lal 2004).

3. Conservation of natural forests

The majority of forest cover in the Asia-Pacific region is natural (79 percent) (Houghton 2005). However, most reported gains in forest area and condition in the region are confined to planted forests. The natural forest area decreased at a rate of 0.48 percent per year during the 1990s and by 0.50 percent per year during the 2000s, while planted forest area increased at annual rates of 2.02 percent and 2.85 percent during 1990-2000 and 2000-2010 respectively (FAO 2010c). Conservation of natural forest resources is therefore a critical component of climate change mitigation strategies in the region. Furthermore, natural forests should be of high priority as they contain more biomass than plantations or agroforestry systems: that is, natural forests contain 250 tC/hectare versus 90-120 tC/hectare and 50 tC/hectare for agroforestry systems and plantations, respectively (Pagiola & Bosquet 2009).

4. Reduced emissions from forest degradation

Forest degradation that leads to carbon emissions in the region is significant, especially in South and Southeast Asia. Degradation results from human activities such as shifting cultivation, logging, grazing and fuelwood extraction, as well as natural causes such as forest fires and pests or diseases (Houghton & Hackler 1999, Griscom et al. 2009). Degradation can be reduced through improved forest management practices such as: fire and pest control; adoption of reduced impact logging; reduction of fuelwood collection, grazing management, etc. It is vital that degradation be addressed, not only for its impact on emissions but also for its capacity as precursor to or catalyst of deforestation (Streck et al. 2009).

5. Substitution of harvested wood products for other materials and of wood fuels for fossil fuels

Biomass energy can be used to replace fossil fuels, thereby reducing GHG emissions from fossil fuel. The avoided emissions of a biomass energy system are equal to the fossil fuels replaced minus the emissions resulting from the biomass energy system (IPCC 2000). Under such a system, fuelwood production must be carefully managed so that forests maintain a constant carbon stock. There are two main approaches to fuelwood production: sustainable harvesting of fuelwood from natural forests and commercial harvesting from intensively managed plantations. Both approaches may play a role in increasing substitution of fossil fuels with renewable fuelwood.

In addition to wood fuel, other kinds of biofuels are also being utilized to replace fossil fuels. These include palm oil (for biodiesel), sugar cane (for ethanol production), *Jatropha curcas* (biodiesel) and other crops including canola (rapeseed) and sugar beet. Emission reduction outcomes from burning biofuels are mixed, depending upon the yield of fuel as a percentage of raw product, their efficiency as fuels and the conditions under which they are produced and delivered from producer to consumer. For example, clearing land to make way for oil-palm plantations, especially on peat soils, can result in huge emissions that far exceed any gains from consumption of the resulting biofuel. Alternatively, biofuels that make use of waste biomass grown on degraded lands offer immediate, sustainable emissions reductions (Fargione et al. 2008).

Finally, using wood products to replace other materials in furniture and construction may enable carbon sequestration, although it is unclear whether this will achieve emissions reductions. Other non-wood products such as bamboo and rattan also sequester carbon and may offer greater potential (FAO 2009a).

Adaptation-mitigation synergies and trade-offs

Adaptation is defined as “adjustment in natural or human systems in response to natural or expected climatic stimuli, or the efforts which moderate harm or exploit beneficial opportunities”. Mitigation is defined as “any anthropogenic intervention to reduce sources or enhance the sinks of GHGs”. This has resulted in mitigation and adaptation being distinguished in spatial, temporal and socio-economic terms. Mitigation has been associated with globally- coordinated efforts with a focus on long-term implications, the burden of which lies upon developed nations. Adaptation, on the other hand, concerns the immediate need for vulnerability reduction at the local level, the burden of which will mainly fall on developing and least developed nations which are least able to cope (Ayers & Huq 2009).

Synergies between adaptation and mitigation measures have recently been explored in developing countries within the Asia-Pacific region aiming to identify win-win options for climate change policy and

seeking opportunities to explicitly include adaptation objectives in mitigation projects (Klein et al. 2007, Wilbanks et al. 2007). Venema and Rehman (2007) argue that synergy between mitigation and adaptation is intrinsic to the ecosystem-oriented approach articulated by the World Summit on Sustainable Development.

Synergies are most clearly evident in the LULUCF sector. Forestry, in particular, is relevant to climate change adaptation strategies, with its contribution to biodiversity conservation and livelihood resilience, and to mitigation through enhanced CO₂ sequestration (Ravindranath 2007). Agroforestry offers the highest potential for carbon sequestration among land uses identified by the IPCC, owing to the large area currently devoted or potentially available for such use. The conversion of row crops or pasture into agroforestry systems can greatly enhance stored carbon above and below ground, as well as increase farmers' economic benefit (Verchot et al. 2007).

Verchot et al. (2007) contains numerous references to community-based approaches to forest management. It is therefore no surprise to learn that some of the clearest practical linkages between adaptation and mitigation strategies have emerged in the field of community forestry. For example, since 2008, the FAO has been supporting Nepal's National Agricultural Research Council and other government bodies in a climate risk management project. A key element of the project's strategy is to explore synergy between the economic resilience and adaptive capacity that CFUGs confer on their members and their potential to contribute successfully to forest-based mitigation strategies under REDD (FAO 2009b). Many others have noted this synergy in South Asia (Karky 2009, Ravindranath 2007) and a common understanding of community forestry both as an element of REDD methodology and a local-level adaptation strategy is taking root in the region. Another adaptation policy that improves carbon sequestration is the protection and improved management of ecosystems that serve as buffers against extreme weather events, particularly coastal habitats such as wetlands and mangrove forests (World Bank 2009).

REDD is a clear example of a strategy to address climate change which combines mitigation and adaptation elements. So, although synergies do indeed exist with win-win outcomes, even these require optimal mixes of adaptation and mitigation elements. Trade-offs exist between these two sets of objectives based on a number of complex factors, such as the exhaustibility of forest resources and the conflicting needs and interests of stakeholders (Dang et al. 2003). There are also a number of instances of conflicting approaches to adaptation and mitigation. Many adaptation options, such as improved flood defenses, are known to increase energy use, hence interfering with GHG reduction efforts. Relocation of vulnerable communities, for example from low-lying coastal zones in the Mekong Delta, to currently forested areas further inland, is a central feature of Viet Nam's National Target Plan for Climate Change Adaptation. These plans, if followed through, will conflict directly with the country's strategy to implement REDD nationwide.

The IPCC concludes that there is insufficient information to ascertain whether investment in adaptation could, in effect, buy the time required for mitigation efforts to deliver results, nor what level of investment would be required to achieve this on the global scale (Klein et al. 2007). However, Dang et al. (2003) argue that it is possible to set a national climate policy that takes into account the synergies and trade-offs between adaptation and mitigation. A proper national framework for integrating adaptation and mitigation strategies for ecosystems, resources and sectors should be the first priority for climate change policy-makers.

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Chapter 2: ClimateAP for Downscaling Historical and Future Climate Data

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AN OVERVIEW OF CLIMATEAP

ClimateAP is a standalone MS Windows application written in Visual Basic 6.0. The interface of the program is shown in Figure 2.1. ClimateAP extracts and downscales PRISM (Daly et al. 2002) and WorldClim (Hijmans et al. 2005) 1961-1990 monthly normal data (2.5 x 2.5 arcmin) to scale-free and calculates seasonal and annual climate variables for specific locations based on latitude, longitude and elevation (optional). ClimateAP covers the Asia Pacific region (Figure 2.2).

The program uses the scale-free data as baseline in combination with monthly anomaly data (Mitchell and Jones 2005) of individual years to calculate historical monthly, seasonal, and annual climate variables for individual years and periods from 1901-2012 (to be updated in Project Phase II). This program also downscales and integrates future climate datasets for 2020s (2010-2039), 2050s (2040-69) and 2080s (2070-2099) generated by various global circulation models (GCMs). It currently includes 15 GCMs and two greenhouse emission scenarios (RCP 4.5 and RCP 8.5). The output of the program includes both directly calculated and derived climate variables.



Figure 2.1 The interface of ClimateAP version 1.00

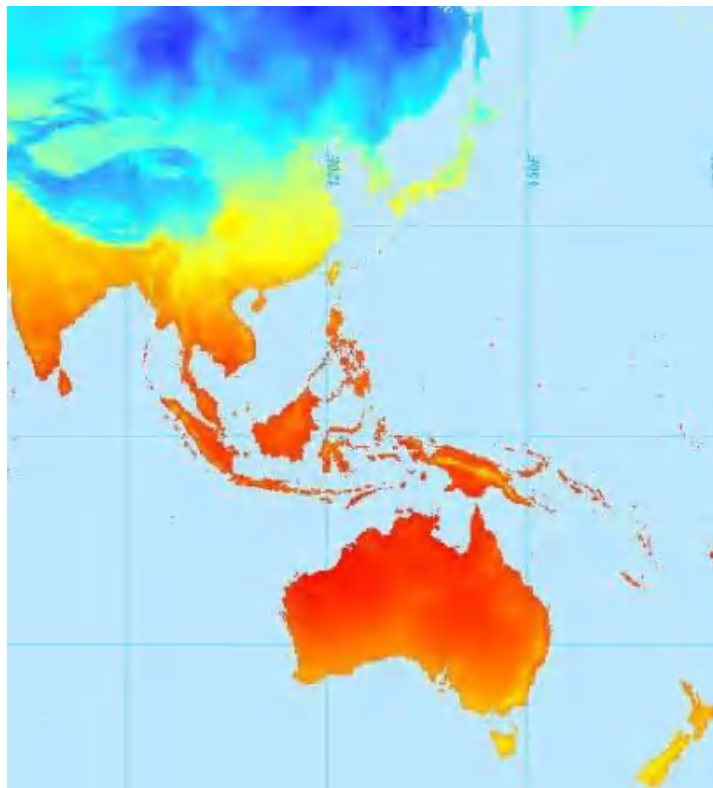


Figure 2.2 The coverage of ClimateAP.

CLIMATE DATA EXTRAPOLATION

Baseline data

ClimateAP uses the best available 30-year-normal monthly climate data for the reference period 1961-1990 as the baseline data. The PRISM monthly data are available for China and Mongolia. The monthly climate data from WorldClim were used for the rest part of the region. The baseline climate data are at the resolution of 0.25×0.25 arcminutes (about 4×4 km). The climate variables obtained from these data sources included three primary climate variables: monthly minimum temperatures (Tmin01-12) and monthly maximum temperatures (Tmax01-12) and monthly precipitation (Pre01-12).

Downscaling

ClimateAP uses a combination of bilinear interpolation and dynamic local regression approaches to downscale the baseline monthly grid data to scale-free point data. Instead of applying the midpoint values of each 4×4 -km tile to all points within each tile, we used bilinear interpolation method to interpolate values between midpoints of the 4×4 -km grids as illustrated in Figure 2.3.

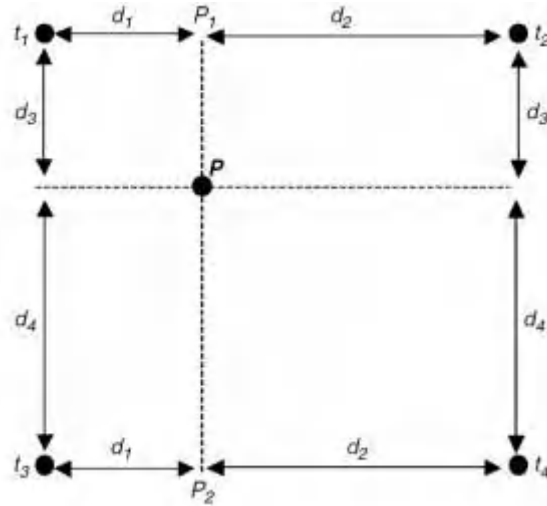


Figure 2.3 Illustration of bilinear interpolation of the baseline climate data (Wang et al. 2006)

P is the location for prediction; t_1 , t_2 , t_3 , and t_4 are the values of climate variables at the centers of the four neighboring tiles; d_1 , d_2 , d_3 , and d_4 are the relative spatial distances. P_1 and P_2 are predictions based on simple linear interpolations of the climate variable values t_1 and t_2 , and t_3 and t_4 , respectively, and the prediction for P is the simple linear interpolation between P_1 and P_2 . 36

After the grid data, including elevation, are interpolated into continuous surfaces, we applied dynamic local regression to estimate lapse rates for the location of interest to account for elevational effects. ClimateAP retrieves monthly climate data and elevation values from 9 closest neighbors and calculates differences in climate variables and elevation between all 36 possible pairs. A simple linear regression of the differences in a climate variable on the difference in elevation allows the estimation of the lapse rate for the climate variable. A lapse rate is estimated for each of the 36 monthly primary climate variables. Figure 2.4 shows the relationships between the differences in temperature and precipitation and the differences in elevation. The dynamic local linear regressions can explain a majority of climate variation at a local scale. It can even capture temperature inversion along an elevational gradient for winter months (Figure 2.4a).

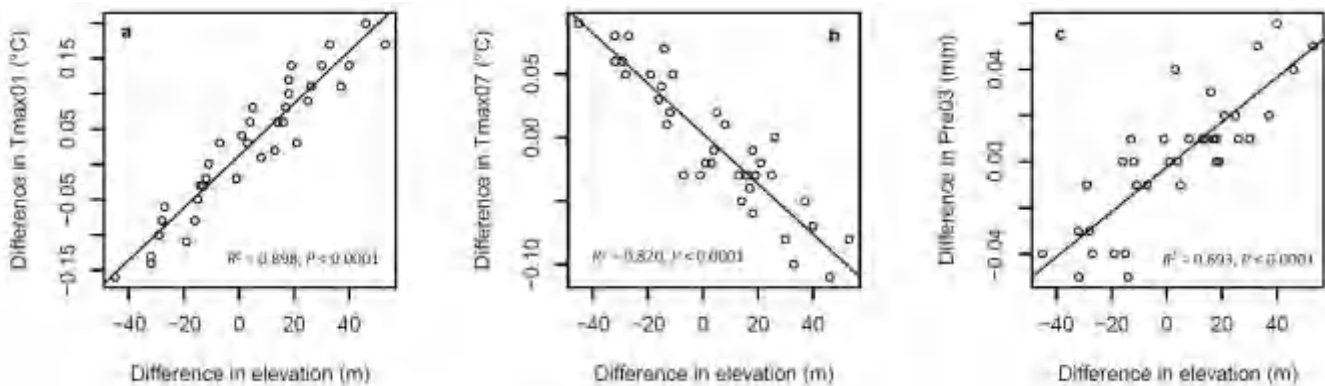


Figure 2.4 Relationships between the differences in maximum temperature in January (a) and July (b), and precipitation in March (c), and the differences in elevation.

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The effect of the downscaling can be visualized in Figure 2.5. The limitation of the relatively low resolution of the grid data and power of the downscaling approach applied in ClimateAP can be clearly seen on the map.

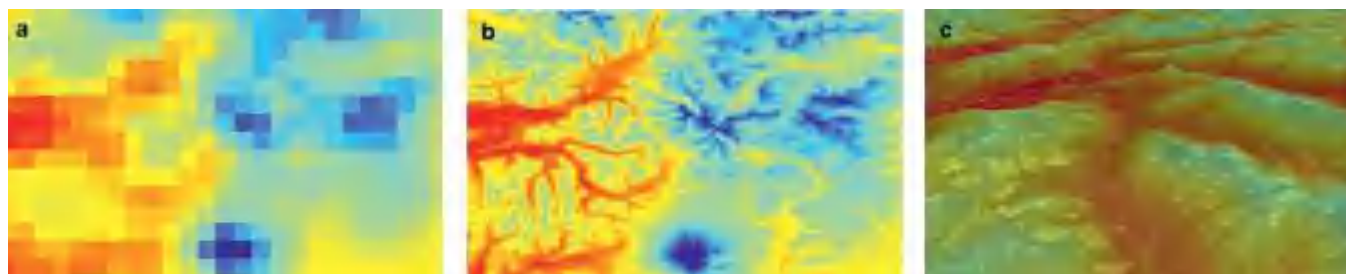


Figure 2.5 Illustration of the effect of downscaling approach applied in ClimateAP shown on the maps. a) mean annual temperature (MAT) of the baseline data at 4 x 4 km; b) downscaled MAT through ClimateAP (100 x 100 m); c) downscaled MAT (100 x 100 m) by ClimateAP

Calculated climate variables

The baseline data contain 36 primary monthly climate variables including monthly maximum (Tmax01-12) and minimum (Tmin01-12) temperatures and precipitation (PPT01-12). ClimateAP calculates many additional climate variables at run-time based on these primary climate variables listed in Table 2.1.

Table 2.1 Climate variables directly calculated based on the 36 primary climate variables included in the baseline data.

Variable category	Variable short name	Variable long name
Annual	MAT	Mean annual temperature
	MWMT	Mean warmest month temperature
	MCMT	Mean coldest month temperature
	TD	Continentality, temperature difference between MWMT and MCMT
	MAP	Mean annual precipitation
	AHM	Annual heat-moisture index $(MAT+10)/(MAP/1000)$
Seasonal	Tmax_DJF – SON	Tmax for December to February, and so on
	Tmin_DJF – SON	Tmin for December to February, and so on
	Tave_DJF – SON	Tave for December to February, and so on
	PPT_ DJF – SON	PPT for December to February, and so on
Monthly	Tave01-12	Monthly average temperatures

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Derived climate variables

In addition to the primary climate variables included in the baseline data, directly calculated variables using the primary variables, ClimateAP also derived many biologically relevant climate variables from monthly climate variables, such degree-days, and number of frost-free days, extreme temperatures and moisture deficit. These variables can be calculated from daily climate data. However, daily data are not available in ClimateAP or other interpolated climate data. We developed functions based on the relationships between these climate variables calculated from weather station data and the monthly climate variables from the same weather stations.

In order to model these relationships, we obtained daily climate data from 1,805 weather stations in Asia Pacific region. The distribution of the weather stations is shown in Figure 2.6.

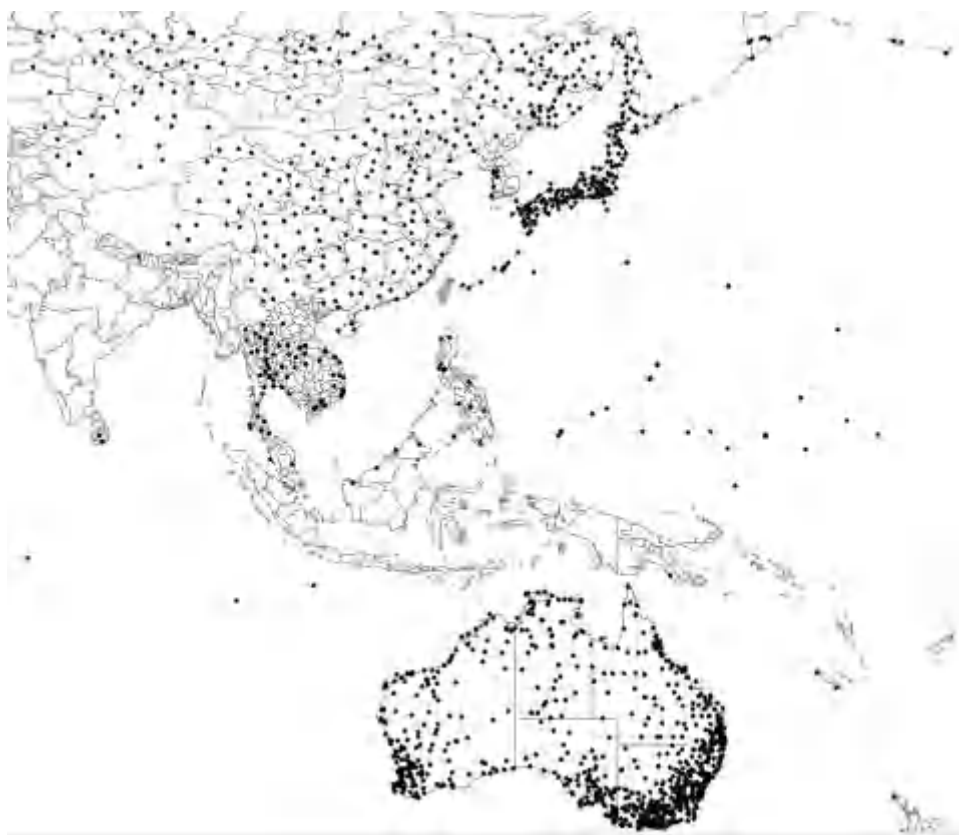


Figure 2.6 The distribution of weather stations that were used to derive the relationships between biologically relevant climate variables and monthly climate variables

Due to the wide range of variation in climate variables in the Asia Pacific region, no single linear, polynomial or nonlinear function can reflect such relationships for most of these climate variables. Thus, we applied piecewise functions, which are combinations of a linear function and a sigma nonlinear function, to model these relationships. Some of these relationships are demonstrated in Figure 2.7.

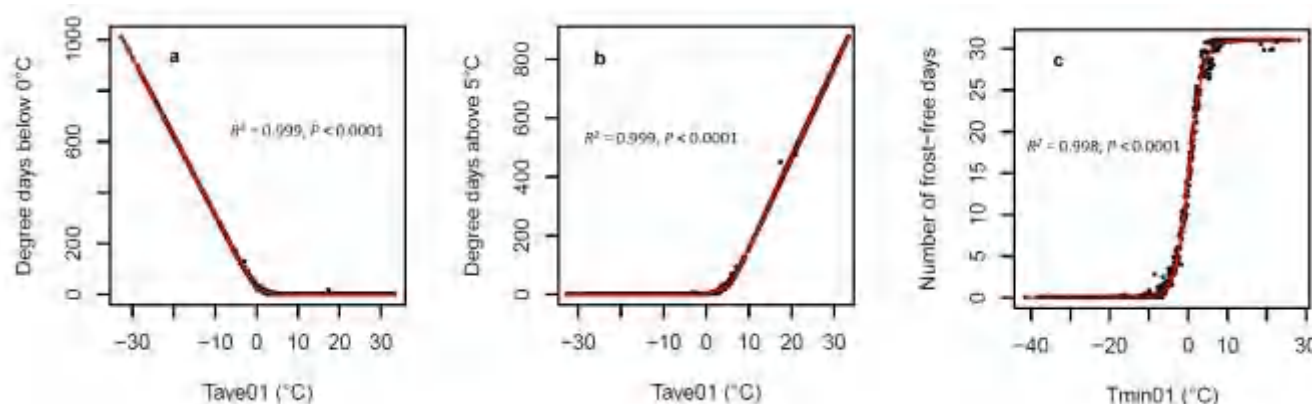


Figure 2.7 Relationships between derived monthly climate variables and monthly climate variables for degree-day below 0°C, degree-day above 5°C and number of frost-free days in January

Derived climate variables generated by ClimateAP includes climate variable at annual, seasonal and monthly time scales (Table 2.2). Two of these variables are not based on the relationships modeled from weather station data. They are Hargreaves reference evaporation and Hargreaves climatic moisture deficit (Wang et al. 2012).

Table 2.2 Annual climate variables derived based on relationships between calculated climate variables from daily data and primary monthly climate variables based on observation from weather stations.

Variable	Variable short name	Variable long name
Annual	DD<0 (DD_0)	Degree-days below 0°C, chilling degree-days
	DD>5 (DD5)	degree-days above 5°C, growing degree-days
	DD<18 (DD_18)	degree-days below 18°C, heating degree-days
	DD>18 (DD18)	degree-days above 18°C, cooling degree-days
	NFFD	the number of frost-free days
	PAS	Precipitation as snow (mm)
	EMT	Extreme minimum temperature over 30 years.
	EXT	Extreme minimum temperature over 30 years.
	Eref	Hargreaves reference evaporation
	CMD	Hargreaves climatic moisture deficit

Climate variables for historical years and future periods

Monthly temperature and precipitation data for 1901-2012 used in ClimateAP are based on Mitchell and Jones's (2005) interpolated historical data at 0.5 x 0.5° resolution (CRU TS 3.22). This will be updated to most recent years in the project phase II. Temperature was expressed as a difference in degrees Celsius, and the delta surfaces for precipitation were calculated as percentage difference from the 1961-1990 normal values, e.g. -50% represents half and 200% twice the normal precipitation value for a particular month.

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For future climate, the monthly temperature and precipitation data for future periods were from General Circulation Models (GCMs) of the Climate Model Intercomparison Project 5 (CMIP5) corresponding to the Fifth Assessment Report of the Intergovernmental Panel for Climate Change (IPCC, 2014). Fifteen GCMs were selected all major clusters of similar AOGCMs. Two greenhouse gas concentration trajectories or Representative Concentration Pathways (RCP) were included including RCP 4.5 and RCP 8.5. In RCP 4.5, emissions peak in the 2040s and then decline. RCP 8.5 assumes that emissions continue to increase throughout the century. When multiple runs were available for each GCM, an ensemble average was taken over the available (up to five) runs. Annual Monthly GCM projections into 30-year time periods referred to as 2020s (2011-2040), 2050s (2041-2070), and 2080s (2071-2100). Anomalies were calculated relative to the reference period 1961-1990.

ClimateAP integrates both historical and future climate data with a delta method. Anomaly grids are interpolated using bilinear interpolation in run-time to avoid step-artifacts at grid boundaries, and the difference is added to the downscaled baseline climate normal data (scale-free) to arrive at the final climate surface with high-resolution (Figure 2.8).

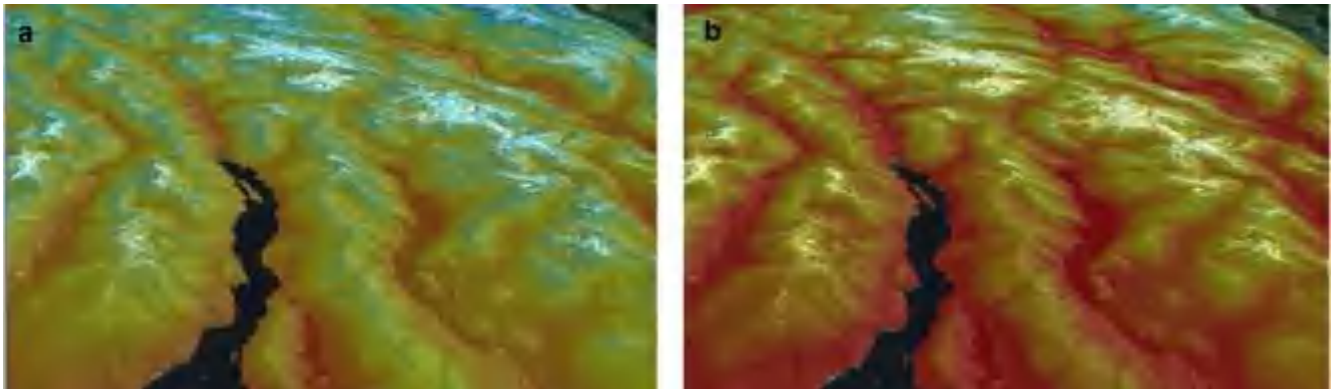


Figure 2.8 Demonstration of the high-resolution climate data (MAT) generated by ClimateAP for the reference (1961-1990) and a future period (2050s).

With this approach, the original baseline data (absolute values for 1961-1990 normal period) of the historical data and future projections are replaced by scale-free climate data generated by ClimateAP and improve the prediction accuracy.

Improvements of ClimateAP output for historical and future climate data over the original CRU and GCM data for the baseline data is shown in Figure 2.9. On average over the 1805 weather stations tested, the prediction standard errors were reduced by 0.5°C for monthly minimum temperatures, 0.8°C for monthly maximum temperatures, 21mm for monthly precipitation. The amount of improvement was even greater as expected; it was up to 2°C for monthly temperatures and 35mm for monthly precipitation on average. For example, we found in our previous study that the error in mean annual temperature associated with the baseline climate data is 6°C at the Vancouver International Airport (Figure 2.10).

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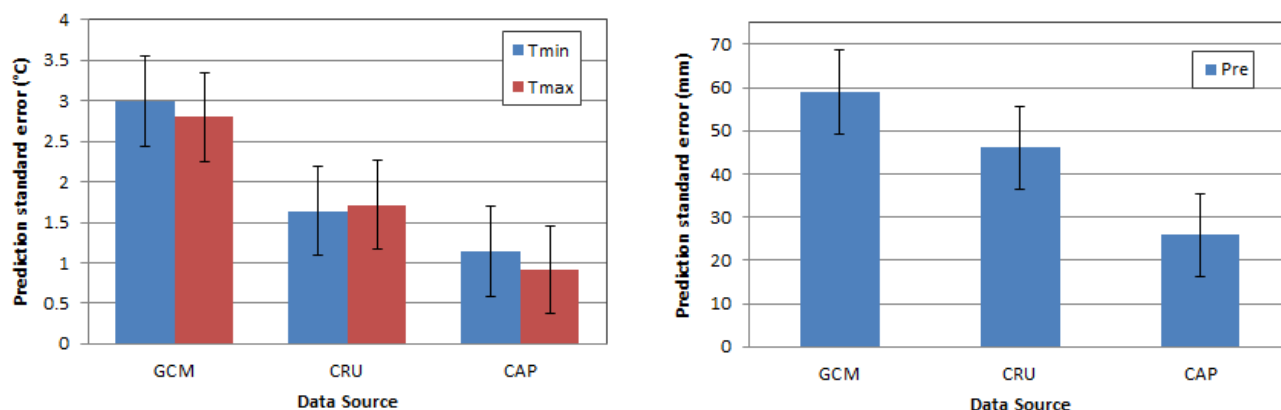


Figure 2.9 Comparisons in prediction standard errors among three data sources: IPCC GCM predictions (GCM), Climate Research Unit (CRU) and ClimateAP output (CAP).

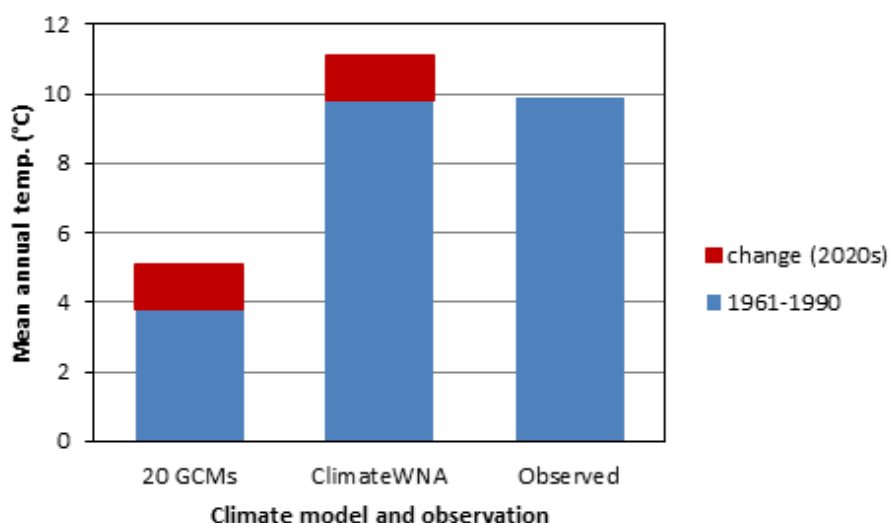


Figure 2.10 Illustration of ClimateAP downscaling method for GCM projections by removing errors in mean annual temperature associated with baseline climate data. Data shown are from a previous study using ClimateWNA that applied the same delta approach as ClimateAP.

GUIDE FOR CLIMATEAP

Installation

The installation of ClimateAP is very simple because it does not require installation process. That is why we stick with Visual Basic 6 instead of the new version of VB.NET. Users need simply copy two files ("ClimateAP_v1.00.exe" and "Help.rtf") and three subfolders ("prismdat", "perioddat", "GCMdat") into the same location on your hard disk and double click the file ClimateAP_v1.00.exe". The program can run from USB drive, but it does not work properly on network drives.

In case it does not run on your computer, you may need to download the library file and install it. http://www.genetics.forestry.ubc.ca/cfcg/res_climate-models/libraryfiles.exe.

CHAPTER 2

Interactive mode

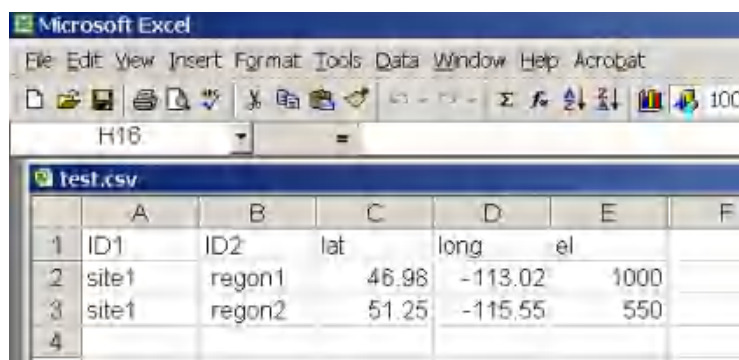
It is easier to use the interactive mode for a single location or a small number of locations. The users just need to input the latitude, longitude and elevation (optional), and click the “Start” button. Options are available for latitude and longitude input in either decimal degree or degree-minute-second. If elevation is missing, the elevation in the baseline data will be used and no elevational adjustment will be performed. A drop-down box is for choosing the targeted period.

By clicking the “Start” button, climate variables for all the three time scales (annual, seasonal and monthly) will be displayed on the screen. The output can be copy and passed to a file. It can also be saved to a Comma-separated-value (csv) file by clicking the “Save button”.

Multi-location mode

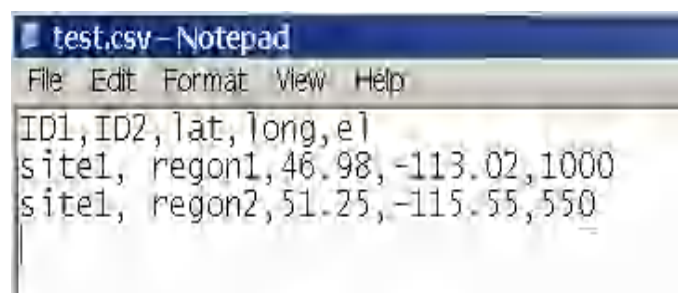
It is much more efficient to the Multi-location mode to process multiple locations than to use the Interactive mode. The program does not have an upper limit for the number of locations to be processed. In order to use the Multi-location mode, a coordinate input file needs to be prepared.

The input file requires two columns of IDs, latitude and longitude in decimal degree, and elevation in meter. A header row is also required. It can be prepared in MS Excel,



	A	B	C	D	E	F
1	ID1	ID2	lat	long	el	
2	site1	region1	46.98	-113.02	1000	
3	site1	region2	51.25	-115.55	550	
4						

or in any text editor:



```
ID1,ID2,lat,long,el
site1, region1,46.98,-113.02,1000
site1, region2,51.25,-115.55,550
```

If the input file is prepared in Excel, it needs to be saved in CSV format. If it is prepared in a text editor, the columns have to be separated by commas.

When the input file is ready, users can select a target year or a period, then click on **Select input file** to read your spreadsheet and on **Specify output file** to specify your output file folder and file. By clicking the **Calculate** button, output climate variables will be generated.

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APPLICATIONS

Climate is the primary factor regulating the geographic distributions of forest ecosystems and tree species (Woodward 1987, McKenney et al. 2007). It is also the main driver affecting the health and productivity of trees and other plants. Due to the difficulty in accessing climate data, research scientists have been using geographic variables, such as latitude, longitudes and elevation, as substitutes to climate variables for experimental design and data analysis. However, results obtained from such studies are limited to specific locations. For example, a relationship developed between the performance of a plant and elevation gradient in Kunming, China will not be valid in Beijing. This is because the effect of elevation on climate is very different between the south and north. In contrast, a relationship between the performance of a plant and climate variables will be applicable to anywhere. In addition, a relationship with geographic variables will not be useful for predicting the impact of climate change.

ClimateAP makes our access to climate variables as easy as to geographic variables. Therefore, it can be used for different areas of research and applications, such as:

1. Climate based experimental design and data analysis. Climatically based experiments will be more effective than geographically based in most cases. This is because the effect of climate on tree health and productivity is more direct than that of geographic variables. A typical example is the experimental design of the Lodgepole pine provenance trial in British Columbia. It has 60 test sites in the province and well represents the geographic distribution of this species. However, when plot the test sites against the mean annual temperature (MAT), the most important climate variable for this species, we found that the majority of the tests are located in a very narrow range of MAT and are redundant (Figure 2.11). A climatically based experimental design would save 60-70% of the cost.

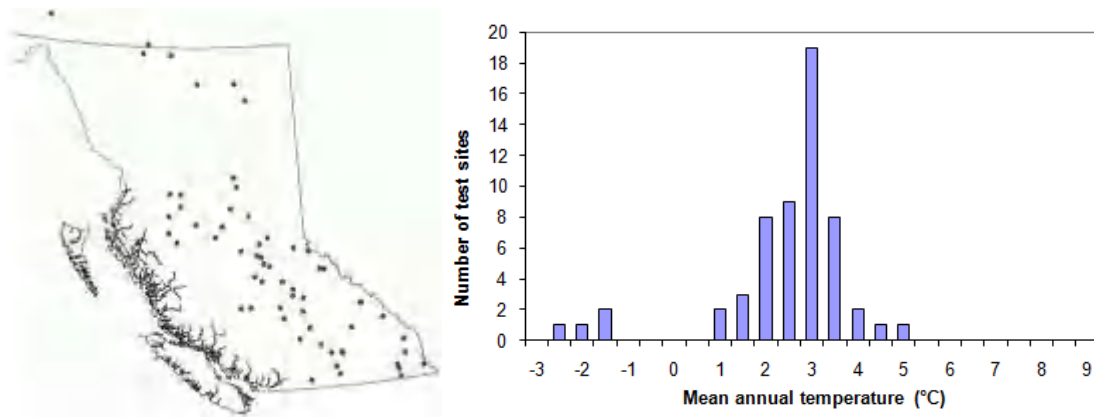


Figure 2.11 Geographic (left) and climatic (right) distributions of planting sites of the provenance test in British Columbia.

2. Generating climate surfaces. The output of ClimateAP is in the format of spreadsheet file. It can easily be imported to ArcGIS to generate maps. The resolution of the map depends on the resolution of the input file, which means that it is up to the user to determine the resolution of the climate surface.
3. Modelling climate niches for ecosystems and species. Such modelling exercises require climate data to well match the actual locations of the vegetation data. The scale-free climate data generated by ClimateAP can well meet this requirement. More details can be found in the next section.

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Chapter 3: Climate Niche Modelling for Ecosystems and Species

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BIOCLIMATE ENVELOPE MODELLING FOR ECOSYSTEMS

Ecological land classification systems are often used for natural resource management, such as in British Columbia (BC), Canada. The ecosystem classification system is called Biogeoclimatic Ecosystem Classification (BEC) (Meidinger and Pojar 1991). It divides the province into 16 ecological zones that reflect terrestrial ecosystem differences along large-scale climate gradients related to changes in altitude, latitude and continentality (Figure 3.1a). These zones are subdivided into increasingly smaller units called subzones and subzone-variants, reflecting plant community composition and structure differences along finer-scale climate gradients. These ecological units are widely used for resource management planning and decision-making in BC.

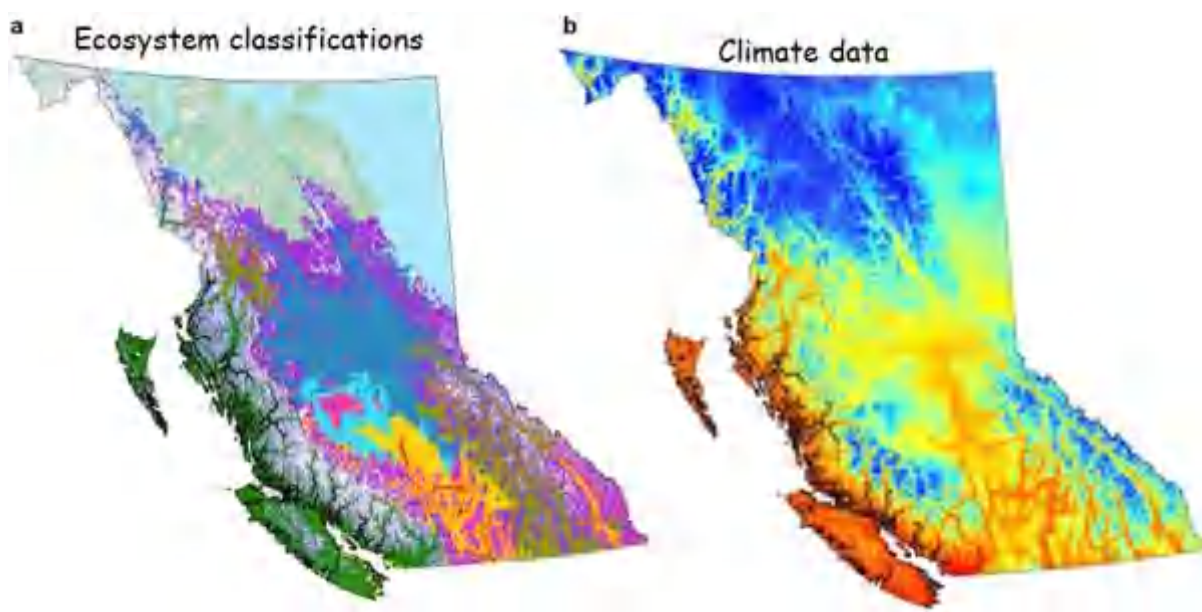


Figure 3.1 Maps of BC ecosystem classifications (a) and spatial climate data (mean annual temperature) (b).

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Ecosystem data

The digital map of the BEC system was rasterized to grid resolutions of 1600 m (370,205 cells) and 800 m (1,904,654 cells) in ArcGIS (version 9.2) for model building and model validation, respectively. Each grid was assigned to the ecosystem (i.e., zone, subzone, and subzone-variant) occurring at the center of each cell.

Climate data

ClimateWNA (version 4.6) (Wang et al. 2012b) was used to generate climate data. An input file containing point location coordinates (latitude, longitude, and elevation) for each rasterized grid cell was queried by ClimateWNA to generate 12 annual, 16 seasonal, and 48 monthly climate variables for each grid cell. The climate data were generated for: 1) the reference period (Figure 3.1b) to develop and validate our model, 2) the last decade (2001-2009) to assess the effects of recent climate change, and 3) three future periods (2020s, 2050s and 2080s) to project impacts of future climate change.

Model building

We used the R version (Liaw and Wiener 2002) of Breiman's (2001) of the Random Forests (RF) algorithm to model relationships between climate for the 1970s reference period and the geographic distribution of ecosystems in BC. RF produces many classification trees, collectively called a 'forest', and aggregates the results over all trees. Each of these decision trees in the forest is constructed using a bootstrap sample of the input data (i.e., a random sample with replacement) so that the resulting dataset ('bagged sample') contains about 64% of the original observations, and the remaining observations comprise the 'out-of-bag' (OOB) sample. Tree nodes (bifurcations in a branch) are created using the climate predictor variable that has the smallest classification error among a randomly selected subset of predictor variables. By default, the number of predictors randomly selected at each node is the square root of the total number of predictors. Using the trees grown with the bootstrap sample, each of the independent observations in the OOB sample is classified (assigned to an ecosystem) and a model prediction error, called the OOB error (% of incorrectly classed observations), is calculated.

To calibrate the model, we compared OOB prediction errors for models using four different sets of climate variables: 1) 12 annual variables, 2) 16 seasonal variables, 3) 48 monthly variables; and 4) all 76 climatic variables. The variable set with the lowest OOB error was used to build the model. The number of predictors selected at each node was optimized using the function *tuneRF*. RF was run with 200 classification trees; use of a larger number of these decision trees did not reduce OOB error. For the model that included all 76 climate variables, importance values (as determined by a decrease in Gini values, see Brieman 2001) generated by RF were used to reduce the number of climate variables included in the model without compromising model accuracy.

In Random Forest, each sample data point has the same contribution to the model. Therefore, the model is more weighted by the ecosystem classes with a large number of sample data points. A sampling strategy is often needed to balance the sample size among the ecosystem classes. The sampling strategy applied in this modelling process is described in Wang et al. (2012).

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Model accuracy

The model predicted current ecosystem distributions with high accuracy at BEC zone, subzone (Figure 3.2) and variant levels. The predictions used independent dataset; the data points used to build the model were not used for the predictions.

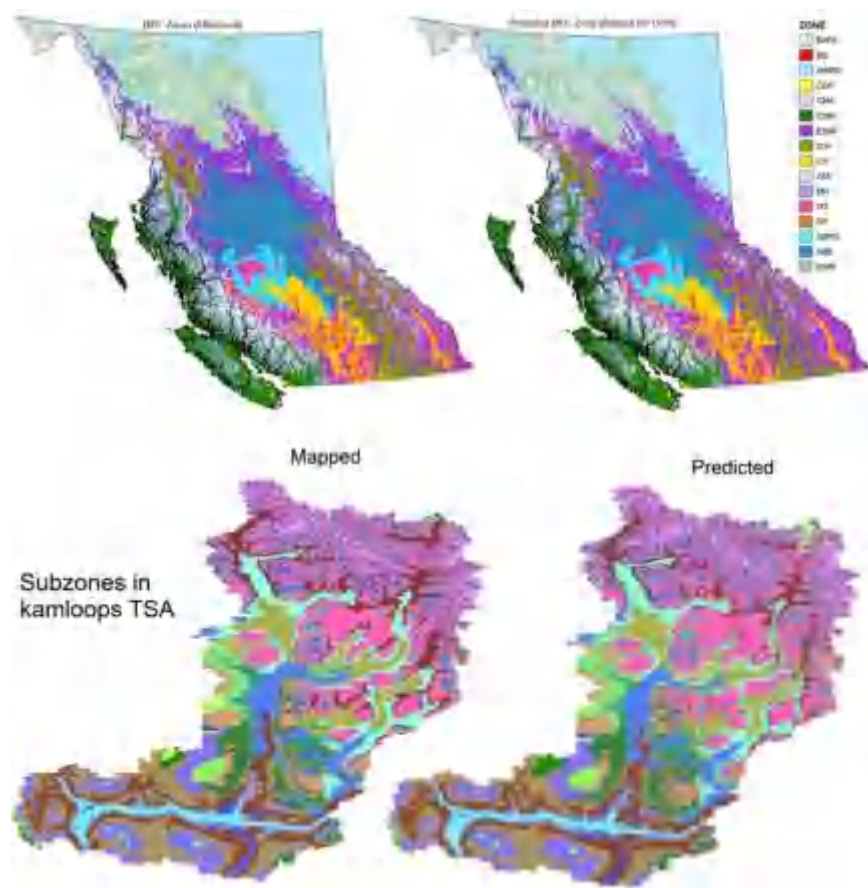


Figure 3.2 Comparisons between currently mapped ecosystems (left) and predicted ones (right) at BEC zone (upper) and subzone (lower) levels.

Variability among the projections using different climate change scenarios

Predicted climate changes from difference greenhouse gas emission scenarios and different General Circulation Models (GCMs) varied with a wide range. There are over 140 combinations of emission scenarios and GCMs, which were collectively called climate change scenarios. We chose 20 of them to represent the range and crowd (Figure 3.3).

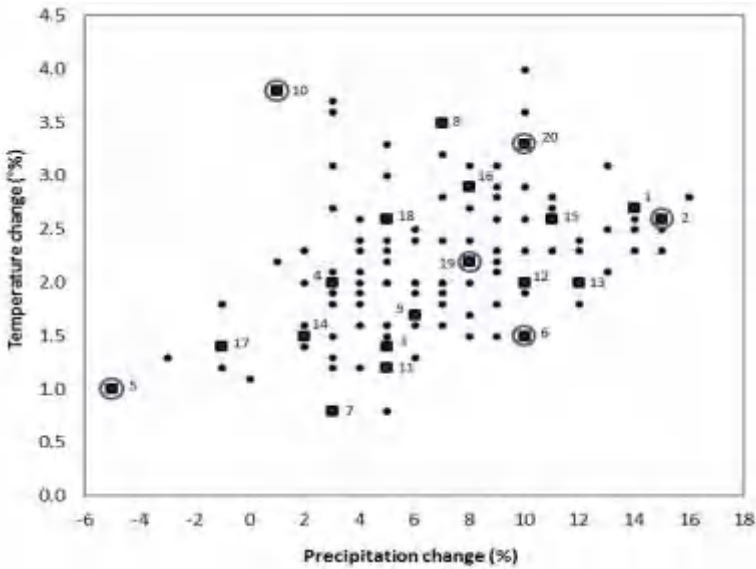


Figure 3.3 Predicted changes in temperature and precipitation for BC by 134 climate changes scenarios for 2050s.

Projections for one future period (2050s) differed substantially depending on climate change scenarios used. The differences are shown using six climate change scenarios (Figure 3.4).

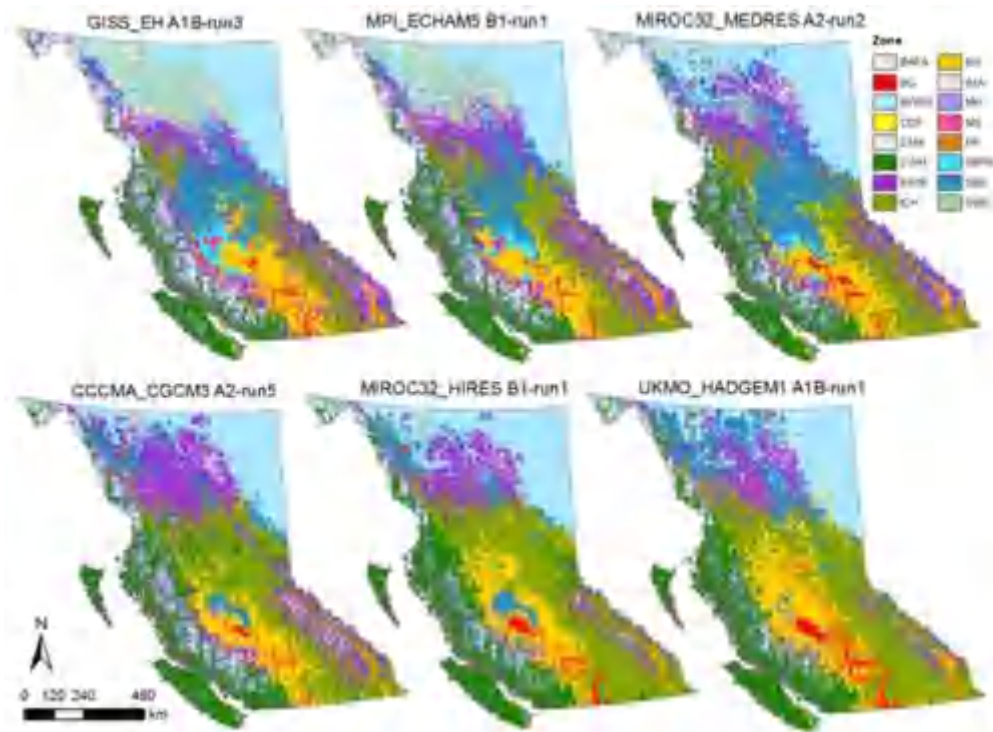


Figure 3.4 Differences in projections for 2050s using different climate change scenarios.

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Consensus projections

A consensus projection for a future period was generated based on the most frequently projected ecosystem zone for each pixel among the 20 individual projections. We used the level of the model agreement among the 20 individual projections to represent the level of uncertainty (or consensus strength) of the ecosystem climate niches under climate change (Figure 3.5).

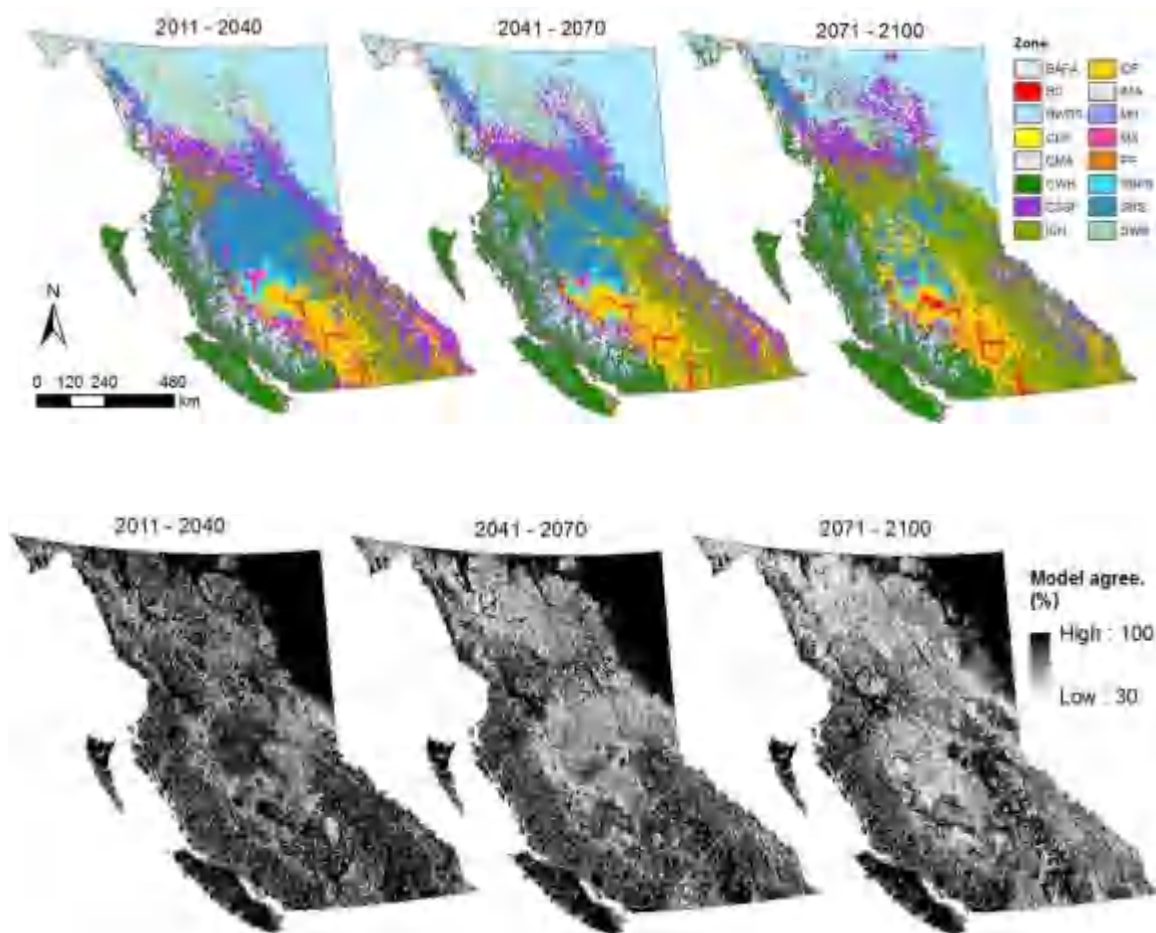


Figure 3.5 Consensus projections based 20 projections using different climate change scenarios. The upper maps show the projections, while the lower maps are the levels of the model agreement.

Variability in the impact of climate change on ecosystems

Impacts of climate change ecosystems differ considerably. The bioclimate envelopes of some ecosystems are projected to contract, while some others to expand (Figure 3.6). In BC, several spruce dominated ecosystems are projected to move upward and northward, and their suitable climate niches are going to decline. However, several productive forest ecotypes are projected to expand. Their dominant species include Douglas-fir, interior redcedar and western hemlock. These species are fast-growing and economically important species. Climate change would make more areas suitable for planting these species and potentially could increase the productivity in BC.

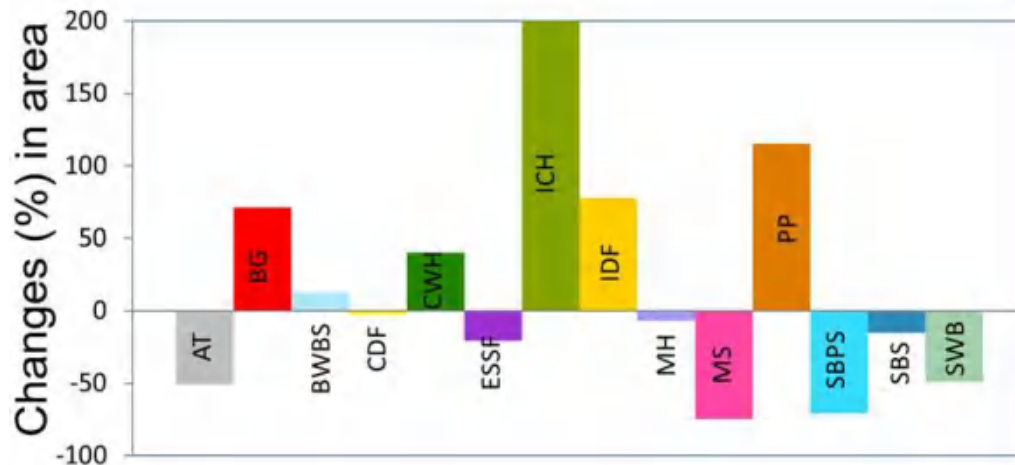


Figure 3.6 Projected changes in area for different forest ecosystems in BC. Climates suitable for Interior Cedar-Hemlock (ICH), Ponderosa Pine (PP), Interior Douglas-fir (IDF), Bunchgrass (BG) and Coastal Western Hemlock (CWH) zones are projected to expand. Meanwhile, Climates characterized for Montane Spruce (MS), Sub-Boreal Pine - Spruce (SBPS), Spruce - Willow - Birch (SWB) and Alpine Tundra (AT) zones are projected to contract.

BIOCLIMATIC MODELING FOR SPECIES

Ecosystem niche based modelling

Species bioclimate envelopes can be modeled by associating species distributions with ecosystem classes if such data are available. In British Columbia, we associated species frequencies with Biogeoclimatic subzone-variant (Wang et al. 2012a). After the bioclimate envelope of a subzone-variant was projected, the projection of the associated species was also achieved. Figure 3.7 shows the projections of the suitable climate niche for Douglas-fir in three future periods.

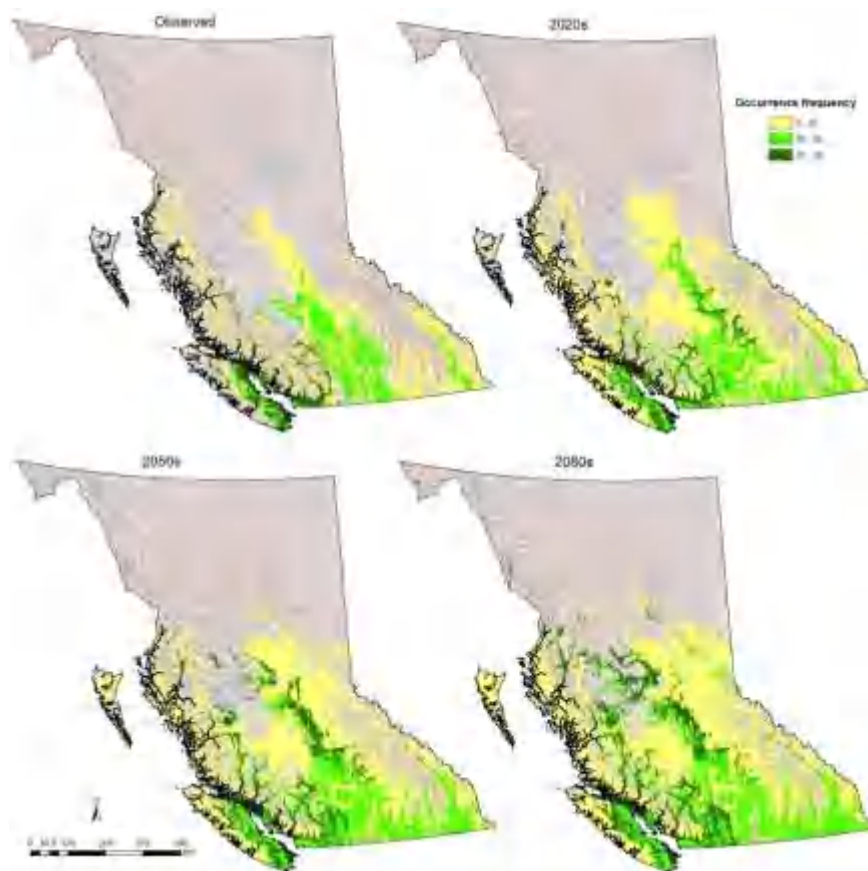


Figure 3.7 Projections of the bioclimate envelopes of Douglas-fir for 2020s, 2050s and 2080s based on consensus projections using 20 climate change scenarios.

Species present-absent data based modelling

If the present-absent data are available for a species, the same modelling approach used in modelling ecosystem classes can be used to model the bioclimate envelopes for individual species. However, to balance the sample sizes between present and absent categories is more critical in modelling for species than for ecosystems as the number of data points for the absent category is often much larger than that for the present category. By simply making the samples equal between these two categories do not work well in most cases because climate conditions in the areas for the absent category are more heterogeneous and need a larger sample to represent it. We applied a “multiple- forests” approach to solve this problem.

With the multiple-forests approach, a balanced sample dataset was constructed for each of 10 Random Forests. Among the 10 training datasets, the *present* data points were identical, but the data points for the *absent* data points were randomly sampled. Using this approach, balanced datasets satisfy the Random Forest requirements, while the repeated random sampling of the area for absent improves the representation of the heterogeneous climate conditions for this category. Predictions of the 10 Random Forest models (or sub-models) were aggregated for the final model output.

We modeled Chinese Fir, Chinese pine and Masson pine using this approach. Climate variables for the reference period 1961-1990 and future periods were obtained for each data points in the training datasets

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using ClimateAP. For this study, we generated 66 annual and seasonal climate variables for the point locations with presence and absence of the species for the reference normal period 1961–1990. A backward optimization approach was applied to eliminate the least important climate variable through each model run. This process was iterated until the best fit of the model was achieved. The identified climate variables were used in each of the 10 sub-models. The final model prediction was based on the consensus of among the 10 sub-models.

For the future period, gridded climate data were generated using ClimateAP for 12 climate change scenarios including six AR5 GCMs and 2 emission scenarios (RCP4.5 and RCP8.5). The six GCMs include: ACCESS1-3, BCC-CSM1, CanESM2, CNRM-CM5, CSIRO-Mk3-6-0, and HadGEM2-ES. A projection was generated using the species climate niche model for each of the 12 climate change scenario. A consensus projection was then produced using the 12 projections for each future period. Model predictions for current and the three future periods are shown in Figure 3.8 and Figure 3.9 for Chinese fir and Masson pine.

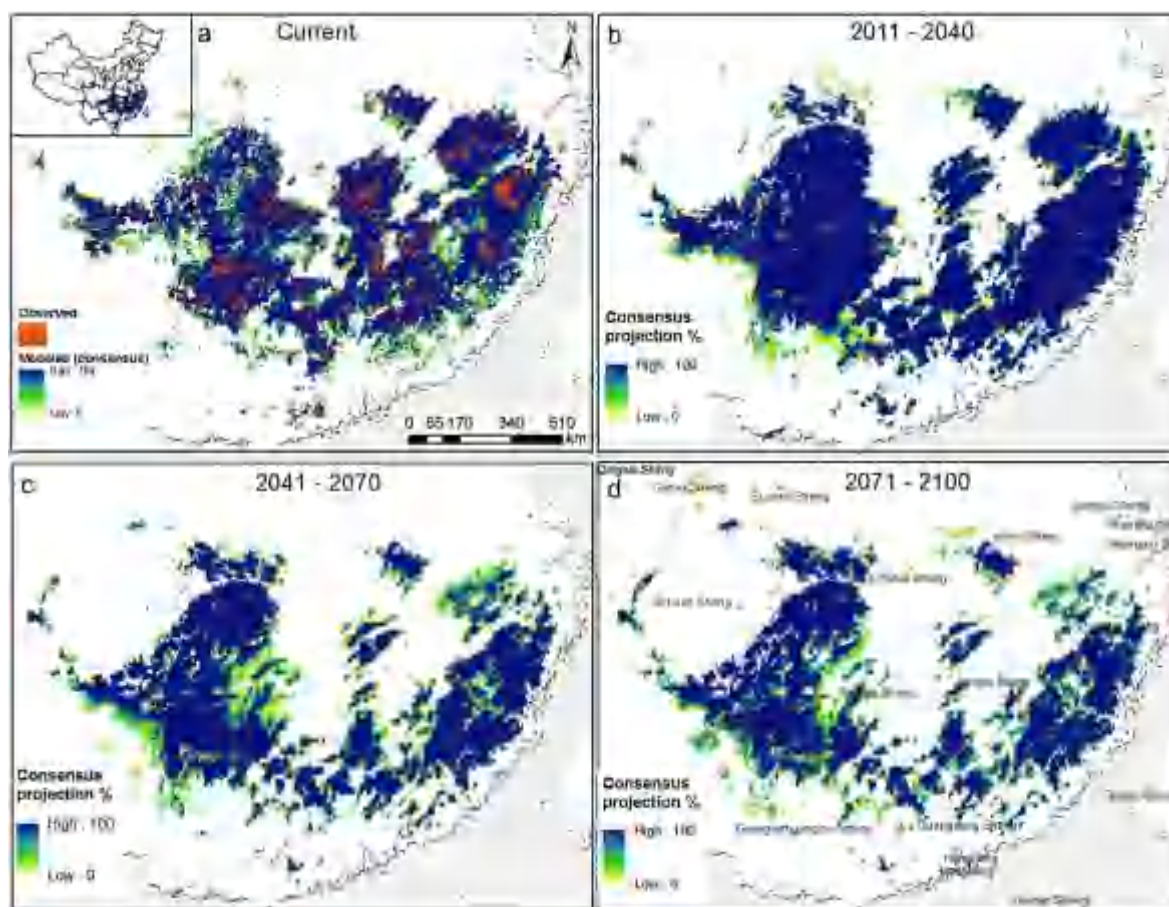


Figure 3.8 Projected shifts in climate niches for Chinese fir: a) current geographic distribution; b) projected climate niche suitable for this species in 2050s based consensus projections.

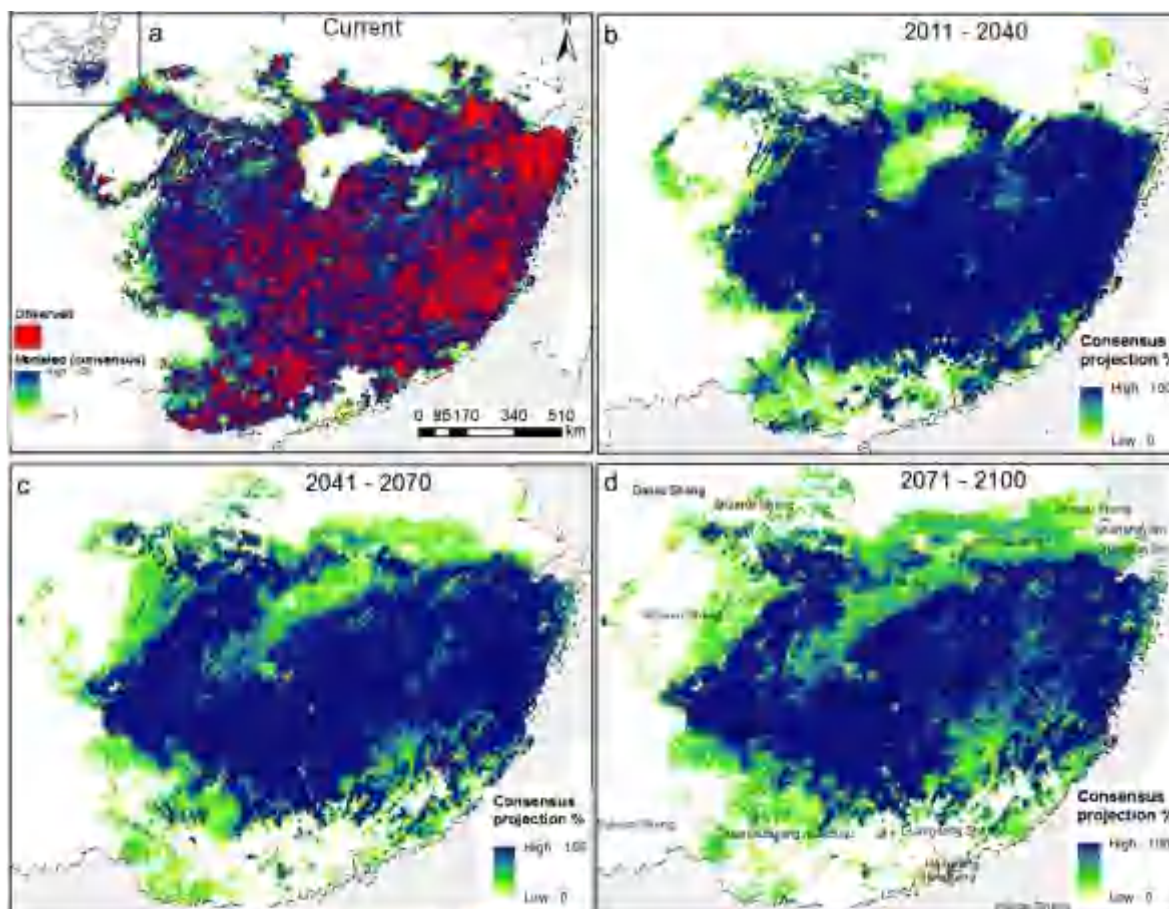


Figure 3.9 Projected shifts in climate niches for Masson pine: a) current geographic distribution; b) projected climate niche suitable for this species in 2050s based consensus projections.

MODELLING THE RESPONSE OF TREE POPULATIONS TO CLIMATE

Although tree species as a whole can be characterized by their bioclimatic envelopes, variation in response to climate among populations within a tree species is well recognized (Matyas 1994, Rehfeldt et al. 1999, Wang et al. 2006, Wang et al. 2010), and local adaptation of tree populations along climatic gradients has been demonstrated (Epperson 2003, Howe et al. 2003). For example, peripheral populations of lodgepole pine (*Pinus contorta*) from cold environments at the northern limit of its distribution grow much slower under favorable temperatures for this species than populations from central populations (Wang et al. 2006). This suggests that localized northern populations would be unable to take full advantage of warming temperatures attributed to climate change while some populations in the south are likely to be growing outside their bioclimatic envelopes (Rehfeldt et al. 1999, Wang et al. 2006). Therefore, climate change will also cause climate mismatches at the population level within a tree species.

Climate has long been recognized as playing a key role in both these determinants of phenotype in plants: in the short term, through direct effects on phenotypes via environmental effects on survival, growth, and reproduction and in the longer term, through acting as a major selection force affecting plant genotypes.

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Genetic and environmental effects of climate on phenotypes have previously been used to develop population transfer functions and population response functions using provenance test data for climate change studies.

A transfer function relates the performance of multiple populations to the climatic transfer distances between their provenances and a particular planting site (i.e., site climate minus provenance climate). A general transfer function (Rehfeldt et al. 1999) and climate response functions (Wang et al. 2006) for Lodgepole pine are shown in Figure 3.10.

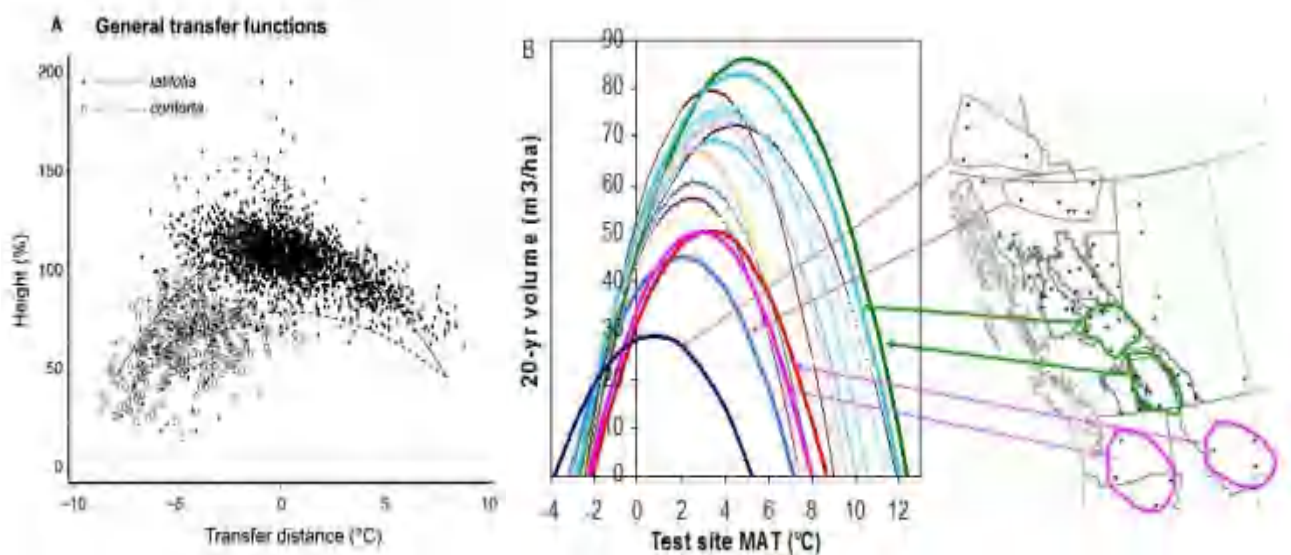


Figure 3.10 A general transfer function (Rehfeldt et al. 1999) and climate response functions (Wang et al. 2006) for Lodgepole pine.

Both transfer functions and response functions have limitations. By pooling data from multiple sites in developing a general transfer function, it is assumed that the shape and position of individual transfer functions are the same across different environments. However, this assumption is often not valid (Wang et al. 2010). Thus, individual transfer functions or genecology functions are developed to overcome this limitation. However, the genecology functions are test site specific (i.e., only valid for the specific test). Similarly, response functions are population specific; each response function is valid only for the specific population for which it is developed. Recently a new approach has been developed by integrating the genecology and response functions into a universal response function to overcome these limitations (Wang et al. 2010) (Figure 3.11).

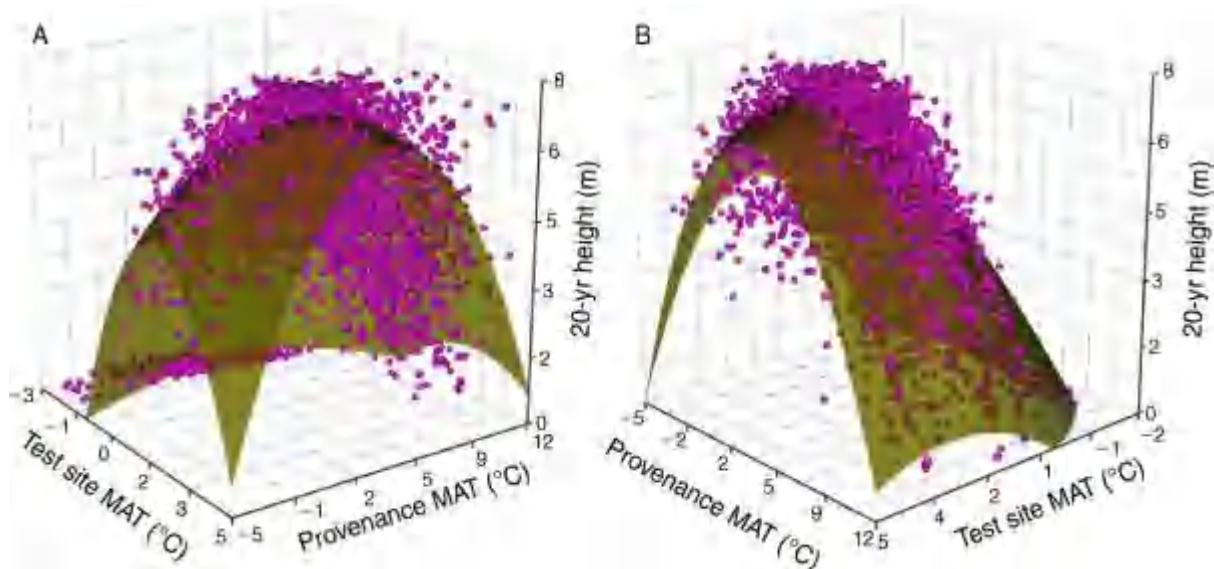


Figure 3.11 The universal response function for Lodgepole pine adopted from Wang et al. (2010).

The universal response function has the following advantages over the conventional transfer functions and response functions: (1) improve predictions of climate change impacts on phenotypes; (2) reduce the size and cost of future provenance trials without compromising predictive power; (3) more fully exploit existing, less comprehensive provenance tests; (4) quantify and compare environmental and genetic effects of climate on population performance; and (5) predict the performance of any population growing in any climate.

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Chapter 4: Modelling Climate Impacts on Forest Growth and Mortality

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FORWADY: THE FOREST HYDROLOGY SUBMODEL USED IN FORECAST CLIMATE

ForWaDy (Forest Water Dynamics; Seely et al. 1997; Seely et al. 2006) is a vegetation-oriented, forest hydrology model. A diagram illustrating the model structure and function is shown in Figure 4.1. The model can be used as a stand-alone application, and it is integrated within FORECAST Climate where it is coupled to the main tree growth engine and the tree ring model (Seely and Welham 2010).

ForWaDy simulates potential evapotranspiration (PET) using an energy balance approach based on the Priestly-Taylor equation. Incoming radiation is partitioned among vertically stratified canopy layers (vegetation type) and the forest floor to drive actual evapotranspiration (AET) calculations. The model has a representation of soil physical properties dictating moisture availability, storage, and infiltration, and it simulates the relative impact of soil cover depth, minor vegetation competition and climate on the water availability for trees. A detailed description is provided in Seely et al. (1997, 2006).

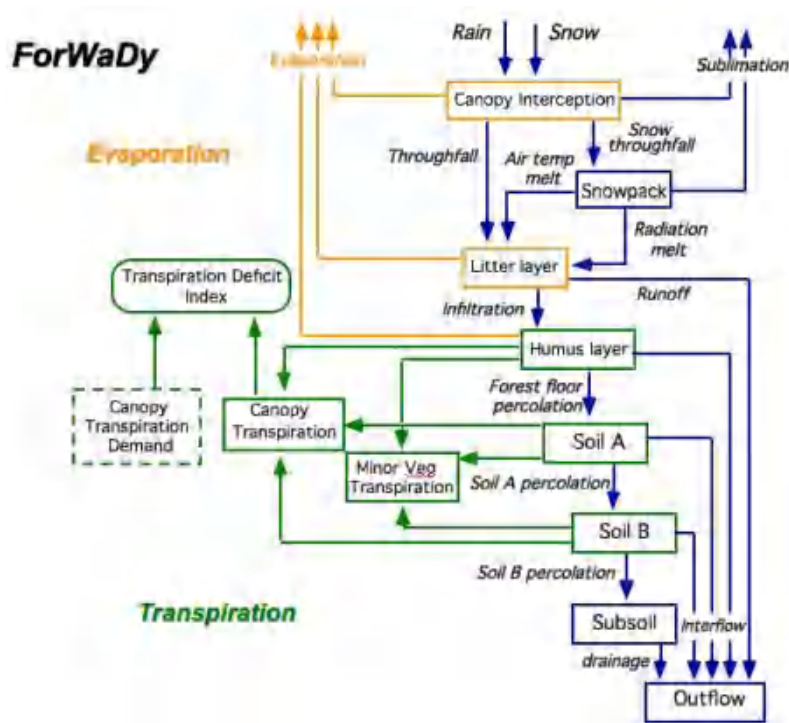


Figure 4.1 Schematic illustration of the structure of ForWaDy indicating the flow pathways and storage compartments represented in the model.

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Water stress in ForWaDy is calculated as a transpiration deficit index (TDI). In essence, the TDI represents the difference between potential transpiration (as dictated by available energy) and actual transpiration (limited by available moisture), as follows:

$$\text{TDI} = (\text{CanT}_{\text{Total}} - \text{CanT}_{\text{Actual}}) / \text{CanT}_{\text{Total}}$$

where:

$\text{CanT}_{\text{Total}}$ = energy limited transpiration: f (leaf area index, intercepted short- wave radiation, canopy albedo, and canopy resistance)

$\text{CanT}_{\text{Actual}}$ = actual tree transpiration: f ($\text{CanT}_{\text{Total}}$, root occupancy, available soil moisture)

CALIBRATION OF FORECAST CLIMATE FOR THE MKFR STUDY AREA

The following section describes the calibration data that have been assembled to drive the FORECAST Climate model for the MKRF project area. Table 4.1 provides a summary of the data used to calibrate the ForWaDy submodel of FORECAST Climate for the different tree species represented within the model. The calibration data used in its application within FORECAST Climate are listed in Tables 4.1 and 4.2.

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Table 4.1 Species-specific parameter values used in the ForWaDy submodel that are specific to simulating evapotranspiration.

Species	Maximum LAI ¹			Canopy	Permanent Wilting Point (%) ⁴					Max. Root Depth (cm)
	SM ²	M	H		Albedo	Resist ³	Mineral Soil			
				Humus			SM	M	SM	
Trees ⁵										
Hw	4.5	5.5	6	0.12	0.14	0.11	0.08	0.14	0.20	75
Cw	4	5	5.5	0.12	0.18	0.1	0.07	0.12	0.18	100
Fd	3.5	4.5	5	0.12	0.25	0.08	0.06	0.11	0.17	>100
Dr	3	4	4.5	0.12	0.11	0.11	0.08	0.13	0.19	75
Understory vegetation ⁶										
Rubus		NA		0.12	0.11	0.11	0.08	0.13	0.19	60
Vacc.		NA		0.12	0.13	0.11	0.08	0.13	0.19	60
Salal		NA		0.12	0.22	0.09	0.06	0.11	0.17	85

¹ Sets the upper limit for LAI by species. LAI is determined as a function of simulated foliage biomass. Not required for understory vegetation.

² Edaphic Class: SM=Submesic site; M = Mesic site; SH = Subhygric site

³ “Canopy resistance” represents a general measure of the resistance to water loss from foliage via stomata and cuticle.

⁴ Refers to the volumetric moisture content at which the species can no longer extract moisture from the soil. Dependent upon the soil texture class.

⁵Trees include: Hw- Western Hemlock (*Tsuga heterophylla*); Cw- Western redcedar (*Thuja plicata*); Fd- Douglas-fir (*Pseudotsuga menziesii*); Dr-Red Alder (*Alnus rubra*)

⁶Understory vegetation include: Rubus – Salmon berry shrub (*Rubus spectabilis*); Vacc. – generally blueberry-type shrub (*Vaccinium spp.*); Salal shrub – (*Gaultheria shallon*)

Table 4.2 Parameter values used in ForWaDy that are specific to simulating soil water availability by edaphic class.

Edaphic class	Soil Texture class	Coarse Fragment (%)	Mineral soil depth (cm)
Submesic	Loamy sand	35	65
Mesic	Silt loam	25	85
Subhygric	Sandy clay loam	15	110

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LINKING TREE GROWTH WITH FOREST HYDROLOGY

The linkage between the FORECAST and ForWaDy models underpins the operation of FORECAST Climate. This linkage is based upon the iterative sharing of information between models through the creation of feedback loops (see Figure 4.2). One challenge is the fact that the ForWaDy model operates on a daily time step (since this is the relevant interval for many hydrological processes), whereas FORECAST calculates productivity on a yearly time step. The latter model thus provides annual estimates of the key variables used by ForWaDy. These are listed in Table 4.3. ForWaDy output in turn is provided to FORECAST as a series of annual summaries of soil and forest floor moisture conditions, and cumulative measures of water stress for trees and plants.

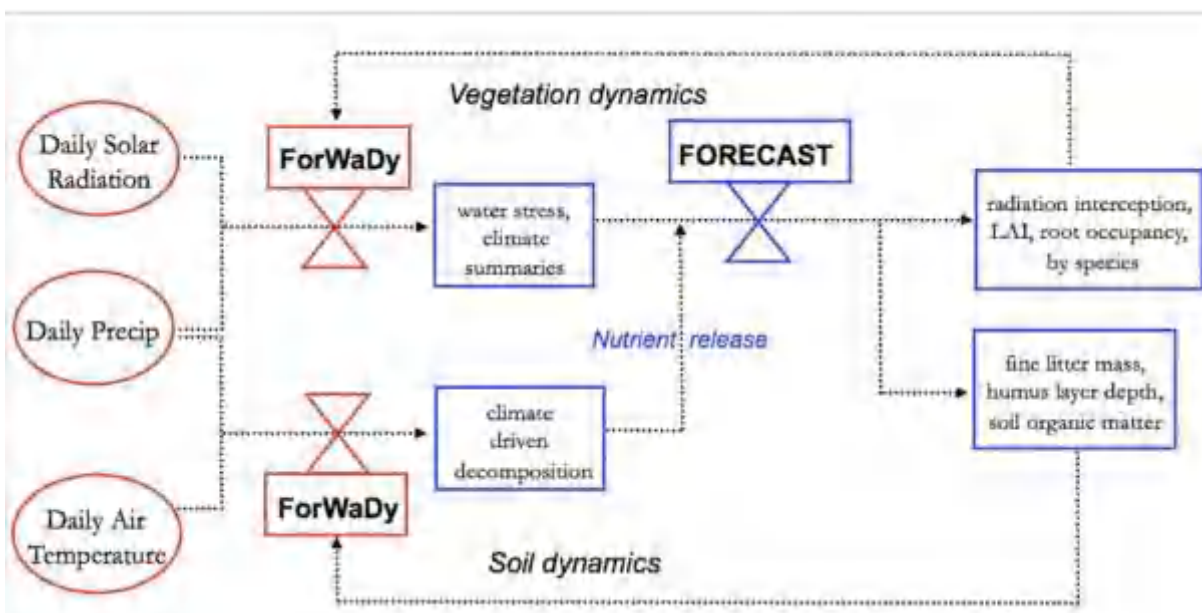


Figure 8.2 A schematic diagram illustrating the feedback loops established to facilitate the linkage of FORECAST and ForWaDy.

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Table 4.3 A list of vegetation and soil condition variables passed from the forest growth model (FORECAST) to the hydrological model (ForWaDy). The function of each variable in ForWaDy is also described.

FORECAST	ForWaDy	
<i>Variable</i>	<i>Receiving variable</i>	<i>Function</i>
Canopy light interception	Canopy radiation interception	Drives species specific transpiration
Foliage biomass	LAI ¹	Canopy interception
Fine root biomass	Lateral root occupancy	Soil water uptake capacity within a specific soil layer
Tree age	Rooting depth	Soil water uptake capacity from vertical soil layers
Fine litter mass ²	Litter mass	Litter layer moisture content
Humus mass	Humus depth ³	Humus layer water holding capacity

¹ Leaf area index is estimated using a species-specific conversion factor.

² Fine litter mass includes foliage, bark, and fruit (cone) litter types.

³ Humus depth is estimated from humus mass, based on a parameter that defines the proportion of new humus transferred to non-surface layers and an estimate of surface humus bulk-density.

ACCOUNTING FOR CLIMATE IMPACTS ON TREE AND PLANT PRODUCTIVITY

The impact of climate on tree growth and ecosystem development in FORECAST Climate is focused, in part, on their relationship to temperature and water stress. These relationships are represented using curvilinear response functions, simulated on a daily time step and summarized annually. The temperature response functions (see Figure 4.3) encapsulate the multiple and complex physiological growth processes governing the response of trees and understory growth to mean daily temperature. The relative effect of temperature as a limiting factor on tree growth is captured annually through the sum of daily values. The positive effect of a lengthening growing season can also be represented with this approach. Note, however, that increases in summer temperatures may not necessarily have a positive impact on annual growth rates (Wilmking et al. 2004; see Figure 4.3).

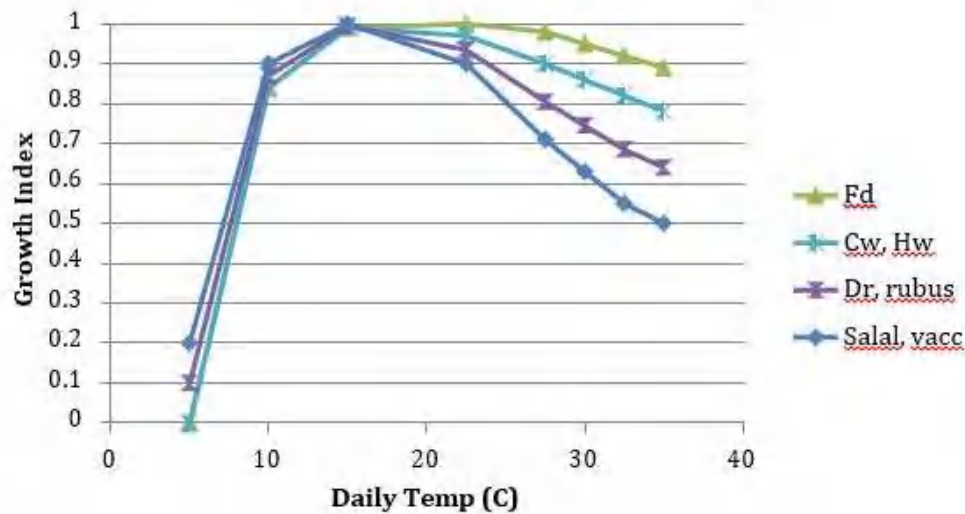


Figure 4.3 Temperature response functions used for trees and understory vegetation.

The effect of moisture availability on plant growth rates in FORECAST Climate is simulated by ForWaDy and calculated as the Transpiration Deficit Index (TDI, see ForWaDy description above). The daily TDI value represents the degree to which a tree species was able to meet its energy-driven transpiration demands; a higher TDI value indicates more moisture stress. As the TDI increases, plants close their stomata to conserve water and there is an associated reduction in photosynthetic production (see McDowell et al. 2008). An evaluation of alternative TDI growth response curves based on tree ring chronologies (see Seely and Welham 2010) indicated that a negative exponential curve best reflected the effect of TDI on daily and annual productivity (Figure 4.4).

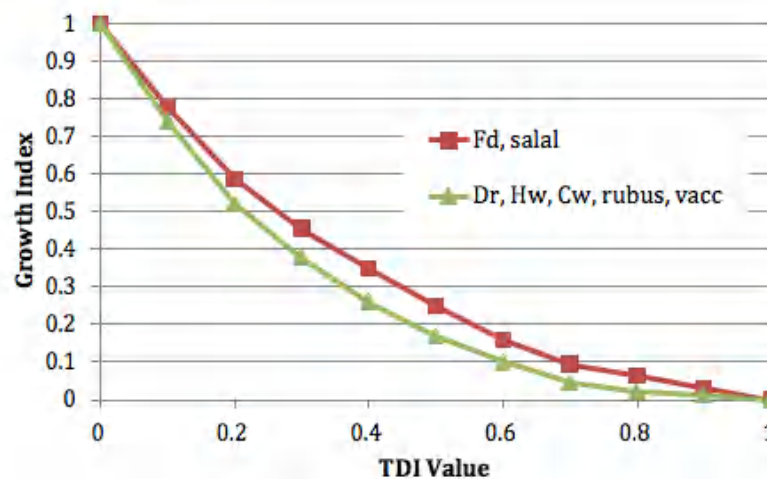


Figure 4.4 TDI response functions used for different tree and understory vegetation species

The temperature and moisture response functions are incorporated into FORECAST Climate through their inclusion in a climate response index function (CRI_{growth}). The CRI_{growth} function is first calculated daily as the product of the temperature multiplier (Figure 8.3) and the TDI multiplier (Figure 4.4), and then summed over the year to create an annual index. Two types of CRI_{growth} values were calculated. First, a

climate-normal growth value ($\text{normal\_CRI}_{\text{growth}}$) was determined using a 30-year (1975 to 2004) historical climate data set from the weather station associated with each ecogroup. The process of determining a 'normal' value for $\text{CRI}_{\text{growth}}$ involves calculating a $\text{CRI}_{\text{growth}}$ value for each year of the historical climate data set and then calculating an average value for the climate response index ($\text{normal\_CRI}_{\text{growth}}$) over the 30-year period. The second type of $\text{CRI}_{\text{growth}}$ ($\text{current\_CRI}_{\text{growth}(i)}$) is calculated during an actual simulation, for each year, i . A weighted adjustment value is then derived using the $\text{normal\_CRI}_{\text{growth}}$ value as the comparative standard (see equation below). The potential growth rate (based on light and nutrient availability) in a given year is multiplied by the weighted climate response index to yield the actual annual growth rate in year, i :

$$\text{Annual growth rate}(i) = \text{potential growth rate}(i) * (\text{current\_CRI}_{\text{growth}(i)} - \text{normal\_CRI}_{\text{growth}}) / \text{normal\_CRI}_{\text{growth}}$$

where:

potential growth rate(i) = expected growth based on light availability and site quality

current_ $\text{CRI}_{\text{growth}(i)}$ = the climate response index for a given year, i

normal_ $\text{CRI}_{\text{growth}(i)}$ = average climate response index based upon long-term historical climate data

REPRESENTATION OF DROUGHT MORTALITY

In addition to the changes in growth, climate variability can also induce mortality events (e.g. Daniels et al. 2011). A drought mortality function was developed and implemented within FORECAST Climate to represent these effects. The function, illustrated in Figure 4.5, simulates drought mortality using a response curve in which a two-year running average of species specific TDI is used as a predictor of annual mortality rates. The use of the 2-year running average TDI allows for a decrease in drought mortality when a dry year is preceded or followed by a wet year, but will cause greater mortality in consecutive dry years. An exponential sigmoidal function curve was selected as a good approximation of the significant increase in expected mortality associated with consecutive years with high levels of water stress. The shape of the curve takes into account evidence of enhanced vulnerability of stands to biotic disturbance agents (e.g. bark beetles) during extended periods of extreme moisture stress. The amplitude of the function curve was fit for each species using the historical climate data simulations for reference (to assure that historical climate data led to mortality rates that are consistent with past observations). Two different mortality curves (low and high) were simulated for each tree species to illustrate the sensitivity of the model to varying assumptions with respect to tree susceptibility to drought stress (Figure 4.5).

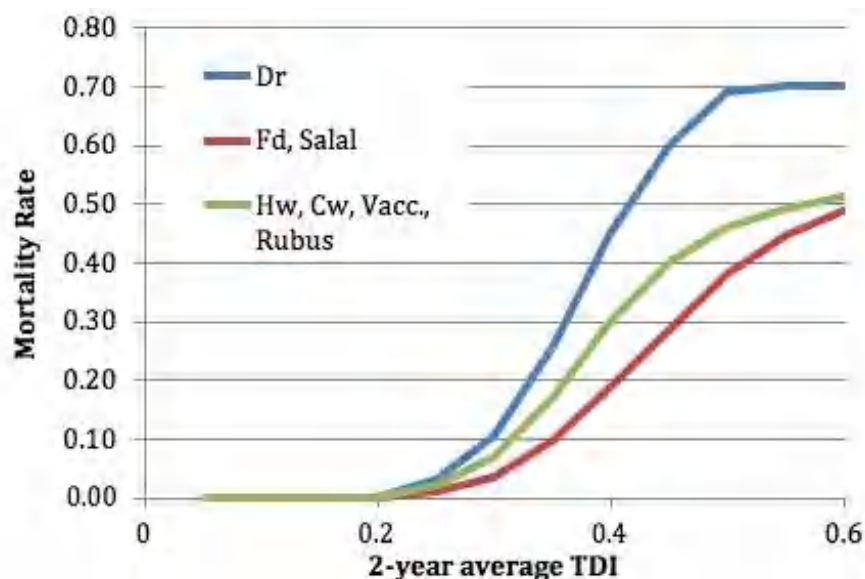


Figure 4.5 Drought-related mortality function showing the relationship between mortality and running 2-year average of the transpiration deficit index (TDI).

ACCOUNTING FOR CLIMATE IMPACTS ON DECOMPOSITION RATES

The decomposition of dead organic matter (litter and soil organic matter) in FORECAST is represented by grouping litter created through the death of specific biomass components into different litter types, each with defined mass loss rates (see Kimmins et al. 1999). In FORECAST Climate, these litter decomposition rates and their associated nutrient mineralization rates are adjusted based on soil moisture content and temperature. A base mass loss rate is provided for each litter and humus type (parameterized from field or literature values) that reflects both the quality of the litter and a 'normal' climate regime. These mass loss rates are then modified within the model to account for the effect of climate, as follows.

Temperature

A variety of techniques have been developed to quantify the effect of temperature on decomposition. The most common are simple calculations of weight loss using litterbags, field soil respiration measures (either by eddy covariance or gas chambers), and laboratory or ^{14}C studies. Consumption of dead organic matter by heterotrophic microbes and fungi is generally faster in warmer environments (Chen et al. 2000, Gholz et al. 2000, and references therein).

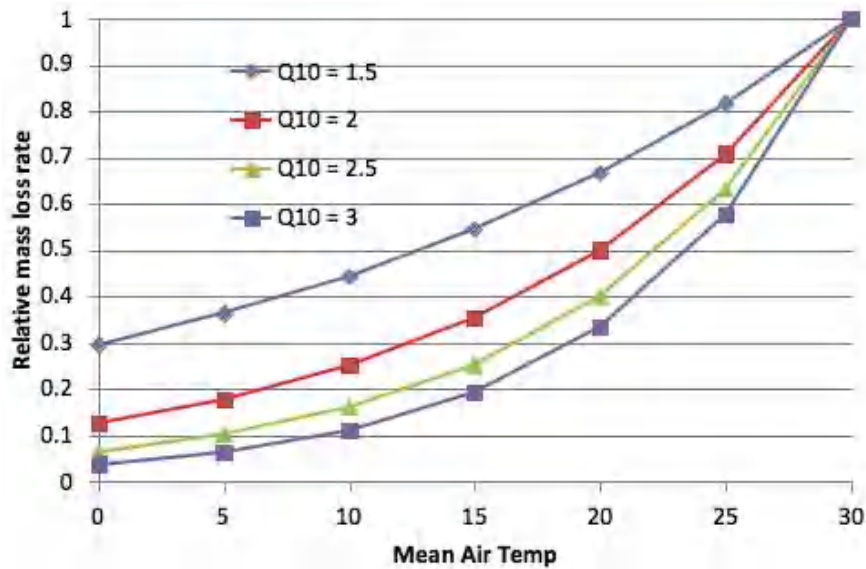


Figure 4.6 Illustration of the effect of a range of Q10 values on the calculation of a relative mass loss rate as a function of mean daily air temperature using the Q10 equation.

Many studies use the Q_{10} equation to describe effect of temperature on organic matter decomposition rates:

$$Q_{10} = (R_2/R_1)^{10/(T_2-T_1)}$$

where:

R_1 = mass loss rate at temperature 1 (T_1 °C)

R_2 = mass loss rate at temperature 2 (T_2 °C)

In FORECAST Climate, the impact of temperature on the decomposition rates of litter and humus is simulated based on the Q_{10} equation. A default value of 2 was selected for Q_{10} based on published studies in similar forest types (Chen et al. 2000, Gholz et al. 2000, and references therein). The effect of this value on relative mass loss rates is illustrated in Figure 8.6.

PRECIPITATION AND LITTER MOISTURE CONTENT

Precipitation as a factor in decomposition rates has received much less attention than temperature despite the fact its importance has been clearly demonstrated (e.g., Chen et al. 2000, Ise and Moorcroft 2006, Prescott et al. 2004). A key feature of these studies is that decomposition rates are directly correlated to precipitation until a threshold is reached, after which there is little or no additional effect.

A daily relative mass loss rate is calculated within FORECAST Climate for each litter and humus type using a curvilinear function based upon simulated moisture content in the litter and humus layers (Figure 4.7). Litter moisture content is used to drive mass loss rates for forest floor litter types while humus moisture content is used for any below-ground litter and humus.

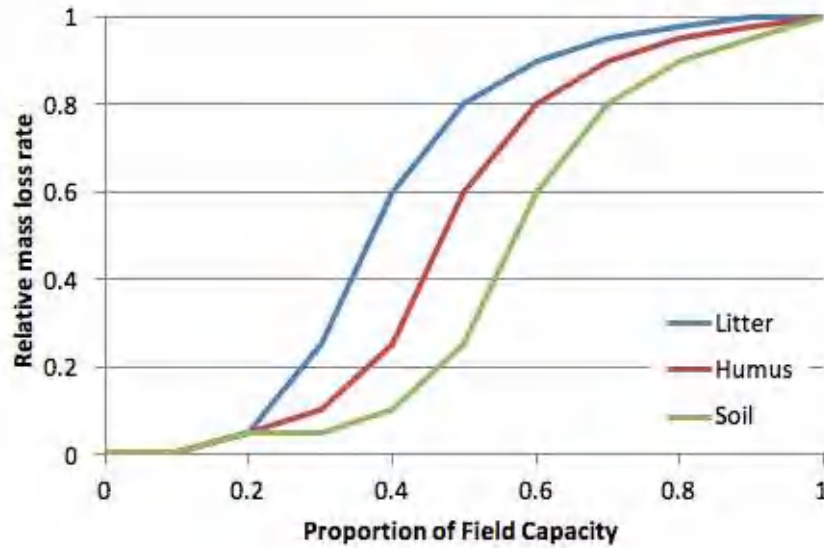


Figure 4.7 Response curves of the effect of daily moisture content (as a proportion of the Field Capacity value) on the relative mass loss rate of litter and humus.

FORECAST Climate employs a similar method for scaling decomposition rates to climate as was used for scaling annual growth rates (see above). The temperature-limited relative mass loss rate (Figure 4.6) is multiplied by the daily moisture-limited rate (Figure 4.7 for each litter and humus type, j , to produce a daily decomposition climate response index, CRI_{decomp} , that is then summed over the year to provide an annual index. A $normal\_CRI_{decomp}$ value is calculated for each litter and humus type based on historical climate data using the same approach described for adjusting tree growth above. A second type of CRI_{decomp} ($current\_CRI_{decomp(i)}$) is calculated during an actual simulation, for each year, i . A weighted adjustment value is then derived using the $normal\_CRI_{growth}$ value as the comparative standard (see equation below).

The base mass loss rate of a given litter or humus type, j , is multiplied by the weighted climate response index to yield the actual mass loss rate in year, i (Annual mass loss rate(i,j)):

$$Annual\ mass\ loss\ rate(i,j) = base\_rate(j) * (current\_CRI_{decomp(i,j)} - normal\_CRI_{decomp(j)}) / normal\_CRI_{decomp(j)}$$

where:

$base\_rate(j)$ = expected mass loss rate for each litter and humus type, j

$current\_CRI_{decomp(i,j)}$ = climate response index for each litter and humus type, j , for the current year, i

$normal\_CRI_{decomp(j)}$ = average response index for each litter and humus type, j , based upon long-term historical climate data

DEVELOPMENT OF FORECAST CLIMATE ANALYSIS UNITS FOR MKRF

A series of representative forest analysis units were created and assigned to facilitate the simulation of the 26,467 ha MKRF study area using FORECAST Climate (Table 4.4).

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Table 4.4 A description of the analysis units created for the simulation of climate change impacts on the Pitt River pilot study area using FORECAST Climate.

FC_AU	Type	Description	SI range	Age	Avg. SI	Area (ha)
101	Natural	Alder Poor-Medium		All	20.5	842.8
102	Natural	Alder Good		All	27.7	766.9
103	Natural	At/Ep		All	28.8	345.8
104	Natural	Hw-Ba-Pl Poor	<16	>40	9.7	2565.5
105	Natural	Hw-Ba-Pl Med	16-24	>40	19.4	3483.2
106	Natural	Hw-Ba-Pl Good	>24	>40	29.3	4633.2
107	Natural	Cw-Yc-Xc Poor	<16	>40	11.1	501.6
108	Natural	Cw-Yc-X Med	16-24	>40	19.3	1529.9
109	Natural	Cw-Yc Good	>24	>40	29.4	1077.8
110	Natural	Fd-Med	<25	>40	20.2	976.9
111	Natural	Fd-Good	>24	>40	29.5	1,105.9
204	Managed	Hw-Ba-Pl Poor	<16	<41	13.1	66.7
205	Managed	Hw-Ba-Pl Med	16-24	<41	21.2	595.2
206	Managed	Hw-Ba-Pl Good	>24	<41	30.2	1,122.8
207	Managed	Cw-Yc-Xc Poor	<16	<41		0.0
208	Managed	Cw-Yc-X Med	16-24	<41	20.4	138.2
209	Managed	Cw-Yc Good	>24	<41	32.5	32.8
210	Managed	Fd-Med	<25	<41	21.1	181.7
211	Managed	Fd-Good	>24	<41	28.7	306.6
Subtotal						20,273.5
299	non-productive	maple+willow				421.8
999	Non-forested	Non-forested				5,771.6
Total						26,466.9

CHAPTER 4

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APPENDIX A: Climatic niche models and their consensus projections for future climates for four major forest tree species in the Asia-Pacific region

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ABSTRACT

Modeling and mapping the climatic niches of forest tree species and projecting their potential shift in geographic distribution under future climates are essential steps in assessing the impact of climate change on forests and in developing adaptive forest management strategies. It is particularly important for selecting suitable tree species to match future climates for afforestation and restoration of forest ecosystems. Large scale afforestation and reforestation projects have occurred or planned in Asia-Pacific region; however, the direct impact of climate change has not been widely considered. This has been at least partially due to the lack of availability of robust inventory data on forest vegetation and lack of access to appropriate climate data. In this study, we used our recently developed model, ClimateAP, to generate a large number of climate variables for point locations and used an ensemble modeling approach with Random Forest to overcome some limitations that exist with vegetation data. Uncertainty in future climates was incorporated into the analysis through consensus based projections using 12 climate change scenarios. We modelled the climatic niches for four economically and ecologically important forest tree species in the region and projected their shift in geographical distribution under climate change. Unusual patterns in the shift of geographic distributions of climatic niches were found in two species in Southern China. The implications of the projections in forest management for adaptation to climate change are discussed.

INTRODUCTION

Climate is the primary factor regulating geographic distributions of plant species (Woodward and Williams, 1987; Davis and Shaw, 2001; McKenney and Pedlar, 2003). Most forest tree species are adapted to a range of climatic conditions, which is referred to as their climatic niche (Peterson et al., 1999; Pearson and Dawson, 2003). Due to the long lifecycle and slow rate of migration of forest trees, unprecedented rapid climate change will likely result in a mismatch between the climate that trees are historically adapted to and the climate that trees will experience in the future (Aitken et al., 2008). Individuals or populations exposed to climate

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conditions outside their climatic niches will likely be maladapted, resulting in compromised productivity and increased vulnerability of species to disturbance such as insects and pathogens (Hamann and Wang, 2006; Kurz et al., 2008; Fettig et al., 2013). Therefore, understanding the climatic niches of forest tree species and projecting their potential shift in spatial distributions for the future are important to assess the vulnerability of tree species and to develop adaptive forest resources management strategies under a rapidly changing climate, including assisted migration (Huntley et al., 2010; Alfaro et al., 2014; Rehfeldt et al., 2014a).

Climatic niches can be defined as constituting the climatic component of Hutchinson's (1957) fundamental niche (Pearson and Dawson, 2003). As they are often built based on the observed distribution of the target species, these models thus reflect a realized climatic niche (i.e., resulting from climatic and biotic constraints, such as interspecific competition) (Pearson and Dawson, 2003; Holt, 2009) as opposed to the fundamental niche (i.e., solely based on the species' environmental requirements) (Hutchinson, 1957). As models of this form involves biological and ecological components, thus they are typically referred to as climatic niche models, bioclimatic envelope models or ecological niche models. We used these terms interchangeably in this study.

The volume of literature using climatic niche models has been rapidly growing in recent years, while debate about the usefulness of the approach has also followed. A recent review suggests that the criticism has often been misplaced in regard to the objectives of the climatic niche models (Araujo and Peterson, 2012). A climatic niche model defines and predicts the suitable climatic habitat rather than the actual distribution of a species, which involves a series of evolutionary and ecological processes (Aitken et al., 2008). Therefore, a climatic niche model is technically not a species distribution model (SDM) but a habitat suitability model (Keith et al., 2008; Anderson et al., 2009). Confusion between these two kinds of models has led to unrealistic expectations about the outcomes from climatic niche models (Araujo and Peterson, 2012). As a result, many now feel that these so-called SDMs cannot meet users' expectation in adaptation decision making or species conservation strategies (Keenan, 2015).

The distribution and potential shift of climatically suitable habitats are the target of many ecosystem management activities. This information allows users to assess the vulnerability and climate change impact for species or ecosystems for adaptation and conservation (Schueler et al., 2014; Keenan, 2015). Bioclimatic envelope models are reasonably suited for informing species selection and assisted migration in reforestation or afforestation (McLane and Aitken, 2012; Gray and Hamann, 2013; Alfaro et al., 2014). Using the species that best match both current and future climates, regenerating stands will have a better chance of remaining healthy, productive and able to maximize their ecological and/ or economic value under a changing climate. This is particularly important given the stated policy aim of planting 20 million hectares of forests in the Asia Pacific over the coming years (Rozelle et al., 2000). Climatic niche models, if properly established and interpreted, can provide valuable, first-order assessments of the potential impacts of climate change and provide a scientific basis for developing adaptive strategies in forest management (Huntley et al., 2010; Fettig et al., 2013; Alfaro et al., 2014; Rehfeldt et al., 2014b).

Bioclimatic envelope models have widely been used in North America (Hamann and Wang, 2006; Rehfeldt et al., 2006; McKenney et al., 2007; Wang et al., 2012a) and Europe (Araujo and New, 2007; Buisson et al., 2010; Lindner et al., 2014). However, related studies in Asia Pacific are lagging behind. This is partially due to the lack of vegetation data and limited access to high quality climate data and to a large number of

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projections for future climates. In this study, we chose three major forest tree species in China including Chinese fir (*Cunninghamia lanceolata* (Lamb.) Hook), Masson Pine (*Pinus massoniana*) and Chinese pine (*Pinus tabulaeformis* Carr.). We also chose a major plantation tree species in Australia, blue gum (*Eucalyptus globulus* Labill.). Chinese fir and Masson pine are the two most important subtropical coniferous species in China. Chinese fir occupies about 30% of all plantations in China accounts 25% of China's national commercial timber production, thus it plays a major role in environment, timber supply, and human society (FAO, 2006). Chinese pine is the most widely distributed conifer in North China, with a natural range that stretches from northeastern to northwestern China, between latitudes 31°00' and 44°00' N and longitudes 101°30' and 124°25' E (Xu 1993). Within this range it grows as discrete populations in mountain areas at elevations from 100 to 2700 m (Xu et al., 1993). Blue gum, an evergreen broadleaved tree species, is one of the most widely cultivated trees native to Australia (Booth, 2013). It has four subspecies distributed across southeast Australia. The main objectives of our study is to 1) develop climatic niche models for each of the four major forest tree species in the Asia Pacific considering the limitation of vegetation data; 2) identify climate variables that are important in determining the climatic niche for each species; and 3) project climatic niches for future periods addressing the uncertainty in future climates.

DATA AND METHODS

Vegetation data

Presence-absence observations for Chinese fir, Masson pine and Chinese pine were obtained from the digital version of Vegetation Map of China (1:1000,000) provided by "Environmental & Ecological Science Data Center for West China, National Natural Science Foundation of China"(link: <http://westdc.westgis.ac.cn>). A shape file of the distribution for each species was generated from polygons with the species present. The shape file was then rasterized at the spatial resolution of 0.008333 arc minute (approximately 1 km). Each data point (i.e., a raster pixel) within a polygon of presence was assigned as presence of the species. Similarly, a data point within a polygon of absence was assigned as absence within the range of the species distribution and expanded by 200 km in each of the four directions if possible following Barbet-Massin et al. (2012). Due to a long history of anthropogenic disturbances to forests in China the current distributions of the species are likely to be underestimated. Thus, some of the absence data points were assumed to be false absences. An adjustment was applied to our modeling process to address this consideration (see below).

For blue gum, 7, 172 presence observations were obtained from the Atlas of Living Australia (Atlas) (<http://www.ala.org.au>). These observations were aggregated from a wide range of data providers including museums, herbaria, community groups, government departments, individuals and universities. As there were no absences demarcated in the observations, pseudo-absence data points (Elith and Leathwick, 2007; Barbet-Massin et al., 2012) were generated with the following steps: 1) generation of grid locations at the spatial resolution of 0.008333 arc minute for areas within the range of the species distribution and extended by 200 km in each of the four directions if possible; 2) randomly sampling 50,000 pseudo-absence data points from the grid locations; and, 3) elimination of false-absence data points in the modeling process as described below. After the presence-absence datasets were constructed, the elevation for each data point was extracted, based on its geographic coordinates, from a 90 × 90 m digital elevation model (DEM) obtained from the

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Shuttle Radar Topography Mission (SRTM). The latitude, longitude and elevation of the datasets were then used to extract climate data.

Climate data

The availability of a climate data for the Asia Pacific was achieved through the development of a high-resolution climate model, ClimateAP. This model was used to generate climate data across the region. ClimateAP is a climate data downscaling tool developed for the Asia-Pacific region using the same downscaling algorithms used in ClimateWNA (Wang et al., 2012b) which extracts and downscales PRISM (Daly et al., 2008) and WorldClim (Hijmans et al., 2005) 1961-1990 monthly normal data (2.5 x 2.5 arcmin) to produce seasonal and annual climate variables for specific locations (scale-free) based on latitude, longitude and elevation. The program uses the scale-free data as a baseline, in combination with monthly anomaly data (relative to the 1961-1990 normals) from IPCC AR5 general circulation models (GCMs) to calculate and downscale (i.e., a delta downscaling approach) monthly, seasonal and annual climate variables for future periods. The output of the program includes both directly calculated and derived climate variables. For this study, we generated 66 annual and seasonal climate variables for the point locations with presence and absence of the species for the reference normal period 1961-1990. Monthly climate variables were not considered due to the large number of annual and seasonal climate variables. For the predictions and projections of the geographic distribution of each species for the reference period (1961-1990 normal) and three future periods (2020s, 2050s and 2080s), gridded climate data were generated at the spatial resolution of 4 x 4 km for each of these periods for China and Australia. For future projections, the gridded climate data were generated for 12 climate change scenarios including six AR5 GCMs and 2 emission scenarios (RCP4.5 and RCP8.5) (Taylor et al., 2012). The six GCMs include: ACCESS1-3, BCC-CSM1, CanESM2, CNRM-CM5, CSIRO-Mk3-6-0, and HadGEM2-ES (<http://cmip-pcmdi.llnl.gov/cmip5/availability.html>).

Statistical analysis

We used the R version (Liaw and Wiener, 2002) of (Breiman, 2001) of the Random Forests (RF) algorithm to model relationships between climate variables for the reference period and the presence and absence of each of the four species. RF produces many classification trees, collectively called a 'forest', and aggregates the results over all trees. Each of these decision trees in the forest is constructed using a bootstrap sample of the input data (i.e., a random sample with replacement) so that the resulting dataset ('bagged sample') contains about 64% of the original observations, and the remaining observations comprise the 'out-of-bag' (OOB) sample. Using the trees grown from a bootstrap sample, each of the independent observations in the OOB sample is classified (assigned to either presence or absence) and a model prediction error, called the OOB error (% of incorrectly classed observations), is calculated. RF is designed for overcoming collinearity and over-fitting problems (Breiman, 2001; Dormann et al., 2013) and considered as one of the most credible statistical methods for climatic niche model building (Rehfeldt et al., 2006; Elith et al., 2008; Wang et al., 2012a).

RF works best if the samples are relatively balanced between classes (Breiman, 2001; Rehfeldt et al., 2006; Barbet-Massin et al., 2012). Our sample data were unbalanced with the number of locations for absence much greater than that for presence. One way to balance the samples was to randomly sample the data points for absence to match the number of samples for presence. However, this can lead to a poor representation of the areas for the absence of the species. We applied a multiple "forests" approach to build

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an ensemble of RF models; each RF model was built with randomly sampled data points for absence while the data points for presence remained the same. The final prediction was based on the ensemble of the 10 individual model predictions. This also is a recommended method when using machine-learning based modeling approaches (Barbet-Massin et al., 2012).

To remove the false-absence samples from the absence data points for the three species in China, we eliminated absence samples with an absence probability of less than 0.20 in each RF model, which removed about 10% of the absence data points. To maintain the balance in sample size between presence and absence, 10% more absence samples were taken at the initial sampling step as mentioned above. The same approach was also used to eliminate the false-absence samples from the pseudo-absence data points for blue gum in Australia. However, we increased the threshold probability from 0.20 to 0.25 based on the assumption that there were more false-absence samples in the pseudo-absence data. This also removed about 10% of the pseudo-absence samples.

RF generates importance values for each of the predictors. We used the importance values to optimize the model and to identify the climate variables that were important for determining the climatic niche of each species. All 66 climate variables were included in the initial RF model. The least important climate variables were iteratively removed until only two climate variables remained in the model (i.e., the least possible number of predictors for RF). By comparing the accuracies of different RF models composed of a different number of climate variables the best RF model was identified and selected. The final RF models were therefore built using the optimal combination of climate variables for each of the four species.

The models were also optimized for the number of trees in each forest and the number of predictors selected at each node. We used 300 trees, which was more than adequate, for all species. The effect of the number of predictors selected at each node was minor, so we used the default square-root of the number of climate variables (Breiman, 2001).

The final RF models were then fed with climate variables for the gridded data points to generate spatial distributions of the climatic niche for each species for the reference period (1961-1990 normal period) and future periods (2020s, 2050s and 2080s). For the reference period, the ensemble predictions for presence of a species was determined from 10 forests generated for each gridded pixel. For future periods, the frequency was calculated at two levels; the first was among the 10 forests and the second was among the 12 climate change scenarios. We set it as “presence” if the number of predictions for presence was equal or larger than five (i.e., 50%), so that we only needed to count predictions for “presence” among the climate change scenarios to determine the consensus of the projections. Since blue gum was modeled at the subspecies level, we could not count the frequency for multiple categories. Instead, we used the mode of predictions as the final outputs. The final outputs were then imported into ArcGIS (v10.2.1) to generate maps.

RESULTS

Climatic niches of the species and important climate variables

The overall accuracies of the models were high (> 90%) for all species modelled (Table A.1). The climatic niche for each species in terms of the most commonly used climatic variables (mean annual temperature and precipitation) were defined by the models (Table A.1). The OOB error rate was higher for absence than for

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presence except for blue gum. This was expected as the sampling rate for absences was much smaller for blue gum which in turn affects the error rate.

Table A.1 Model error rate and major climate profiles for the climatic niches of the four major forest tree species.

Species	Model error rate (%)			Mean annual temperature (°C)	Mean annual precipitation (mm)
	Presence	Absence	Overall		
Chinese fir	5.4	11.8	8.6	16.9 (9.2–22.6)	1637 (834–3062)
Masson pine	3.0	9.7	6.4	17.6 (6.4–23.5)	1553 (650–3199)
Chinese pine	7.1	12.4	9.8	7.3 (0.4–14.7)	620 (228–1122)
Blue gum	9.7	6.8	8.1	12.0 (4.6–18.4)	887 (455–2928)

Through the removal of the least important climate variables from the RF model each time, we identified the best combination of climate variables for the RF model for each species. The change in the OOB error rate with various number of climate variables is illustrated for Chinese fir in Figure A.1. The level of the change was not substantial when the number of climate variables was greater than 20. The 10 most important climate variables for each species are listed in Table A.2.

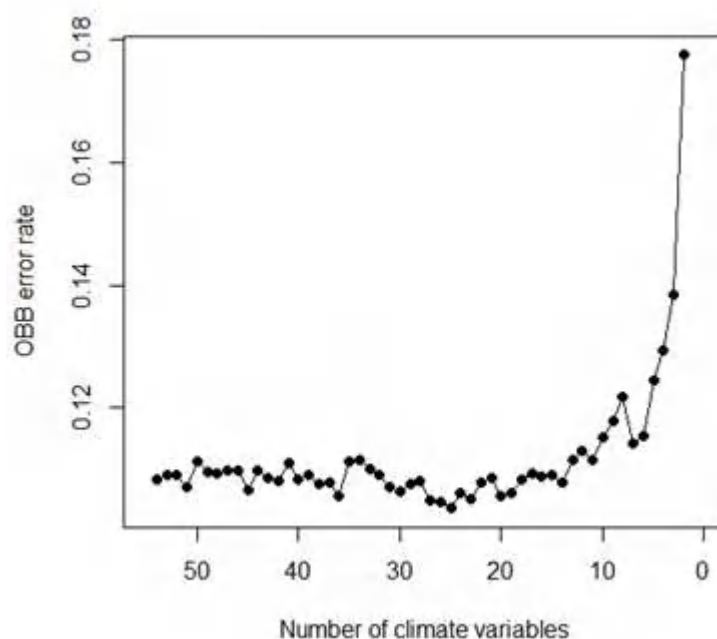


Figure A.1 Changes in error rate of RF model prediction for out-of-box (OOB) samples with the least importance climate variable removed step by step.

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Table A.2 The 10 most important climate variables for each of the four forest species based on the importance values (Imp. value) generated from the Random Forest models.

Chinese fir		Masson pine		Chinese pine		Blue gum	
Climate variable	Imp. value	Climate variable	Imp. value	Climate variable	Imp. value	Climate variable	Imp. value
PPT_MAM	40.6	TD	33.8	CMD_JJA	39.9	PPT_DJF	41.1
TD	35.6	PPT_MAM	32.8	PPT_JJA	37.8	Eref_MAM	32.1
Tmin_JJA	34.6	CMD_DJF	31.4	Tmin_JJA	32.6	PPT_JJA	39.3
PPT_SON	30.4	PPT_JJA	26.9	TD	31.1	Eref_JJA	26.6
Tmin_DJF	29.6	PPT_DJF	22.9	DD5_SON	25.4	TD	30.7
Eref_MAM	29.1	DD5_JJA	22.2	MAP	24.0	CMD_DJF	27.7
PPT_JJA	28.9	Tmax_MAM	22.0	MWMT	23.8	DD5_DJF	26.6
CMD_SON	27.8	CMD_SON	20.5	CMD_SON	23.7	EXT	28.7
Tmin_SON	27.7	Eref_JJA	19.8	DD5_JJA	23.1	PPT_SON	26.5
DD5_JJA	27.6	Tmin_JJA	19.2	CMD	22.8	Tmin_MAM	27.5

PPT = precipitation; Tmin = mean minimum temperature; Tmax = mean maximum temperature; MAP = mean annual precipitation; EXT = extreme maximum temperature over 30 years; Eref = Hargreaves reference evaporation; CMD = Hargreaves climatic moisture deficit; MWMT = mean warmest month temperature; MCMT mean coldest month temperature; TD = the difference between MWMT and MCMT, also referred to as continentality; DD5 = degree-days above 5°C, growing degree-days; MAM = March-May; JJA = June-August; SON = September-November; DJF = December-February.

The ensemble predictions of the geographic distribution of the climatic niche for each species are illustrated in Figures A.2a, A.3a, A.4a and A.5a. The predictions of the 10 RF models using random samples for absence agreed for vast majority of the areas, while the disagreement only occurred at margins of the climatic niches for all the four species. The predicted geographic distribution of each species climatic niche was larger but congruent with its current distribution. This was particularly the case for Chinese fir.

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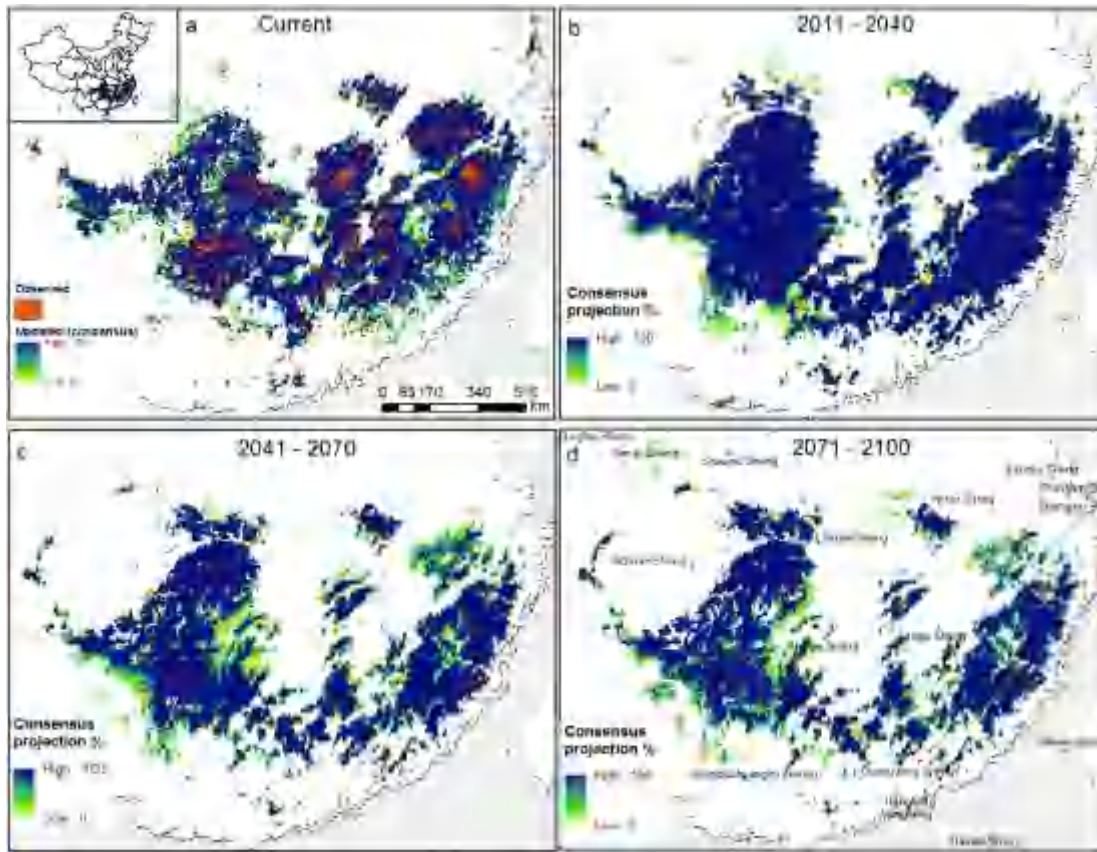


Figure A.2 Geographic distributions of current and potential climatic niches for Chinese fir based on ensemble predictions for the current (1961-1990) and consensus projections for the three future periods 2020s, 2050s and 2080s.

Consensus projections of the geographic distribution of the climatic niches for future periods

Consensus based projections of the future geographic distribution of the climatic niches among the four species shared some common features (Figure A.2, A.3, A.4 and A.5). The projections were highly consistent among the 12 different climate change scenarios for the 2020s, suggesting that the uncertainty in projections of the change in species geographic distribution is relatively low for the near future. However, the consistency declined in the 2050s and 2080s scenarios. Another common feature, was the upward shift in elevation of the projected distribution for each species. The magnitude of the shift was substantial (up to 1100m by the 2050s). Interestingly, no clear shift in latitude was projected as commonly expected for species with the exception of blue gum, which showed a slight southward shift. The size of the climatic niches were projected to contract for most of the species (3 out of 4) and ranged between 24 – 34% by the 2050s.

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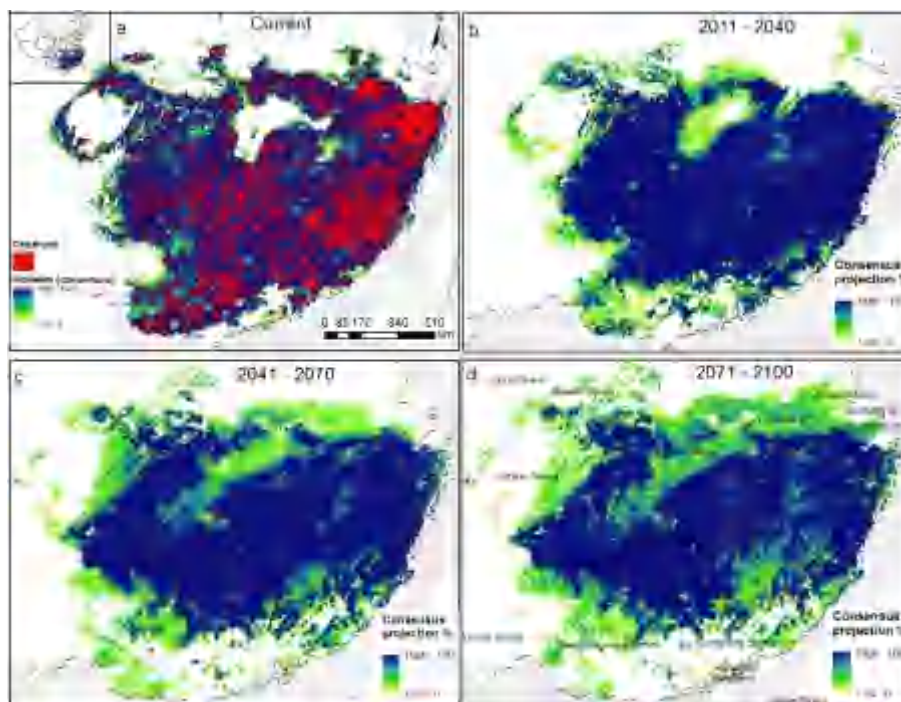


Figure A.3 Geographic distributions of current and potential climatic niches for Masson pine based on ensemble predictions for the current (1961-1990) and consensus projections for the three future periods 2020s, 2050s and 2080s.

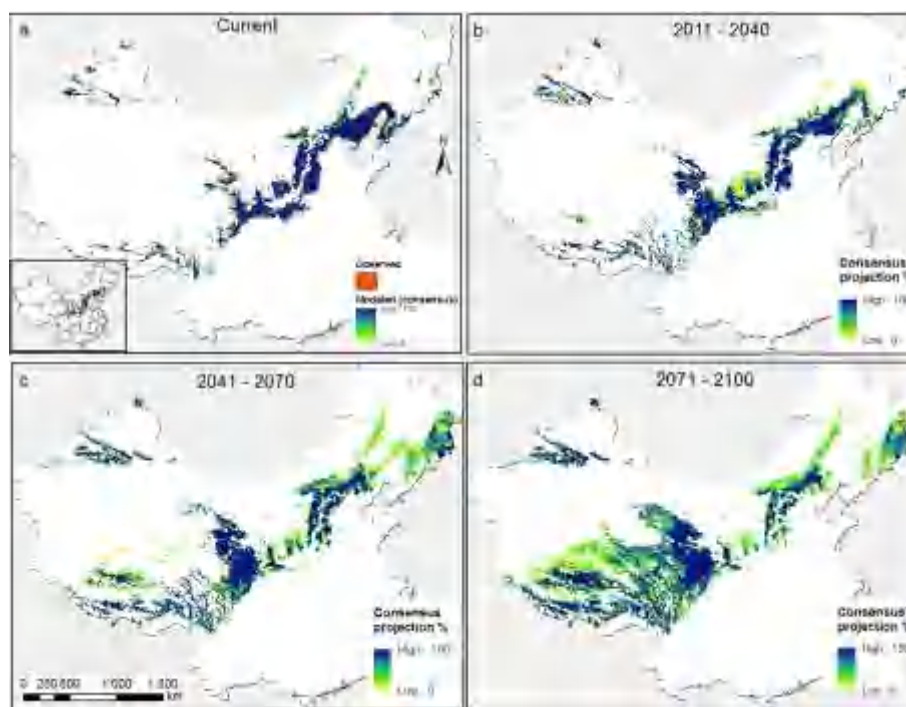


Figure A.4 Geographic distributions of current and potential climatic niches for Chinese pine based on ensemble predictions for the current (1961-1990) and consensus projections for the three future periods 2020s, 2050s and 2080s.

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For Chinese fir and Masson pine, contractions along the trailing edge of their climatic niches were projected (Figure A.2 and A.3). Surprisingly, the expansion of their climatic niche along the leading edges was not predicted. For Chinese pine (Figure A.4), the expansion of its climatic niche was substantial (47% by the 2050s) (Table A.3). Interestingly, the expansion was predicted to occur westward instead of northward. For blue gum, the projected shift under future climates was southward towards the edge of the continent, resulting in a considerable contraction of its geographic distribution (-24% by the 2050s) (Figure A.5 and Table A.3). Projected changes in the area of the climatic niches varied considerably among subspecies (Table A.4). The distribution of the climatic niche of *E. globulus ssp. pseudoglobulus* was projected to nearly disappear by 2050s. In contrast, the size of projected climatic niche for *E. globulus ssp. globulus* remained almost the same. The contraction for *E. globulus ssp. bicostata* was also substantial (-50%).

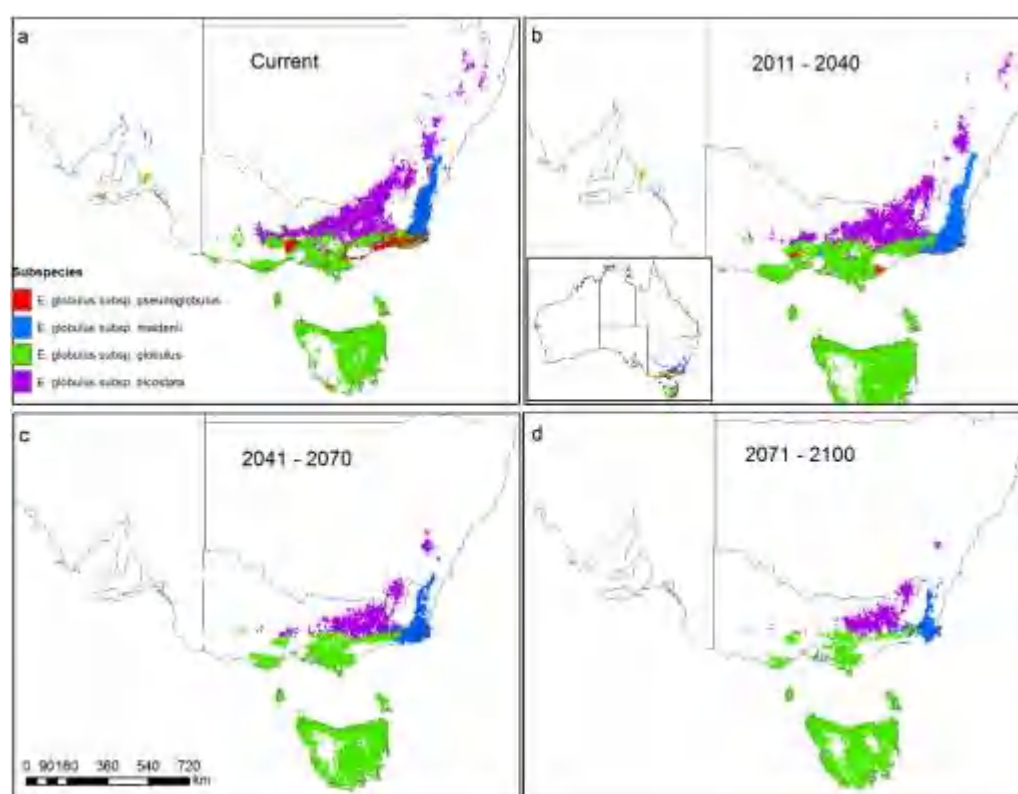


Figure A.5 Geographic distributions of current and potential climatic niches for the four subspecies of blue gum based on ensemble predictions for the current (1961-1990) and consensus projections for the three future periods 2020s, 2050s and 2080s.

Table A.3 Changes in average latitude, longitude, elevation and areas of climatic niches for each species by 2050s relative to the reference period 1970s.

Species	Latitude (°)	Longitude (°)	Elevation (m)	Area (%)
Chinese fir	0.1	-0.7	244	-34.2
Masson pine	0.4	0.5	61	-17.0
Chinese pine	-0.7	-5.6	1129	46.8
Blue gum	-1.2	-0.1	3	-24.3

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Table A.4 Changes in average latitude, longitude, elevation and areas of climatic niches for subspecies of blue gum by 2050s relative to the reference period 1970s.

Subspecies	Latitude (°)	Longitude (°)	Elevation (m)	Area (%)
<i>bicostata</i>	-6.8	-9.6	230	-50.7
<i>maidenii</i>	-0.9	-0.4	3	-10.9
<i>globulus</i>	-0.6	0.3	-1	-1.4
<i>spseudoglobulus</i>	-0.2	-2.1	-224	-99.0

DISCUSSION

Climatic niches of the species

Our results suggest that the climatic niches of the major forest species in the Asia-Pacific region can be modeled with a combination of climate variables at an accuracy consistent with other regions (Rehfeldt et al., 2006; Gray et al., 2011; Rehfeldt et al., 2014a). The application of following approaches in this study contributed to the low error rates observed in the climatic niche models for the four tree species. These approaches included: 1) the removal of false-absence samples; 2) the optimization of the combination of climate variables; and 3) the use of multiple forests to address the issue of an unbalanced dataset. The developed climatic niche models thereby produced credible predictions of the current geographic distributions for four important tree species in the Asia Pacific (Figure A.2a, A.3a, A.4a, and A.5a). The predicted distribution of the climatic niche included both the areas where the species are currently occupied and areas where the climatic conditions are suitable for the species, but where they may not be present due to various factors including physical barriers, adaptational lag and/or human interference. The models do not consider the role of soil properties and the incidences of disease, insects or fire regimes that may limit a species occurrence/ expansion into climatically suitable areas.

Consensus projections for the future

Uncertainty in future climate is probably the greatest challenge in assessment of the impact of climate change on forest ecosystems and tree species and therefore in developing adaptive strategies in forest management for the future. There are four greenhouse gas emission scenarios and over 20 general circulation models (GCMs) in the latest IPCC report (IPCC, 2014). For a given period, there are over 80 (4 scenarios x 20 GCMs climate change scenarios) different projections of climate conditions. From a modeler's point of view, projections for a large number of climate change scenarios are resource demanding and time consuming as the spatial datasets are usually huge. Therefore, most of the future projections involve only a small number of climate change scenarios. Some studies used ensembles by averaging over GCMs or emission scenarios. However, such ensembles may cancel out the spatial and seasonal patterns of specific GCMs as discussed in Wang et al. (2012a). From a practitioner's point of view, the large range of scenarios makes it almost impossible to develop multiple adaptive options to accommodate a range of potential futures. Consensus projections that aggregate multiple individual projections provide an effective option for practical applications (Wang et al., 2012a). We believe that the consensus projections provide a solid basis for the assessment of climate change impacts on species and for the development of adaptive strategies in forest resources management under a changing climate. Specific characteristics of the consensus projections for each species are described below.

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Chinese fir

Our results suggest that the geographic distribution for Chinese fir may substantially contract under predicted climate change. The contraction in its current distribution, particularly in the south, was not a surprise as warmer climate conditions are projected to occur in the southern parts of its current distribution (Figure A.2). What was a surprise was the lack of a predicted northward shift for this wide spread species. The northward expansion of trees in response to climate change is commonly predicted in other studies (Hamann and Wang, 2006; McKenney et al., 2007; Rehfeldt et al., 2014a). The limited northward expansion is likely attributable to the spatial pattern of precipitation in China. Current species distribution and its predicted current climatic niche occur in areas with a mean annual precipitation (MAP) above 830 mm. Under future climates, the geographic distribution of temperatures suitable for this species is projected to move northward; however, the geographic distribution of mean annual precipitation is projected to remain about the same as for the reference period (Figure A.6). The areas with MAP above 830 mm are mostly south of the Yangzi River. The sharp contrast in precipitation between northern and southern China appears to play an important role in the direction of future projections and may limit the northward expansion of this species. In addition, the new combinations of temperature and precipitation may represent some novel climates (Williams and Jackson, 2007) in the region and impose new challenges to model predictions.

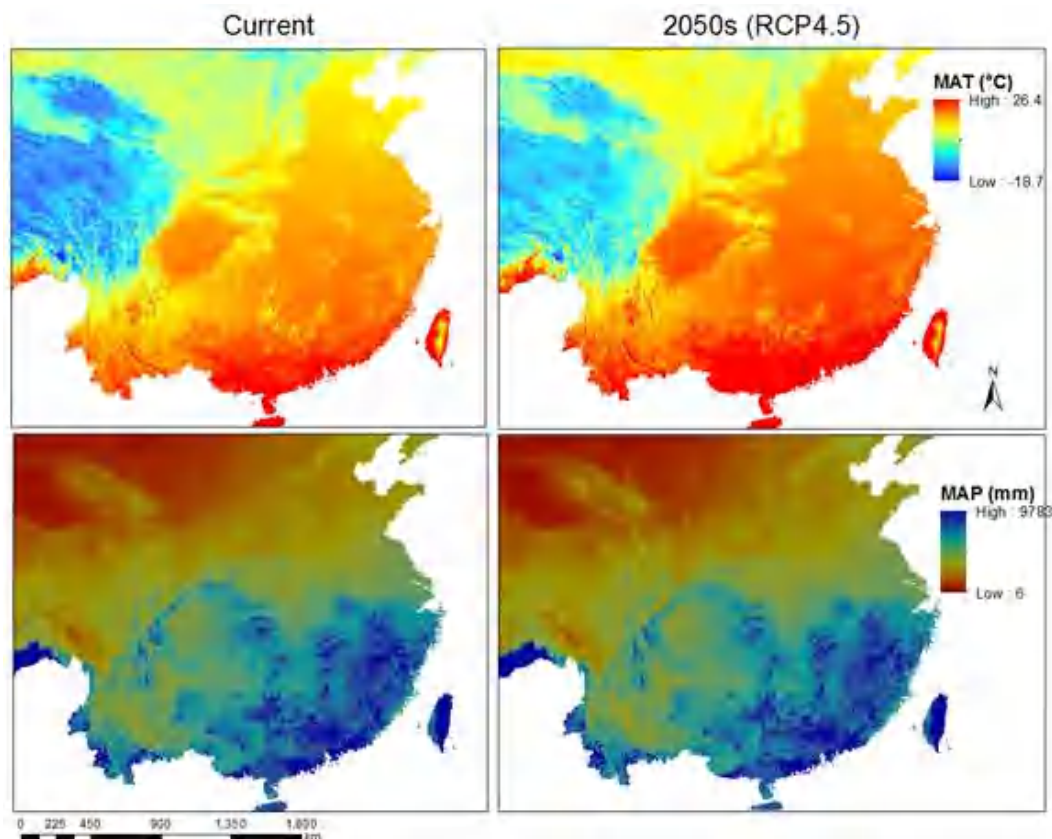


Figure A.6 Distribution of mean annual precipitation (MAP) for 1961-1990 (left) and 2080s (right) projected by one of the AR5 GCM: HadGEM2.

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It is worth noting however that the climatic niche modelled in this study (or in the vast majority of other studies) is a realized climatic niche. It reflects the climate conditions currently occupied by the species. Whether or not Chinese fir can grow outside of the current climatic niche is unknown and needs to be further explored through field experiments, such as provenance tests. A recent study using a process-based model 3-PG (Physiological Principles to Predict Growth) reported a northward expansion for this species, but the projected growth potential was extremely low (Lu et al., 2015). The limiting factor appeared to be the soil water content. The findings of Lu et al. (2015) are therefore in agreement with our realized niche-based projections.

The dramatic decline in the area suitable for Chinese fir projected in this study is concerning as this species is one of the most important forest species in China in term of both its economic value and role in ecosystem functioning (FAO, 2006; Jiang et al., 2011). Our results should provide an early warning for policy makers and practitioners to develop adaptive strategies in species selection and forest management practices in order to adapt the management of Chinese fir forests/plantations to future climate. Managing this species within its current geographical distribution will become increasingly problematic as its current climatic niche becomes fragmented which may lead to a loss in economic value of plantations and impair forest ecosystem functioning.

Masson pine

The climatic niche of Masson pine almost entirely overlaps that of Chinese fir, but it has a broader range in term of both temperature and precipitation (Table A.1 and Figure A.3). Projected contraction in its current distributions was much less (-17%) than that of its counterpart Chinese fir (-34%). Like Chinese fir, Masson pine exhibited no substantial northward expansion under future climate conditions. The contraction of its geographic distribution was projected to mostly occur along the trailing end of its current distribution in the south of China. This is in contrast to the projections for Chinese fir, for which a contraction was also projected to occur in the central areas of its distribution. This is probably attributable to the broader climatic niche of this species compared to Chinese fir. Masson pine may therefore provide a good alternative to Chinese fir for reforestation and afforestation under a future climate in these regions of China.

Chinese pine

The consensus projections for Chinese pine falls into line with our expectations of species response to climate change. This species' distribution was modelled to contract along the trailing edges and expanded along the leading edges of its range. Instead of shifting northward, our projected distribution for this species showed a westward expansion. This is not a surprise as the topography in China is characterized by an increase in elevation as one moves from the east to the west. A dramatic increase in elevation (+1100 m) was projected for the distribution of this species' climatic niche by the 2050s. The potential distribution of the climatic niche for this species is projected to increase substantially (~ 50%). Chinese pine is a drought tolerant forest tree species with a relatively fast growth rate (Farjon, 2013). Drought is projected to be more frequent in northern and western China under climate change (IPCC Fifth report (<http://www.ipcc.ch/report/ar5/>)). These trends, together with our projected increase in areas suitable for Chinese pine, suggest that Chinese pine could play an important role in afforestation/ reforestation in north and western China in the future. Assisted migration to help the species expand westward to new locations in the future could be an option in adaptive forest resource management.

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Blue gum

As a whole species, the geographic distribution of climatic niche for blue gum is projected to shift southward towards cooler conditions. The shift pole ward will be constrained by the Tasman Sea at the leading edge and likely result in a contraction of its total distribution under future climates (by 24% in 2050s, Table A3). The level of the contraction varied considerably among subspecies. The most impacted subspecies were *E. globulus ssp. pseudoglobulus* and *E. globulus ssp. bicostata*. The climatic niches of these two subspecies are predicted to almost completely disappear and contract by 50% by the 2050s, respectively (Table A.4). This clearly indicates that climate change could bring in new challenges in maintaining the current level of genetic diversity within this species. However, *E. globulus ssp. bicostata* is regarded as being better adaptive to drought than other subspecies (Wang et al., 1988). It will be interesting to observe the response of this subspecies to the impact. In contrast, the total distribution of the climatic niche for the major subspecies *E. globulus ssp. globulus* is projected to exhibit little change in overall area; however, contraction is predicted to occur on the mainland with expansion in Tasmania compensating for this loss.

The contraction in the overall climatic niche of blue gum on the mainland of southeast Australia could have negative implications for the productivity and vitality of blue gum plantations into the future but positive outcomes for plantation and forest managers in Tasmania. However, the adaptive capacity of eucalypt plantations is considered high with many eucalypts grown on short rotations (< ten years). This provides managers with opportunities to adapt their silvicultural practices and/ or plant different genotypes or species to match changing climatic conditions with relative ease (Booth, 2013).

It is important to keep in mind that climatic niche models predict the realized climatic niche rather than the fundamental climatic niche or the actual distribution of a species. The realized climatic niche represents a range of climate conditions currently occupied by a species within its fundamental niche. It is a result of a long term evolutionary and ecological processes of the species involving migration, local adaptation and its interactions with other species and perturbations (Rosenzweig, 1995; Wiens and Graham, 2005). The process is complicated and remains a challenge to be fully understood. However, the objective of climatic niche models is to model a range of climate conditions rather than to model the process and to predict the actual species distributions as is done by species distribution models (Elith and Leathwick, 2009). The projected expansion in the geographic distribution of a species climatic niche at the leading edges of its distribution is therefore a conservative estimate of its potential distribution based on climate, not other factors. It provides baseline information to aid in decision making around assisted migration for a given species (Gray et al., 2011; McLane and Aitken, 2012; Gray and Hamann, 2013). It is up to the forest managers to consider other factors such as soil and disturbance agents that can constraint the predicted climatic niche. Compared to a changing climate, the factors can be static (i.e. soil) and so simple to consider or stochastic (i.e, insects, disease, fire) and therefore difficult to consider.

An additional utility of the climatic niche approach is the identification of areas of a species distribution where they are more vulnerable to climate change. For example, the predicted changes at the trailing edge of a species distribution suggests that there may be populations that will occur outside their climatic niche which lead to maladaptation. Under these conditions the productivity, resilience and competitive advantage of a species may be compromised, which in turn will increase the species vulnerability to abiotic and biotic disturbances (Fettig et al., 2013; Gray and Hamann, 2013). Monitoring and genetic conservation (Hamann

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and Aitken, 2013) should be a priority for these areas. However, if these populations are still within their fundamental niches, which were not modeled, these problems related to their survival or even productivity may not eventuate.

In this study, the climatic niches of four economically and ecologically important tree species in the Asia Pacific were modelled and their geographic distributions estimated with a high level of accuracy. This was achieved despite a paucity of vegetation and climate data highlighting that the methodology developed for this study is robust and useful for assessing the impacts of climate change on forests in other regions of the Asia Pacific where similar data issues exist. Understanding how the climatic niches and future distributions of these tree species may change should be useful for informing managers undertaking afforestation and ecosystem restoration in the studied regions. The consensus based projection approach for aggregating multiple climate change projections in this study provides a solid basis for the assessment of climate change impact on tree species and for developing adaptive strategies around species selection in consideration of the uncertainty of future climates.

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APPENDIX B: Modelling forest ecosystem net primary production: the hybrid simulation approach used in FORECAST

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ABSTRACT

In order to evaluate the impacts of alternative stand-level management scenarios on long-term site productivity, forest resource managers need ecologically based forest growth models. The FORECAST forest ecosystem management simulation model combines the traditional bioassay modelling approach with process-based simulation modelling to provide a method of projecting future forest biomass yield as well as a variety of other ecosystem variables and social values under a range of management conditions. A review of the hybrid simulation approach to modelling forest ecosystems is provided, and the representation of stand-level net primary production and nutrient cycling in FORECAST is described. The major driving function in the model (shade-corrected foliage nitrogen efficiency), the concept of site quality, and the simulation of site quality change are discussed. The value of an accurate definition of the state of the simulated ecosystem at the start of a run is emphasized, and the use of the ECOSTATE (STATE of the ECOSystem, as generated by FORECAST) file in this process is described. Limitations of the FORECAST modelling approach are reviewed.

1. INTRODUCTION

With the steady increase in the demand for both traditional timber and non-timber forest values from a shrinking land base and the global commitment to the concept of sustainability, the need for credible forecasts of the probable consequences of alternative forest management strategies has never been greater. For nearly two centuries, volume-age curves, height-age curves, and yield tables have been the basis on which foresters have predicted future yields. This "historical bioassay" method is valid for the species involved and the particular set of biotic and abiotic growth conditions that pertained over the period of growth. However, if changes in future management regimes, human impacts on the environment (e.g. climate change, atmospheric chemistry), and/or changes in soil fertility significantly alter future growth conditions, the predictions of the bioassay are unlikely to be accurate (Kimmins, 1988, 1990; Korzukhin et al., 1996). In addition, these empirically based growth and yield models were not designed to project the effects of management on future trends of a wide variety of wood and non-wood forest products and values. They do

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not provide an adequate basis for comparing the impacts of different forest management strategies for multiple resource values, nor are they suitable for stand-level analysis of various measures of sustainability.

Because of the inflexibility of this traditional growth and yield approach, a great deal of interest and research has been focused recently on mechanistic models. These process-based models consist of empirically derived relationships between a series of independent variables and the dependent variable, tree (stand) growth. Examples of such models developed for forests and other ecosystems can be found throughout the literature (e.g. Sollins et al., 1979; Running, 1984; Running and Coughlan, 1988; Barclay and Hall, 1986; Parton et al., 1987; Bossel and Schäfer, 1989; Dixon et al., 1990). While process-based models have great heuristic value, most of them are not ecosystem-level models and they are rarely used in practical applications in forestry. This is primarily because we do not know enough about the key ecosystem processes and their interactions to combine them for the purpose of making accurate predictions of forest growth (Mohren and Burkehart, 1994).

A third, 'hybrid' approach to yield prediction has been developed which attempts to combine the strengths of the other two approaches and thereby compensate for their individual weaknesses. The most developed models in this category, designed for the assessment of harvesting impacts on long-term site productivity, include LINKAGES (Pastor and Post, 1985), FORCYTE-11 (Sachs, 1991, Kimmins, 1993), and FORECAST (the successor to FORCYTE-11; e.g. Kimmins and Scoullar, 1994; Comeau et al. 1995; Wang et al. 1995; Morris et al., 1997). These models take the yield (production) predictions from a historical-bioassay model (or from raw field data), and modify these predictions according to a simulation of the temporal variation in competition for light and in the availability of one or more nutrients. Nutrient availability is the focus of the process simulation because it is often the factor which most limits forest growth at the stand level, and it is the site factor that is most subject to change as the type and/or intensity of forest stand management changes. Light competition is also a central component of the simulation of stand development. Moisture limitations and moisture competition are not well represented in these models, which are, therefore, restricted in their application to sites that do not have severe site moisture deficits or severe soil moisture competition. A moisture and temperature submodel, based on an extension of Arp and Oja (1996a,b) and Arp and Yin (1992), is being added to Forecast to address this shortcoming (Seely et al., 1997).

The objective of this paper is to provide a description of the simulation algorithms controlling ecosystem net primary production in the FORCYTE-FORECAST series of hybrid-simulation, forest ecosystem models. Future papers will describe other aspects of the model, evaluate its performance, and report on its applications. For discussions of the predecessor model, FORCYTE, and some preliminary evaluations of FORECAST, see: Comeau and Kimmins (1986); Kimmins et al. (1986); Sachs and Sollins (1986); Yarie (1986); Kellomäki and Seppala (1987); Kimmins (1988, 1990); Kimmins et al. (1990); Sachs and Trofymow (1991); Kimmins and Scoullar (1994); Comeau et al. (1995); Wang et al. (1995); and Morris et al. (1997).

2. FORECAST: GENERAL DESCRIPTION

2.1 Model structure

Figure B1 depicts a flowchart of the files and programs that are contained within the Forecast ecosystem management model. Kimmins (1993) has provided an in-depth review of the scientific foundations and

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programming logic used in the development of FORCYTE-11, which is conceptually and structurally similar to FORECAST. Basic empirical data (TREEDATA, PLANTDATA, BRYODATA, and SOILDATA) are fed into the 'setup' programs (TREEGROW, PLNTGROW, BRYOGROW, and SOILS) which use the information to derive a set of simulation rules and values for various process rates that are used in the ECOSYSTEM program to simulate the management of the ecosystem (see Figure B.1). The algorithms in FORECAST's setup process are analogous to the curve fitting procedures that produce the coefficients defining the shape of mathematical relationships in conventional process-based models. The characteristics of the simulation rules and rate estimates, contained in the *TRND output files, may be evaluated with diagnostic graphs produced as output from each setup program. The SOILDATA 'setup' also produces an INITSTAT file, which, used in conjunction with a special run of ECOSYSTEM, results in a description of the initial values for organic matter and nutrient inventories for the start of future runs (the ECOSTATE file). The ecosystem simulation performed by ECOSYSTEM is under the control of the ECODATA file. This file is analogous to the 'scheduler' files in other models; it defines the starting site quality, plant community species composition, and run conditions: it prescribes the various management options and duration of the runs imposed on the ecosystem. Output files are then fed into the NAVIGATOR output management program for viewing and printing the results generated from the ECOSYSTEM runs. The entire user-model interaction is conducted through the FORECAST NAVIGATOR software which facilitates entry and editing of calibration data, program running, scenario generation, and tabular and graphical output analysis.

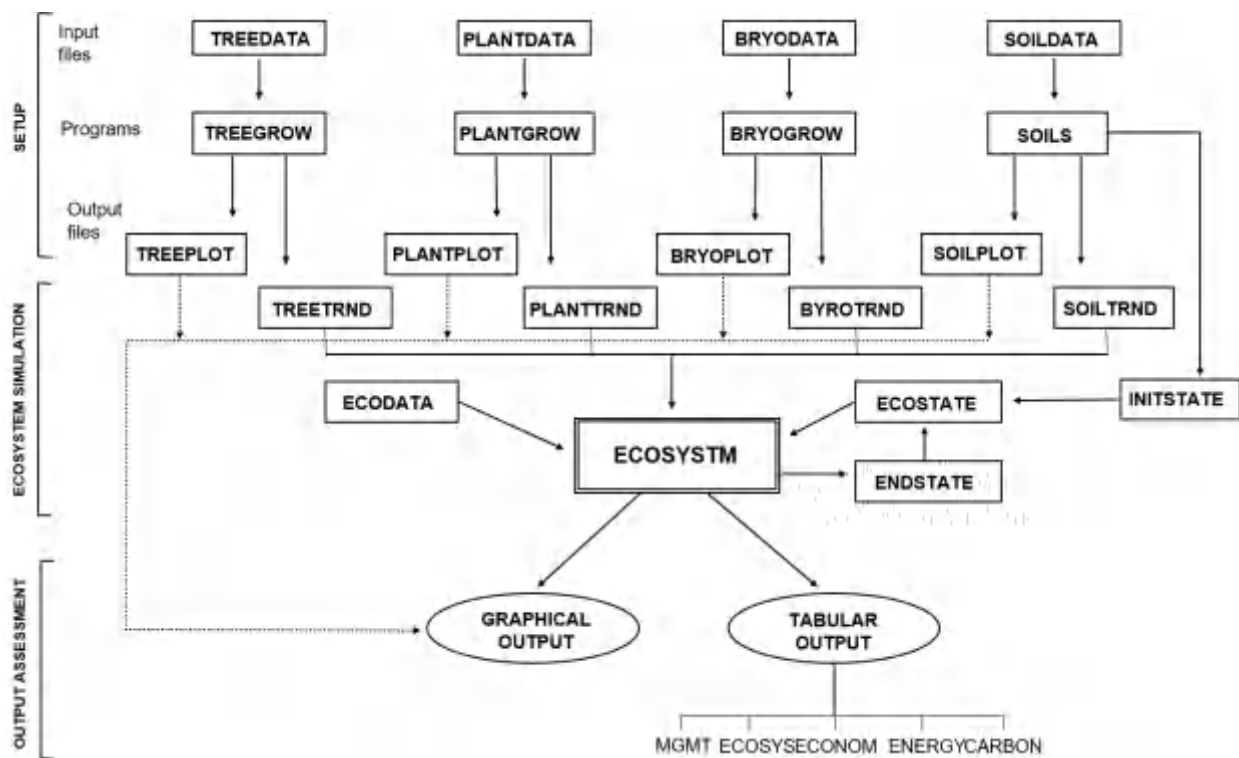


Figure B.1 A flowchart of the setup programs, data files, and management files that are contained within the FORECAST modelling structure.

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2.2 Data requirements

The complete data requirements for the calibration of FORECAST are specified in Appendices A-D. Because the development of indices or coefficients for the various ecosystem processes is conducted within the model itself, and because the model represents, or has the capability to represent, a variety of ecosystem processes and management activities (Figure B.2), the input data requirements to run the model are substantial. They are much larger than in comparable 'gap' models (e.g. LINKAGES, Pastor and Post, 1985), because in such models this preparatory 'setup' work has been done external to the model, and the average model user never actually works with the data that calibrate the model. However, if the full data requirements for the estimation of all the coefficients, simulation rules and other data requirements of gap models are compared for similar simulation capabilities, the difference between gap models and FORECAST is much less than it appears to be. Data are required on height, stand density, stem size frequencies, biomass accumulation, nutrient concentrations in the various biomass components, atmospheric nutrient inputs, foliar leaching (optional), biomass to litterfall transfer rates, photosynthetic adaptations of foliage (e.g. photosynthetic light saturation curves for sun and shade foliage), and a variety of other stand and soil (physical and chemical properties) information from a chronosequence of stands on sites that vary in nutritional site quality. By providing empirical data that describe different process rates and growth strategies in response to varying nutrient availability (i.e. data from sites varying in nutritional site quality), the model is able to establish simulation rules that permit the simulation of shifts in production and carbon allocation in response to management-induced changes in soil resource availability.

FORECAST was designed to be used at various levels of ecosystem representation. The lower the level of representation, the lower the associated input requirements. For example, the user may switch off the representation of nutrient feedback and site quality change and reduce the data requirements substantially. However, the light-limited population or community model that results is incapable of addressing soil-related sustainability issues. Thus, the wider the range of questions the user wishes to explore, greater the data requirements. This flexible approach permits the analysis of the prediction implications of including or omitting various key ecosystem processes.

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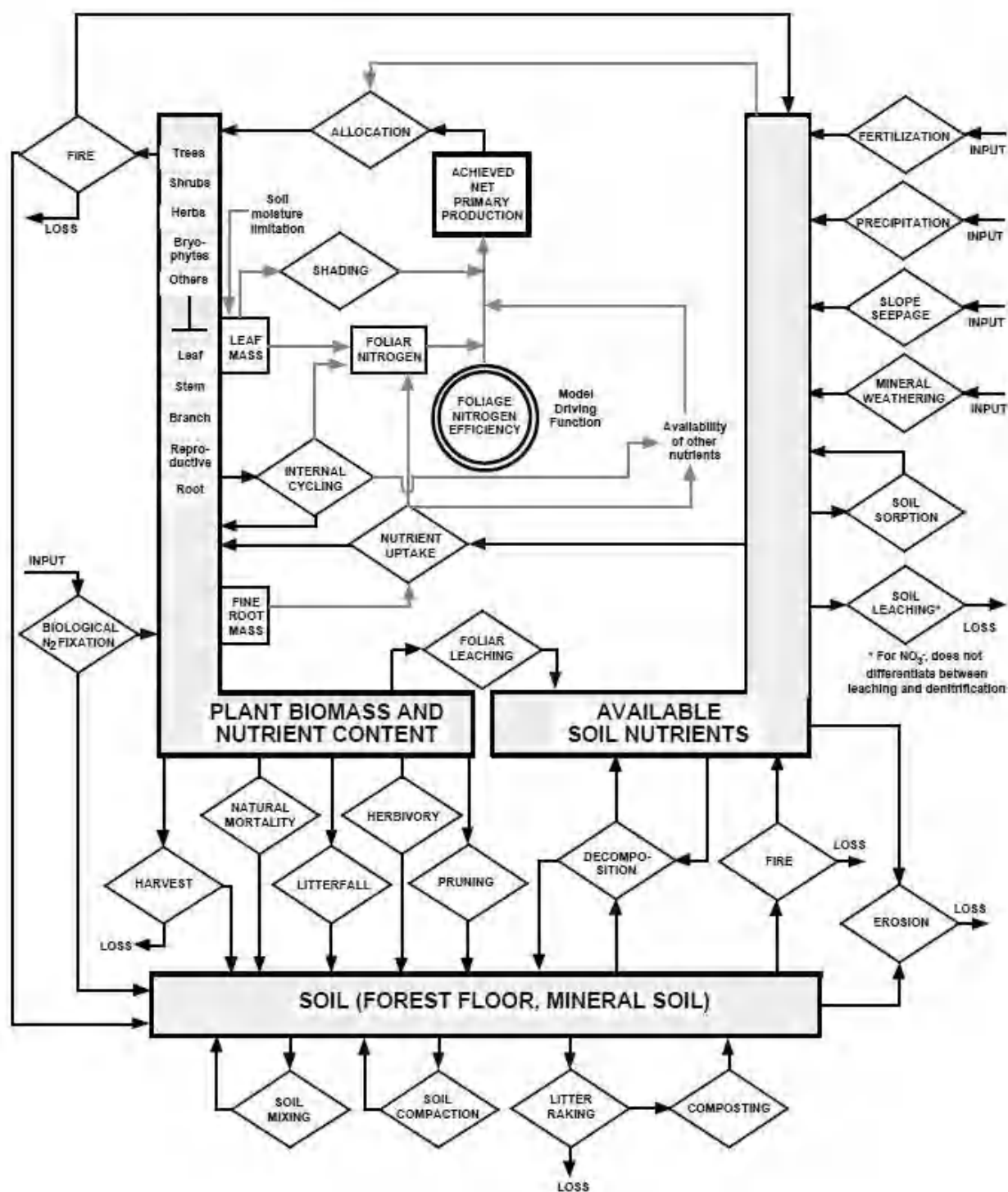


Figure B.2 A schematic of the major ecosystem compartments and transfer pathways represented in FORECAST.

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3. DERIVATION OF TOTAL NET PRIMARY PRODUCTION (TNPP) FROM THE HISTORICAL BIOASSAY

The setup plant growth programs (TREEGROW, PLNTGROW, BRYOGROW) derive, for each plant species for which historical bioassay data are provided, the total net primary production that occurred for each annual time step (TNPP_t) based upon the following equation:

$$\text{TNPP}_t = \Delta \text{biomass}_t + \text{ephemeral litterfall}_t + \text{mortality}_t \quad (1)$$

where:

$\Delta \text{biomass}_t$ = the sum of the change in mass of all the biomass components of the particular species in time step t ,

litterfall_t = the sum of the mass of all ephemeral tissues that are lost in time step t (e.g. leaf, branch, bark and reproductive litterfall, and root death),

mortality_t = the mass of individual plants that die in time step t .

This estimation of past, net ecosystem production is used as the basis to predict potential growth in the ecosystem simulation module of FORECAST (ECOSYSTEM). The simulation algorithms used for estimating $\Delta \text{biomass}_t$, litterfall_t , and mortality_t are explained below. FORECAST calculates Total Net Primary Production (TNPP), rather than only Aboveground (ANPP) or Stemwood Net Primary Production (SNPP). This total ecosystem approach allows for a representation of the important effects of belowground biomass allocation (Keyes and Grier, 1981, Comeau and Kimmins, 1989, Kurz, 1989) in the simulation of management-induced changes in aboveground production. It also permits a more complete representation of soil organic matter dynamics (Morris et al., 1997).

3.1 Change in biomass

Change in biomass ($\Delta \text{biomass}_t$) in each time step is derived from a series of age-biomass data pairs in the input file using an interpolation (data-smoothing) algorithm that functions as follows: 1) the individual setup programs calculate the rate of change in biomass (the slope of the rate-lines) between successive biomass/age data pairs for each biomass component; 2) the slopes of the lines joining the age midpoints of these rate-lines are estimated by linear interpolation and subsequently used to reconstruct a change-of-biomass-over-age-curve with a yearly time step; 3) this curve is forced through the origin and through the maximum value given in the input data file; 4) the smoothed curve becomes the basis for calculating the change in mass for each biomass component ($\Delta \text{biomass}$) in each simulation time step. When the program has created a smoothed biomass/age array, it selects 30 biomass/age pairs from the array (the model assumes that the user will want to be able to run the model for at least 30 time steps) and saves these as a data base. The "ages-for-saving" are defined by the user and should be concentrated over the sections of the biomass/age curve at which there is rapid change in the accumulated biomass; fewer data pairs are assigned to other portions of the curve that are changing more slowly. Reduced array sizes are used to economize on memory. The program uses linear interpolation to generate points between the saved data ages. The same "ages-for-data-saving" array is used for all biomass components of a species.

The smoothing/interpolation algorithm described above produces curves that track the input data quite closely. Most mathematical equations have their own "character" or shape that may not fit a particular

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biomass/age curve well. While it may be appropriate to use such equations for monotonically-increasing functions (e.g. most examples of stem wood accumulation), the smoothing technique accommodates variables such as foliage biomass and fine-root biomass, which may have a variety of characteristic temporal patterns, including a bimodal pattern or a single early peak followed by decreasing values. It also allows for cases in which stem biomass accumulation may be bimodal (e.g. *Abies balsamea* in central Newfoundland, Dr. Bill Meades, Canadian Forestry Service, unpublished data). Since the algorithm tracks the input data quite faithfully, the user is responsible for editing the field data to exclude or adjust any data points that might deviate from the expected "normal" biomass/age relationship for that species on that site. The problem of "spurious" or questionable data points in a chronosequence data set [i.e. data that violate the assumption of the chronosequence method, that the only variable that differentiates the sites is time (Dyck and Mees, 1989; Dyck and Cole, 1994)], can be avoided by using averages of data from several or many replicates of a particular site, or output from a well-calibrated and reliable historical bioassay model based on a large data set. Where this solution is not available, the user should exercise judgment concerning unexpected trends in biomass/age data, and hand-smooth the data appropriately.

3.2 Ephemeral litterfall

For the calculation of annual TNPP (Eq. 1) the growth setup programs use input data to define the proportions of roots of various sizes and of bark that die and become "litterfall" in each time step. The number of years of leaf and dead-branch retention must also be given; the reciprocals of these values give the proportions of the foliage and dead-branch biomass that fall as litter each year. These proportions are applied to the existing mass of each of these biomass components at the end of each time step, and the result is an estimate of the ephemeral litterfall in that time step (litterfall_t).

3.3 Mortality

3.3.1 Changes in stand density

The growth setup programs treat input data on tree stand density, in self-thinning stands, as a function of stand age in much the same manner as the biomass/age input data. The rate of change between successive stand density-age input data pairs is calculated and the slope of the lines joining the median age of each of these rate-lines is used to produce a smoothed density-age curve, forced through the origin and the maximum value in the input data. This smoothed density curve then becomes the basis for the array of mortality rate/age data pairs used to simulate mortality (mortality_t). Thirty data pairs from this array are saved. As was the case for the biomass/age data, it is the responsibility of the user to ensure that the input data on stand density represent the best available estimate of the characteristic temporal pattern of stand self-thinning for a normally-stocked stand for that site. Where data from self-thinning stands are not available, best estimates of stand density time trends can be obtained from stand density diagrams (Drew and Flewelling 1979).

3.3.2 Calculation of individual tree size

In conjunction with the natural tree mortality simulated in each time step (mortality_t), the model also uses a simulation of individual tree size to define the biomass transfers associated with mortality. TREEGROW (the tree growth setup module) simulates the stemwood biomass of individual trees using an index of individual tree size differentiation calibrated with data contained in the TREEDATA file that describe stem biomass size

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frequencies for a given stand age. This data may be derived from DBH class distributions obtained from the remeasurement of even-aged permanent plots or from chronosequence data from unthinned stands. Tree size distribution data may be presented for as many as ten stand ages, but the model will simulate tree size variation even if size distribution data are given for one age only. In this case, it is simply assumed that the shape of the stem size frequency distribution given for one age remains constant over all stand ages.

The simulation algorithm works by using the stem biomass class distribution data at the specified stand ages to calculate the rate of size increase in each time step for the median tree in each distribution. Individual trees are divided into as many as 10 biomass classes according to the distributions specified in the input data. The rates of growth of all trees at a particular stand age are expressed relative to the growth rate of the median tree (set to 1.0) at that age and the annual net stand stemwood biomass production is allocated to individual trees (Eq. 2). It then calculates the rate of growth of trees in: a) the largest size classes, b) trees in the smallest size class that remain alive over the time period (it is assumed that the smallest trees will die first), and c) trees distributed into the intermediate size classes (Figure B.3).

$$\text{Growth of tree } i = \frac{\text{RGR tree}_i}{\sum_{i=1}^n \text{RGR tree}_i} \cdot \text{Net stand stemwood production} \quad (2)$$

where:

Growth of tree_i = the proportion of total stand stemwood production allocated to tree_i,

RGR tree_i = growth rate of tree_i relative to the median tree in the distribution

Net stand stemwood production = total stand stemwood biomass production for an annual time step (kg ha⁻¹).

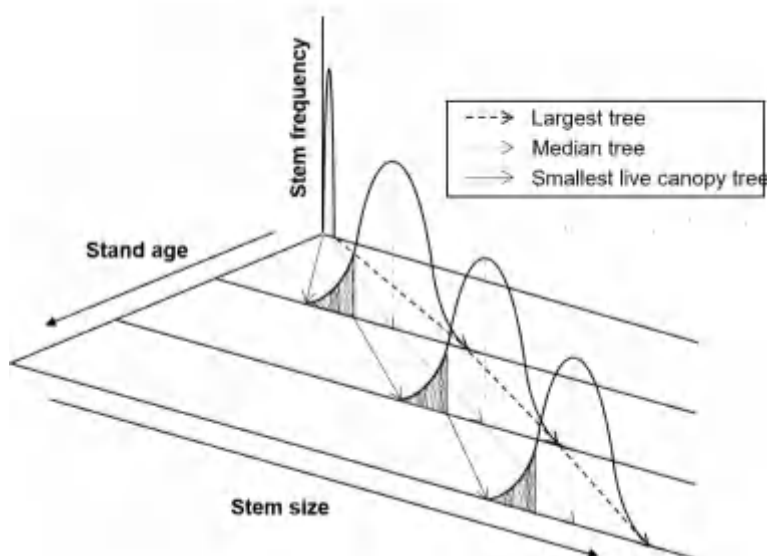


Figure B.3 A diagram of FORECAST's representation of individual tree size of a group of cohorts through time.

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When mortality occurs, the transfer of biomass to the litter pool is based on the stem biomass of the dying trees. The mass of other components of the dying trees is estimated by multiplying the mass of total mortality stemwood by the ratio of stemwood to the other individual tree components obtained from the biomass input data adjusted for stand age. There is no individual plant mortality or stand self-thinning component in the net primary production calculation for life forms other than trees, because these understory plants are not represented as individuals. For herbs, shrubs, and bryophytes, all biomass losses, including both litterfall and mortality, are represented as ephemeral litterfall. Height growth is determined for individual trees using a similar method bounded by data-defined shortest-live tree and canopy top height for a series of stand ages.

4. CALCULATION OF ANNUAL POTENTIAL GROWTH (APG) IN THE ECOSYSTEM SIMULATION MODULE (ECOSYSTEM)

Annual potential growth (APG) of vegetation in the ecosystem simulation module of FORECAST is driven by the photosynthetic production of the foliage biomass (Figure B.4). The productive capacity of a given quantity of foliage biomass is assumed to be dependent on its nitrogen content, corrected for shading. Photosynthetic rates are expressed per kilogram of foliage nitrogen (FN) rather than per kilogram of foliage biomass because N content is believed to be a better measure of the function of the photosynthetic "apparatus" (Brix, 1971, and H. Brix, personal communication). The production efficiency of foliar nitrogen (FNE) is derived in the plant setup programs by dividing the annual TNPP for a particular species by the total quantity of foliar nitrogen present in a given time step (Eq. 3). However, FNE, by itself, is not suitable for use as a driving function as it has been shown to vary as a function of foliage biomass (due to self shading; Ågren, 1983), and of the degree to which a plant can alter its foliage morphology and physiology as light intensity changes. While the latter factor is a fixed characteristic of a species, the first requires either: a) an equation describing how FNE varies as a function of foliage biomass, or b) an explicit simulation of the effect of shading on photosynthetic activity.

$$FNE_t = TNPP_t / FN_t \quad (3)$$

$$FN_t = \text{foliage biomass}_t \times \text{foliar N concentration} \quad (4)$$

where:

FN_t = total foliar N content of a given species at time t (kg ha^{-1}).

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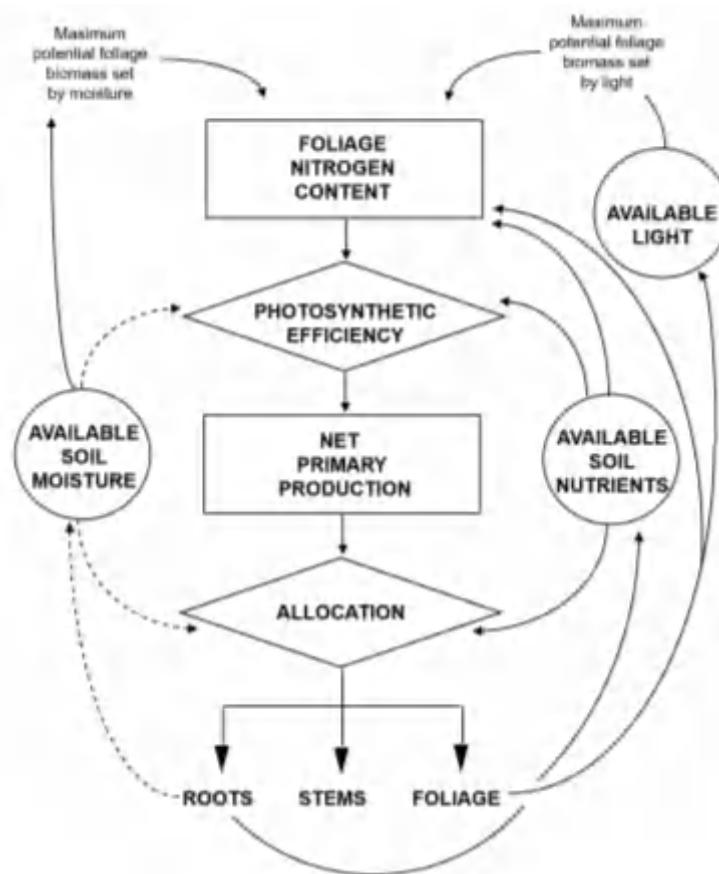


Figure B.4 A diagrammatic representation of the structure and function of the ecosystem simulation module in FORECAST. The dashed arrows indicate connections that will be facilitated by linkage to the hydrology submodel.

The major difference between these two approaches is whether the calculations are performed externally to, or internally in the model. The FORECAST model adopts the latter approach because it permits greater flexibility in the simulation of events such as thinning, pruning, and defoliation. This choice of modelling strategy also reflects the philosophy that the user should be responsible for the quality of all the calibration data. Thus, instead of using foliage nitrogen efficiency estimated for different values of foliage biomass and associated foliar N content, the ecosystem simulation module of FORECAST calculates APG as a function of shade-corrected foliar nitrogen efficiency (SCFNE) (Eq. 5). APG is calculated separately for each plant species represented in the model. The actual annual growth achieved by vegetation is subsequently determined based on the availability of nutrients (described in Section 5).

$$APG_{(t+1)} = SCFN_t \times SCFNE_t \quad (5)$$

where:

$APG_{(t+1)}$ = annual potential growth (kg ha^{-1}) for a given species in the next time step ($t = t+1$),

$SCFN_t$ = shade-corrected foliar N content at time t (kg ha^{-1}), defined below,

$SCFNE_t$ = shade-corrected foliar N efficiency at time t (kg ha^{-1}), defined below.

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4.1 Shade-Corrected Foliar Nitrogen Efficiency (SCFNE)

4.1.1 Canopy representation

To account for the effect of shading on photosynthesis, the TREEGROW setup program uses a simulation of the distribution of foliage biomass within the canopy to estimate the degree of self-shading associated with specific quantities of foliage biomass. Input data define the average relative intensity of photosynthetically active radiation (PAR, as a percentage of that above the canopy) beneath stands that cover a range of canopy biomass values. These data can be obtained in the same stands that were used for the input data on stand biomass (including canopy biomass). Alternatively, data could be obtained using Beer's Law with published light extinction coefficients. The canopy is represented as an "opaque blanket" with foliage distributed uniformly over a simulated hectare, and uniformly with height in the canopy. The setup program establishes a relationship between relative PAR and the amount of foliage biomass (comparable to using a Beer's Law equation), and uses this as a basis to simulate canopy light profiles. For each time step, the foliage biomass is distributed uniformly into quarter-metre canopy height increments between the top and bottom of the live canopy (defined in input data). The percentage of above canopy light (PAR) reaching each quarter-metre canopy level is calculated based on the total amount of foliage biomass above it (Figure B.5).

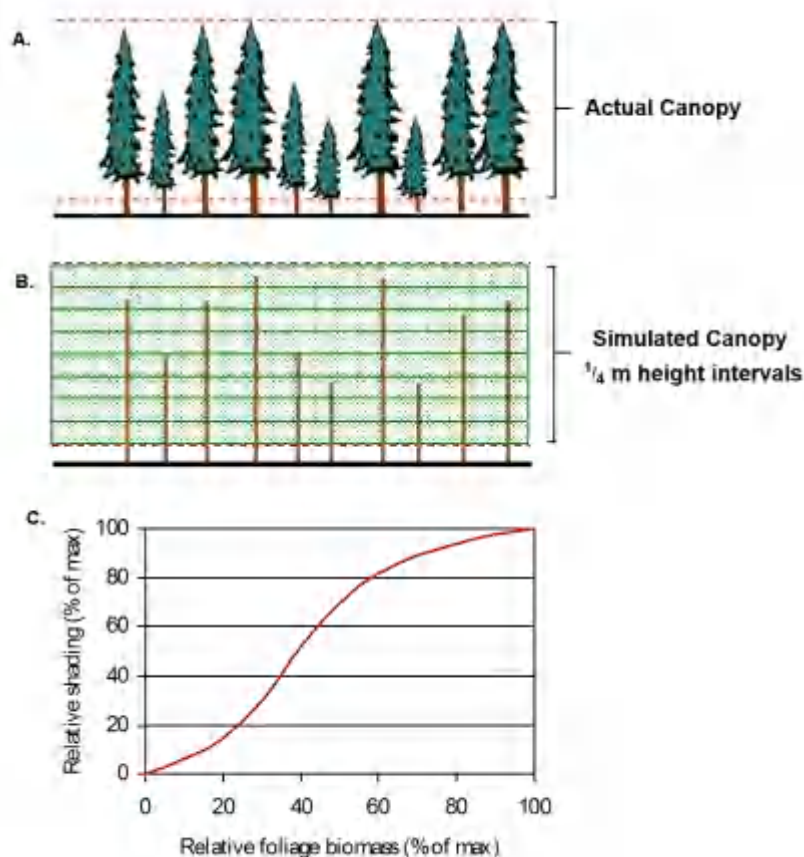


Figure B.5 (A) The representation of an actual canopy in FORCAST with (B) foliage biomass distributed evenly into 0.25 m thick layers, and (C) the relative shading estimated for each canopy layer.

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Species-specific photosynthetic light saturation curves (PLSC), based on a proportion of the maximum photosynthesis rate determined as a function of PAR levels, are used to define the extent of the photosynthetic activity associated with the foliage N content of each quarter-metre height increment in the canopy. Since sun-adapted foliage has higher absolute rates of photosynthesis at high PAR, and lower rates at low PAR, in comparison with shade-adapted foliage, the PLSC curves defined in the input data for sun and shade-adapted foliage characteristically cross (Figure B.6). The TREEGROW setup program uses this cross-over point to determine whether shade or sun-adapted foliage should be produced in each canopy level. Thus, at canopy levels where PAR is less than the PAR at the cross-over point for the PLSC graphs, shade foliage is produced; at higher PAR levels new foliage is defined as sun foliage. When there is no difference in the PLSC for foliage in the upper and lower canopy, a single set of PLSC values will be given. The model does not simulate the acclimation of a given foliage type to changes in light intensity, nor does it directly simulate changes in photosynthetic activity as a function of foliage age, both of which can occur in real foliage. It does however, allow for a representation of the different productive capacities of young and old foliage in evergreen species. This achieved by providing input data for N concentration values for each foliage type as well as data specifying the number of time steps each foliage type is retained. The reduced N concentration typically observed in old foliage renders it less productive per unit of foliage mass relative to new foliage.

The canopy of understorey species (herbs and shrubs) is represented using a similar but simplified approach in which only a canopy top and bottom height are specified. Foliage is distributed evenly throughout.

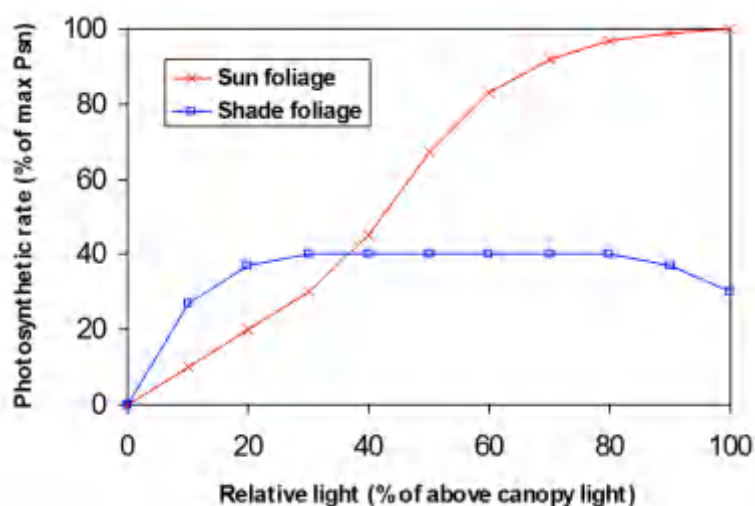


Figure B.6 An example of the photosynthetic light saturation curves used in FORECAST to represent the relative photosynthetic efficiency of sun and shade foliage.

4.1.2 Calculation of Shade-corrected Foliar N content (SCFN)

Once an estimation of self-shading has been completed for a particular time step using the canopy representation method described above, the setup program calculates a foliar N content value adjusted for the effects of self-shading (Eq. 6). This shade-corrected foliage N content (SCFN) represents the amount of fully illuminated foliage N (in sun foliage) that would be required to produce the same TNPP as is produced by the current sun and shade foliage at the simulated levels of illumination. The mean photosynthetic rate of

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the foliage in canopy level i is calculated by combining simulated light intensities in canopy level i with input data that define photosynthetic light saturation curves for the foliage type in question. These calculations are repeated for every time step (t), spanning the time from the seedling stage ($t=1$) to the maximum tree age ($t=\text{max age}$) to be simulated, thus producing a species-specific time series curve of SCFN values. A plot of SCFN and FN over a stand development time sequence illustrates the relationship between total foliage biomass and self-shading (Figure B.7).

$$\text{SCFN}_t = \sum_{i=1}^n (\text{FN}_i \times \text{PLSC}_i) \quad (6)$$

where:

FN_i = mass of foliage nitrogen in the i th quarter-metre height increment in the live canopy,

PLSC_i = Photosynthetic light saturation curve value for the associated light level in the i th quarter-metre height increment in the live canopy,

n = number of quarter-metre height increments in the live canopy.

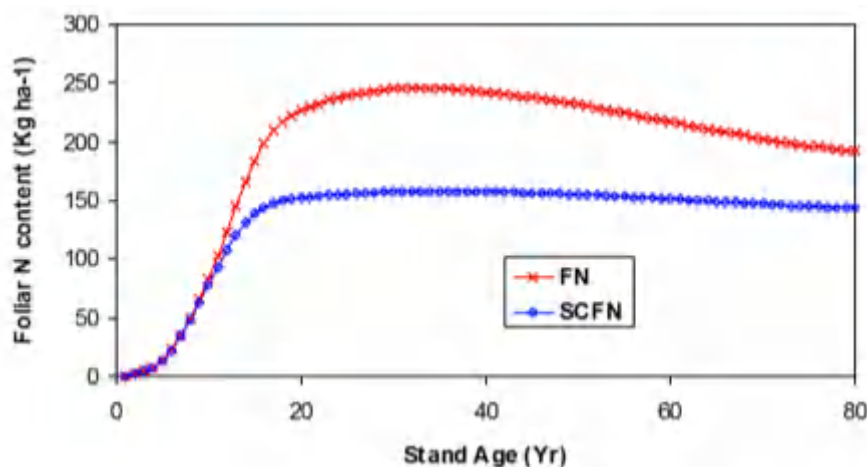


Figure B.7 An example plot of shade-corrected foliar nitrogen content (SCFN) vs. total foliar nitrogen (FN) over a stand development time sequence in FORECAST.

4.2 Use of SCFNE as the driving function in ECOSYSTEM

The driving function curve for potential growth of a given species in the ecosystem simulation module of FORECAST is obtained by dividing TNPP_t by SCFN_t to yield SCFNE_t for each annual simulation time step (as described for SCFN above) (Eq. 7). Wherever self-shading within the canopy reduces photosynthesis, SCFNE will have a higher value than FNE. When data describing the growth of a species on more than one site quality are provided, SCFNE function curves will be generated in the setup program for each site quality. The ecosystem simulation module interpolates between these curves when simulated site quality change occurs (see below).

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$$\text{SCFNE}_t = \frac{\text{TNPP}_t}{\text{SCFN}_t} \quad (7)$$

Calibration of FORECAST with several different data sets has resulted in SCFNE curves that are highest during the seedling stage and decline with time to reach a level that remains fairly constant over the rotation (Kimmins et al., 1986). The consistency of the pattern among species suggests that the decline represents, in part, an increasing respiration tax as the ratio of photosynthetic biomass to respiring nonphotosynthetic biomass decreases as the stand ages. The pattern of initial decline in SCFNE is not a precise mirror image of the increase in the total quantity of nonphotosynthetic live biomass, however. Nonphotosynthetic live biomass is dominated by sapwood and large root biomass, which have lower respiration rates than fine and medium roots (Szaniawski, 1981, Amthor, 1984), and branches. Interestingly, these biomass components show a pattern of increase in biomass that mirrors the decline in SCFNE more closely than does the biomass of stem sapwood and large roots. The higher early SCFNE values could also reflect the higher nutrient availability early in the life of a plantation as a result of the "assart flush" (Kimmins, 1997 p. 119).

5. SIMULATION OF NUTRIENT CYCLING IN ECOSYSTEM

While the annual potential growth (APG) of vegetation in ECOSYSTEM is determined as a function of SCFNE, the actual annual growth (AAG) achieved in a given time step will depend upon whether the nutrient uptake demand created by this potential growth can be satisfied by the available nutrient resources. The quantity of available nutrient resources in a given time step is a function of: a) the simulated internal translocation of nutrients within the plants (based on input data on nutrient concentration and specific gravity changes with tissue death), b) simulated net canopy uptake / leaching losses, and c) the simulated level of available nutrients in the soil that is accessible to the plants.

Nutrient cycling in the ECOSYSTEM module is based on a mass balance approach where nutrients can exist in three distinct pools: 1) The plant biomass pool, 2) the available soil nutrient pool, and 3) the soil organic matter / forest floor pool (see Figure B2). The storage of nutrients in the available soil nutrient pool from one time step to the next is limited by the nutrient-specific ion exchange capacities defined for the soil in the SOILDATA file. The size of these exchange capacities can be defined to change as a function of simulated site quality. Nutrients exceeding the capacity of the exchange sites are assumed to be lost from the system (see below).

5.1 The geochemical cycle

The imports and exports from the geochemical cycle are represented as part of the annual mass balance calculations performed for each nutrient simulated the ECOSYSTEM module.

5.1.1 Geochemical inputs

Input data are provided on rates of inputs of nutrients in precipitation, mineral weathering, and slope seepage for each of the nutrients to be simulated for sites representing the range of nutritional qualities associated with the growth data. These defined input rates are assumed to be determined by a site's location in the landscape, its soil physical characteristics, and its surficial and bedrock geology, and thus do not change with simulated site quality during a simulation run. However, the proportion of these available nutrients in a

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given ionic form (e.g. nitrate/ammonium ratios for N) is assumed to be related to the simulated site quality, and therefore will change with site quality as specified in the input data. The user can also specify rates of nutrient additions in the form of fertilizer.

In addition to the mineral inputs, the user has the option to provide rates of N fixation by symbiotic N-fixing plant species that are being simulated or by free-living N-fixing microbes. The former is determined by a user-provided rate that is a function of the amount of foliage (kilograms of N fixed per kilogram of shade-corrected foliage-N carried by the N-fixing plant) derived from published data on N-fixation rates for N-fixing plants of known foliage biomass. This approach is based on the assumption that N fixation is an energy-requiring process, and that the best single estimate of energy-availability in FORECAST is SCFN. Symbiotically fixed N is assumed to be captured directly by the N-fixing plants, where it is used to satisfy their N demand for new growth prior to their simulated uptake of N from the soil. The fixed N eventually reaches the soil via litterfall, plant death, foliar leaching, or defoliation from the N-fixing plants. Free-living N fixation by bacteria or other soil organisms living nonsymbiotically can be specified as a constant annual input rate directly to the available soil nutrients compartment. Alternatively, substrate-specific N-fixation rates may be specified for decomposing litter types (e.g. foliage, decomposing wood). The geochemical inputs are either incorporated directly into plants (symbiotic N fixation or uptake by foliage from precipitation) or into the available soil nutrient pool (see Figure B.2). Many of the geochemical input data are optional (see Appendix A), and the user is not required to address each of the inputs described above. However, the user then accepts the responsibility for the omission of an input that may have an important effect on the overall nutrient budget for a site.

5.1.2 Geochemical outputs

The FORECAST model represents the geochemical losses of nutrients from the available soil nutrient pool by volatilization of fertilizer N and leaching. The percentage of fertilizer N that is lost to volatilization is described as part of the management data in the ECODATA file. This loss will occur prior to any simulated uptake of nutrients by plants. Following the simulation of geochemical inputs, volatilization, immobilization, and plant uptake, any nutrients remaining in the available nutrient pool in excess of the defined ion exchange capacities of a site (cation exchange capacity [CEC] or anion exchange capacity [AEC]) are assumed to be lost from the ecosystem via leaching. Leaching is thus likely to occur with various combinations of reduced plant uptake (e.g. following clearcutting), or accelerated input of nutrients into the available soil pool. Leaching of nitrate-N is more accurately defined as the "disappearance" of nitrate-N because the model does not explicitly simulate the process of microbial denitrification. Loss of soil nitrate is assumed to represent the combination of both leaching and denitrification. Most of the simulated leaching in FORECAST will be of nitrate-N rather than ammonium-N because the simulated soil will normally have a higher CEC than AEC. The failure to deal explicitly with denitrification, which can be a major source of post-harvest N loss in some types of forest (Davidson et al., 1990; Struwe and Kj  ller, 1990), is a limitation of FORECAST's representation of the geochemical cycle.

Nutrients may also be lost from the other two pools represented in FORECAST (see Figure B.2). Nutrient loss from the soil organic matter pool (other than via mineralization) can occur by simulated wildfire or a management-controlled slash burn. Loss of forest floor nutrients can also be simulated as loss due to litter raking, or mechanical removal of logging slash. Removals by fire include losses of fly ash and volatilization

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during simulated burning. The model can simulate various types of fire (wildfire, crown, surface, or ground; slash burning; or stand underburning), with nutrient loss being predicted on the basis of user-provided input data on the percent loss of each nutrient being simulated from material that is converted to ash. Harvest removals from the biomass nutrient pool are simulated by accounting for the nutrient content of each of the biomass components removed from the site during any intermediate or final harvest (e.g., a clear-cut). The model predicts the long-term site nutrient budget as the balance of the geochemical inputs and outputs, and simulates consequences of this balance on the circulation of nutrients and plant nutrition within the ecosystem.

5.2 The biogeochemical or within-ecosystem cycle

5.2.1 *Decomposition: mineralization/immobilization*

The simulation of litter decomposition in FORECAST is driven by empirical input data describing the following: a) weight loss rates as a function of the type of decomposing material and its age (since litterfall), b) the concentrations of nutrients in fresh litter and in humus, and c) the temporal pattern of change in nutrient concentration between fresh litter and humus. These data are combined to calculate the change in the total content of nutrients in a cohort of decomposing material in each time step from fresh litter to humus. An increase in content is interpreted as microbial immobilization; a decrease as mineralization. This approach is applied to annual cohorts of all the different types of litterfall simulated by the model, or the user can opt to combine different litterfall types that have similar decomposition characteristics into a few generalized decomposition types. Decomposition rates given in the input file may be modified by a set of exposure factors provided by the user in the soils input file. These control the simulation of the response of humus and litter decomposition rates to the removal of vegetation by harvest or other disturbance. Empirical data on decomposition rates must be provided for each climate region in which the model is to be used because the present version of FORECAST lacks any representation of the effects of temperature and moisture on decomposition processes.

5.2.2 *Competition for and uptake of available nutrients by plants*

Within the ECOSYSTEM module of FORECAST, plants can take up nutrients from precipitation inputs, throughfall inputs (understory plants), symbiotic N fixation (if applicable) or from the available soil nutrient pool. Uptake from precipitation (net canopy uptake) or throughfall is defined by input data on the difference in the nutrient content of precipitation or throughfall above and below the plant canopy. Mosses are assumed to be able to withdraw from throughfall as much nutrient as is required to support their expected new growth. In FORECAST, mosses are assumed to be of the feather moss type, which obtain their nutrients from throughfall or precipitation (Tamm, 1953) and do not take up nutrients from the available soil nutrient pool.

Competition for nutrient resources among simulated plant species is represented in the ECOSYSTEM module as a function of simulated nutrient uptake demand, the size of the available nutrient pool, and the relative occupancy of the soil by fine roots of each species. The annual uptake demand (UD) for a given species is determined using a mass balance approach driven by the potential growth in which the nutrient demands to meet potential growth are calculated while accounting for internal cycling, canopy uptake and foliar leaching (Eq. 8).

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$$UD_i = (APG_i \times EC_i) - (IC_i + CU_i) + L_i \quad (8)$$

where:

UD_i = annual uptake demand for species i (kg ha^{-1}),

APG_i = annual potential growth for species i (kg ha^{-1}),

EC_i = average expected nutrient concentration for new biomass of species i (%),

IC_i = annual net nutrient gain from internal cycling for species i (kg ha^{-1}),

CU_i = annual direct canopy uptake from precipitation or throughfall for species i (kg ha^{-1}),

L_i = total annual foliar leaching from species i (kg ha^{-1}).

Once the nutrient demand for each species has been calculated, the actual uptake for a given species from the available soil nutrient pool is simulated. The size of the available pool at the start of a simulation time step depends on the quantity of nutrients held on exchange sites at the end of the last simulation time step, plus precipitation, weathering, seepage, nonsymbiotic N-fixation, and fertilization inputs in the current time step. Nutrients are then added or removed from this pool depending on the outcome of the decomposition subroutine (see above). The quantity of available nutrients accessible to plants of a given species is dependent on the proportion of the soil occupied by the fine roots of that species (RO) (Eq. 9). This proportion is derived from the ratio of the current biomass of fine roots to the site maximum biomass of fine roots. The site maximum fine-root biomass is assumed to be equal to the maximum value observed over time for a particular species in a fully stocked stand on the site, as specified in the input data file. (Eq. 10).

$$NAP_i = TAN \times RO_i \quad (9)$$

$$RO_i = FRB_i / MFRB_i \quad (10)$$

where:

NAP_i = quantity of available nutrients accessible to species i (kg ha^{-1}),

TAN = total size of the available nutrient pool in the current time step (kg ha^{-1}),

FRB_i = the fine root biomass of species i for the current time step (kg ha^{-1}),

$MFRB_i$ = the maximum fine root biomass for species i on a given site quality (kg ha^{-1}).

When the total combined uptake demand by all species is less than the total available nutrient pool, nutrient uptake by different plant species occurs simply in response to the individual species uptake demand according to equation 11.

$$AU_i = \min (UD_i, NAP_i) \quad (11)$$

$$AU_i = \min \left(\frac{UD_i}{\sum UD_{\text{total}}}, NAP_i \right) \quad (12)$$

where:

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AU_i = annual actual nutrient uptake for species i (kg ha^{-1}),

UD_{total} = annual total uptake demand for all species (kg ha^{-1}).

However, when the combined total uptake demand is greater than the available nutrient supply, competition occurs. In this situation, the available supply of nutrients is divided between species according to their relative uptake demands and root occupancies (Eq 12). There is no representation of the vertical distribution of fine roots, and they are assumed to be distributed uniformly across the site. This lack of spatial representation is also true for the available soil nutrients and the decomposing litter.

5.2.2 Distribution of nutrients within plants

Nutrients taken up by plants and internally cycled nutrients are allocated to new growth of different biomass components according to the relative magnitude of new biomass multiplied by the expected concentration, calculated separately for each biomass component. Where there are insufficient nutrients from internal cycling and uptake, this "new growth demand" is limited to that which can be provided with sufficient nutrients to achieve the expected concentrations. The ratios of the different biomass components in the new growth, and thus the distribution of nutrients among different new biomass components, are defined by input data on biomass ratios for different site qualities given in the setup data files, and are not affected directly by the difference between "new growth demand" and supply (uptake + internal cycling). The FORECAST model cannot simulate changes in internal cycling or the internal distribution of nutrients within plants as a function of changing competition due to stand density effects. These changes are limited in the model to site quality, and site quality is determined by the total availability of nutrients on the site. There is no simulation of change in site quality due to between-species competition or changes in stand density.

5.2.3 Internal cycling and nutrient losses from plants

It is impractical to simulate the biochemistry of internal cycling in rotation-length modeling of entire stands. Instead, FORECAST adopts the empirical approach of requiring data on the concentrations of nutrients in plant tissues of various ages or condition, and on weight change at the time of tissue senescence. If a representation of the effects of site quality change on internal cycling is desired, such data are required for sites that vary in their nutritional quality. As the model simulates nutritional site quality change within a run, it interpolates between the input data for various site qualities to find the concentrations and weight loss appropriate for the current site quality. It then calculates the quantity of nutrients retranslocated at the time of senescence, or during tissue aging, from the appropriate concentration and weight change data.

Nutrient loss from plants as ephemeral litterfall is determined by the mass of litterfall and the concentration of nutrients in dead tissue relative to the associated live biomass component. The mass of ephemeral litterfall that occurs during each timestep is defined in the data set as a proportion of the dead tissue produced by the senescence of each biomass component. With the exception of fine roots, litterfall mass in any time step cannot exceed the mass of the biomass subcompartment from which it came. For fine roots, the user can simulate litterfall within a single time step that exceeds the biomass of that component at the start of that time step. For example, the biomass of fine roots that die in the time step might be 150% of the quantity of fine roots at the start of that time step because of death, regrowth, and death of this size class of roots within the time step.

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Foliar leaching loss is simulated on the basis of the difference in the nutrient content of precipitation and throughfall above and below the foliage canopy of a given species. Input values for these nutrient contents are given in the input setup plant growth modules, in conjunction with estimates of the foliage biomass associated with the measured difference in content. This permits a simulation of leaching per kilogram of foliage (this also applies to the estimates of uptake from precipitation or throughfall), and thereby a simulation of the change in the amount of nutrients transferred by foliar leaching as the biomass of foliage changes (e.g. by a thinning). Simulation of these throughfall processes, and the data to calibrate them, are optional unless simulating bryophytes that depend on throughfall for their nutrition. Defoliation-related losses of nutrients are simulated on the basis of the user-defined removal of foliage biomass by defoliation and the current concentration of nutrients in that foliage biomass (i.e., there is no internal cycling before the foliage is lost by defoliation).

6. SITE QUALITY CHANGE IN FORECAST

Site quality evaluation is an important part of silviculture and forest management because silvicultural and management prescriptions must be site-specific. Traditional historical-bioassay yield predictors have always been tied to some system of site quality evaluation. Since such yield predictors are not able to predict site quality improvement or deterioration in response to management, foresters have relied on independent assessments of site quality to suggest the need to switch to a new yield table class or site index curve when sites are degraded or improved. Process-simulation growth and yield models have generally not addressed this deficiency. The JABOWA class models, and models such as Mohren's (1987) model and ecophysiological canopy models do not simulate changing site quality during a run. The lack of site quality simulation in community succession and most ecosystem-level models is understandable. There is still disagreement on many of the details of both the ecology of site quality change, and of the physiological response of plants to such change. However, it has been demonstrated that change in crop yield in response to changing resource availability is as much or more a function of changing allocation of photosynthates as it is of absolute changes in net primary production (e.g. Keyes and Grier, 1981; Kurz, 1989). Tissue chemistry, internal cycling, foliage leaching losses, decomposition rates, nitrate-ammonium ratios, and a variety of other important processes and site characteristics may also change as a function of nutritional site quality change. In FORECAST, the user has the option to simulate the changes in these variables when nutritional site quality is either improved or degraded during a simulation run.

6.1 Representation of ecosystem response to site quality change

The FORECAST model adopts an empirical approach to the representation of site quality change. Site quality in FORECAST is defined in the input data files by entering data for both plant growth and a number of plant and ecosystem processes for several sites that vary in nutritional site quality. Each of these site quality data sets is given a number on some user-specified scale of site quality. This can be a conventional site index value (height at a given age), a yield table site quality class, or an arbitrary scale set by the user. The choice of scale is not important, as long it is kept consistent throughout the data set. The specified site quality scale is used to reference the nutritional data that define the site quality (discussed below). FORECAST uses linear interpolations between different site quality reference values to define changes in variables in response to simulated site quality change.

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6.2 Estimation of the relative nutrient abundance associated with site quality

In each of the plant growth setup programs, the nutrient uptake that is estimated to have been associated with the historical pattern of growth and biomass accumulation by the species in question is calculated for each site quality class. For each of the nutrients that are defined in the data input files, the setup growth programs estimate the total level of the nutrient that was available in the soil to support such a level of uptake, accounting for the degree of soil occupancy by fine roots. For example, if trees of species 'x', whose growth is nutrient limited, are calculated to have taken up 20 kg/ha of nutrient 1 in time step t , but to have only had 50% of the maximum observed fine-root biomass in that year, the model assumes that the total amount of nutrient 1 available on the site in that time step must have been 40 kg/ha. Using this approach, the setup programs estimate the temporal pattern of nutrient availability that probably occurred on each of the various site qualities to have supported the observed pattern of growth on each of those sites. For each site, the program then takes the highest value in this temporal pattern as the definition of the availability of that nutrient for a specified site quality. If the availability of a particular nutrient is indeed limiting plant growth, it is expected that the availability of that nutrient will increase as site quality (and consequently tree growth) increases. Where setup program output does not confirm this expectation, the input data are in error, or the assumption that the nutrient is limiting growth must be wrong. In such a case, input data and the assumptions made about the role of the nutrient in regulating growth must be reexamined. If only one nutrient is being simulated as growth limiting in an ECOSYSTEM run, then nutritional site quality will be defined in that run by comparing simulated total availability of that nutrient on the site with the defined maximum value for nutrient availability for each of the site qualities defined in the setup modules. If two or more limiting nutrients are simulated in a single run, the model defines site quality in terms of the nutrient that is most limiting.

6.3 Site quality for plant versus site quality for soil processes

Two types of site quality are defined in FORECAST: 1) nutritional site quality as perceived by individual plant species, and 2) site quality for soil processes. Forest soils have a considerable "nutritional inertia" that reflects the characteristically large mass of high C/N ratio organic matter in the forest floor, the prevailing soil fauna and flora, and the prevailing understory vegetation and litterfall quality. Several years of sustained alterations of litterfall quality and nutrient availability are required to cause the fundamental changes in soil processes that result in significant changes in site quality. Representation of this inertia is achieved by having the site quality for soil processes follow site quality for trees and plants, but with a user-defined damping function defined as the proportion of the change in site quality for the trees and other plants that can occur for soil site quality in each time step. However, individual tree and plant species can define the nutrient availability on a given site differently in terms of site quality; consequently, the user must specify a weighted average of the site qualities defined by the various simulated trees and plants. It is this average that the soil site quality follows.

Plant growth response to changing soil nutrient availability will normally be much faster than changes in soil processes; consequently, the basis for the site quality change damping function is different for plant growth versus soil processes. A second damping function for site quality change in plants must be specified as a percentage of the change possible in one time step, based on the plant's annual potential growth (APG). In contrast, the site quality change damping function for soils is specified as a percentage of the actual

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achieved change in plant-defined site quality in one time step based on the nutrient-limited achieved growth. As noted, both percentages are defined by the user in the ECODATA input file.

A shortcoming of the definition of site quality used in FORECAST is that the setup input data used to represent sites of different nutrient status may also reflect variations in environmental variables not explicitly represented in the model. For example, differences in nutrient site quality are frequently accompanied by differences in moisture availability. When nutrient site quality change on a given site is simulated in ECOSYSTEM, it is based on input data from sites that may differ in moisture conditions as well as nutrient conditions. This problem is partly rectified by putting user-defined constraints on certain variables (e.g., maximum foliage biomass that can be carried on the site). The value of these variables is fixed at the start of the run by the definition of starting site quality and remain unaltered even if nutritional site quality changes during a run.

7. INITIAL ECOSYSTEM CONDITION: THE ECOSTATE FILE

The response of a given ecosystem to a particular set of management activities or other types of disturbance depends to a large degree on its condition at the time of disturbance. Levels of organic matter resources and competing vegetation are typically altered by silvicultural treatments or natural disturbance events. Thus, the condition of an ecosystem at any given time reflects past treatments, harvests and natural disturbance, stand growth, and stand development. The effects of past management and natural disturbance events on ecosystem condition and future productivity are dealt with in FORECAST through the use of the ECOSTATE file. The function of the ECOSTATE file is to initialize values for all of the types and ages of decomposing organic matter in the forest floor and the levels of soil humus at the start of the run including: total mass, nutrient content and stage of decomposition. The file also defines the existing populations of each of the tree and other plant species to be represented in the simulation. It considers, for example, whether one is starting with a clear-cut devoid of living mosses, herbs, shrubs, and trees, or if there is an established community with both aboveground and below ground live biomass, or below ground live biomass only. In the latter case, whether this below ground biomass constitutes a budbank that will sprout or sucker at the start of the new rotation is considered. Rather than attempting to define an ecosystem starting condition through the measurement of hundreds of state variable for a given site, an initial ecosystem state is established by running the ecosystem module without nutrient feedback to force the vegetation to grow as it has historically and to allow the ecosystem to accumulate soil organic matter, forest floor litter and coarse woody debris as expected under a defined historical scenario. The output of this run is saved as an ECOSTATE file for future use.

Experience with FORECAST to date indicates that the model's predictions are very sensitive to the initial ecosystem state as defined by ECOSTATE (Morris et al. 1998). This is particularly evident in the first simulated rotation of tree crops, or the first 100 or more time steps. Careful preparation of an appropriate ECOSTATE file can be just as important a modeling activity as getting accurate calibration data. It is, in fact, one aspect of model calibration, and a major component of the setup activity of FORECAST.

8. OTHER PROCESSES IN FORECAST

A detailed description of the algorithms used to represent the various ecosystem compartments and processes in FORECAST is beyond the scope of this paper. The reader is referred to Kimmins (1993) for more

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information on the following simulation processes: regeneration, representation of understorey growth dynamics, coppice resprouting or root suckering, tree mortality, height growth, nutrient cycling and competition for nutrients, nutrient availability in the soil, and light competition among species.

9. SOME LIMITATIONS OF THE FORECAST APPROACH

As is the case with all models, FORECAST has a number of limitations in its application that should be considered by the user. For example, many of the representations of soil processes in FORECAST are relatively simplistic. The lack of representation of soil horizons, soil mixing, and root distribution limits the ability of FORECAST to address issues of soil compaction and soil erosion. The model's approach for estimating ephemeral litterfall (see Section 3.2) may result in an overestimate of litterfall in the first few time steps of the simulation, and this may contribute to the higher values of shade corrected foliage nitrogen efficiency (SCFNE) early in the simulation. The early overestimates of litterfall rates, however, are applied to a very small biomass, so in terms of rotation-length simulations, the error involved should be very small. The representation of the tree canopy in FORECAST as an "opaque blanket" also poses some difficulties for the simulation of individual tree growth, thinning response, agroforestry, shelterwood, and mixed-age stand management. Modifications have been made to the simulation of the canopy to improve the model in this respect. A detailed description of these modifications will be reported in a subsequent paper. There is no representation of seasonality in FORECAST. This places a limitation on the use of time steps of less than 1 year in climatic regions that have seasonally variable climatic conditions. The model does account for winter photosynthesis by evergreens while deciduous competitors are leafless, and it can simulate mortality and regrowth of fine roots on time steps shorter than one year. There is, however, no detailed representation of the variation of the other ecosystem processes between seasons.

In spite of these limitations, experience to date suggests that, within the limits of model design, FORECAST performs predictably and that it is able to address most of its design objectives. The following works summarize different evaluations to date of FORCYTE-11 and FORECAST: Chan and Peterson (1987), Apps et al. (1988), Peterson et al. (1988), Apps and MacIsaac (1989), Grewal et al. (1989), Peterson and Apps (1989), Pike and Meades (1989), Sachs et al. (1989), Grewal et al. (1990), Sachs and Trofymow (1991), Trofymow and Sachs (1991), Wang et al. (1995) and Morris et al. (1997).

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Appendix A

Data resources necessary for the calibration of FORECAST's TREEDATA file

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application ^a	Relative sensitivity of model to data ^b	General function in FORECAST
Stemwood biomass	(mg ha ⁻¹)	Y	N/A	Required	***	Biomass accumulation
Stembark biomass	(mg ha ⁻¹)	Y	N/A	Optional	*	Biomass accumulation
Branch biomass	(mg ha ⁻¹)	Y	N/A	Optional	**	Biomass accumulation
Foliage biomass	(mg ha ⁻¹)	Y	N/A	Required	****	Driving function, light competition, biomass accumulation
Maximum stand foliage biomass	(mg ha ⁻¹)	Y	N/A	Required	**	Moisture limited maxi- mum
Maximum foliage biomass for an individual tree	(kg tree ⁻¹)	N	N/A	Required	*	Limit individual tree foliage
Tree age associated individual tree biomass maximum	(year)	N	N/A	Optional	*	Limit individual tree maximum
Stand age at canopy closure	(year)	N	N/A	Required	**	Light competition
Large root biomass (arbitrary definition)	(mg ha ⁻¹)	Y	N/A	Optional	**	Biomass accumulation
Medium root biomass (arbitrary definition)	(mg ha ⁻¹)	Y	N/A	Optional	**	Biomass accumulation
Small root biomass (< 5 mm diameter)	(mg ha ⁻¹)	Y	N/A	Required	****	Nutrient competition
Fruit biomass	(mg ha ⁻¹)	Y	N/A	Optional	*	Biomass accumulation
Stand density	(stems ha ⁻¹)	Y	N/A	Required	****	Mortality calculations
Proportion of mortal- ity density indepen- dent	(None)	Y	N/A	Required	**	Mortality calculations
Canopy reduction to stop shade mortality	(%)	Y	N/A	Optional	*	Light competition
Average top height	(m)	Y	N/A	Required	****	Light competition
Top height of shortest live canopy tree	(m)	Y	N/A	Required	***	Light competition, canopy representation
Average height of canopy bottom	(m)	Y	N/A	Required	***	Light competition, canopy representation
Photosynthetic light saturation curve (PLSC) for sun foliage	(% of max. rate)	N	N/A	Required	***	Used in calculation of driving function

APPENDIX B: Published Research

Appendix A (Continued)

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application ^a	Relative sensitivity of model to data ^b	General function in FORECAST
Photosynthetic light sat- uration curve (PLSC) for shade foliage	(% of max. rate)	N	N/A	Optional	**	Used in calculation of driving function
Shading by maximum foliage biomass	(% of full light)	N	N/A	Required	***	Light competition
Curve defining shading as % of maximum foliage biomass	(% of max.)	N	N/A	Required	***	Light competition
Amount of photosynthe- sis that occurs when competitors are leafless	(%)	N	N/A	Optional	**	Winter photosynthesis in conifers
Amount of reduction in stemwood biomass production at which stunted height growth occurs	(%)	N	50%	Optional	*	Height growth in low light
Soil volume occupied at maximum small root biomass	(%)	N	100%	Optional	***	Nutrient competition
Efficiency of root cap- ture for each nutrient	(%)	N	100%	Optional	***	Nutrient competition
Proportion of trees in stem biomass classes (for up to ten stand ages but only one required)	(% in each class)	N	N/A	Required	**	Individual tree size dis- tribution in an age co- hort
Mean stemwood biomass for each size class above	(kg tree ⁻¹)	Y	N/A	Required	**	See above
Nutrient concentration in all simulated biomass components, live and dead (up to five nutrients)	(%)	N	N/A	Optional	***	Uptake demand, inter- nal cycling, litter nutri- ent concentration
Nutrient concentration in young foliage	(%)	N	N/A	Required	****	Uptake demand, driving function
Nutrient concentration in old foliage	(%)	N	N/A	Optional	****	Internal cycling, driving function

APPENDIX B: Published Research

Appendix A (Continued)

Data type	Units ()	Data from chronosequence required	Default value	Data required for simplified application ^a	Relative sensitivity of model to data ^b	General function in FORECAST
Nutrient concentration in dead foliage	(%)	N	N/A	Required	***	Nutrient concentration in foliage litter
Annual atmospheric deposition to canopy surface	(kg ha ⁻¹)	N	0	Optional	**	Net canopy uptake
Annual throughfall below canopy	(kg ha ⁻¹)	N	0	Optional	**	Net canopy uptake
Foliage biomass associated with throughfall data	(mg ha ⁻¹)	N	0	Optional	**	Net canopy uptake
Symbiotic N-fixation per kg foliage biomass	(kg N)	N	0	Optional	***	Symbiotic N-fixation
Annual transfer of stemwood to sapwood	(%)	N	5%	Optional	**	Internal cycling
Annual transfer of live to dead tissue for branches, large and medium roots	(%)	N	10, 4, 5, 5%, respectively	Optional	***	Internal cycling
Annual transfer of dead tissue to litterfall for bark, large, medium and small roots, and fruit	(%)	N	3, 0.1, 2, 1, 50, 100%, respectively	Optional	***	Ephemeral litterfall
Retention time for dead branches, young foliage and old foliage	(year)	N	N/A	Young foliage required; branches Optional	***	Biomass accumulation, branch litterfall and foliage productivity
Change in mass at death: all biomass components	(%)	N	0%	Optional	*	Internal cycling
Change in mass with foliage aging and death	(%)	N	0%	Optional	*	Internal cycling

^a The data are specified as optional or required for each tree species to be simulated in FORECAST. A simulation of the effect of site quality change on any variables related to these data requires input data from two or more sites varying in nutritional quality.

^b * = Low sensitivity, **** = high sensitivity.

APPENDIX B: Published Research

Appendix B

Data resources necessary for the calibration of FORECAST's PLANTDATA file

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application ^a	Relative sensitivity of model to data ^b	General function in FORECAST
Stem biomass	(kg ha ⁻¹)	Y	N/A	Optional	***	Biomass accumulation
Rhizome biomass	(kg ha ⁻¹)	Y	N/A	Optional	**	Biomass accumulation
Root biomass	(kg ha ⁻¹)	Y	N/A	Optional	****	Biomass accumulation
Fruit biomass	(kg ha ⁻¹)	Y	N/A	Optional	*	Fruit production
Foliage biomass	(kg ha ⁻¹)	Y	N/A	Required	****	Driving function, light competition, biomass ac- cumulation
Maximum site foliage biomass	(kg ha ⁻¹)	Y	N/A	Required	**	Moisture limited maxi- mum
Average top height of plants	(m)	Y	N/A	Required	****	Light competition
Average height of canopy	(m)	Y	N/A	Required	***	Light competition, canopy representation
Photosynthetic light saturation curve (PLSC) for sun foliage	(% of max. rate)	N	N/A	Required	***	Used in calculation of driving function
Photosynthetic light saturation curve (PLSC) for shade foliage	(% of max. rate)	N	N/A	Optional	**	Used in calculation of driving function
Shading by maximum foliage biomass	(% of full light)	N	N/A	Required	***	Light competition
Curve defining shading as % of maximum foliage biomass	(% of max. shading)	N	N/A	Required	***	Light competition
Amount of photosyn- thesis that occurs when competitors are leafless	(%)	N	N/A	Optional	**	Winter photosynthesis
Amount of reduction in stem biomass pro- duction at which stunted height growth occurs	(%)	N	50%	Optional	*	Height growth in low light
Soil volume occupied at maximum small root biomass	(%)	N	100%	Optional	***	Nutrient competition

APPENDIX B: Published Research

Appendix B (Continued)

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application ^a	Relative sensitivity of model to data ^b	General function in FORECAST
Efficiency of root capture for each nutrient	(%)	N	100%	Optional	***	Nutrient competition
Nutrient concentration in all simulated biomass components, live and dead (up to five nutri- ents)	(%)	N	N/A	Optional	***	Uptake demand, internal cycling, litter nutrient concentration
Nutrient concentration in foliage, live and dead	(%)	N	N/A	Required	****	Uptake demand, driving function
Annual atmospheric deposition to canopy surface	(kg ha ⁻¹)	N	0	Optional	**	Net canopy uptake
Annual throughfall below canopy	(kg ha ⁻¹)	N	0	Optional	**	Net canopy uptake
Foliage biomass associ- ated with throughfall data	(kg ha ⁻¹)	N	0	Optional	**	Net canopy uptake
Symbiotic N-fixation per kg foliage biomass	(kg N)	N	0	Optional	***	Symbiotic N-fixation
Annual transfer of live tissue to dead litterfall for stem, rhizomes, roots, and fruit	(%)	N	N/A	Roots required; others optional	***	Ephemeral litterfall
Retention time for foliage	(year)	N	N/A	Required	***	Foliage litterfall
Change in mass at death: all biomass components	(%)	N	0%	Optional	*	Internal cycling
Growth from seed in first year: stem, foliage, rhizome, root, and fruit	(kg ha ⁻¹)	N	N/A	Optional	**	Growth from seed
Remaining biomass after cutting back: stem foliage, rhizome, root, and fruit	(kg ha ⁻¹)	N	N/A	Optional	*	Growth from sprouts fol- lowing cutting
Growth from sprouting in first year: stem, foliage, rhizome, root, and fruit	(kg ha ⁻¹)	N	N/A	Optional	**	See above

APPENDIX B: Published Research

Appendix B (Continued)

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application ^a	Relative sensitivity of model to data ^b	General function in FORECAST
Mortality after cutting: root, rhizome	(%)	N	N/A	Optional	*	See above
Loss of vigor at each successive cut	(%)	N	N/A	Optional	*	See above

^a The data are specified as optional or required for each plant species to be simulated in FORECAST. A simulation of the effect of site quality change on any variables related to these data requires input data from two or more sites varying in nutritional quality.

^b * = Low sensitivity, **** = high sensitivity.

APPENDIX B: Published Research

Appendix C

Data resources necessary for the simulation of a moss complex in FORECAST

Data type	Units ()	Data from chrono- sequence required	Default value	Data required for sim- plified application	Relative sensitivity of model to data ^a	General function in FORECAST
Moss complex biomass	(kg ha ⁻¹)	Y	N/A	Required	***	Biomass accumulation, driving function
Photosynthetic light- saturation curve (PLSC)	(% of max. rate)	N	N/A	Required	***	Used in calculation of driving function
Amount of photosyn- thesis that occurs when competitors are leafless	(%)	N	N/A	Optional	*	Winter photosynthesis
Nutrient concentration in biomass, live and dead (up to five nu- trients)	(%)	N	N/A	Required	****	Uptake demand, driving function
Symbiotic N-fixation per kg foliage biomass	(kg N)	N	0	Optional	**	Symbiotic N-fixation
Retention time of live and dead biomass	(year)	N	5, 10 years, respectively	Required	***	Ephemeral litterfall
Change in mass at death: biomass	(%)	N	0%	Optional	*	Internal cycling

A simulation of the effect of site quality change on any variables related to these data requires input data from two or more sites varying in nutritional quality.

^a * = Low sensitivity, **** = high sensitivity.

APPENDIX B: Published Research

Appendix D

Data are specified as optional or required for the simulation of soil process in FORECAST

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application	Relative sensitivity of model to data ^a	General function in FORECAST
Define litter types: each biomass component is assigned a litter type (up to 40)	(None)	N	N/A	Required	N/A	Each litter type can have unique decomposition characteristics
Define humus types: each litter type is assigned a humus type (up to 40)	(None)	N	N/A	Required	N/A	Each humus type can have unique decomposition characteristics
Curves describing relative change in nutrient in concentration for each litter type during decomposition from fresh litter to humus (for each nutrient)	(Proportion)	Y	Linear curve	Required	***	Controls mineralization and immobilization rates
Total annual nutrient input to site in precipitation	(kg ha ⁻¹)	N	N/A	Optional	**	Geochemical cycle input
Annual upslope seepage nutrient input to site	(kg ha ⁻¹)	N	0	Optional	**	Geochemical cycle input
Annual nutrient input from weathering	(kg ha ⁻¹)	N	0	Optional	**	Geochemical cycle input
Annual non-symbiotic N-fixation	(kg ha ⁻¹)	N	0	Optional	**	Geochemical cycle input
Proportion of each nutrient in anionic form	(Proportion)	N	N/A	Optional	*	Effects leaching
CEC of mineral soil (for each nutrient)	(kg ha ⁻¹)	N	N/A	Optional	***	Controls storage of available nutrients in soil
CEC per ton of humus (for each nutrient)	(kg)	N	0.1	Optional	*	See above
AEC of mineral (for each nutrient)	(kg ha ⁻¹)	N	N/A	Optional	**	See above
AEC per tone of humus (for each nutrient)	(kg)	N	0.1	Optional	*	See above

APPENDIX B: Published Research

Appendix D (Continued)

Data type	Units ()	Data from chronosequence re- quired	Default value	Data required for sim- plified application	Relative sensitivity of model to data ^a	General function in FORECAST
Concentration of nutri- ents in each humus type	(%)	N	N/A	Required	****	Controls mineralization and immobilization rates
Decomposition rate for each Humus type	(% year ⁻¹)	N	N/A	Required	***	Humus accumulation and see above
Concentration of nutri- ents in ashed material	(%)	N	N/A	Optional	**	Nutrient release following burn
Ash produced per kg of burned material	(kg)	N	0.015	Optional	**	Nutrient release following burn
Mass loss rate over time for each litter type	(proportion)	Y	N/A	Required	****	Controls mineralization and immobilization rates
Total time to become humus for each litter type	(year)	N	N/A	Required	**	See above
Delay in conversion of total fresh tree heart- wood to decomposing matter (enter values for log from trees in an age series)	(years)	Y	N/A	Optional	**	Log persistence
Measured N-fixation rates in specific litter types	(nmol C ₂ H ₄ g litter mass ⁻¹ day ⁻¹)	Y	0	Optional	**	N-fixation associated with coarse woody debris

A simulation of the effect of site quality change on any variables related to these data requires input data from two or more sites varying in nutritional quality.

^a * = Low sensitivity, **** = high sensitivity.



APPENDIX C: Application of a hybrid forest growth model to evaluate climate change impacts on productivity, nutrient cycling and mortality in a montane forest ecosystem

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ABSTRACT

Climate change introduces considerable uncertainty in forest management planning and outcomes, potentially undermining efforts at achieving sustainable practices. Here, we describe the development and application of the FORECAST Climate model. Constructed using a hybrid simulation approach, the model includes an explicit representation of the effect of temperature and moisture availability on tree growth and survival, litter decomposition, and nutrient cycling. The model also includes a representation of the impact of increasing atmospheric CO₂ on water use efficiency, but no direct CO₂ fertilization effect. FORECAST Climate was evaluated for its ability to reproduce the effects of historical climate on Douglas-fir and lodgepole pine growth in a montane forest in southern British Columbia, Canada, as measured using tree ring analysis. The model was subsequently used to project the long-term impacts of alternative future climate change scenarios on forest productivity in young and established stands. There was a close association between predicted sapwood production and measured tree ring chronologies, providing confidence that model is able to predict the relative impact of annual climate variability on tree productivity. Simulations of future climate change suggest a modest increase in productivity in young stands of both species related to an increase in growing season length. In contrast, results showed a negative impact on stemwood biomass production (particularly in the case of lodgepole pine) for established stands due to increased moisture stress mortality.

INTRODUCTION

Worldwide, forest health and productivity are being affected by anthropogenic climate change. The frequency and intensity of catastrophic natural disturbance agents, for example, are rising [1-4]. Moreover, evidence suggests that unusually severe drought events have triggered a significant rise in mortality rates in forested regions throughout the world [5, 6]. Climate change is expected to influence long-term forest productivity through its effect on moisture availability [7, 8], temperature-limited net photosynthetic rates [9, 10] and nutrient cycling [11]. After litter quality, temperature and soil moisture are the key determinants of heterotrophic respiration and nutrient mineralization rates in temperate forests [12, 13].

APPENDIX C: Published Research

Efforts at modeling the impact of climate on forests can be divided into three broad categories: dynamic global vegetation models (DGVMs), statistical models derived from climate envelope analysis, and stand-level, process-based models. The overall objective of DGVMs is to evaluate the influence of climate on the biogeochemical and hydrological processes regulating vegetation growth dynamics [14]. Although they can be detailed with respect to process simulation, these models are designed to predict general patterns of vegetation development over large spatial and temporal scales [15] and have limited application for evaluating alternative forest adaptation strategies (see, for example, [16]). In general, DGVMs may be best suited to evaluating the impact of changing climate regimes on regional patterns of forest productivity and hydrology.

Models based on the climate envelope approach rely on detailed statistical analyses of historical climate data collected from a species' observed range. Deviations from climate normals are calculated for future climate scenarios and then used to project changes in growth rates, mortality, and species distributions. Examples include a modified version of the Forest Vegetation Simulator (FVS) model [17], and adjustments to site index based on anticipated changes in growing-degree days [18]. The strength of this approach is that it provides a method for predicting climate change impacts with relatively small calibration data requirements. Challenges with the approach include, 1) limited insight with respect to the underlying mechanisms of response, 2) an assumption that current species distributions are dictated exclusively by climate, and 3) the issue that if the range of variation in future climate exceeds the historical climate regime then applications of the model are beyond the scope of its statistical foundations.

The third category of model is the stand-level, process-based models. These models employ physiological and physical principles in conjunction with simulated edaphic conditions to project forest development and productivity under a changing climate. They vary widely in their complexity and application, from comprehensive, research-oriented ecosystem models (e.g. Ecosys; [19]) to less complex, management-oriented models such as CABALA [20] to relatively simplified models designed for broad application such as 3PG [21]. The more complex models can be difficult to calibrate because they usually comprise many site and species-specific parameters. This can necessitate expensive, multi-year field research programs to support their application (e.g. [20]). Highly simplified process models usually have lower calibration requirements but they often cannot adequately address the complexity of forest management in the face of climate change. A compromise approach is embodied in 'hybrid' process-based models, in which empirical data inputted to the model are used to 'self-calibrate' at least some of the algorithm parameters associated with ecosystem processes (see [22]). This makes it possible to retain adequate model complexity while minimizing the calibration load [23].

Climate change introduces considerable uncertainty into forest management planning and outcomes, potentially undermining efforts at achieving sustainable practices [24, 25]. There is a need for models capable of projecting the potential impact of climate change on long-term patterns of forest growth and development while being reasonably accessible to forest managers. Ideally, such models should: 1) be capable of representing the effects of climate change on forest productivity and drought-related mortality, 2) include the ability to simulate a variety of forest management options to allow for an evaluation of adaptive management strategies, 3) provide broad outputs relevant to multi-objective forest management, and 4) be relatively straightforward to calibrate.

APPENDIX C: Published Research

Here we describe the development and application of the hybrid simulation model FORECAST Climate. The model is evaluated with respect to its ability to reproduce the effects of historic annual climate variability on the annual variation of Douglas-fir and lodgepole pine growth in a montane forest located in southern British Columbia, Canada as measured using tree ring analysis. Simulations of the long-term impacts of alternative future climate change scenarios on forest productivity in young and established stands were conducted with the verified model.

METHODS

2.1 Model Description

FORECAST Climate was developed as an extension of FORECAST [26] which is a stand-level, management-oriented forest growth simulator. FORECAST was designed to accommodate a wide variety of harvesting and silvicultural systems in order to compare and contrast their effect upon forest productivity, stand dynamics and a series of biophysical indicators of non-timber stand values. The model has been used in a wide variety of applications and has been evaluated against field data for growth, yield, ecophysiological and soil variables [27-30].

FORECAST is a 'hybrid' model and many of its parameters are calibrated using historical bioassay data inputted to the model. As with any model of this type, a fundamental assumption with respect to its successful calibration and application is that the past climate regime constitutes a faithful representation of future climate conditions. The validity of this assumption is now questionable given anticipated trends in greenhouse gas emissions and their associated impacts on future temperature and precipitation patterns [31]. The FORECAST model simulates the effect of light and nutrient availability on forest productivity but it has no explicit representation of moisture or temperature on ecosystem processes. Thus, the rationale in developing FORECAST Climate was to incorporate these two factors. The foundation for FORECAST Climate was established through the creation of a dynamic linkage with a forest hydrology model including direct feedback to the core processes driving forest ecosystem production.

2.1.1 The basic FORECAST model

In FORECAST, the rates of key ecosystem processes are combined with data describing rates of decomposition, nutrient cycling, light competition, and other ecosystem properties to simulate annual changes in forest growth (Figure C.1). Plant populations can be initiated from seed and/or vegetatively, and stand development can occur with or without competition from non-target tree species and understory populations. Decomposition and dead organic matter dynamics are simulated using a method in which specific biomass components (eg. foliage, fine roots, branches, etc.) are transferred at the time of tissue death to one of a series of independent litter types. Residual litter mass and its associated nutrient content are transferred to active and passive humus pools when the mass remaining is within 15 - 20% of the original litter mass. Typically, mean residence times for active and passive humus types are 50 and 600 years, respectively. See [26] for further details.

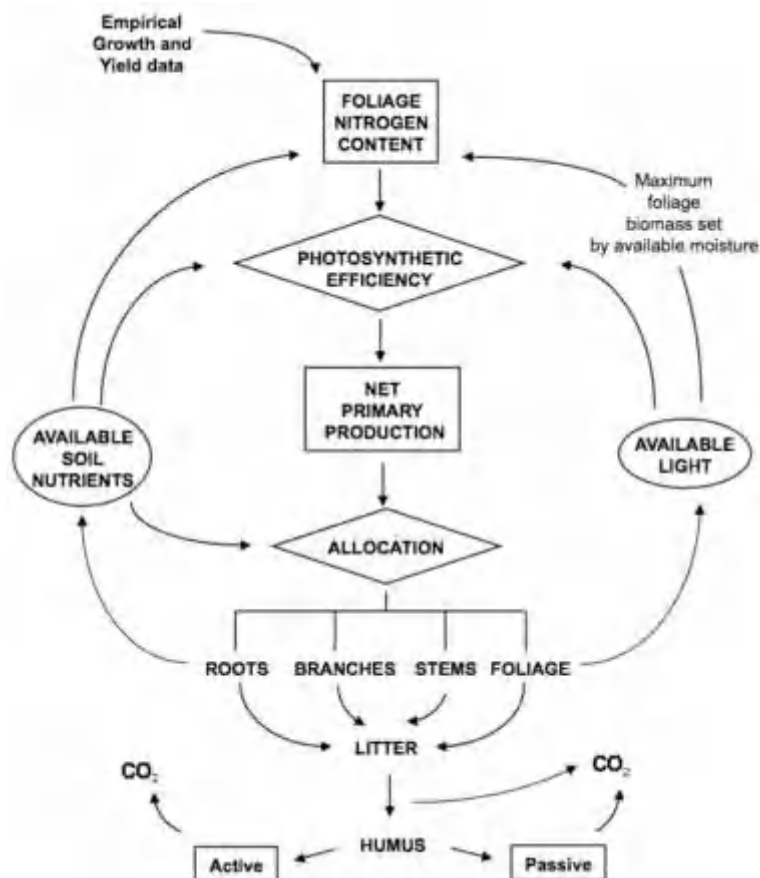


Figure C.1 Schematic illustration of the key ecosystem processes and flows represented in FORECAST (after [30]).

2.1.2 The ForWaDy Model

The Forest Water Dynamics (ForWaDy; [32]) model simulates the hydrologic dynamics of a forest stand on a daily time step for a given set of climatic and vegetation conditions. The model was specifically designed with a structure to facilitate its linkage to FORECAST [32]. It has been shown to perform well for predicting the effect of forest management on evapotranspiration [33] and temporal patterns in soil moisture content under field conditions [33, 34]. The model represents potential evapotranspiration (PET) using an energy balance approach based on a modified version of the Priestly-Taylor equation [35]. This equation is effective in predicting evapotranspiration under a wide variety of forest types and conditions [36-39]. Net shortwave solar radiation interception is used to drive the PET calculations. It is calculated for each tree and plant species from a light competition submodel built into FORECAST (see [26]) and surface albedo. ForWaDy includes a representation of the vertical flow of water through canopy and soil layer compartments (Figure C.2). Movement of water through each soil layer is regulated by its physical properties that dictate moisture holding capacity, permanent wilting point moisture content, and infiltration rate.

Water stress is calculated for each species separately on a daily time step and is expressed as a transpiration deficit index (TDI). The TDI is the relative difference between potential energy-limited transpiration demand and actual transpiration:

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$$TDI_{i,d} = (CanT_{Demand,i,d} - CanT_{Actual,i,d}) / CanT_{Demand,i,d} \quad (1)$$

where:

$CanT_{Demand,i,d}$ = energy-driven transpiration demand for species i (mm) on day d , as a function of leaf area index, intercepted short-wave radiation, canopy albedo, and canopy resistance,

$CanT_{Actual,i,d}$ = actual tree transpiration for species i (mm) on day d , as a function of $CanT_{Demand,i,d}$, root occupancy, and available soil moisture.

A detailed description of the ForWaDy model is provided in the Supplementary Material S1 (at the end of this paper). Its general data requirements are listed in Table C.1.

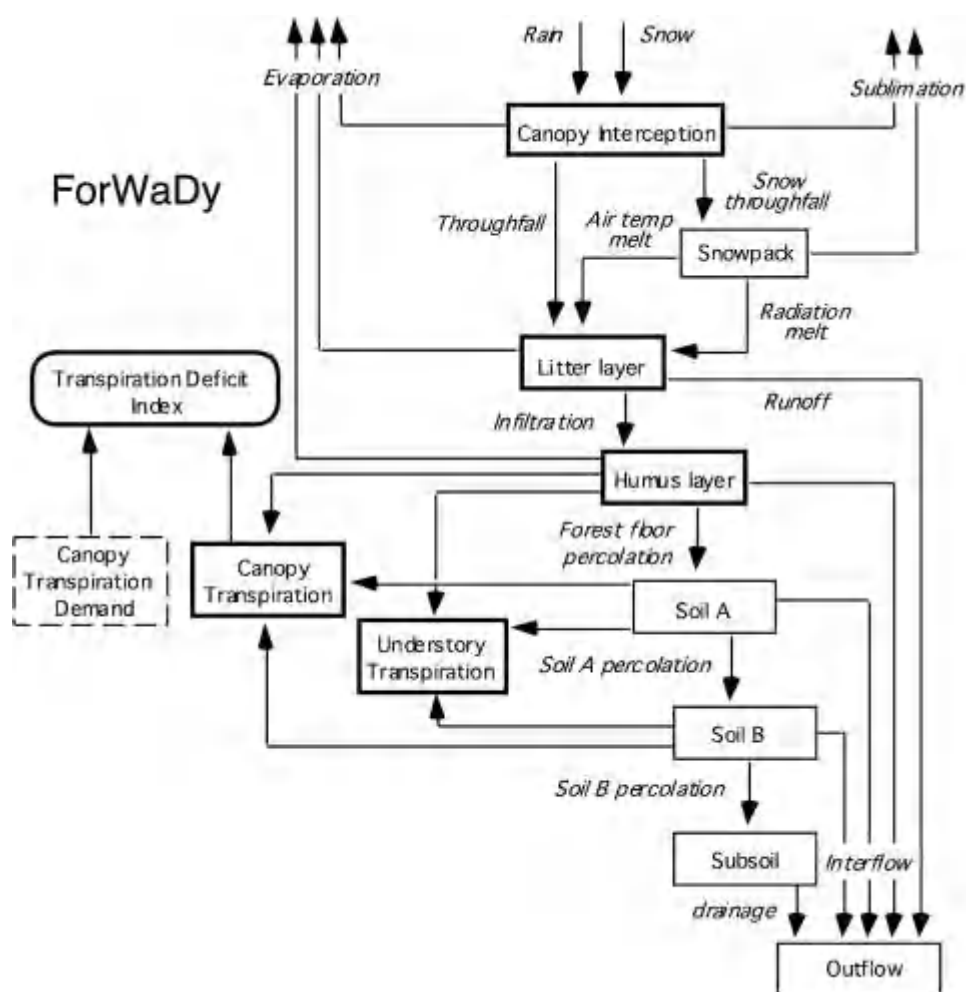


Figure C.2 Schematic diagram of the ForWaDy model indicating water flow pathways and storage compartments.

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Table C.1 General data requirements for the ForWaDy model.

Climate data (daily)	Vegetation data	Forest floor & soil data
mean, max and min air temperature (°C)	seasonal conifer and hardwood LAI	fine litter mass (kg/ha)
solar radiation ¹ (MJ/m ²)	seasonal understory % cover	humus layer depth (cm) and bulk density (g/cm ³)
total precipitation (mm)	rooting depths for trees (cm)	depth of mineral soil layers (cm)
snow fraction	rooting depths for understory (cm)	soil texture ³ (by layer)
atmospheric [CO ₂] ²	canopy resistance and albedo (by species)	coarse fragment content (% by layer)

¹ Solar radiation may be estimated from max and min air temperature, elevation, latitude, slope and aspect using published radiation models.

² Only annual data required.

³ Standard texture classes used to estimate clay content.

2.1.3 Simulating the effect of increasing CO₂ on forest growth

Higher atmospheric CO₂ concentrations (c_a) are associated with lower stomatal water vapour conductance [40, 41] and greater water use efficiency [42, 43]. These processes are represented in ForWaDy using a function that modifies canopy resistance in each species in relation to projected changes in c_a [44]. The functional curve is derived from the physiological relationship between relative net assimilation rate and changes in c_a relative to a reference atmospheric CO₂ concentration (Eq. 2A). The impact of c_a on stomatal conductance is given in Equation 2B [44], and stomatal conductance in relation to canopy resistance in Equation 3 (see Figure C.3B, for an example).

$$A_{n(\text{rel})} = [(c_a - r') * (c_{a0} + 2r')] / [(c_a + 2r') * (c_{a0} - r')] \quad (2A)$$

where:

$A_{n(\text{rel})}$ = relative net assimilation rate

c_a = current atmospheric CO₂ concentration (ppm)

c_{a0} = reference atmospheric CO₂ concentration (determined from reference climate data, ppm)

r' = CO₂ compensation point = 40 ppm

and the relative stomatal conductance for water vapour ($g_{w(\text{rel})}$; dimensionless) is

$$g_{w(\text{rel})} = A_{n(\text{rel})} / c_{a(\text{rel})} \quad (2B)$$

where:

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$c_{a(\text{rel})}$ = relative atmospheric CO₂ conc = c_a/c_{a0} (dimensionless)

Adjusted canopy resistance ($R_{\text{Can,adj}}$; dimensionless) is

$$R_{\text{Can,adj}} = R_{\text{Can,ref}} + R_{\text{Can,ref}} \cdot (1 - g_{w(\text{rel})}) \quad (3)$$

where:

$R_{\text{Can,ref}}$ = reference canopy resistance (dimensionless)

Many models incorporate a representation of the direct effect of CO₂ fertilization on tree growth [45] based on evidence from short-term studies [46, 47]. There is little evidence, however, supporting the long-term impacts of CO₂ fertilization on forest growth [48, 49]. As such, the FORECAST Climate model does not presently include this as a control on growth.

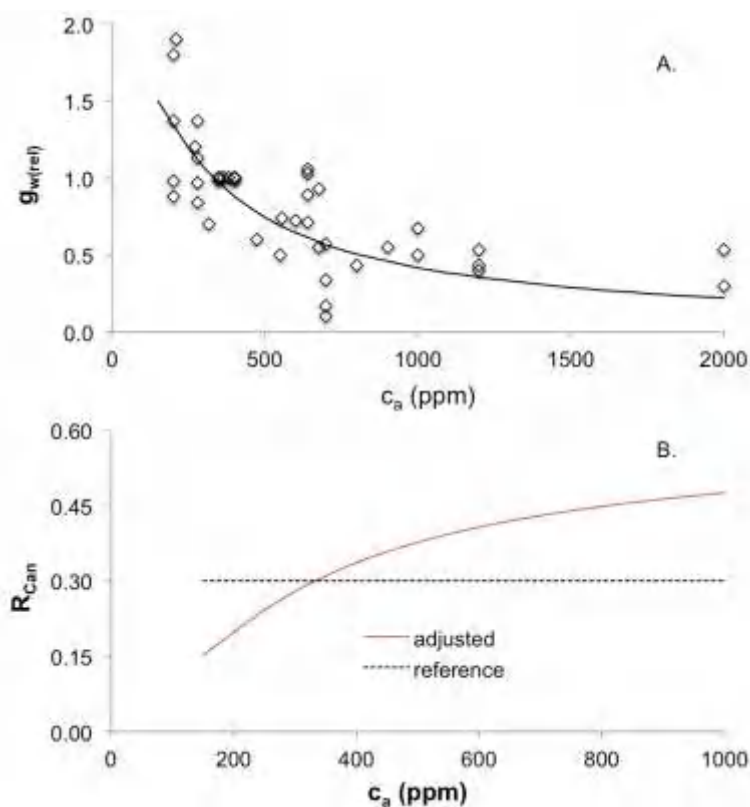


Figure C.3 Relationships between atmospheric CO₂ concentration (c_a) and (A) relative stomatal conductance and (B) canopy resistance. (A) Observations of relative stomatal conductance of water vapour ($g_{w(\text{rel})}$) under changing atmospheric CO₂ concentrations (c_a ; data from [44] re-plotted). The solid line is derived from Eq. 2B where $c_{a(\text{rel})} = c_a/c_{a0}$, c_{a0} is 360 ppm, and $A_{n(\text{rel})}$ is obtained from Eq. 2A. (B) An example of the calculation of adjusted canopy resistance ($R_{\text{Can,adj}}$) as a function of c_a , using a reference canopy resistance ($R_{\text{Can,ref}}$) value of 0.3.

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2.1.4 Linkage of FORECAST and ForWaDy

The ForWaDy - FORECAST linkage couples forest water availability directly with ecosystem process simulation. Furthermore, this linkage is dynamic in that the respective functions from each model are continuously updated in response to the iterative sharing of information encoded within a series of feedback loops (see Figure C.4). One aspect of this linkage is reconciling FORECAST's annual time step with the daily time step used in ForWaDy, the latter of which is required to properly capture short-term moisture limitations. This was accomplished by aggregating the daily ForWaDy output into an annual index that was then used as input to FORECAST (Figure C.4). FORECAST, in turn, supplies input to ForWaDy at the beginning of each growing season with respect to vegetation and forest floor conditions (Figure C.4).

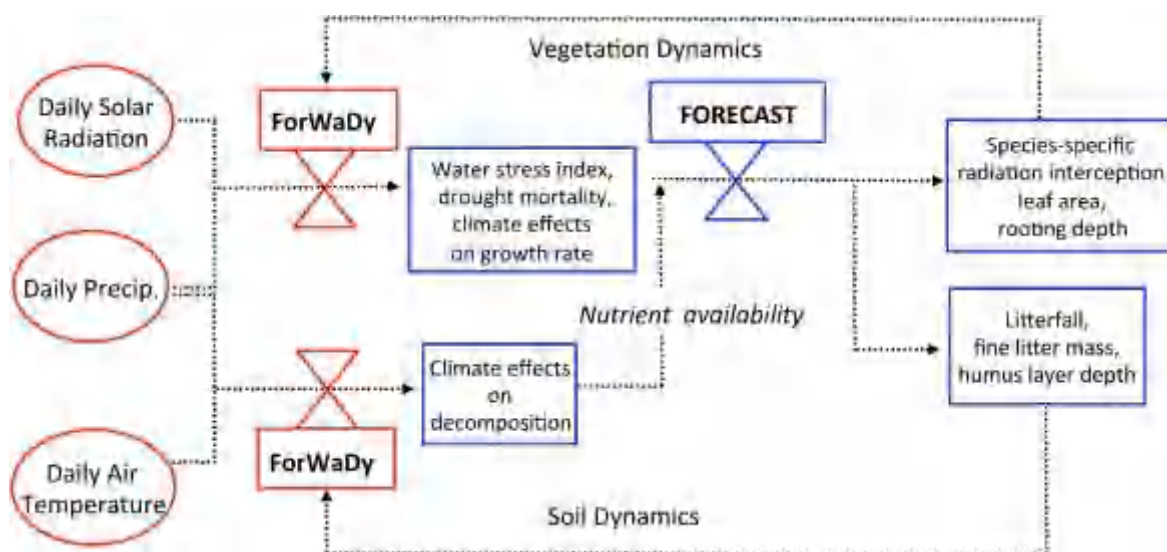


Figure C.4 A schematic diagram illustrating feedback loops and data transfer pathways between FORECAST and ForWaDy.

2.1.5 Accounting for climate impacts on productivity

The impact of climate on tree and plant growth in FORECAST Climate is focused primarily on the relationships between growth rate, temperature and water stress. These relationships are represented using species-specific, curvilinear response functions simulated on a daily time step. The net daily growth response index of species i on day d ($GRI_{Day,i,d}$) is derived as the product of two indices, calculated as temperature and water stress response functions:

$$GRI_{Day,i,d} = T_{Growth,i,d} * S_{Growth,i,d} \quad (4)$$

where:

$T_{Growth,i,d}$ = The temperature response index (range 0-1; dimensionless) for species i on day d . Specified in the model as a user-defined graphical function of daily mean air temperature (see Section 2.2.3).

$S_{Growth,i,d}$ = The water stress response index (range 0-1; dimensionless) for species i on day d . Specified in the model as a user-defined graphical function of the daily mean water stress index (see Section 2.2.3).

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The temperature response index is designed to encapsulate the complex physiological growth processes governing tree and understory response to variations in mean daily temperature. It is intended to represent net effect of variations in temperature on primary productivity (NPP) by accounting for the impact of temperature on both photosynthesis and respiration. Data for calibrating the index can be derived from greenhouse studies and/or in situ measurements of seasonal primary productivity (eddy covariance, for example; see [50]).

The water stress response index is calculated from TDI (see Section 2.1.2). The daily TDI value represents the degree to which a species was able to meet its energy-driven transpiration demands (a higher TDI value indicates greater moisture stress). Plants typically respond to water stress by closing stomata to conserve water, leading to an associated reduction in photosynthetic production (see [51]). A negative relationship between S_{Growth} and TDI is therefore expected.

The net daily growth response index is summed to calculate an annual growth response index for year, y ($GRI_{\text{Year}, i, y}$; Eq. 5).

$$GRI_{\text{Year}, i, y} = \sum_{d=1}^{365} GRI_{\text{Day}, i, d} \quad (5)$$

This index is used as a weighting factor that reflects the ‘quality’ of a given climate year relative to an expected growth rate (further details below).

The climate response functions within FORECAST Climate are calibrated using historical daily climate data. A ‘reference’ daily climate series must be compiled with data derived from a climate station near the forest area to be modeled, and should span a minimum 20-year time period. A summary of the climate data required is provided in Table C.1.

Using the reference data set, a calibration run is conducted from which the annual growth response index is calculated (Eq. 5). By averaging the annual values for the length of the reference climate period, a normalized growth response index is derived for each species (Eq. 6) that reflects growth conditions in an average historical climate year. This index is used in subsequent calculations.

$$NGRI_i = \left(\sum_{y=1}^n GRI_{\text{Year}, i, y} \right) / n \quad (6)$$

where:

$NGRI_i$ is the normalized growth rate index for species i derived from the reference climate data set (dimensionless)

$GRI_{\text{Year}, i, y}$ is the annual growth response index for species i (Eq. 5).

n = the number of years in the historical climate data set

Simulation of growth response to climate in FORECAST Climate is achieved by modifying base growth rates (as determined in the underlying FORECAST model – section 2.1.1) according to the climate relationships described in section 2.1.4. A climate-limited growth rate is calculated by multiplying the base growth rate (Eq. 7A) by a climate response factor (Eq. 7B).

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$$CGR_{i,y} = BGR_{i,y} * CRF_{i,y} \quad (7A)$$

$$CRF_{i,y} = (GRI_{year,i,y} - NGRI_i) / NGRI_i \quad (7B)$$

where:

$CGR_{i,y}$ is the climate-limited growth rate for species i in year y (tons ha⁻¹),

$BGR_{i,y}$ = the base growth rate for species i and year y determined in FORECAST as the light and nutrient-limited growth rate (tons ha⁻¹),

$CRF_{i,y}$ is the climate response factor for species i in year y (dimensionless), and $GRI_{year,i,y}$ and $NGRI_i$ are as defined in Equations 5 and 6, respectively.

2.1.6 Climate and decomposition rates

The decomposition of dead organic matter in FORECAST is represented based upon user-defined mass loss rates associated with litter quality and derived from field incubation experiments. A maximum of 40 dead organic matter types may be defined and simulated within the model [26]. In FORECAST Climate, decomposition rates are modified by soil moisture content and air temperature with the calculation of a daily decomposition response index (Eq. 8). The model does not include any representation of the potential effects of mixing different litter types on mass loss rates.

$$DRI_{Day,l,d} = T_{Decomp,d} * M_{Decomp,l,d} \quad (8)$$

where:

$DRI_{Day,l,d}$ = daily decomposition response index (range 0-1; dimensionless) for soil layer l on day d

$T_{Decomp,d}$ = Temperature decomposition response (range 0-1; dimensionless). Specified in the model as a user-defined graphical function of daily mean air temperature (see Figure C.5A).

$M_{Decomp,l,d}$ = Moisture decomposition response (range 0-1; dimensionless). Specified in the model as a user-defined graphical function of daily moisture content (see Figure C.5B).

Assuming moisture is not a limiting factor, the decomposition rate of dead organic matter is generally faster in warmer environments [52, 53]. The default temperature response function is shown in Figure C.5A, and is based upon a Q₁₀ factor of 2 [52, 54]. The moisture response functions for litter, humus, and soil, are shown in Figure C.5B.

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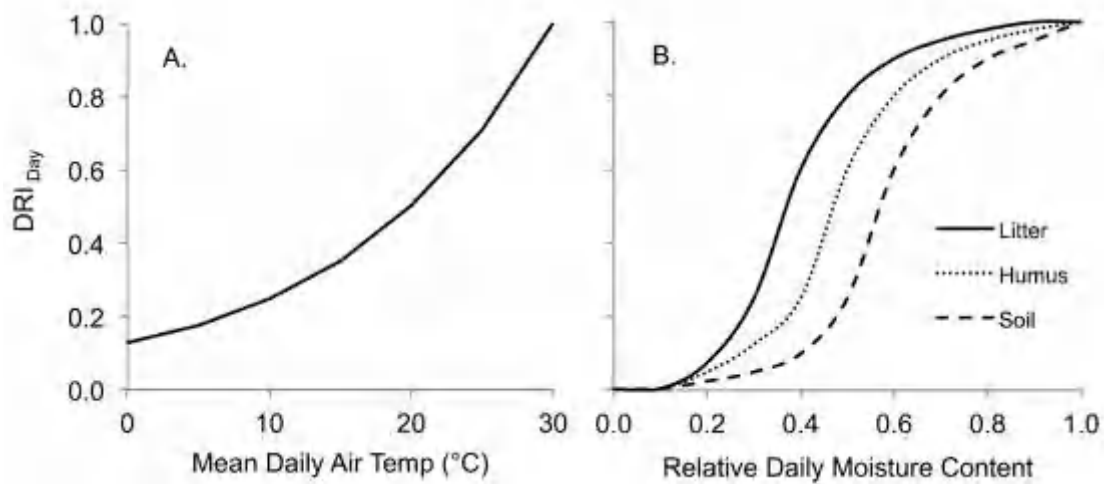


Figure C.5 Daily decomposition index in relation to (A) daily air temperature, and (B) relative daily moisture content. (A) The relationship with mean daily air temperature is based upon a Q_{10} function where $Q_{10} = 2$. (B) Moisture content relationships are shown for litter, humus, and mineral soil (see text for details).

The climate impact on decomposition rates is represented using the same procedure as the growth response index calculation (Section 2.1.5). First, a normalized decomposition response index (NDRI_{*l*}) is calculated for each soil layer *l* using the reference climate series:

$$NDRI_{l,i} = \left(\sum_{y=1}^n DRI_{Year,l,y} \right) / n \quad (9)$$

where:

NDRI_{*l*} is the normalized decomposition response index for layer *l* derived from the climate calibration data (dimensionless)

DRI_{Year,*l*,*y*} is the annual decomposition response index for each soil layer *l*

n = the number of years in the reference climate data set

A climate decomposition factor (CDF_{*x,y*}; Eq. 10A) is then calculated as the relative difference between the current and normalized decomposition response indices (Eq. 9). Climate feedback is represented by a climate decomposition rate index (CDR_{*l,y*}) for each soil layer *l* and year *y* (Eq. 10B).

$$CDF_{x,y} = (DRI_{Year,l,y} - NDRI_{l,i}) / NDRI_{l,i} \quad (10A)$$

$$CDR_{x,y} = BDR_{x,y} * CDF_{x,y} \quad (10B)$$

where:

CDF_{*x,y*} is the climate decomposition factor for litter type *x* in year *y* (dimensionless)

DRI_{Year,*l*,*y*} and NDRI_{*l*} are as defined above (Eq. 9),

CDR_{*x,y*} is the expected climate decomposition rate for litter type *x* and year *y* (tons ha⁻¹)

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$BDR_{x,y}$ is the base decomposition rate for litter type x in year y determined as a function of litter quality (tons ha^{-1})

2.1.7 Representation of drought-related mortality

Extended periods of drought can lead to plant mortality, either directly or by increasing vulnerability to biotic disturbance agents [5, 55]. FORECAST Climate includes a drought mortality function in which a two-year running-average TDI is used to predict annual mortality. The two-year running average reflects the negative impact of consecutive years of drought (see, for example, [56]). The drought mortality relationship is specified in the model as a user-defined graphical function of species-specific, two-year running average TDI (see Section 2.2.3).

2.2 Evaluating model performance using tree-ring analysis

FORECAST Climate was calibrated for a montane forest in south central British Columbia. The model was used to predict annual sapwood production (a proxy measure of tree ring growth), which was then compared against measured 30-year ring chronologies.

2.2.1 Study area

The study area was located in south central British Columbia, Canada near the city of Kamloops ($50^{\circ}40'00''$ N, $120^{\circ}20'00''$ W), and is classified as a dry cool subzone of the Interior Douglas-fir biogeoclimatic zone [57]. The site, located in crown-owned forest land, is dominated by stands of interior Douglas-fir (*Pseudotsuga menziesii* var. *glauca*) and lodgepole pine (*Pinus contorta*). These species are common in montane regions in the southern interior of British Columbia, ranging from 900 to 1400m in elevation. The closest local climate station with a complete climate record (Red Lake: Elevation = 1162m, $50^{\circ}56'06''$ N, $120^{\circ}48'00''$ W) was selected from which 30 years of daily data (spanning the years 1975-2004) were obtained. Average monthly temperature and precipitation for Red Lake are shown in Figure C.6.

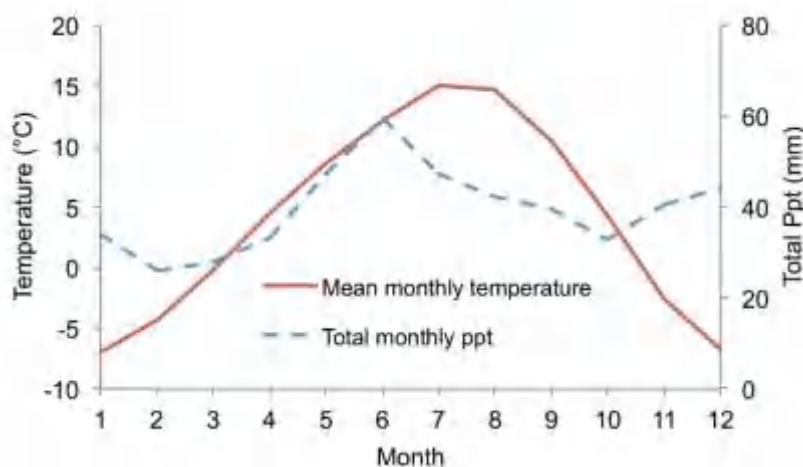


Figure C.6 Average monthly temperature and precipitation from the Red Lake climate station (1975-2004).

2.2.2 Tree-ring analysis

A total of 5 plots were randomly selected from a series of candidate stands identified using forest inventory data from the study site. Plots were split with 3 Douglas-fir and 2 lodgepole pine-dominated stands. Stands

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with clear signs of fire scars or damage from biotic agents that could have masked a climate signal were avoided. Plot centers were established using a variable radius to define plot area such that a total of 20 dominant and/or co-dominant trees were identified within the plot area. Species, elevation, slope, aspect, and slope position were recorded for each plot. The stands ranged in age from 36 to 150 years (Table C.2).

Within each plot, a total of 20 dominant or co-dominant trees were cut down and a slice (cookie) approximately 4 cm thick removed from the base of each stem, within 20 cm of the soil surface. The cookies were prepared for analysis in the Tree-Ring Laboratory at the University of Northern British Columbia, using standard procedures [58]. Annual tree ring width was measured to the nearest 0.01mm using a Windendro system. The ARSTAN software [59] was used to prepare and cross-date the final chronologies. All series were de-trended by fitting a spline of 50% frequency response across 67% of the series length to remove the low frequency age trend. Slight modifications were made to spline stiffness for two of the series to improve their fit to the data. De-trended data were used to isolate the impacts of year-to-year climate variability on relative tree productivity. Chronologies for each plot were constructed using the final ARSTAN tree ring index. Each chronology was restricted to the 1975-2004 period and normalized by dividing by the average ring index. Typically, tree rings are compared against two consecutive years of climate data (current and previous year) [23, 60]. This is because early season wood growth is partly a function of climate suitability in the previous year and its impact on carbohydrate reserves [61].

Table C.2 Characteristics of sample plot locations from which trees were harvested for tree-ring analysis and choronology statistics.

Plot ID	Species	Average Age (y)	Elevation (m)	Slope (%)	Aspect (deg.)	Slope Position	Mean sensitivity	Serial correlation
4	Fd	54	1250	25	295	mid	0.288	0.836
9	Fd	67	978	20	50	mid	0.275	0.812
14	Fd	36	1125	18	64	mid	0.244	0.812
34	Pl	60	1300	8	26	low	0.124	0.946
71	Pl	150	1356	2	322	flat	0.159	0.846

A total of 20 trees per plot were sampled. Fd = Douglas fir, Pl = lodgepole pine

2.2.3 FORECAST Climate calibration

Detailed descriptions of FORECAST calibration data requirements are provided in [26] and [62]. The base FORECAST model was calibrated with an existing data set from the Interior Douglas-fir dry cool subzone [63]. The data set includes both Douglas-fir and lodgepole pine, and two minor vegetation functional groups (grasses and shrubs) common to the area. Calibration of the climate response functions in FORECAST Climate is described in the following sections.

The hydrological submodel requires data describing characteristics of the soil profile (Table C.3) and characteristics of simulated trees and minor vegetation with respect to the calculation of daily

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evapotranspiration and water stress (Table C.4). Average soil characteristics were inferred from soil pits dug in each of the plots.

Table C.3 Parameter values in the hydrological submodel specific to the simulation of plant-available water within soil layers.

Soil layer	Soil Texture Class	Coarse Fragment Content (%)	Soil Depth ¹ (cm)	Field Capacity Moisture Content ²
Humus	N/A	0	12.5	0.32
Mineral A	Silt loam	25	40	0.25
Mineral B	Silt loam	25	45	0.25
Mineral C	Silt loam	25	50	0.25

¹ The starting humus depth is shown, but humus depth can change over time depending on rates production and decomposition.

² Volumetric water content above which drainage occurs.

Table C.4 Parameter values in the hydrological submodel specific to the simulation of evapotranspiration and water stress for trees and minor vegetation.

Species	Canopy Parameters		Permanent Wilting Point ³		Maximum Root Depth (cm)
	Albedo ¹	Resistance ²	Humus	Mineral Soil	
<i>Trees</i>					
Douglas-fir	0.12	0.3	0.08	0.12	100
Lodgepole pine	0.12	0.24	0.1	0.13	100
<i>Minor vegetation</i>					
<i>Calamagrostis grass</i>	0.12	0.15	0.09	0.11	75
<i>Vaccinium shrub</i>	0.12	0.10	0.10	0.11	75

¹ Estimated values.

² Reference relative canopy resistance to water loss through stomata ($R_{Can,i}$) [64]. Higher values indicate greater resistance.

³ Relative volumetric moisture content (proportion of total volume) at which soil water uptake is suspended [65, 66].

Calibration of climate response functions was completed as follows. Daily temperature and water-stress growth response curves were developed for Douglas-fir [67,68] and lodgepole pine [69, 70] based upon

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literature reviews of climate-growth relationships (Figure C.7A-B). The sharp increase in growth beginning around 5°C for both species is indicative of the heat sum required to break dormancy. Each curve varies with respect to the optimal temperature range for growth and the relative rate of decline beyond the optimum, depending on a plant's tolerance characteristics. The decline at higher temperatures represents the increase in respiration associated with elevated temperatures [50].

A relative drought mortality curve was developed for each tree species based on its ecological characteristics within the subzone (Figure C.7C). Douglas-fir was assumed to be slightly more tolerant of drought stress relative to lodgepole pine. Each species-specific mortality function was evaluated using provincial forest health survey data (not shown) to verify that it produced realistic mortality projections when the model was run with the historical reference climate data.

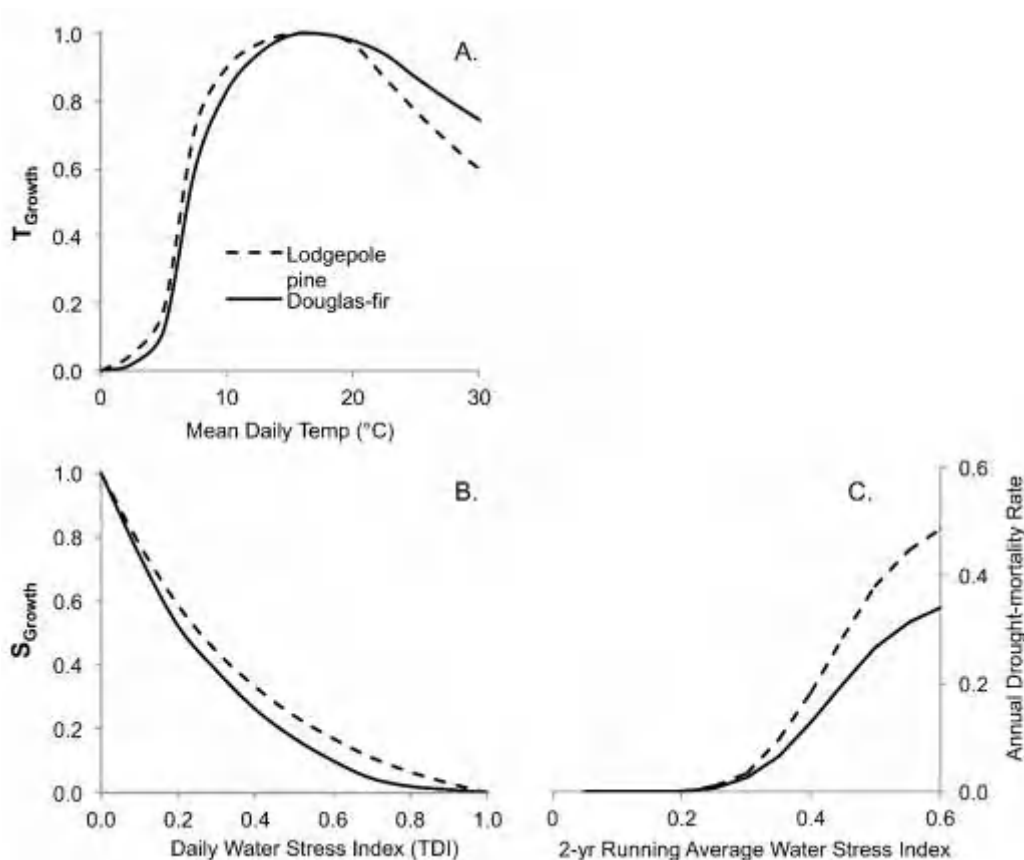


Figure C.7 Climate response functions showing the effect of temperature and water stress on growth (A,B) and mortality (C). (A) Relationships between mean daily temperature and the T_{growth} parameter, and (B) daily water stress and S_{growth} parameter used in Eq. 4. (C) The drought-related mortality rate as a function of the 2-year running average water stress index.

2.2.4 Growth simulation using historical climate data

To evaluate the capability of FORECAST Climate to reproduce the measured, climate-related annual variation in tree ring growth, the model was run using the historical climate data from the period of 1975 – 2004. The 30-year climate data set was cycled 5 times to generate 150 years of daily data. Model projections of annual

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sapwood production were subsequently compared against the normalized tree ring indices for the corresponding climate years using regression analysis. However, because annual ring growth is fueled both by carbohydrates stored from the previous year and the current year's production, each ring index was compared against a normalized average of the previous and current year's simulated sapwood production.

2.3 Simulation of long-term climate change impacts

2.3.1 Development of climate change scenarios

To illustrate the potential of FORECAST Climate to simulate the impacts of climate on the growth and development of forests within the study area, climate change projections were derived from two established general circulation models (GCMs) included as part of the Intergovernmental Panel on Climate Change AR5 analysis [31], HadGem2 (www.enes.org/models/earthsystem-models/metoffice-hadley-centre/hadgem2-es) and CanESM2 (www.cccma.ec.gc.ca/data/cgcm4/CanESM2/rcp45/index.shtml). A medium range emissions pathway was selected for the two models (Figure C.8A). It is based on a representative CO₂ concentration pathway that generates a radiative forcing of 4.5 Wm⁻² (RCP 4.5, [71]). These models and scenario were selected to be representative of the middle of the range of potential climate change scenarios. It should be noted that other scenarios could generate different results. Atmospheric CO₂ concentration for the reference climate scenario was constrained to 2005 values (380 ppm). The regional monthly output from the GCMs for the 2020s, 2050s and 2080s was downscaled to daily data using a direct approach based upon the Red Lake daily climate data series from the years 1975-2004. The resulting data set spanned a 100-year period (2012-2111). Projected changes in mean growing season temperature and precipitation are shown in Figure C.8B-C. Mean growing season temperature is predicted to increase from approximately 12.5°C in 2013 to 16-17°C by 2111. In contrast, both GCMs predicted only a very gradual declining trend in growing season precipitation during the same period. It should be noted that the interannual variability in temperature and precipitation characteristic of the base reference data is retained as a result of the direct downscaling process.

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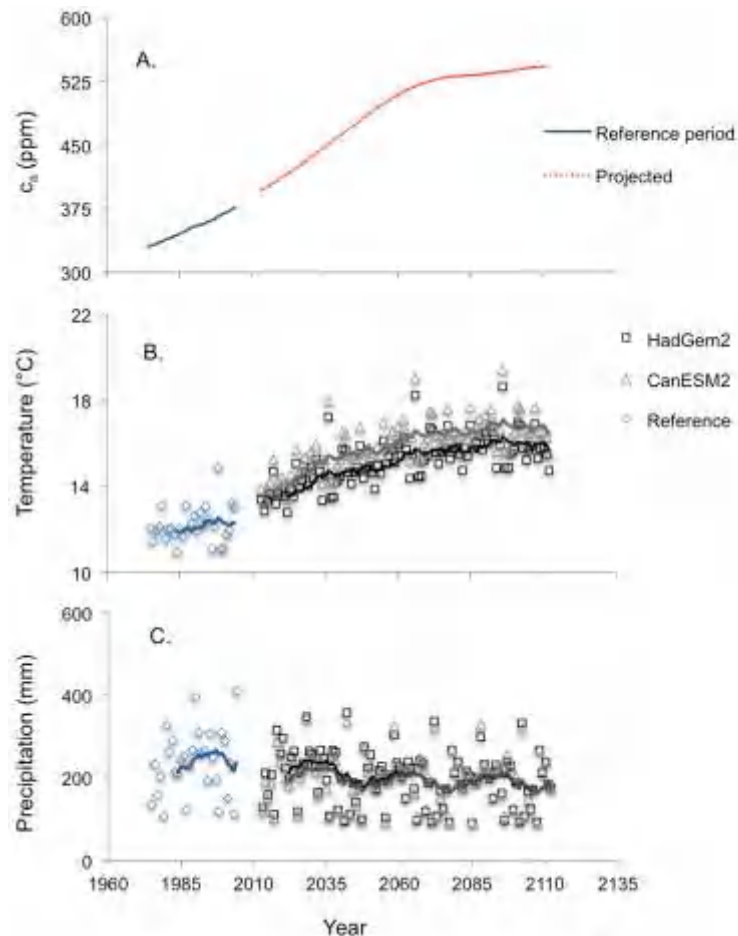


Figure C.8 Reference climate data and projected atmospheric [CO₂] (A), growing season temperature (B), and precipitation (C). (A) Projected increase in atmospheric [CO₂] (ca) for the RCP 4.5 emissions scenario, (B) projected growing season (MAY – SEP) mean daily air temperature, and (C) projected total growing season precipitation for the next 100 years based on two downscaled climate change projections (see text). Lines represent the 10-year moving average for each series in panels B and C.

2.3.2 Model application for climate change simulation

FORECAST Climate was used to simulate the long-term impact of climate change on stand growth and development for both Douglas-fir-dominated and lodgepole pine-dominated stand types. Growth in newly planted (age = 1 year) and established stands (starting age = 60 years) was simulated for a 100-year period. In the newly planted stands, the climate began to change immediately (see Figure C.8). For established stands, however, the 30-year historical climate data were copied and appended to create 60 years of data before the climate change period began at age 61. A total of eight runs were completed (2 climate scenarios * 2 species * 2 age classes).

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RESULTS

3.1 Model evaluation against tree ring data

Sapwood production predictions were concordant with 48% to 73% of the variation in measured annual ring widths in 4 of the 5 plots (Figure C.9). One Douglas-fir plot (Plot #9) showed no significant correlation with the other plots suggesting that annual variation in tree growth in this plots was likely a consequence of factors other than climate. This plot was therefore excluded from subsequent analysis. The average slopes of the regression lines were 1.04 and 1.05, for the remaining Douglas-fir (#4 & #14) and pine (#71 & #34) plots, respectively.

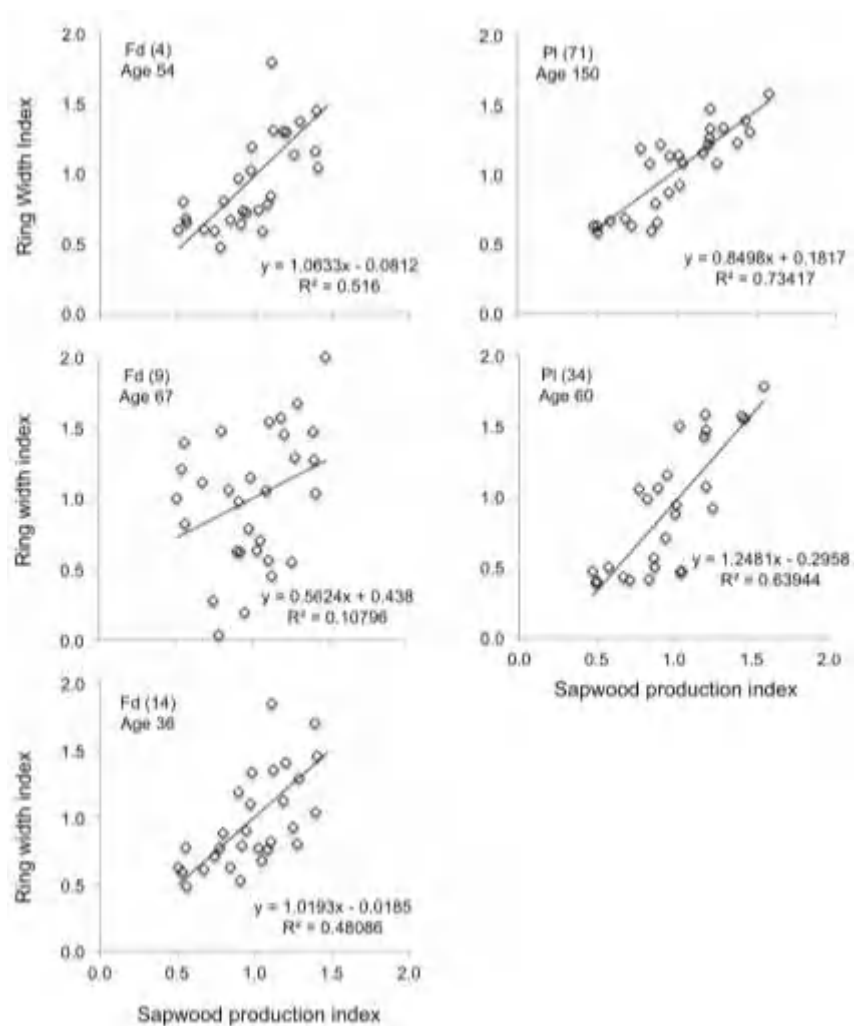


Figure C.9 Comparison of the simulated sapwood production index with the measured ring width index. Data are shown for Douglas-fir (Fd) and lodgepole pine (Pl) plots for the 30-year climate reference period. Average tree age is shown for each plot.

3.2 Climate change impacts on tree growth

Both climate change scenarios had a net positive impact on growth rates for newly planted stands, as indicated by the climate response factor (CRF, Eq. 7; Figure C.10A). Ten-year running averages show that the

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CRF values under the historical (reference) climate oscillate around zero, while those for the climate change scenarios are consistently higher. The impact of climate change on stemwood biomass was generally positive for both tree species, except in pine stands 85 years and older (Figure C.10B). In Douglas-fir, stemwood biomass was 11 to 17% higher at rotation age (80 years), and 4 to 7% higher in pine. Climate change triggered more drought-related mortality (Figure C.10C), which was associated with an increase in both the frequency and intensity of water stress (Figure C.11B-C). The increase in water stress in the climate change scenarios occurred despite an increase in canopy resistance associated with higher CO₂ concentrations (Figure C.11A).

In established (60 year-old) stands, the impact of climate change was projected to be positive in terms of the CRF (Figure C.12A). This was not the case for stemwood biomass, however. For Douglas-fir, there was little difference among the historical and climate change scenarios, though biomass under the latter was lower when stands were very old (Figure C.12B). In pine, however, climate change reduced stemwood biomass early in the simulation. This discrepancy became more pronounced over time. Lower stemwood biomass was associated with elevated drought-related mortality in both species but more so in pine (Figure C.12C).

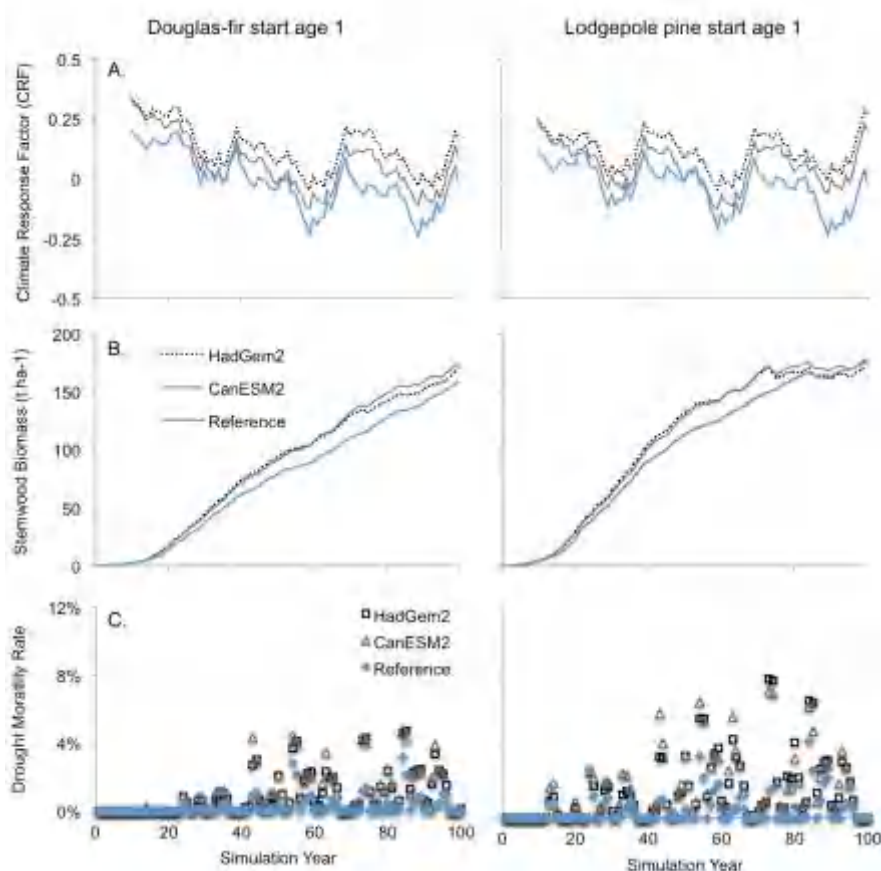


Figure C.10 Impact of climate change on: (A) growth response (CRF), (B) stemwood biomass, and (C) drought-related mortality. Simulations results for newly planted stands of Douglas-fir are shown on the left and for lodgepole pine on the right. Climate change simulation was initiated at year 1 of the simulation. Lines represent 10-year running averages of annual values. A CRF value near zero indicates that the simulated climate year was similar to the historical average year.

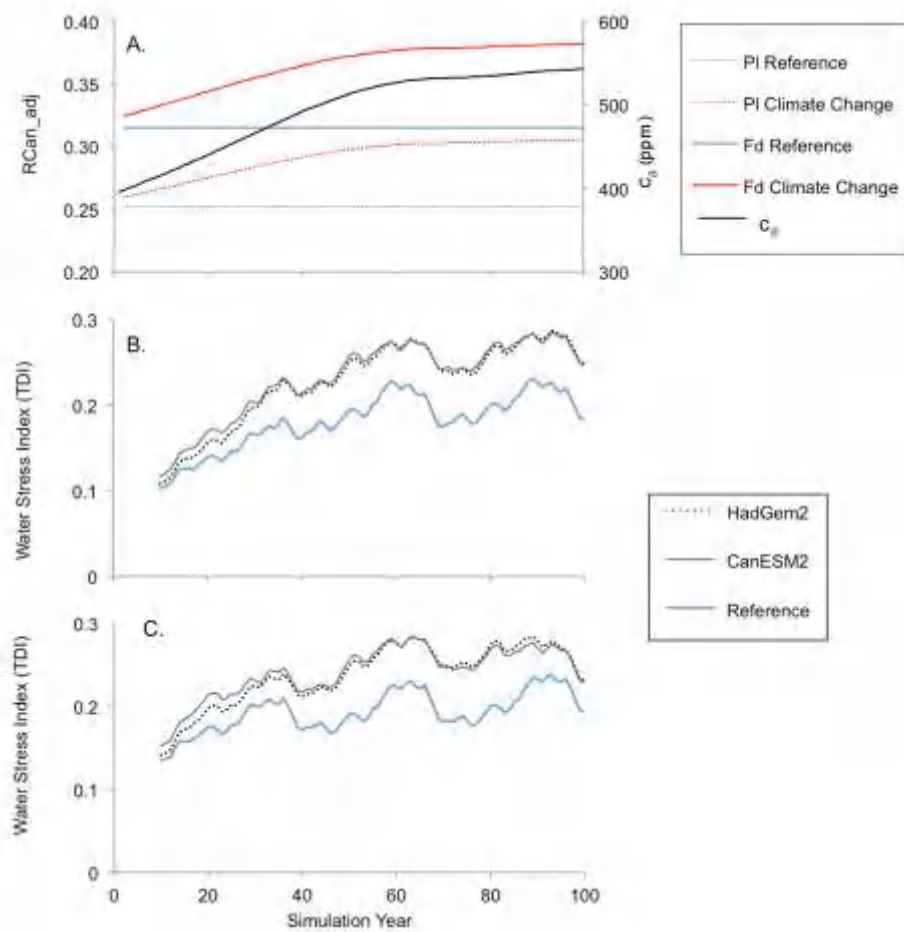


Figure C.11 Simulated effect of c_a on canopy resistance (A) and of climate change on tree water stress (B-C). (A) Projected atmospheric [CO₂] (c_a) for the climate change scenarios is based on the RCP 4.5 emissions scenario while reference scenario levels were constrained at 2005 values (380 ppm). The impact of c_a on canopy resistance ($R_{Can,adj}$) is shown for both species and for both climate scenarios (see Eq. 3). Lower panels show simulated water stress for newly planted stands of (B) Douglas-fir and (C) lodgepole pine. Water stress results represent the 10-year running averages of annual transpiration deficit index (TDI) values.

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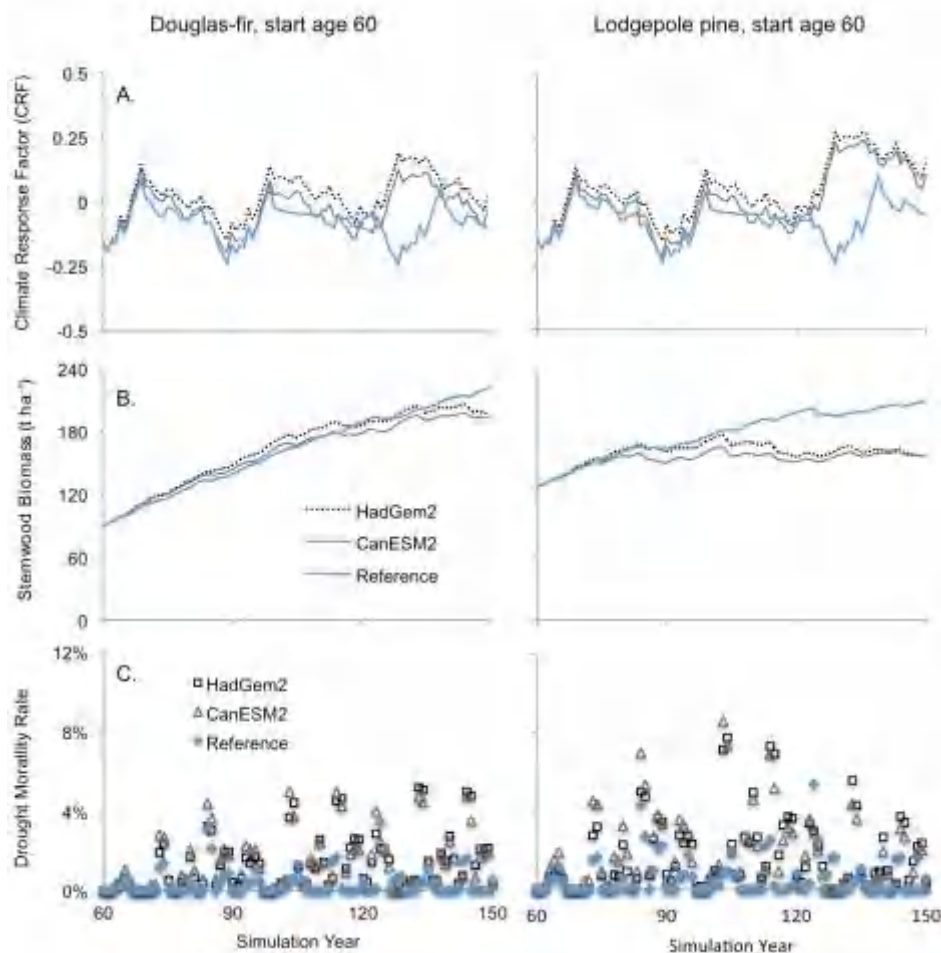


Figure C.12 The impact of climate change for on: (A) growth response (CRF), (B) stemwood biomass, and (C) drought-related mortality. Simulation results for established (60 years old) stands of Douglas-fir are shown on the left and for lodgepole pine on the right. Climate change simulation was initiated at year 60 of the simulation. Lines represent 10-year running averages of annual values. A CRF value near zero indicates that the simulated climate year was similar to the historical average year.

Projected impacts in newly planted stands of the reference climate and climate change (CanESM2) scenarios on the daily growth response index are shown for three future climate periods (Figure C.13). The daily growth response index (GRI_{Day}) is determined as the product of the daily growth response to temperature (T_{Growth}) and water stress (S_{Growth}) (Eq. 4) and is summed for the year to determine the annual growth response index (GRI_{Year}). The model predicts a considerable lengthening of the temperature-limited growing season, as approximated by the number of calendar days where the value of $T_{Growth} \geq 0.25$ (data not shown). The average length of the temperature-limited growing season for both species increased by 42 days in the period from 2073-2102 relative to the reference period (1975-2004). The increase, however, was also accompanied by higher daily drought stress during the growing season leading to a mid-summer decline in average GRI_{Day} (Figure C.13).

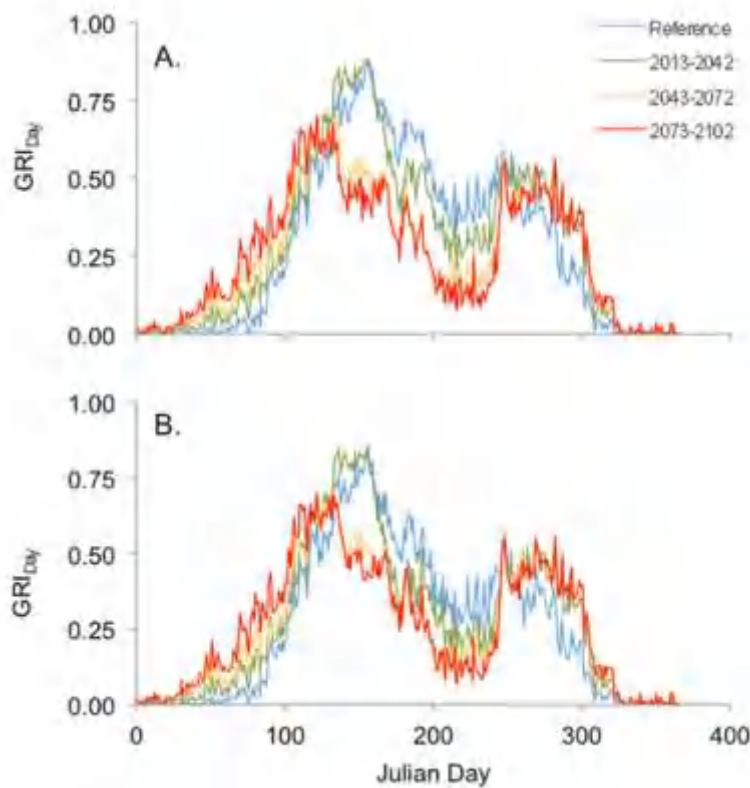


Figure C.13 Simulated impact of climate change on GRI_{Day} for Douglas-fir (A) and lodgepole pine (B). Results for mean daily growth response index (GRI_{Day}) are shown for newly planted stands and reflect data from the 30-year historical time period (reference), and three sequential 30-year future climate periods (2013-2042, 2043-2072, and 2073-2102) based upon the CanESM2 climate scenario.

Over the first 30 years of the simulation, climate change led to reduced levels of litter mass due to increased mass loss rates (Figure C.14A). Thereafter, total litter mass in the climate change scenarios increased to levels above that of the reference climate. Nitrogen (N) release was consistently higher under both climate change scenarios (Figure C.14B).

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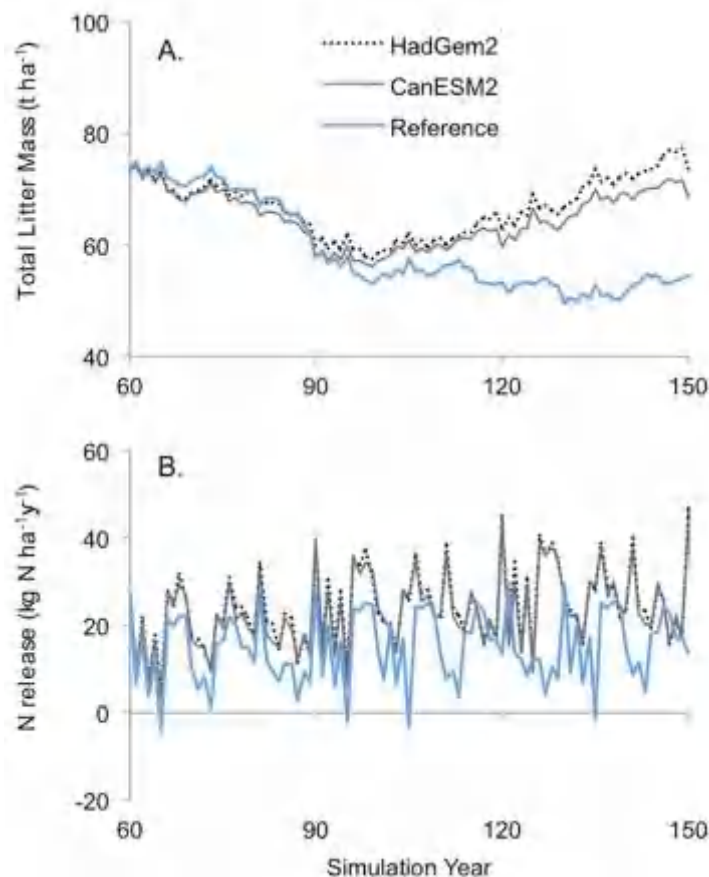


Figure C.14 Simulated impact of climate change on (A) total litter mass, and (B) net N release. Results are shown for established (60 years old at the start of the climate change simulation) Douglas-fir stands.

DISCUSSION

4.1 Model evaluation using tree-ring analysis

A variety of metrics have been useful in establishing the relationship between climate and plant productivity (see [72]). One metric used extensively is dendrochronology, in which changes in ring width are linked to annual variation in climate, particularly temperature and moisture [73]. Dendrochronology thus provides a means of assessing how well a forest model can project the impact of climate on plant performance (i.e., annual ring growth). If a model can successfully reproduce ring chronologies as a function of historical climate conditions, it should be reasonable to use these same relationships to predict the future growth response to a changing climate regime (see, for example, [74, 23, 60, 75]).

Dendrochronological records indicate that, in general, annual tree growth in temperate regions tends to be more sensitive to variations in water stress than temperature [76, 77]. FORECAST Climate performed well in capturing the historical effect of climate on ring width indices in 4 of the 5 measured plots. Model output was consistent with years when measured radial growth rates were reduced due to water stress as well as years in which growth was above average.

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The positive impacts of temperature on ring width were captured directly by FORECAST Climate as a lengthening of the growing season, and indirectly through the positive influence of enhanced nitrogen mineralization on site productivity.

One of the challenges in using tree ring data is that climate signals can be obscured by other factors that influence growth, such as abiotic and biotic disturbance agents, and competition for site resources from neighboring trees and/or other vegetation types [73]. In our case, one of the two plots with lower R² values (Douglas-fir, plot #9; see Table C.2) displayed unusual patterns whereby ring widths declined to near zero for a three-year period before returning to 'normal' levels (data not shown). The other Douglas-fir plots showed no such pattern suggesting that the decline was not climate related. Abrupt disruption and subsequent recovery in tree radial growth is indicative of insect attack. In Douglas-fir that might be from budworm or bark beetle [78]. Regardless of its source, the ring pattern was sufficiently skewed that it effectively obscured the climate signal.

4.2 Effects of climate change on productivity and mortality

FORECAST Climate predicted an overall increases in annual growth rates under future climate conditions in both Douglas-fir and lodgepole pine (Figures C.10 & C.12). An increase in growing season length was the dominant factor in this regard and served to counteract an increase in the frequency and intensity of summer moisture stress, the latter of which represented a downward pressure on growth (Figure C.11). Summer moisture stress trended upwards under climate change despite simulated increases in canopy resistance associated with elevated atmospheric CO₂ concentrations (see Figure C.11). [23] also reported an antagonistic effect of growing season length and moisture stress on forest productivity in the boreal forest. [79] found that Douglas-fir growth rates in warm-dry regions correlated well with annual precipitation while growth in populations from cooler and wetter regions was better correlated with temperature and other climatic variables. Summer moisture deficit was the key climatic factor limiting interior Douglas-fir growth rates in montane ecosystems in the northwestern US [77]. In the Cascade Range, Washington, USA, [80] observed that growing season precipitation was the climate variable most strongly correlated with growth rates in mid-elevation lodgepole pine stands, indicating that summer water stress was a key limiting factor. They noted that temperature-regulated growing season length was the most important factor influencing growth rates in high elevation stands.

Higher drought-related mortality was predicted by FORECAST Climate in all climate change scenarios. This resulted in lower biomass production except for newly planted Douglas-fir stands. Established stands were vulnerable to the warmer and drier climate conditions due to a high leaf area. This is because older stands originated and developed under historical climate conditions, which can support a greater leaf area. The latter, however, is poorly adapted to an increasingly water-limited future environment. High evapotranspirational demand in older stands thus triggered widespread mortality during drought and a significant loss of live biomass. Although newly planted stands also incurred elevated mortality, the impact on long-term productivity was relatively low and surviving trees developed canopies with a lower leaf area. Finally, it should be noted that the intensity of predicted water stress declined after a mortality event. This was because mortality reduced stand leaf area (data not shown) resulting in a lower canopy water demand.

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Evidence of increased drought-related mortality has been documented in forest ecosystems around the world [5, 81, 14]. Moreover, [82] observed widespread growth decline despite increases in water use efficiency in temperate and boreal forests in a study combining standard dendrochronological techniques with isotopic analysis. The complex physiological response of vegetation to water stress, however, has made it difficult to represent accurately within forest ecosystem models [78]. Prolonged moisture stress increases mortality generally [5, 83] and both hydraulic failure and carbon starvation have been implicated as direct causal factors [84, 51]. Trees suffering from water stress are also more vulnerable to abiotic and biotic disturbance, including fire and insect attack [6, 83]. The water-stress mortality function employed in FORECAST Climate was designed to encapsulate both the direct and indirect aspects of drought-related mortality. It can be parameterized through an iterative process whereby modeled mortality derived using historical reference climate data is adjusted to achieve a reasonable match to measured rates.

It should be noted that the projections of the impact of climate change on long-term growth and productivity in these ecosystems do not include any impacts from extreme climate events nor the effect of climate on population dynamics of natural disturbance agents. Both of these factors have the potential to substantially impact forest productivity as the climate continues to change.

4.3 Climate effects on decomposition and nutrient cycling

FORECAST Climate predicted a net increase in mass loss associated with litter decomposition over most years in the climate change scenarios and there was an increase in simulated litter mass over the long-term (Figure C.14A). The latter was a result of the higher mortality rates that occurred under climate change relative to historical conditions (see Figures C.10C & C.12C). Though warmer temperatures had a positive impact on decomposition rates there were periods when litter water content was low, which exerted a downward pressure on rates. Nevertheless, the net increase in decomposition led to an associated increase in N mineralization and thus a positive benefit to tree productivity. [11] provided evidence that soil warming leads to pronounced increases in litter mass loss and net N mineralization rates. In an experimental manipulation of soil warming over 7-years, [85] showed enhanced biomass production relative to controls, which they attributed largely to increased N availability. The representation of such feedback loops in models is thus paramount to improving their capability to capture climate change impacts on forest growth and development.

4.4 Hybrid modelling approach

FORECAST Climate employs a series of climate response functions to represent the impact of temperature and moisture stress on plant growth. The benefits of this approach are: 1) it represents a relatively simple and transparent approach to predicting the independent and combined effects of temperature and moisture stress on growth, 2) the shape of the response functions can be easily established and evaluated empirically, 3) it provides a convenient means of summarizing daily responses into annual indices, and 4) is easily calibrated using historical reference climate data. Further potential improvements to the model include a representation of the phenological responses of plants to climate, such as bud break or the onset of dormancy, and frost events.

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Supporting Information for *Application of a hybrid forest growth model to evaluate climate change impacts on productivity, nutrient cycling and mortality in a montane forest ecosystem*

1. FORWADY DESCRIPTION

The ForWaDy (Forest Water Dynamics) model was constructed around the foundation of FORHYM, a general water balance model designed by [2] for the simulation of water fluxes through temperate forest ecosystems. It includes a representation of the vertical flow of water through canopy and soil layer compartments (Figure S.1). Movement of water through each soil layer is regulated by its physical properties that dictate moisture holding capacity, permanent wilting point moisture content, and infiltration rate.

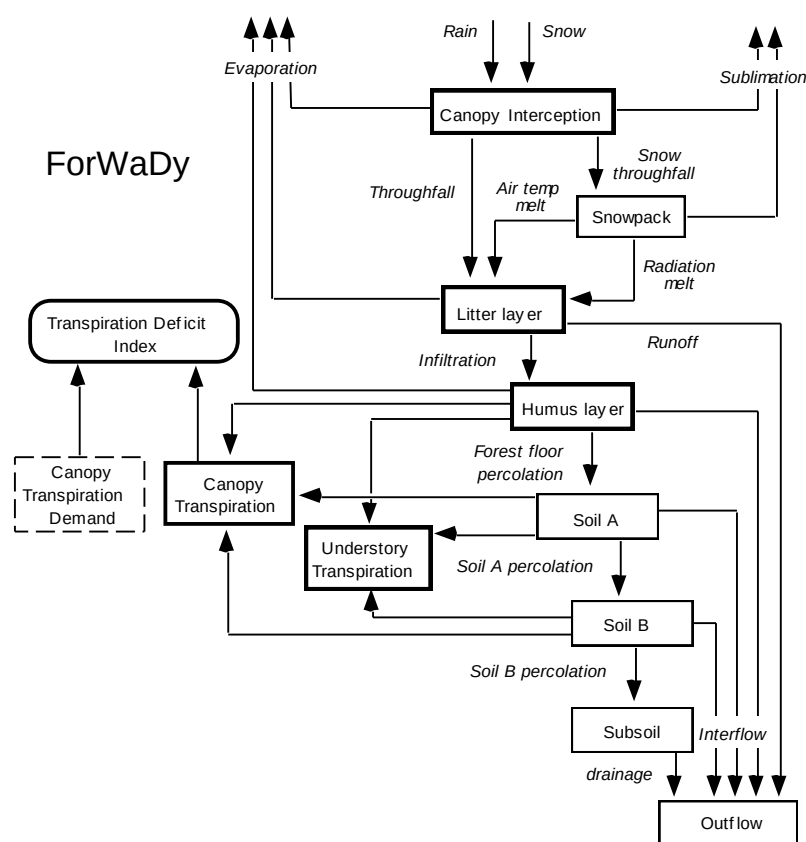


Figure S.1. Schematic diagram of the ForWaDy model indicating water flow pathways and storage compartments.

The daily energy available for evapotranspiration is divided among canopy trees, understory plants and the forest floor based on the proportional interception of incoming solar radiation by each layer adjusted for reflection depending on surface albedos. Subsequently, a passive competition for available soil moisture is simulated through the use of an algorithm that combines species-specific root occupancy information with energy-limited transpiration and evaporation demands. Canopy water stress is determined as a function of energy-limited canopy transpiration demand and soil-limited actual canopy transpiration through the

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calculation of a cumulative water stress index. This index represents a dynamic measure of tree water stress over a given time period and may be used as a parameter to limit tree growth rates based on light and nutrient availability in models such as FORECAST and FORCEE. The simulation of snowfall and snowpack dynamics in ForWaDy is based on the RHYSSys Snow Model [4].

All equations describing water flow within the model are solved using a simulation Δt of 0.25 days. The use of a Δt less than one day enables the model to divide the flux of water from a particular soil reservoir among competing outflows.

S1.1. Data Requirements

One of the goals in model development was to produce a model that is portable and suitable for use in forest management; thus, climate and site-specific soil and vegetation data requirements were kept to a minimum. The use of parameters that must be calibrated for each site was also avoided when possible. Data requirements are shown in Table S.1.

Table S.1 Data requirements for ForWaDy

Climate data (daily)	Vegetation data	Forest floor & soil data
mean, max and min air temperature	seasonal conifer and hardwood LAI	fine litter mass (kg/ha)
solar radiation ¹	seasonal understory % cover	humus layer depth and bulk density
total precipitation	rooting depths for trees	depth of mineral soil layers
snow fraction	rooting depths for understory	soil texture (by layer)
atmospheric [CO ₂] ²	canopy resistance and albedo (by species)	coarse fragment content (by layer)

¹ Solar radiation may be estimated from max and min air temperature, elevation, latitude, slope and aspect using published radiation models.

² Only annual data required.

S1.2 Radiation interception

Radiation interception in ForWaDy may be estimated from a host model as is the case with FORECAST Climate or it may be done using the default equations within ForWaDy as follows. The energy available for driving evapotranspiration is estimated separately for the canopy, understory, and forest floor based upon the proportion of adjusted total daily solar radiation intercepted by each layer. The interception and extinction of radiation as it passes through the canopy and subsequently through the understory is calculated as a function of LAI using a simple formulation of Beer's Law with an extinction coefficient of 0.4 (Figure S.2). Forest floor radiation is calculated as the total remaining radiation following simulated canopy and understory interception. For simplification purposes, the transmittance of net radiation (S_n) is assumed to

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be equal to that of shortwave radiation [10] following the reflection of a portion of total incident shortwave radiation according to a surface albedo (a) (Eq. S1). The default albedo (a) for the canopy and understory is set at 0.12 which is representative of typical values reported for forests [18, 9] and should be used as a reasonable approximation in the absence of a measured value. The forest floor albedo is determined as a function of solar zenith angle and moisture content according to [22].

$$S_n = Rad * (1 - a) \quad (S1)$$

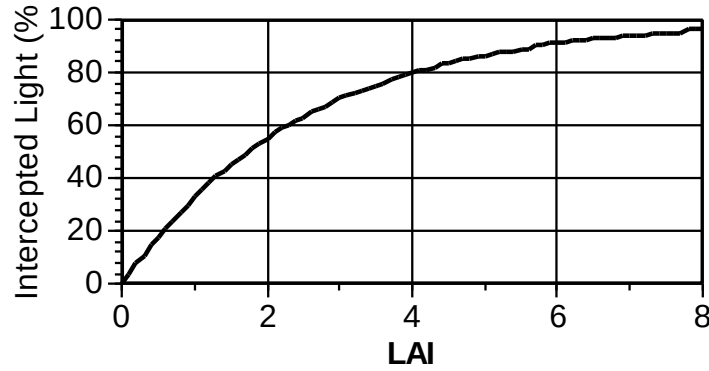


Figure S.2 The relationship between leaf area index (LAI) and intercepted light as a percent of total above canopy light according to Beer's Law with an extinction coefficient of 0.4.

S1.3 Energy-limited evapotranspiration

Energy-limited or potential evapotranspiration (PET) is calculated for each layer represented in the model based on the following simplification of the Penman-Monteith equation proposed by [16]:

$$PET = \alpha \frac{s}{s + \gamma} (S_n - G - M) \left(\frac{1}{L} \right) \quad (S2)$$

where α is an experimentally determined coefficient, s , γ , and L are respectively, the slope of the saturation vapor pressure curve, the psychrometric constant, and the latent heat of vaporization of water each evaluated at the daily average air temperature and S_n , G and M represent the daily (24-hour) values of net radiation, soil heat flux and energy storage in the canopy. The daily value of M is ignored in this model as it generally represents less than 5% of S_n in coniferous forests [13]. Thus, using the S_n values calculated for each layer according to the radiation interception submodel, PET is calculated separately for the canopy, understory and forest floor using equations (S3-S5), respectively.

$$PET_{Can} = \alpha \frac{s}{s + \gamma} S_{nCan} \left(\frac{1}{L} \right) \quad (S3)$$

$$PET_{Us} = \alpha \frac{s}{s + \gamma} S_{nUs} \left(\frac{1}{L} \right) \quad (S4)$$

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$$PET_{FF} = \alpha \frac{s}{s + \gamma} (Sn_{FF} - G) \left(\frac{1}{L} \right) \quad (S5)$$

In (Eq. S5) soil heat flux is estimated as a function of Sn_{FF} (Eq. S6) [7]. The default values for the a and b parameters are -43.1 and 0.335, respectively but may be adjusted the soil heat flux parameters if necessary.

$$G = a + b * Sn_{FF} \quad (S6)$$

Typically, the use of (Eq. S2) has been limited by the fact that, for dry canopy conditions, α must be calibrated against actual evapotranspiration rates for a particular site using Bowen ratio / energy balance techniques [19] which can be prohibitively expensive. For a range of dry forest conditions, α has been shown to vary from 0.6 to 1.1 [7]. However, for a wide range of relatively smooth, freely evaporating (wet) surfaces α is generally equal to 1.26 [16, 20, 5]. Values of α less than 1.26, typical in most forests with dry canopies, are thought to be the result of surface control of evaporation through stomatal resistance [11]. In an effort to eliminate the need for α to be experimentally determined for each new site, we suggest the use of a canopy resistance term (R_{Can}) based on mean literature values of α for dry canopies of various forest types (Table S.2). Using this method α is set at 1.26 for wet canopy conditions and adjusted under dry canopy conditions (where evaporated water must pass through stomata) through the use of R_{Can} . The use of an approximated R_{Can} will undoubtedly lead to some error in the calculation of canopy PET, but it should provide a reasonable estimate suitable for the intended use of the model.

Table S.2 Estimated canopy resistance (R_{Can}) for three forest types based on reported literature values of α' .

Forest Type	α'	$R_{Can} = 1 - (\alpha' / 1.26)$	References
Dry Pine	0.7*	0.45	* Estimation based on reported range [19]
Douglas-fir	0.84	0.33	[3, 8, 19]
Broadleaf / understory	1.1*	0.13	[14, 19] * Estimation based on reported range

S1.4 Canopy water, throughfall and canopy evaporation

The amount of water held in the canopy at time t ($C_{Wat(t)}$) is calculated as the difference between incoming rainfall (P) and the sum of throughfall (TF) and canopy evaporation (E_{Can}) evaluated at each time step (dt) (Eq. S7). The fraction of rainfall intercepted by the canopy is determined as a function of canopy vegetation area index (VAI), where a maximum canopy storage term is calculated based on the assumption that at saturation the upper surface of leaves and branches can hold a film of water 0.2 mm in depth (Rutter, 1975), thus $C_{Max} = 0.2 * VAI$.

$$C_{Wat(t+dt)} = C_{Wat(t)} + (P_{(t)} - TF_{(t)} - E_{Can(t)}) * dt \quad (S7)$$

Throughfall and canopy evaporation are calculated as follows:

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$$\begin{aligned} TF &= 0 & C_{Wat} < C_{Max} \\ TF &= C_{Wat} - C_{Max} & C_{Wat} \geq C_{Max} \end{aligned} \quad (S8)$$

$$E_{Can} = \min(C_{Max}, C_{Wat}, PET_{Can}) \quad (S9)$$

Stemflow is assumed to be included as part of throughfall.

S1.5 Soil water storage and drainage

Hydrologic dynamics in the forest floor and rooting zone are simulated using a multi-layered approach in which inflows and outflows are estimated sequentially for each soil layer (Figure S.1). Water storage in and vertical movement through the mineral soil layers are simulated using a “tipping bucket” type algorithm based on total porosity adjusted for coarse fragment content, field capacity and permanent wilting point boundaries (inputs to the model). Water stored in the humus and soil layers between field capacity and permanent wilting point boundaries is considered to be available for plant uptake. Water storage in the litter layer is calculated as a function of fine litter mass (i.e. not including coarse woody debris) per area and is assumed to be unavailable for plant uptake. Lateral flow or interflow of water from soil layers into stream channels is only allowed to occur when the water content of a given soil layer is greater than its estimated field capacity and is based on a coefficient related to slope.

S1.6 Soil-limited evapotranspiration

As the forest floor and soil layers begin to dry, evapotranspiration rates are limited by the availability of soil water. Transpiration loss is calculated separately from each layer for both the canopy and understory. Rooting depths of canopy and understory species are used to determine the layers from which water may be extracted. In order to represent the limited capacity of a drying soil to supply water to roots, particularly during periods of high PET, the daily, energy-limited transpiration rate is scaled back through the use of a relative transpiration rate (RTR) term. RTR is estimated as an empirical function of the percent of available water in each layer and PET [6] (Fig. S.3). A root fraction term is also introduced for both the canopy (RF_{Can}) and understory (RF_{Us}) as a scalar to account for the fraction of each layer occupied by roots.

This term is calculated from root depth occupancy data as well as soil layer depths provided by the user.

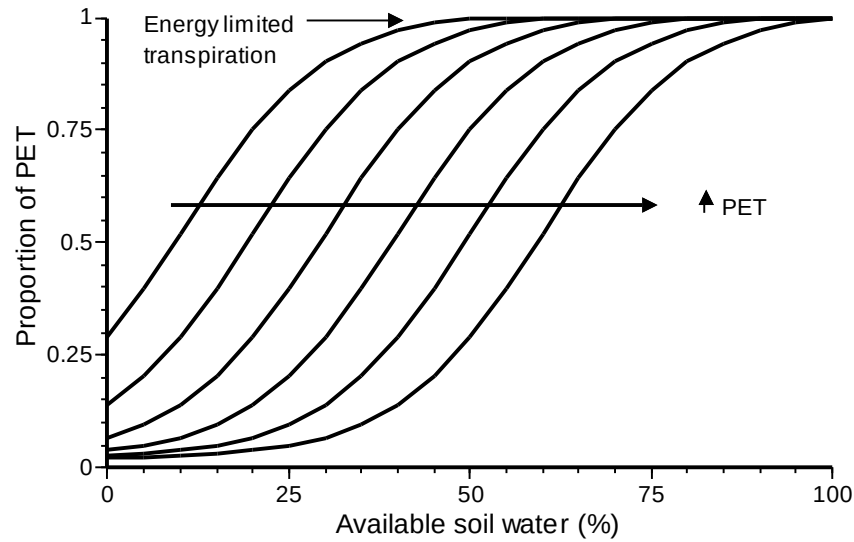


Figure S.3 The relative rate of transpiration determined as a function of available soil water and energy-limited evapotranspiration (PET). The function curve shifts to the right as PET increases.

The daily extraction of water from the various layers via transpiration occurs sequentially from the top downward, beginning with the humus layer and continuing down through the soil B layer. The total amount of energy available for canopy transpiration ($CanT_{(total)}$) is estimated after accounting for the canopy PET energy consumed by canopy evaporation and canopy resistance (Eqs. S10-S11). $CanT_{(total)}$ is then used to drive transpiration loss from each of the soil layers using an energy budget approach, moving from the humus layer downward as the amount of extractable soil water is depleted in each soil layer (Eqs. S12-S14). The daily extractable fraction of available water in a given layer is largely a function of the estimated RTR value and is generally less than the total plant available water in that layer. The transpiration algorithm continues until either all layers have been depleted of extractable water or the energy available for daily transpiration is depleted. Understory transpiration is calculated simultaneously using the same method.

$$GCanT = (PET_{Can} - E_{Can}) \quad (S10)$$

where: $GCanT$ = gross canopy transpiration ($mm\ day^{-1}$)

$$CanT_{(total)} = GCanT * (1 - R_{Can}) \quad (S11)$$

$$CanT_{(humus)} = CanT_{(total)} * RTR_{(humus)} * RF_{Can(humus)} \quad (S12)$$

$$CanT_{(soilA)} = (CanT_{(total)} - CanT_{(humus)}) * RTR_{(soilA)} * RF_{Can(soilA)} \quad (S13)$$

$$CanT_{(soilB)} = (CanT_{(total)} - (CanT_{(humus)} + CanT_{(soilA)})) * RTR_{(soilB)} * RF_{Can(soilB)} \quad (S14)$$

Energy-limited surface evaporation from the LF layer and humus compartments is also regulated as a function of water content through the use of a relative evaporation rate term (RER) estimated using a simple empirical function of available soil moisture. Drying proceeds from the top downwards (Eqs. S15 & S16) and evaporation from the humus layer is only allowed to occur when the litter layer has dried out.

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$$E_{\text{Litter}} = PET_{\text{FF}} * RER_{(\text{litter})} \quad (\text{S15})$$

$$E_{\text{Humus}} = (PET_{\text{FF}} - E_{\text{Litter}}) * RER_{(\text{humus})} \quad (\text{S16})$$

S1.7 Canopy water stress

Typically, models of forest growth which include water stress as a feedback to forest growth have quantified tree water stress using a summed measure of soil water deficit. One of the problems in using a summed water deficit for a measure of water stress is that it frequently fails to capture the dynamic interactions between different components of the hydrological cycle and net effect of such interactions on tree water stress. For example, as part of the Biology of Forest Growth Study near Canberra, Australia, [12] demonstrated that cumulative soil water deficit may not be well correlated with tree water stress as defined by pre-dawn xylem potential, a commonly used physiological indicator of tree water stress. The weakness of the technique is even greater when monthly summaries of climate data are used to calculate the water deficit.

In order to evaluate tree water stress more dynamically we propose the use of a cumulative index termed the transpiration deficit index (TDI) (Eq. S17-S18). TDI provides a means of summarizing the net effect of several factors including canopy evaporation, understory transpiration and surface evaporation on actual tree transpiration. Furthermore the index is calculated on a daily timestep to better capture the cumulative effect of short term water stress events.

$$TDI = \frac{\sum_{i=0}^{i=t} CanT_{(\text{total})i} - CanT_{(\text{actual})i}}{CanT_{(\text{total})i}} \quad (\text{S17})$$

$$CanT_{(\text{actual})} = CanT_{(\text{humus})} + CanT_{(\text{soilA})} + CanT_{(\text{soilB})} \quad (\text{S18})$$

In (Eq. S17) the difference between total canopy transpiration demand ($CanT_{(\text{total})}$) and actual canopy transpiration ($CanT_{(\text{actual})}$) is divided by $CanT_{(\text{total})}$ to normalize the effect of leaf area index on the relative canopy transpiration deficit. This adjustment effectively converts the total canopy water deficit to a per unit leaf area measure of water deficit which should be more representative of the water stress of individual trees.

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A HANDBOOK FOR GUANGDONG TRAINING WORKSHOP

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Chapter 1: An Overview of Forestry in the Asia-Pacific Region and Associated Issues and Challenges

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AN OVERVIEW OF THE ASIA-PACIFIC REGION

The Asia-Pacific region comprised of 4 subregions with 49 countries covering nearly 2.8 billion hectares of land area (roughly 22 percent of world's land area) (FAO 2011) (Figure 1.1 and Table 1.1). This region extends from Pakistan in the west to the small island states in the Pacific in the east, and from the north of Mongolia to the southern borders of Australia and New Zealand (Waggener & Lane 1997). The Asia-Pacific region holds approximately 60 percent of the world population, including 70 percent of the world's poor (UNEP 2011).

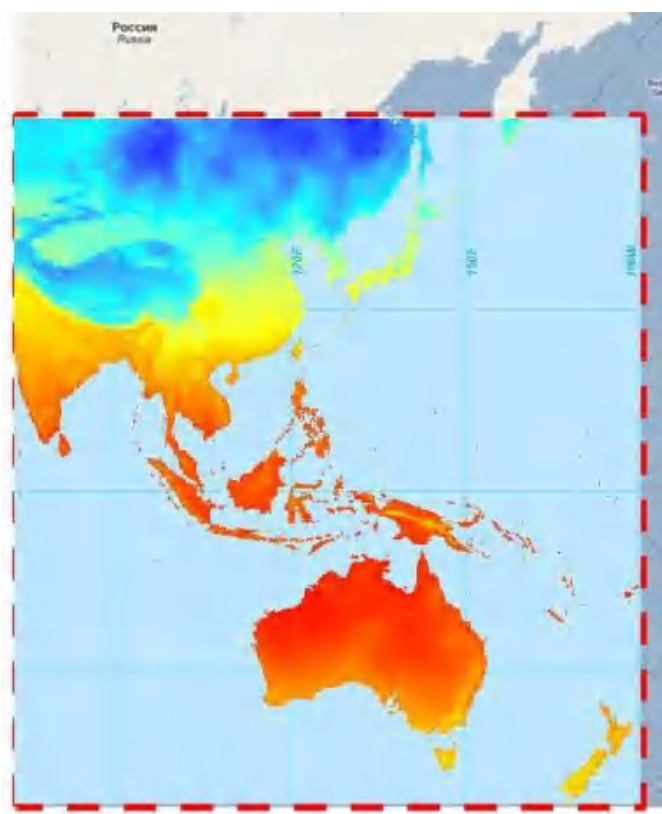


Figure 1.1 The Asia-Pacific Region (Source: <http://asiapacific.forestry.ubc.ca/>)

Table 1.1 Sub-regions and countries in each sub-region (adapted from FAO (2010a))

Sub-regions	Countries
<i>East Asia</i>	China, Democratic People's Republic of Korea, Japan, Mongolia, Republic of Korea
<i>Oceania</i>	American Samoa, Australia, Cook Islands, Federated States of Micronesia, Fiji, French Polynesia, Guam, Kiribati, Marshall Islands, Nauru, New Caledonia, New Zealand, Niue, Norfolk Island, Northern Mariana Islands, Palau, Papua New Guinea, Pitcairn, Samoa, Solomon Islands, Tokelau, Tonga, Tuvalu, Vanuatu, Wallis and Futuna Islands
<i>South Asia</i>	Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka
<i>Southeast Asia</i>	Brunei, Cambodia, Indonesia, Lao People's Democratic Republic, Malaysia, Myanmar, Philippines, Singapore, Thailand, Timor-Leste, Viet Nam

FOREST RESOURCES IN THE ASIA-PACIFIC REGION

State of the Forest

The total forest area in the Asia-Pacific region is estimated to be 723 million hectares, representing nearly 18 percent of the global forest area and accounting for slightly less than one-third of the regional land area (FAO 2015) (Figure 1.2). Due to the relatively high population (~60% of global population), this region is the least forested region in the world on a per capita basis, measuring approximately 0.2 hectares per person. Furthermore, the forest area is disproportionately distributed within the region. For instance, about 71 percent of forests are only found in the following 4 countries: China, Australia, Indonesia and India (Figure 1.3, Table 1.2). There are six countries which reported to have a forest cover less than 10 percent of their total land area. Interestingly, Among these six countries, two countries namely Nauru and Tokelau reported no forest cover at all (FAO 2011). With only 0.2 hectares of forest per person, there is a significant per capita forest area differences between the Asian and the Pacific subregions. In Asian countries, the average per capita forest area is estimated to be lower (about 0.15 hectares) compared to the the Pacific subregion (6.3 hectares) (FAO 2011).

In addition to forest area, the Asia-Pacific region holds roughly 312 million hectares of other wooded land of which Australia and China account for 76 percent. Furthermore, 42.5% of forest area in the Asia-Pacific region is designated for conservation of biodiversity (FAO 2010b).



Figure 1.2 Distribution of forests and woodlands in Asia-Pacific region (adapted from FAO 2010a)

Due to the wide geographical range, forest types found in this region exhibit great variety. The Asia-Pacific region covers 4 climatic zones: boreal, temperate, arid and semi-arid and tropical (UNFCCC 2007), producing a combination of temperate, boreal, subtropical and tropical forests.

Asia-Pacific forest area can be further divided into primary, planted, and modified naturally regenerating forests based on the severity and nature of human intervention. Modified naturally regenerating forest occupies the large majority of forest cover within the region, while primary and planted forests comprise the remainder (FAO 2011) (Figure 1.4).

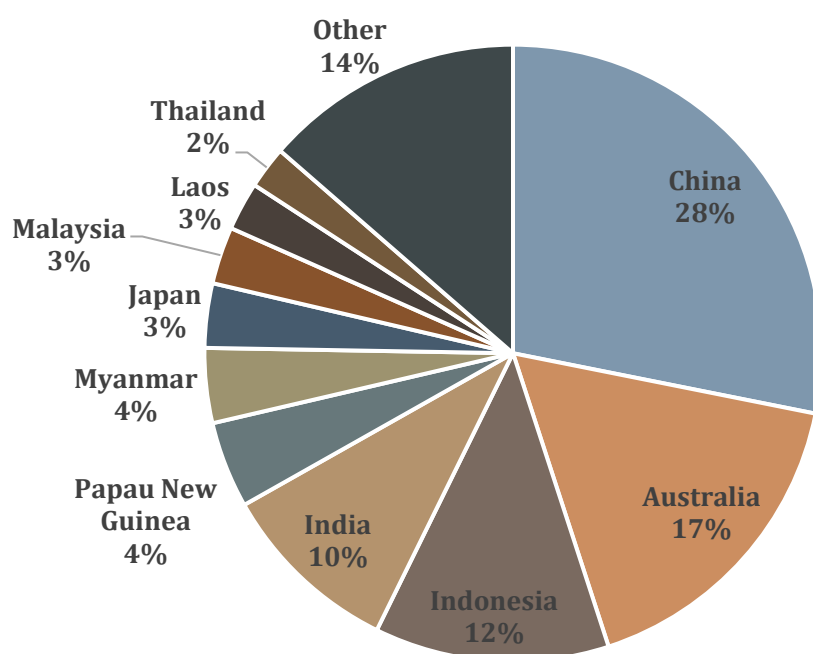


Figure 1.3 Distribution of forest area in the Asia-Pacific Region, based on countries (FAO 2015)

Table 1.2 Distribution of forest area in the Asia-Pacific Region, based on sub-regions (modified from FAO 2010a)

Sub-regions	Forest area 2010 (million area)	Share of the Asia- Pacific forests (%)	Share of the global forest (%)	Share of the global population (%)
<i>East Asia</i>	255	18.3	6.3	22.6
<i>Oceania</i>	191	13.7	4.7	0.5
<i>South Asia</i>	80	5.7	2.0	23.4
<i>Southeast Asia</i>	214	15.3	5.3	8.5
<i>Asia-Pacific</i>	740	100	18.4	55.1

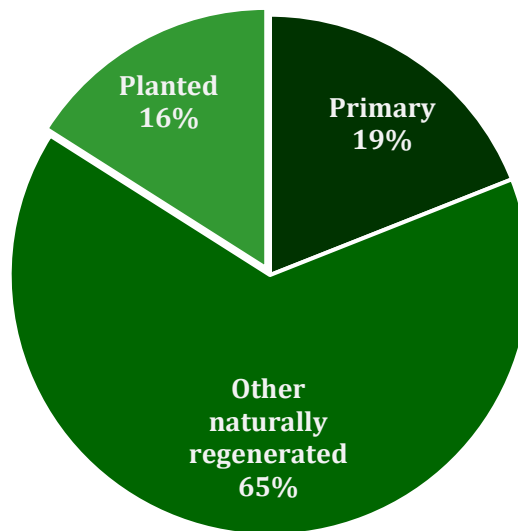


Figure 1.4 Characteristics of Asia-Pacific forests based on human intervention (modified from FAO 2010a)

Change in Forest Area

From 1990 to 2000 total forest area declined by 0.7 million hectares per year, but began to increase at a rate of 0.5 million hectares annually from 2000 to 2010 (Figure 1.5) (FAO 2010a). This change, however, is unevenly distributed amongst countries in the region. Deforestation still persists at a high rate in many nations. Recent data showed Southeast Asia experienced the massive % change (-12.9%) in forest cover from 1990 to 2015 followed by Oceania with -1.9% (FAO 2010a, 2015). It lost 2 million ha of forest while global estimation of deforestation was estimated 4.9 million ha during the 1990s. Primary forest in Southeast Asia with the highest biodiversity experienced the steepest decline from 34% in 1990 to 29% in 2010. In contrast, a net gain of forest area was reported in East Asia (22.9%) and South Asia (5.8%) between 1990 and 2015 (FAO 2010a, 2015) particularly due to large scale afforestation programmes in China and increased forest in India and Vietnam.

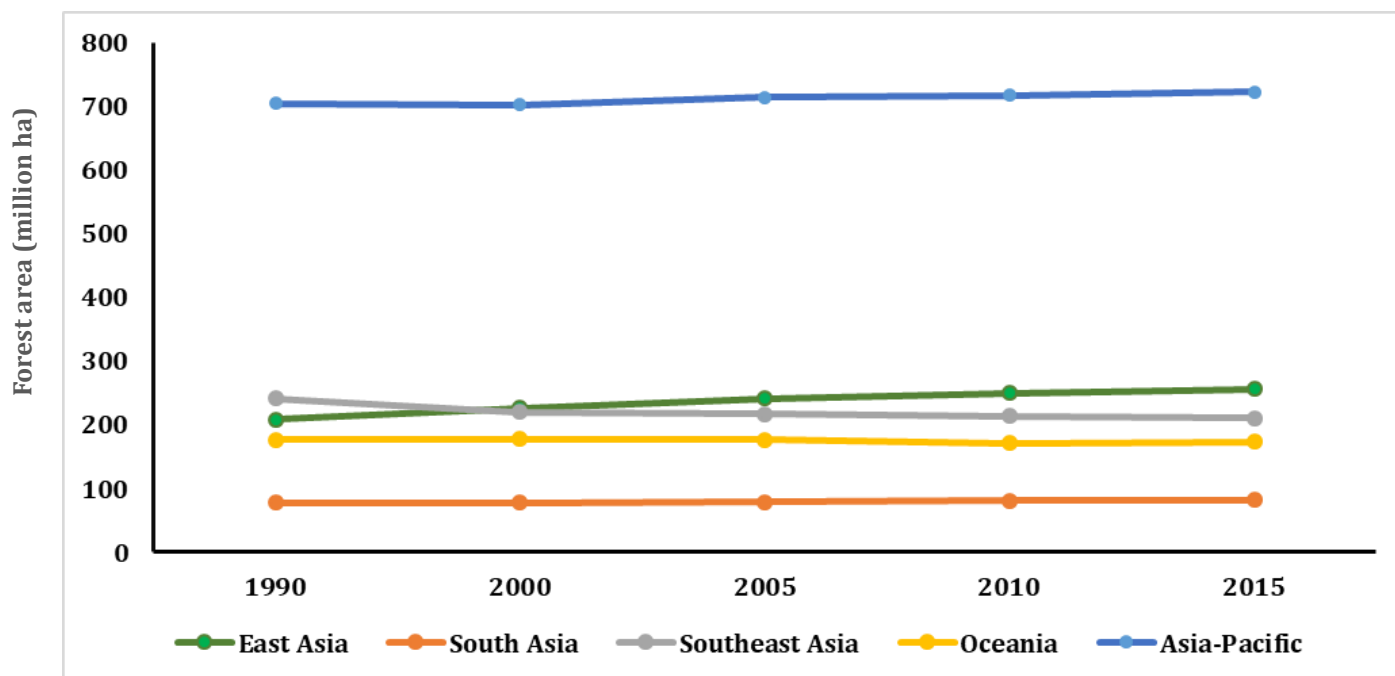


Figure 1.5 Changes of forest areas in Asia-Pacific region from 1990 to 2015 (FAO 2015)

Countries in the Asia-Pacific region can be divided into 3 groups with respect to changes in forest cover over time (FAO 2010c): (1) in countries where agriculture is highly important and the pressure for forest conversion is high; (2) in developing countries where industrialization is considered a priority, and mining, urbanization, and infrastructure construction are the main causes of deforestation; and (3) in developed countries where strong policy incentive is provided for forest conservation to enhance ecosystem services and forest resources, improving forest productivity.

FOREST MANAGEMENT IN THE ASIA-PACIFIC REGION

As previously mentioned, forests in the Asia-Pacific region can be divided into primary forests, modified natural forests, and planted forests. Primary forests account for 19 percent of the total forest area, while modified natural forests comprise 65 percent of the total, reflecting intense human pressure. Planted forests compose the remaining 16 percent of the forest area, with a focus mainly on wood and non-timber products (FAO 2010b) (Figure 1.4). Southeast Asia harbours greater proportion of primary forest compared to other subregions, however this biodiverse area has been experiencing higher rate of deforestation between 1990 and 2010. However lately, the rate of deforestation has been reduced (Fig 1.6; FAO/RECOFT 2016). Similarly, this region also hold higher modified natural forest compared to other sub-region. Higher proportion of Plantation forest was occurred in East Asia, particularly due to large scale afforestation programmes in China as well as some extent in India and Vietnam (Fig. 1.6; FAO/RECOFT 2016). Forest management is much more intensive in the Asia-Pacific region compared with the world average.



Figure 1.6 Status of forest types based on degree of human intervention in sub-region of Asia-Pacific (adapted from FAO/RECOFT 2016)

Natural Forest/Primary Forest

Natural forests have been managed as protection forests and production forests. Relatively easily accessible areas with a high proportion of marketable species are more likely to be managed for wood production. Although the dependence on natural forests as a source of wood supply is declining, wood production remains an important source of revenue for several countries. Overall, the extent of natural forests managed sustainably remains very low (FAO 2010b). In general, there are three approaches to utilizing natural forests in the Asia-Pacific region (Table 1.3): intensive logging; sustained yield management; and banning logging.

Table 1.3 Different forest management approaches to natural forest in Asia-Pacific region (FAO 2010a)

Approaches	Explanations
Intensive logging	Logging activities which give very little attention to the long-term sustainability of wood production and provision of ecosystem services.
Sustained yield management	Forest management which adopts a selective felling system (or variants) aiming to balance production and protection objectives.
Logging bans	Outright bans on logging in response to growing demand for ecosystem services.

To achieve better management in the natural forest sector, several steps have been taken including:

Reduced impact logging (RIL) has been promoted for the last two decades. Although RIL is economically viable in the long term, its adoption is very limited. Conventional logging is easier and commercially more profitable in the short term; hence, most concession holders and logging crews are less willing to adopt RIL. It requires substantial investments in planning, including training of logging crews. In particular,

subcontracting various tasks usually discourages the adoption of RIL, with maximizing short-term profits as the main consideration.

Forest Certification aims to create a separate market for products from sustainably managed areas, providing an incentive to move away from unsustainable production. However, obtaining certification often entails significant costs to fulfill the stipulated criteria, as well as the costs associated with third party verification. While certification enhances market access, to date, price premiums have not been commensurate with the additional costs involved. For countries applying only rudimentary formal management to their forests, reaching a level that will make them eligible for certification will require significant changes in management practices entailing substantial expenditure and, often, significant reductions in volumes of wood extracted and potential revenues. Consequently, the extent of certification adoption remains extremely low. Until mid 2014, about 10% of the global forest area had been certified, 90 percent of which situated in Northern Hemisphere (Kraxner et al. 2017). The Asia-Pacific region holds approximately 5 percent of the 306 million hectares of certified forests in the world, mainly occurring in Australia, New Zealand, Malaysia and Indonesia (ITTO 2008). Two principal international programmes for certifying sustainable forest management are operational in the region. These are the Forest Stewardship Council (FSC) system and the Programme for Endorsement of Forest Certification (PEFC). In addition, several countries have developed their own certification systems, often drawing on the principles outlined by the FSC and PEFC. The most notable of these national certification systems are those of Indonesia, Malaysia, Myanmar, New Zealand and Australia.

In 2008, 4.4 million hectares of forest were certified under the Forest Stewardship Council (FSC) scheme in the Asia-Pacific region. The area is divided relatively evenly between natural forests (28 percent), semi-natural and mixed plantation and natural forests (34 percent) and plantation forests (37 percent). Sixty-nine percent of the total area is divided between three countries: China, New Zealand and Indonesia. Smaller areas exist in Australia, Japan and Malaysia. Growth rates in areas certified have been high in recent years in China and Indonesia, whereas in the Pacific, rates of increase have been much lower and in South Asia the area certified remains negligible (Figure 1.7).

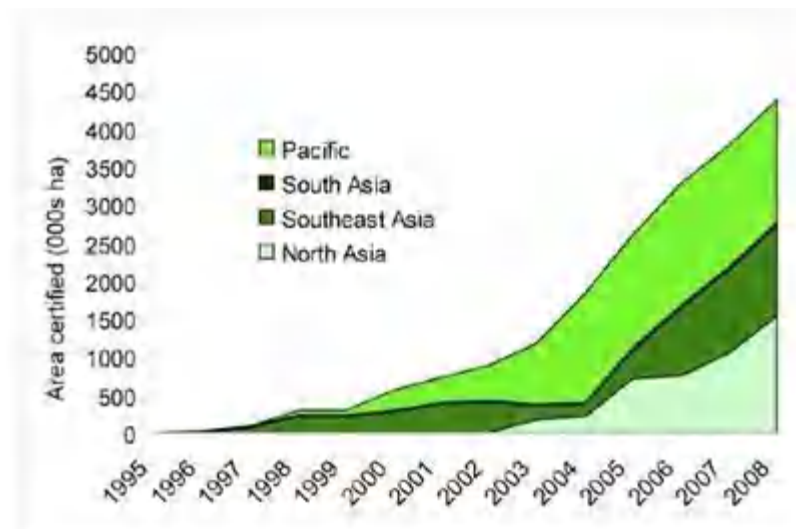


Figure 1.7 Area of FSC-certified forest in each sub-region (Adapted from FAO (2010a))

Partial or total bans on wood production from natural forests have been adopted in several countries. Often natural calamities, such as floods and landslides have triggered such actions (for example, in China and Thailand). Even in countries where natural forests remain important sources of wood supply, large portions of forests have been excluded from wood production, giving them protected status.

Several countries in the Asia-Pacific region have significantly reduced their dependence on natural forests as a source of wood supply. For example, New Zealand obtains almost all of its wood supply from plantations and all natural forests are set aside exclusively for provision of ecosystem services. In the case of Sri Lanka, no logging is allowed in natural forests. Partial or total bans on logging exist in other countries, including China, India, Pakistan, Philippines, Thailand and Viet Nam.

As management of natural forests has become technically and economically more challenging, wood production has shifted towards planted forests.

Planted Forest

Planted forests in the Asia-Pacific region make up approximately 45 percent of global planted forests, with a total area of 120 million hectares. The annual growth rate in the region for planted forests has averaged 2.2 percent from 2005 to 2010 (Table 1.4) and increased slightly in 2015, particularly in East Asia (Fig. 1.6).

Table 1.4 Change of planted forest area in the Asia-Pacific region (FAO 2010b)

	Area of planted forests (millions hectares)				Annual change (%)		
	1900	2000	2005	2010	1990-2000	2000-2005	2005-2010
Asia-Pacific	68.8	90.6	107.5	119.9	2.79	3.50	2.20
World	171.3	214.6	243.0	264.0	2.28	2.51	1.67

Key features of planted forests in the Asia-Pacific region (FAO 2010a) include:

- **A few countries (China, Viet Nam, Thailand, India, Indonesia, Japan and Australia) account for most of the increase of planted forest in the region.** Among these countries, China is the dominant force in planted forests. In 2010, China accounted for 64 percent of planted forests in the Asia-Pacific region and, over the preceding five years, 80 percent of the regional expansion in planted forests was in China. China's rapid expansion of plantations is based on highly focused, state-supported programmes.
- Most of the early efforts in forest plantation establishment focused on slow growing, long rotation species aimed to produce saw and veneer logs. Since 1980, there has been **a significant shift to short rotation fast-growing species**, mainly intended to produce pulp and other fiber products. Changes in wood-processing technologies enabling the use of small dimension logs have particularly influenced the choice of species and management practices, including rotation age.
- Historically, most plantations were under public ownership and management. However, this is changing in view of the **increasing involvement of corporate investors, local communities and**

smallholders. In particular, there was a significant expansion of the area of planted forests under smallholder ownership between 1990 and 2005, with East Asia accounting for a large part of the increase (Figure 1.8).

- Stagnation in planted forest areas under public sector management is indicative of larger institutional and environmental challenges. The replacement of natural forests with plantations is slowing down as a result of increasing emphasis on environmental protection. Future expansion of plantations will be largely driven by the private sector, including smallholders, with commercial viability being a major consideration.

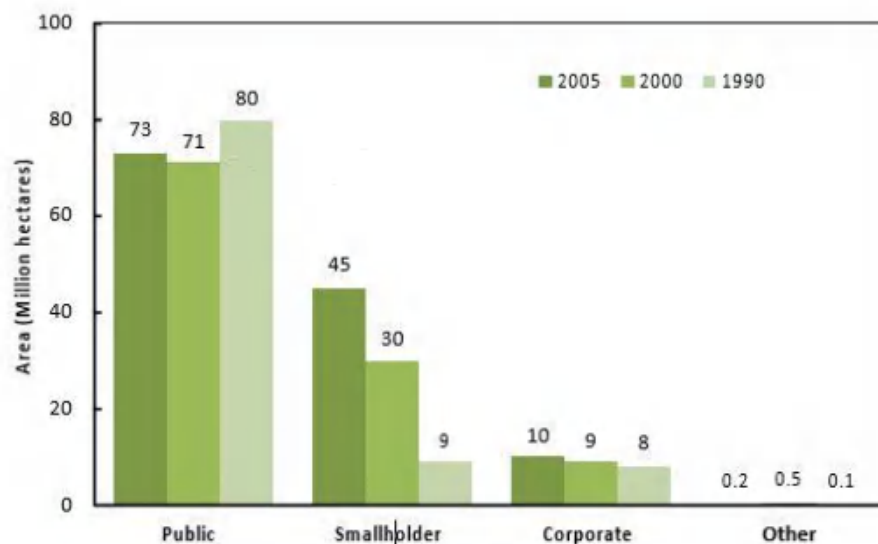


Figure 1.8 Change of planted forest ownership in Asia-Pacific region (modified from FAO (2010a))

Forest Policies Changes

Forest policies in the Asia-Pacific region have undergone major changes, involving a shift from timber-focused management to multiple-use management that grants due attention to a wide range of goods and services. In many cases, the provisioning of ecosystem services has become a major thrust. Economic growth, globalization, trade liberalization and UNCED-related attention on sustainable development have all directly and indirectly influenced forest policies. Some key trends in forest policies include:

- Increased thrust on ecological aspects with provision of ecosystem services gaining primacy.
- Emphasis on increased involvement of stakeholders in forest management, including in forest policy formulation.

A number of internal and external factors have contributed to these changes. Increased pressure from growing populations has undermined the efficacy of traditional approaches to resource management, compelling public sector forest agencies to involve local communities and other players. Major policy changes have often been made in response to natural disasters, as in the case of logging bans in the context of floods and landslides.

Almost all countries in the Asia-Pacific region have adopted sustainable forest management as the main objective of their forest policies, giving due consideration to social, economic and environmental dimensions. Several countries have shifted their orientation from timber production to broader sustainable forest management. In China, for example, one of the main policy objectives is environmental protection and restoration. Chinese Taipei, Laos, Malaysia, and Myanmar have implemented major reforestation and afforestation projects, focusing on environmental improvement, reflecting a shift in policy objectives. However, establishing trade-offs between competing objectives remains challenging. In the quest for rapid economic growth, extraction of minerals, energy production and infrastructure development have become major threats to forests; however, forest policies seldom provide a robust framework to deal with the changing situation (Table 1.5).

In many countries actual implementation of policies based on sustainable forest management has been weak because of field-level issues including high demand for forest land and forest resources, limited sources of alternative employment and low human resources capacity. Poor governance and low demand for alternative outcomes, for example greater production of environmental services, has also played a part. Similarly, permanent forest estates have often not been demarcated, agricultural frontiers have continued to advance and uncontrolled logging has often remained widespread.

In addition to forest policies, a plethora of extra-sectoral policies impinge on forests and forestry. For example, policies dealing with biodiversity, climate change mitigation, protection of wildlife and desertification control all transcend traditional sectoral boundaries. To some extent this has fragmented forestry agendas all the more so when several institutions are involved in policy implementation. Often such overlap mirrors the international situation, where almost every new convention also entails the creation of a new institution.

More importantly, policies in other sectors (agriculture, industry, energy, rural development, trade, etc.) heavily influence the forest sector, although these policies are usually primarily directed at issues far outside the forest sector. While there is considerable awareness with regards to the impact of extra-sectoral policies on forests and forestry (and vice versa), difficulties persist in resolving intra-sectoral issues. In the event of conflicting objectives, forest policy objectives are often superseded by other policies that may appear to more directly and immediately affect human welfare.

ISSUES AND CHALLENGES OF A CHANGING CLIMATE IN THE ASIA-PACIFIC REGION

Climate change may produce many detrimental impacts including the increased frequency and severity of wind and fire events, as well as pest and pathogen invasions, finally reducing forest productivity (Pawson et al. 2013; Grimm et al. 2013). There is already a large body of evidence presented in published reports that climate change has negatively affected forest ecosystems, causing decline in tree growth and dieback, invasive species problems, species distributions and migrations, seasonal patterns in ecosystem processes, demographics and even extinctions (IPCC 2007). Asia-Pacific region being exceptionally vulnerable to climate change, it may threatens the vitality and productivity of natural ecosystems, many of which are already

vulnerable in the AP due to human activities (Wang et al. 2016). Table 1.6 provides few examples of climate change effect on forest and ecosystem in Asia-Pacific region. Table 1.7 summarizes recent changes, future scenarios and broader potential impacts of climate change in each region.

Table 1.5 Examples of current forest policies and their respective objectives in the Asia-Pacific region
(Adapted from APEC 2015; UNFCCC 2015; Zhang et al. 2000)

Country	Current policy	Policy objectives	Remarks
<i>China</i>	National Forest Conservation Program	Restore natural forests in ecologically sensitive areas	Forest policies recently include values beyond timber production, promoting preservation.
		Increase timber production in forest plantations	
		Protect existing natural forests from excessive harvesting practices	
<i>Chinese Taipei</i>	Green Forestation Plan	Encourage reforestation	Forest policies prioritize the rehabilitation of nationally significant areas.
		Regenerate degraded state-owned forest	
		Rehabilitate coastal forests	
<i>Laos</i>	National Forest Strategy	Increase forest cover and maintain future forest health	Forest policies promote general forest health, more recently including climate change adaptation components.
		Enhance forest carbon sinks	
		Protect biodiversity and ecosystem services	
	National Adaptation Programme of Action	Promote technical capacity in the forestry sector	
<i>Malaysia</i>	National Forestry Policy	Promote ecosystem resilience	Forest policies examine demand-side management while also addressing SFM concepts.
		Conserve forests through sustainable forest management (SFM)	
	National Policy on the Environment	Maintain economic benefits from forestry sector	
		Achieve a healthy and productive environment	
		Promote sustainable lifestyles and patterns of consumption and production	

Myanmar	National Forestry Master Plan	Decrease rate of deforestation	Forest policies focus on general preservation while increasing the national capacity to sustainably manage forests.
		Preserve natural forest cover to maintain biodiversity and thriving ecosystems	
		Increase capacity of sustainable forest management (SFM)	
	National Biodiversity Strategy and Action Plan	Increase coastal community and mangrove resilience	

Table 1.6 Examples of climate change effect on forest and ecosystem in Asia-Pacific region.

Climate Change effect	Predicted/observed impact on forest	References
Species and range shifts	Broad leaved forests of East China predicted to shift northward by up to 3 degree latitude	Tsunekawa 1996
	Tree species in British Columbia predicted to shift their distribution 100 km towards northern range per decade	Hamann and Wang 2006
	Rainforest in Queensland Australia expanding to former reaches of Eucalyptus forest and grassland	Hughes 2003
	Tropical montane forests in Southern India transitioning from C3-dominated evergreen forests to C4-dominated grassland	Sukumar et al. 1995
	Desert steppe system of Tibetan Plateau predicted to change into forest and grassland	Preston et al. 2006
	Mt. Hotham <i>Eucalyptus pauciflora</i> in Australia expanding its range replacing subalpine grassland	Wearne and Morgan 2001
	The forests of New Zealand shifting towards higher altitude	Wardle and Coleman 1992
Drought and water stress	<i>Abies Koreana</i> mortality due to waterstress in South Korea	Lim et al. 2008
	Aspen and birch mortality due to drought in Western Canadian Province	Ranson et al. 2011
	Eucalyptus mortality due to water stress in north-eastern Australia	Fensham and Fairfax 2007
	Drought induced outbreak of red turpentine beetle in Chinese Red Pine forest	Wang et al. 2007
	Drought induced outbreak of spruce beetle in the Yukon tettiatory, Canada	Berg 2006
	Drought induced outbreak of mountain pine beetle in British Columbia and Alberta's Rocky mountainy, Canada	Smith et al. 2012

Phenological change	Observation of earlier spring in eastern and temperate part of China	Chen et al. 2005; Chen and Xu 2011
	Early spring flowering in Australia	Gallagher et al. 2009
	Early spring observation in deciduous woody plants in western Canada	Beaubien and Hall-Beyer 2003
	Early winter flowering in the Japanese apricot	Doi et al. 2007

Table 1.7 Recent changes, future scenarios and impacts of climate change

	Asia	Australia and New Zealand	Pacific
<i>Recent Changes</i>	Surface temperature: rose 1- 3 °C over a century; Longer heat waves Precipitation: increased intense rainfall events; decreased total rainfall amount. Extreme events: increased frequency and intensity (tropical cyclones, droughts, etc.). Sea-level: rose 1-3 ml/year.	Surface temperature: rose 0.4 – 0.7 °C since 1950; more heat waves (northwest Australia and southwest New Zealand); hotter droughts. Precipitation: more rainfall in northwest Australia and southwest New Zealand; less rainfall in southern and eastern Australia and north eastern New Zealand. Extreme events: increased extreme rainfall events in north western and central Australia; decreased in the southeast, southwest and central east coast.	Surface temperature: increased faster than 0.6 °C in twentieth century; Increased number of hot days and warm night in the South Pacific. Sea-level: rose about 2 ml/year. Extreme events: increased frequency and intensity of tropical cyclones originated in the Pacific.
<i>Future Scenarios</i>	Increasing extreme events (heat waves and intense rainfall) in South Asia, East Asia and Southeast Asia; sea surface temperature will rise 2 – 4 °C; increasing intensity of tropical cyclones.	Increasing frequency of heavy rainfall events; temperature will rise about 0.1 – 1.3 °C by 2020 within 800 kilometres of Australian coast; 0.1 – 1.4 °C by 2030s in New Zealand; sea-level will rise 0.18 – 0.59 meters by 2100 (±25 percent modification).	Surface temperature will rise greater than 2.5 °C in South Pacific.
<i>Potential Impacts</i>	Rising risk of species extinction; increasing coastal erosion and floods.	Declining productivity of forests.	More frequent and intense floods, storm surge and coastal erosion.

Forest management for climate change adaptation

Adaptation needs in the Asia- Pacific region

The adaptation needs provided below are based on IUFRO's global assessment report on forest and human adaptation to climate change (Seppälä et al. 2009).

1. Combine traditional forest-related knowledge and formal forest science

Traditional forest-related knowledge (TFRK), practices, and institutions have developed over generations by forest-dependent people. Traditional forest and water management practices are very important to climate change adaptation. Expanding markets have weakened traditional cultures and TFRK. TFRK should be recorded, translated and synergized with formal forest science, before it is lost.

2. Increase participatory reform and flexibility in forest-related bureaucracies

Standard operating procedures in forest bureaucracies need to change. Locatelli et al. (2008) stress two key changes that are required:

- Forest-dependent people need to be recognized, to be drawn into the discourse and to contribute to official decision-making.
- Changing attitudes among forestry personnel and strengthening feedback mechanisms within forestry-related bureaucracies.

3. Maintain/enhance biodiversity as a key ecosystem service

Management for maintaining biodiversity includes the prevention of disturbances such as fire (managing fuel load, prescribed burning) and maintaining natural cycles, particularly in arid and semi-arid forest areas. The prevention of invasive species and diseases is also crucial for maintaining biodiversity, through quarantine regimes and phytosanitary procedures. Another option is to assist forests to adapt after a perturbation by establishing priority species according to planned ecological succession (Locatelli et al. 2008).

Increasing landscape connectivity through the establishment and preservation of corridors and reducing forest fragmentation is important to facilitate natural progression and succession within ecosystems. Connectivity and corridors increase the ability of species to adapt through migration and the maintenance of genetic diversity.

In managed natural forests, for example, logging gaps may be planted with a variety of seedlings to maximize genetic diversity. Tree plantations may be established with a range of genotypes, seed sources and age classes to increase their capacity to adapt to expected future climate conditions. Plantation management strategies that mimic natural conditions and avoid monocultures are advocated to take into account climate change adaptation requirements (Roberts 2009). Throughout the region, traditional home gardens have increased the use of drought-tolerant varieties to minimize crop failure in years with severe drought (Altieri & Koohafkan 2008).

4. Create/enhance robust management strategies and extensive communication networks

Because of the uncertainty of climate change impacts, robust, sustainable forest management strategies are needed. Community-based management strategies are an important tool for ensuring responsiveness. These management strategies must also consider the projected increase of forest disturbance regimes in the form of fire, pests and diseases and must be flexible enough to incorporate and respond to new information. Effective adaptation requires the formation of extensive communication networks for monitoring the effectiveness of strategies at local, national and regional levels.

5. Improve inter-sectoral coordination

Policies from agriculture, transportation and land-use sectors will exert significant influence on the forest sector. Forest adaptation should not ignore the many anthropogenic drivers of forest change that originate in other sectors; developments in agriculture, energy, transportation, conservation and macroeconomic policies can have dramatic effects on the incentives to destroy or degrade forests.

6. Mainstream forest adaptation into policy

In order to mainstream forest-based climate change adaptation strategies at the country level, National Forest Programmes (NFPs) must explicitly address both the role of forests for reducing vulnerability to climate change at the national level and the importance of increasing the adaptive capacity of forests themselves.

7. Incorporate new actors and new modes of governance

Many institutions and sectors are becoming increasingly concerned about forest-based climate change adaptation strategies from the local to the global scale. They include local forest-dependent communities, commercial or industrial forest stakeholders, ecotourism ventures, conservation and development NGOs, national agencies concerned with forests, power generation agencies and industries, agriculture and food sectors, disaster risk reduction organizations, intergovernmental organizations, international research/development organizations and funding agencies. Adaptation policies should aim at linking these diverse actors with those engaged in forest conservation and management.

Adaptive forest management

Adaptive forest management for climate change is consistent with SFM (IUFRO 2009). Adaptive management involves design, management and monitoring processes and requires constant learning from the past to plan for the future (FAO 2010c).

The major goal of adaptive management is to enhance and assist resiliency, stress resistance, and dynamic response such that forests can survive under a changing climate (Bottle et al. 2009). Biodiversity conservation is an important measure to achieve this goal as more diverse ecosystem tend to be more resilient to disturbance events, such as insect outbreak. Tree species should be conserved with dispersed and viable populations in order to reduce the risk of extinction (Fischlin et al. 2007). Planting forests with mixed species rather than single species can also lead to greater biodiversity in the ecosystem (Spittlehouse & Stewart 2003).

Other adaptation strategies and practices include: changing rotation periods, salvaging dead timber, shifting to species more productive in altered climatic conditions, taking action to minimize fire and pest damage, connecting corridors and adjusting production objectives to altered wood size and quality (Spittlehouse & Stewart 2003), reducing damage to remaining trees, practicing reduced-impact logging, and employing soil conservation.

From the administrative point of view, forest managers should be allowed “freedom to fail” within an allowable extent when implementing their forest practices, as it is difficult to achieve goals in a first trial given variable environmental factors (Locatelli et al. 2008). Although there are models that can be used to predict the impacts of climate change, results are often limited to a general trend rather than detailed impacts (FAO 2010c). Therefore, forest management strategies need to be robust and diverse considering such uncertainty and the increasing disturbances under climate change. Community-based management can help to ensure the responsiveness of management plans, while monitoring can help to secure the activeness (FAO 2010c).

For example in Nepal and many Indian states, local communities have sole control over forest management and the power in policy-making processes. Community-based management has resulted in more efficient feedback from the direct stakeholders in the community and has also led to improved policies benefited from field experience (Poffenberger 2000).

Estimation of adaptation costs

Adapting to climate change involves a significant transition with far-reaching economic implications. Full economic assessments of the costs associated with adaptation allow countries to prioritize strategic measures and anticipate the associated development impacts. To date, knowledge of anticipated adaptation costs, particularly those costs specific to the forestry sector, remains highly limited and imprecise.

Since 2006, there have been only five global studies estimating climate change adaptation costs for developing countries. The estimated cost is summarized in Table 1.7.

Table 1.7 Estimate of adaptation cost (FAO (2010c))

Estimate year	Estimate by	Cost (US billion/annually)
2006	World Bank	9-41
2006	Stern Review	4-37
2007	Oxfam	50
2007	UNDP	86-109
2007	UNFCCC	27-66

Mitigation options and issues

1. Reduced emissions from deforestation

Between 1850 and 1995, 75 percent of the total carbon emissions in South and Southeast Asia were due to the clearing of forests for permanent crops. This trend is set to continue, even though deforestation rates in tropical Asia have declined since the 1990s (Houghton & Hackler 1999).

Strategies for avoiding deforestation depend upon the drivers of deforestation in each context. However, there appear to be four clear categories of mitigation strategies for avoiding deforestation (see Peskett & Harkin 2007):

- Strengthening existing policy and legislation for forest protection.
- Reclassification of land-use zones or renegotiating concessions.
- Modification of agriculture or infrastructure programmes to reduce pressure on forests.
- Implementation of economic incentives through PES, or disincentives such as taxes or fines.

2. Enhanced carbon sequestration from afforestation, reforestation and other strategies

There is a suite of strategies to create carbon sinks through forestry. Some of these strategies are:

- Afforestation: Establishment of planted forests on lands that historically have not been forested
- Reforestation: Planting of new forests on land that had tree cover recently
- Forest restoration: Restoring degraded forests through assisted or natural regeneration; protecting secondary and other degraded forests to allow them to regenerate naturally; or mechanical/infrastructural means, such as damming canals that drain peatlands.
- Forest landscape restoration: A process to regain ecological integrity and enhance human well-being in deforested or degraded landscapes withing biomes with the natural potential to support trees (WRI 2015).
- Modification of forest management practices to increase sequestration: Including prevention of fires, changing harvesting rotations and practices (e.g. reduced impact logging).
- Adoption of agroforestry practices: Increasing tree cover on agricultural or pasture lands.
- Urban forestry: Planting trees in 'vacant areas' for urban green space.
- Increasing soil carbon: Soil restoration and woodland regeneration, no-till farming, introduction of cover crops and set-asides (Lal 2004).

3. Conservation of natural forests

The majority of forest cover in the Asia-Pacific region is natural (79 percent) (Houghton 2005). However, most reported gains in forest area and condition in the region are confined to planted forests. The natural forest area decreased at a rate of 0.48 percent per year during the 1990s and by 0.50 percent per year during the 2000s, while planted forest area increased at annual rates of 2.02 percent and 2.85 percent during 1990-2000 and 2000-2010 respectively (FAO 2010c). Conservation of natural forest resources is therefore a critical component of climate change mitigation strategies in the region. Furthermore, natural forests should be of high priority as they contain more biomass than plantations or agroforestry systems: that is, natural forests

contain 250 tC/hectare versus 90-120 tC/hectare and 50 tC/hectare for agroforestry systems and plantations, respectively (Pagiola & Bosquet 2009).

4. Reduced emissions from forest degradation

Forest degradation that leads to carbon emissions in the region is significant, especially in South and Southeast Asia. Degradation results from human activities such as shifting cultivation, logging, grazing and fuelwood extraction, as well as natural causes such as forest fires and pests or diseases (Houghton & Hackler 1999, Griscom et al. 2009). Degradation can be reduced through improved forest management practices such as: fire and pest control; adoption of reduced impact logging; reduction of fuelwood collection, grazing management, etc. It is vital that degradation be addressed, not only for its impact on emissions but also for its capacity as precursor to or catalyst of deforestation (Streck et al. 2009).

5. Substitution of harvested wood products for other materials and of wood fuels for fossil fuels

Biomass energy can be used to replace fossil fuels, thereby reducing GHG emissions from fossil fuel. The avoided emissions of a biomass energy system are equal to the fossil fuels replaced minus the emissions resulting from the biomass energy system (IPCC 2000). Under such a system, fuelwood production must be carefully managed so that forests maintain a constant carbon stock. There are two main approaches to fuelwood production: sustainable harvesting of fuelwood from natural forests and commercial harvesting from intensively managed plantations. Both approaches may play a role in increasing substitution of fossil fuels with renewable fuelwood.

In addition to wood fuel, other kinds of biofuels are also being utilized to replace fossil fuels. These include palm oil (for biodiesel), sugar cane (for ethanol production), *Jatropha curcas* (biodiesel) and other crops including canola (rapeseed) and sugar beet. Emission reduction outcomes from burning biofuels are mixed, depending upon the yield of fuel as a percentage of raw product, their efficiency as fuels and the conditions under which they are produced and delivered from producer to consumer. For example, clearing land to make way for oil-palm plantations, especially on peat soils, can result in huge emissions that far exceed any gains from consumption of the resulting biofuel. Alternatively, biofuels that make use of waste biomass grown on degraded lands offer immediate, sustainable emissions reductions (Fargione et al. 2008).

Finally, using wood products to replace other materials in furniture and construction may enable carbon sequestration, although it is unclear whether this will achieve emissions reductions. Other non-wood products such as bamboo and rattan also sequester carbon and may offer greater potential (FAO 2009a).

Adaptation-mitigation synergies and trade-offs

Adaptation is defined as “adjustment in natural or human systems in response to natural or expected climatic stimuli, or the efforts which moderate harm or exploit beneficial opportunities”. Mitigation is defined as “any anthropogenic intervention to reduce sources or enhance the sinks of GHGs”. This has resulted in mitigation and adaptation being distinguished in spatial, temporal and socio-economic terms. Mitigation has been associated with globally- coordinated efforts with a focus on long-term implications, the burden of which lies

upon developed nations. Adaptation, on the other hand, concerns the immediate need for vulnerability reduction at the local level, the burden of which will mainly fall on developing and least developed nations which are least able to cope (Ayers & Huq 2009).

Synergies between adaptation and mitigation measures have recently been explored in developing countries within the Asia-Pacific region aiming to identify win-win options for climate change policy and seeking opportunities to explicitly include adaptation objectives in mitigation projects (Klein et al. 2007, Wilbanks et al. 2007). Venema and Rehman (2007) argue that synergy between mitigation and adaptation is intrinsic to the ecosystem-oriented approach articulated by the World Summit on Sustainable Development.

Synergies are most clearly evident in the LULUCF sector. Forestry, in particular, is relevant to climate change adaptation strategies, with its contribution to biodiversity conservation and livelihood resilience, and to mitigation through enhanced CO₂ sequestration (Ravindranath 2007). Agroforestry offers the highest potential for carbon sequestration among land uses identified by the IPCC, owing to the large area currently devoted or potentially available for such use. The conversion of row crops or pasture into agroforestry systems can greatly enhance stored carbon above and below ground, as well as increase farmers' economic benefit (Verchot et al. 2007).

Verchot et al. (2007) contains numerous references to community-based approaches to forest management. It is therefore no surprise to learn that some of the clearest practical linkages between adaptation and mitigation strategies have emerged in the field of community forestry. For example, since 2008, the FAO has been supporting Nepal's National Agricultural Research Council and other government bodies in a climate risk management project. A key element of the project's strategy is to explore synergy between the economic resilience and adaptive capacity that CFUGs confer on their members and their potential to contribute successfully to forest-based mitigation strategies under REDD (FAO 2009b). Many others have noted this synergy in South Asia (Karky 2009, Ravindranath 2007) and a common understanding of community forestry both as an element of REDD methodology and a local-level adaptation strategy is taking root in the region. Another adaptation policy that improves carbon sequestration is the protection and improved management of ecosystems that serve as buffers against extreme weather events, particularly coastal habitats such as wetlands and mangrove forests (World Bank 2009).

REDD is a clear example of a strategy to address climate change which combines mitigation and adaptation elements. So, although synergies do indeed exist with win-win outcomes, even these require optimal mixes of adaptation and mitigation elements. Trade-offs exist between these two sets of objectives based on a number of complex factors, such as the exhaustibility of forest resources and the conflicting needs and interests of stakeholders (Dang et al. 2003). There are also a number of instances of conflicting approaches to adaptation and mitigation. Many adaptation options, such as improved flood defenses, are known to increase energy use, hence interfering with GHG reduction efforts. Relocation of vulnerable communities, for example from low-lying coastal zones in the Mekong Delta, to currently forested areas further inland, is a central feature of Viet Nam's National Target Plan for Climate Change Adaptation. These plans, if followed through, will conflict directly with the country's strategy to implement REDD nationwide.

The IPCC concludes that there is insufficient information to ascertain whether investment in adaptation could, in effect, buy the time required for mitigation efforts to deliver results, nor what level of investment

would be required to achieve this on the global scale (Klein et al. 2007). However, Dang et al. (2003) argue that it is possible to set a national climate policy that takes into account the synergies and trade-offs between adaptation and mitigation. A proper national framework for integrating adaptation and mitigation strategies for ecosystems, resources and sectors should be the first priority for climate change policy-makers.

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Chapter 2: ClimateAP for Downscaling Historical and Future Climate Data

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AN OVERVIEW OF CLIMATEAP

Globally and regionally interpolated climate data are available from various sources and they are all in gridded format at coarse or moderate spatial resolution. Climate data obtained from these data sources represent averages over pixel tiles instead of specific locations. Therefore, the accuracy of ecological models built using these climate data might be compromised depending on the spatial resolution of the climate data. A major objective of our climate model ClimateAP is to overcome this problem.

ClimateAP is a standalone MS Windows software application that extracts and downscales gridded (4 x 4 km) monthly climate data for the reference normal period (1961-1990) from PRISM (Daly et al. 2008) and WorldClim (Hijmans et al. 2005) to scale-free point locations. The downscaling is achieved through a combination of bilinear interpolation and dynamic local elevation adjustment (Wang et al. 2017). Thus, the climate data obtained from this application are for specific locations. Meanwhile, it can also generate interpolated climate data at any desirable spatial resolutions.

ClimateAP also uses the scale-free data as a baseline to downscale historical (1901 - 2016) and future (2011 - 2100) climate variables for individual years and periods. For future climates, the application package currently includes 15 GCMs and two greenhouse emission scenarios (RCP 4.5 and RCP 8.5) for three normal periods (2011-2040, 2041-2070 and 2071-2100). Ensembles of the 15 GCMs are also available for the two scenarios and three periods. Also, monthly climate variables are included for individual years between 2011-2100. Time-series functions are available to generate climate variables for multiple locations and multiple years for historical and future periods.

ClimateAP also calculates and derives many (>200) monthly, seasonal and annual climate variables. Many of the biological relevant climate variables are particularly useful for ecological modeling. Technical details are described in Wang et al. (2017). The interface and the coverage of the application is shown in Figure 2.1 and 2.2. This training material covers the mechanism and the user guide for this application package.

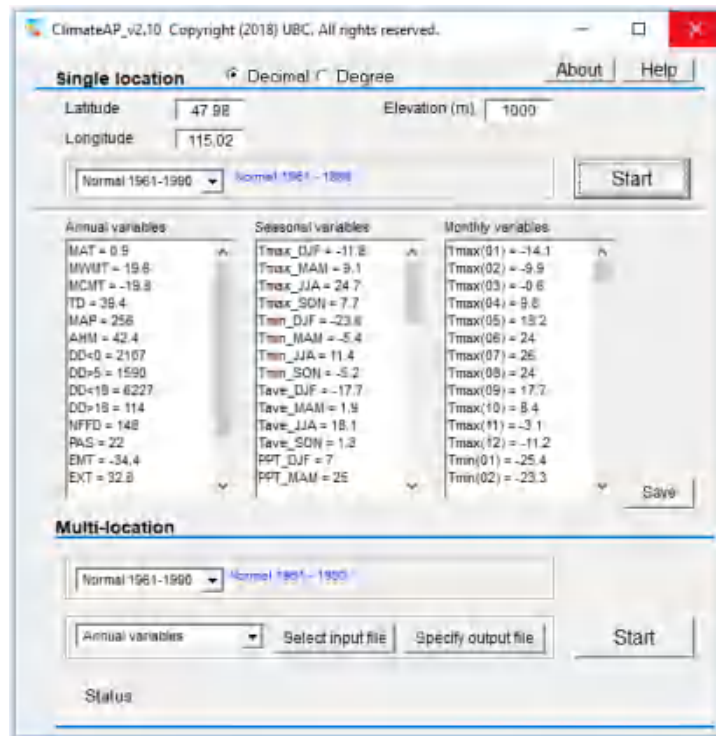


Figure 2.1 The interface of ClimateAP version 2.10

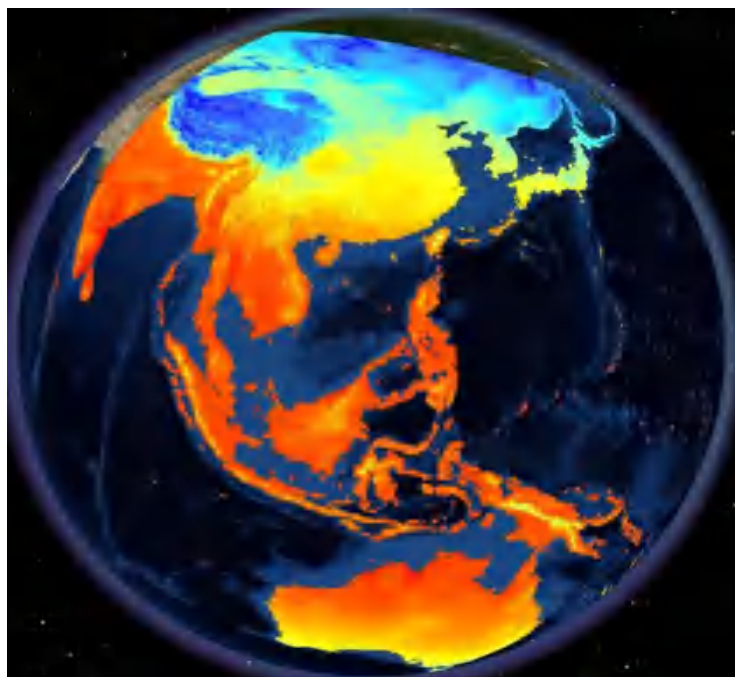


Figure 2.2 The coverage of ClimateAP.

HOW DOES IT WORK?

Baseline data

ClimateAP uses the best available 30-year-normal monthly climate data for the reference period 1961-1990 as the baseline data. The PRISM monthly data are available for China and Mongolia. The monthly climate data from WorldClim were used for the rest part of the region. The baseline climate data are at the resolution of 0.25×0.25 arcminutes (about 4×4 km). The climate variables obtained from these data sources included three primary climate variables: monthly minimum temperatures (Tmin01-12) and monthly maximum temperatures (Tmax01-12) and monthly precipitation (Pre01-12).

Downscaling

ClimateAP uses a combination of bilinear interpolation and dynamic local regression approaches to downscale the baseline monthly grid data to scale-free point data. Instead of using the midpoints (averages) of each 4×4 -km tile to all points within each tile, we used bilinear interpolation method to interpolate values between midpoints of the 4×4 -km grids as illustrated in Figure 2.3.

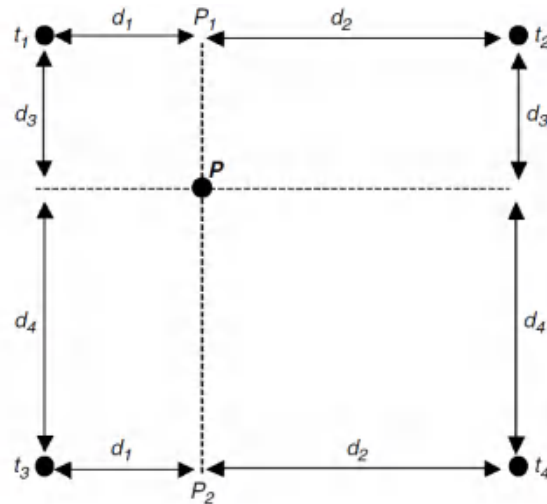


Figure 2.3 Illustration of bilinear interpolation of the baseline climate data (Wang et al. 2006)

P is the location for prediction; t_1 , t_2 , t_3 , and t_4 are the values of climate variables at the centers of the four neighboring tiles; d_1 , d_2 , d_3 , and d_4 are the relative spatial distances. P_1 and P_2 are predictions based on simple linear interpolations of the climate variable values t_1 and t_2 , and t_3 and t_4 , respectively, and the prediction for P is the simple linear interpolation between P_1 and P_2 . 36

After the grid data, including elevation, are interpolated into continuous surfaces, we applied dynamic local regression to estimate lapse rates for the location of interest to account for elevational effects. ClimateAP retrieves monthly climate data and elevation values from 9 closest neighbors and calculates differences in climate variables and elevation between all 36 possible pairs. A simple linear regression of the differences in a climate variable on the difference in elevation allows the estimation of the lapse rate for the climate variable. A lapse rate is estimated for each of the 36 monthly primary climate variables. Figure 2.4 shows the relationships between the differences in temperature and precipitation and the differences in elevation. The

dynamic local linear regressions can explain a majority of climate variation at a local scale. It can even capture temperature inversion along an elevational gradient for winter months (Figure 2.4a).

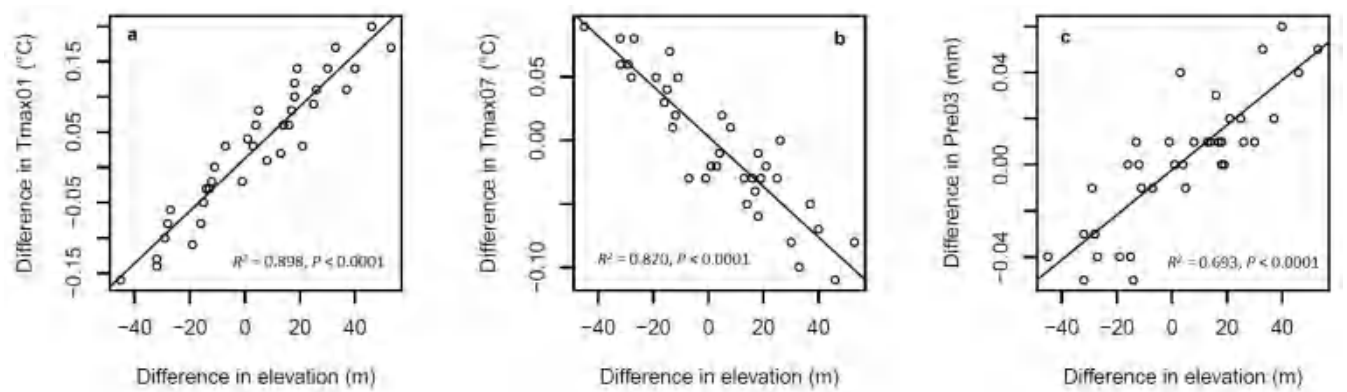


Figure 2.4 Relationships between the differences in maximum temperature in January (a) and July (b), and precipitation in March (c), and the differences in elevation.

The effect of the downscaling can be visualized in Figure 2.5. The limitation of the relatively low resolution of the grid data and power of the downscaling approach applied in ClimateAP can be clearly seen on the map.

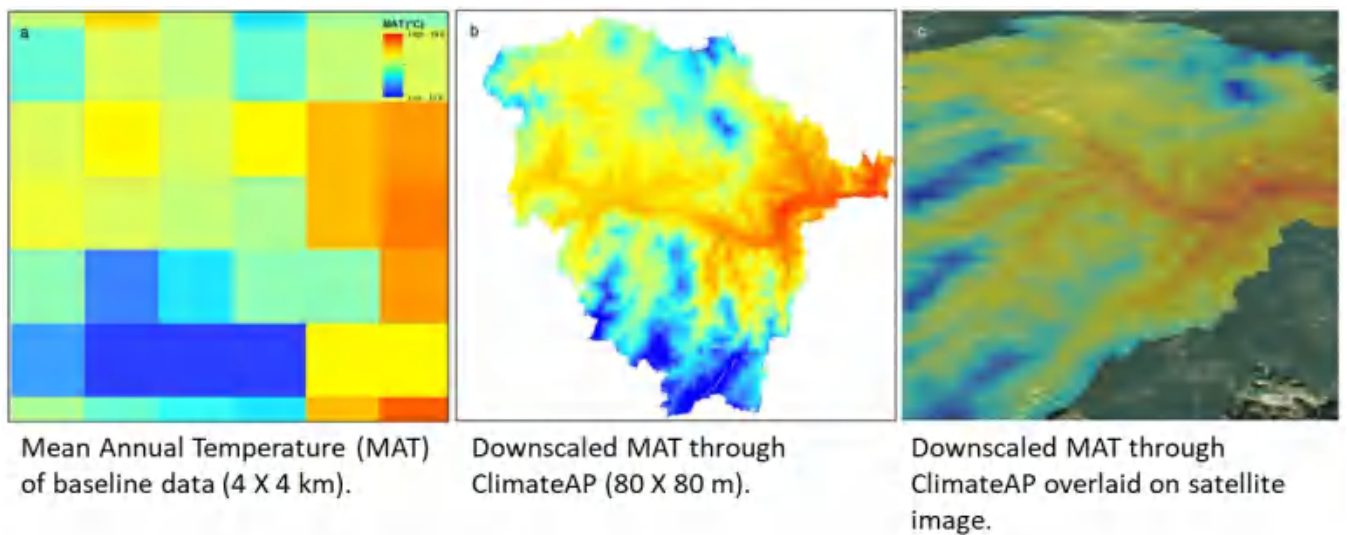


Figure 2.5 Illustration of the effect of downscaling approach applied in ClimateAP shown on the maps. a) mean annual temperature (MAT) of the baseline data at 4 x 4 km; b) downscaled MAT through ClimateAP (80 x 80 m); c) downscaled MAT (80 x 80 m) by ClimateAP

Calculated climate variables

The baseline data contain 36 primary monthly climate variables including monthly maximum (Tmax01-12) and minimum (Tmin01-12) temperatures and precipitation (PPT01-12). ClimateAP calculates many additional climate variables (Table 2.1) at run-time based on these primary climate variables.

Table 2.1 Climate variables directly calculated based on the 36 primary climate variables included in the baseline data.

Variable category	Variable short name	Variable long name
Annual	MAT	Mean annual temperature
	MWMT	Mean warmest month temperature
	MCMT	Mean coldest month temperature
	TD	Continentality, temperature difference between MWMT and MCMT
	MAP	Mean annual precipitation
	AHM	Annual heat-moisture index $(MAT+10)/(MAP/1000)$
Seasonal	Tmax_DJF – SON	Tmax for December to February, and so on
	Tmin_DJF – SON	Tmin for December to February, and so on
	Tave_DJF – SON	Tave for December to February, and so on
	PPT_DJF – SON	PPT for December to February, and so on
Monthly	Tave01-12	Monthly average temperatures

Derived climate variables

In addition to the primary climate variables included in the baseline data, directly calculated variables using the primary variables, ClimateAP also derives many biologically relevant climate variables from monthly climate variables, such degree-days, and number of frost-free days, extreme temperatures and moisture deficit. Daily climate data are required for calculations of these climate variables. However, daily data are not available in ClimateAP or other interpolated climate data. We developed functions based on the relationships between these climate variables calculated from weather station data and the monthly climate variables from the same weather stations.

In order to model these relationships, we obtained daily climate data from 1,805 weather stations in Asia Pacific region. The distribution of the weather stations is shown in Figure 2.6.

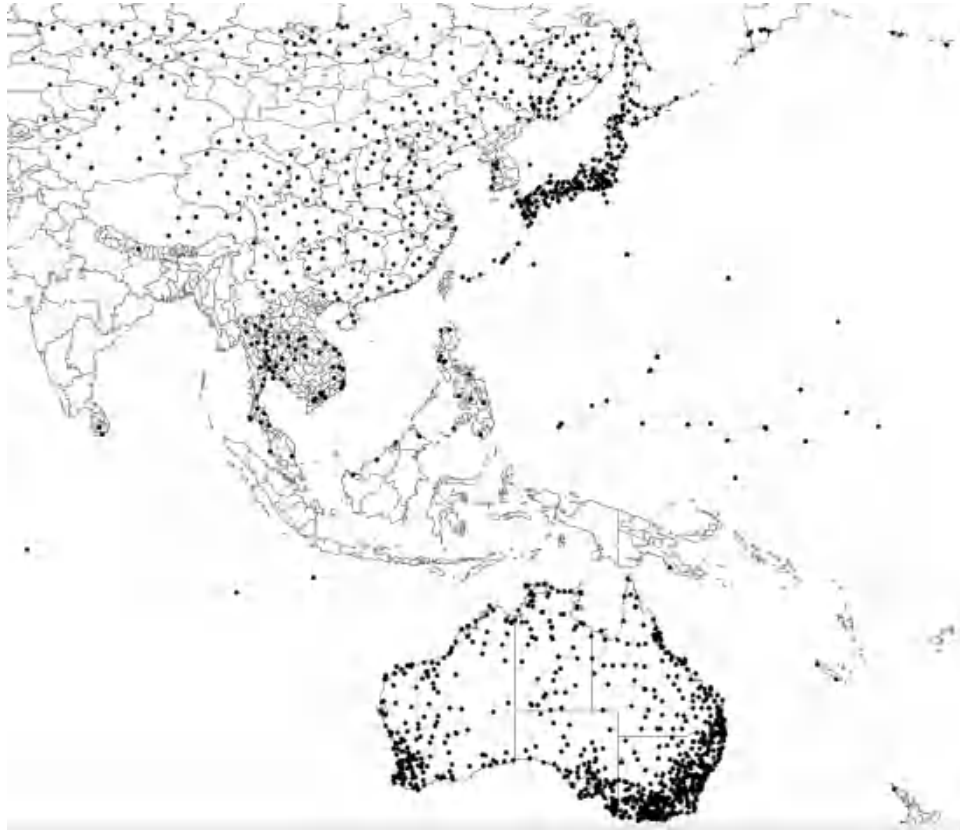


Figure 2.6 The distribution of weather stations that were used to derive the relationships between biologically relevant climate variables and monthly climate variables

Due to the wide range of variation in climate variables in the Asia Pacific region, no single linear, polynomial or nonlinear function can reflect such relationships for most of these climate variables. Thus, we applied piecewise functions, which are combinations of a linear function and a sigma nonlinear function, to model these relationships. Some of these relationships are demonstrated in Figure 2.7.

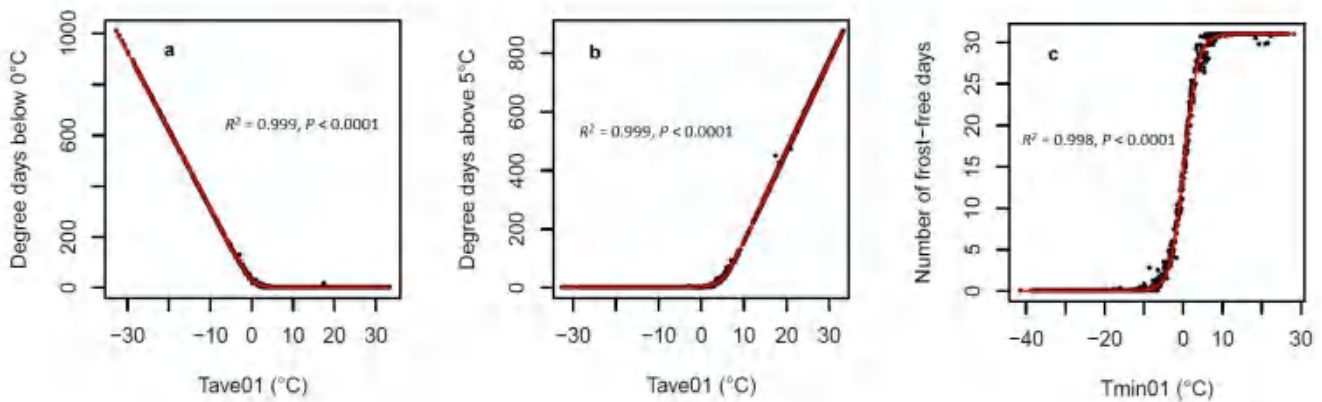


Figure 2.7 Relationships between derived monthly climate variables and monthly climate variables for degree-day below 0°C, degree-day above 5°C and number of frost-free days in January.

Derived climate variables generated by ClimateAP includes climate variable at annual, seasonal and monthly time scales (Table 2.2). Two of these variables are not based on the relationships modeled from weather station data. They are Hargreaves reference evaporation and Hargreaves climatic moisture deficit (Wang et al. 2012).

Table 2.2 Annual climate variables derived based on relationships between calculated climate variables from daily data and primary monthly climate variables based on observation from weather stations.

Variable category	Variable short name	Variable long name
Annual	DD<0 (DD_0)	Degree-days below 0°C, chilling degree-days
	DD>5 (DD5)	degree-days above 5°C, growing degree-days
	DD<18 (DD_18)	degree-days below 18°C, heating degree-days
	DD>18 (DD18)	degree-days above 18°C, cooling degree-days
	NFFD	the number of frost-free days
	PAS	Precipitation as snow (mm)
	EMT	Extreme minimum temperature over 30 years.
	EXT	Extreme minimum temperature over 30 years.
	Eref	Hargreaves reference evaporation
	CMD	Hargreaves climatic moisture deficit

Climate variables for historical years and future periods

Monthly temperature and precipitation data for 1901-2016 used in ClimateAP are based on Mitchell and Jones's (2005) interpolated historical data at 0.5 x 0.5° resolution (CRU TS 3.22). This will be updated to most recent years in the project phase II. Temperature was expressed as a difference in degrees Celsius, and the delta surfaces for precipitation were calculated as percentage difference from the 1961-1990 normal values, e.g. -50% represents half and 200% twice the normal precipitation value for a particular month.

For future climate, the monthly temperature and precipitation data for future periods were from General Circulation Models (GCMs) of the Climate Model Intercomparison Project 5 (CMIP5) corresponding to the Fifth Assessment Report of the Intergovernmental Panel for Climate Change (IPCC, 2014). Fifteen GCMs were selected from all major clusters of similar AOGCMs. Two greenhouse gas concentration trajectories or Representative Concentration Pathways (RCP) are included including RCP 4.5 and RCP 8.5. RCP 4.5 is closest to the target of Paris Agreement in 2016 and assumes emissions peak in the 2040s and then decline. RCP 8.5 assumes that emissions continue to increase throughout the century. When multiple runs were available for each GCM, an ensemble average was taken over the available (up to five) runs. Monthly GCM projections into 30-year time periods referred to as 2020s (2011-2040), 2050s (2041-2070), and 2080s (2071-2100).

In order to reflect the annual variability and extreme climatic conditions, future monthly data were included for individual years from 2011 to 2100 from three widely used GCMs for the two RCPs. As for the

historical data, future monthly values were converted into anomalies relative to the 1961-1990 normals for the purpose of downscaling using the delta approach described below.

ClimateAP integrates both historical and future climate data with a delta method. Anomaly grids are interpolated using bilinear interpolation in run-time to avoid step-artifacts at grid boundaries, and the difference is added to the downscaled baseline climate normal data (scale- free) to arrive at the final climate surface with high-resolution (Figure 2.8).

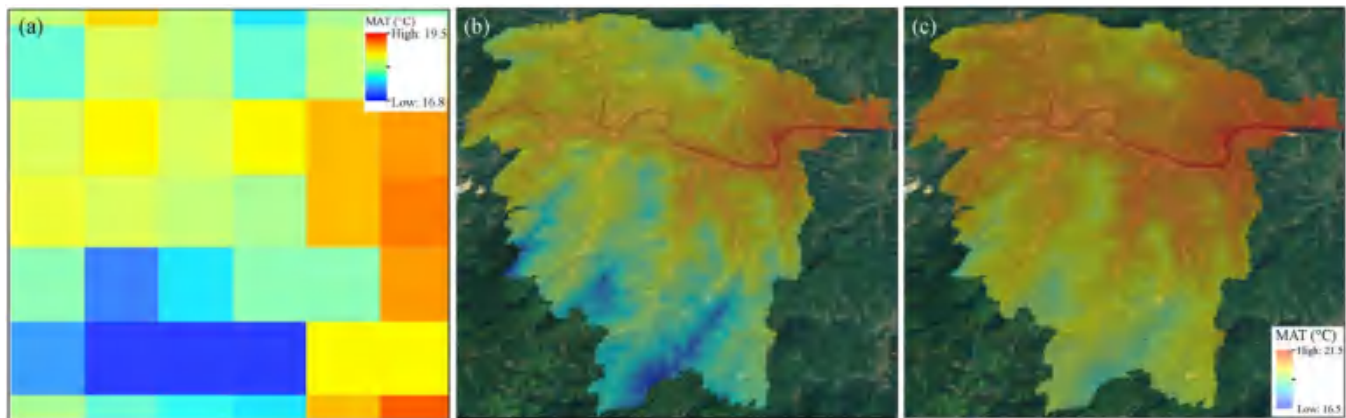


Figure 2.8 Illustration of the effectiveness of the local downscaling applied in ClimateAP shown in a mountainous area in Fujian Province (117.50° E and 26.52° N). (a) Mean annual temperature (MAT) of the baseline data at 4 km 4 km; (b) downscaled MAT (90 m 90 m) by ClimateAP and overlaid on a satellite geographic image for the reference period; (c) downscaled future MAT for the period of 2041–2070 based on the 15 GCMs' ensemble for the RCP 4.5.

With this approach, the original baseline data (absolute values for 1961-1990 normal period) of the historical data and future projections are replaced by scale-free climate data generated by ClimateAP and improve the prediction accuracy.

Improvements of ClimateAP output for historical and future climate data over the original CRU and GCM data for the baseline data is shown in Figure 2.9. On average over the 1805 weather stations tested, the prediction standard errors were reduced by 0.5°C for monthly minimum temperatures, 0.8°C for monthly maximum temperatures, 21mm for monthly precipitation. The amount of improvement was even greater as expected; it was up to 2°C for monthly temperatures and 35mm for monthly precipitation on average. For example, we found in our previous study that the error in mean annual temperature associated with the baseline climate data is 6°C at the Vancouver International Airport (Figure 2.10).

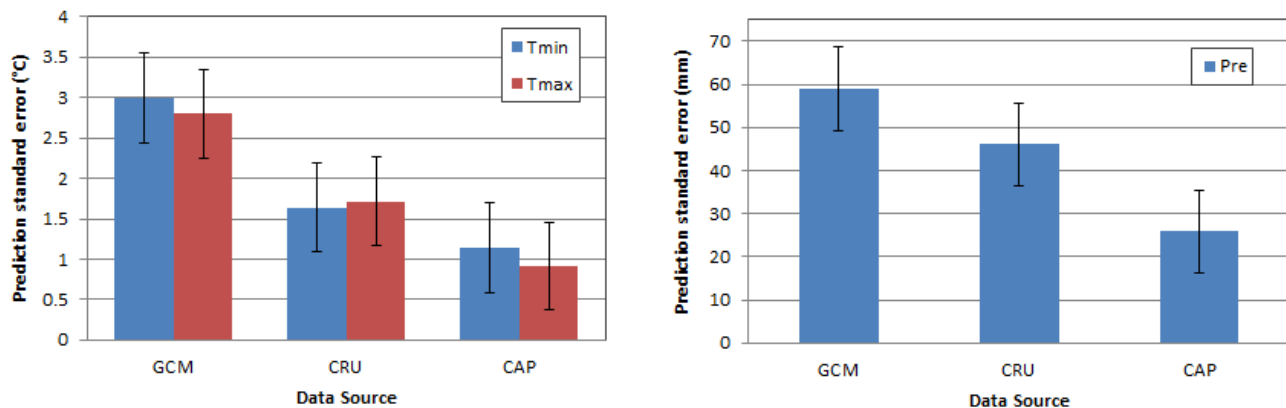


Figure 2.9 Comparisons in prediction standard errors among three data sources: IPCC GCM predictions (GCM), Climate Research Unit (CRU) and ClimateAP output (CAP).

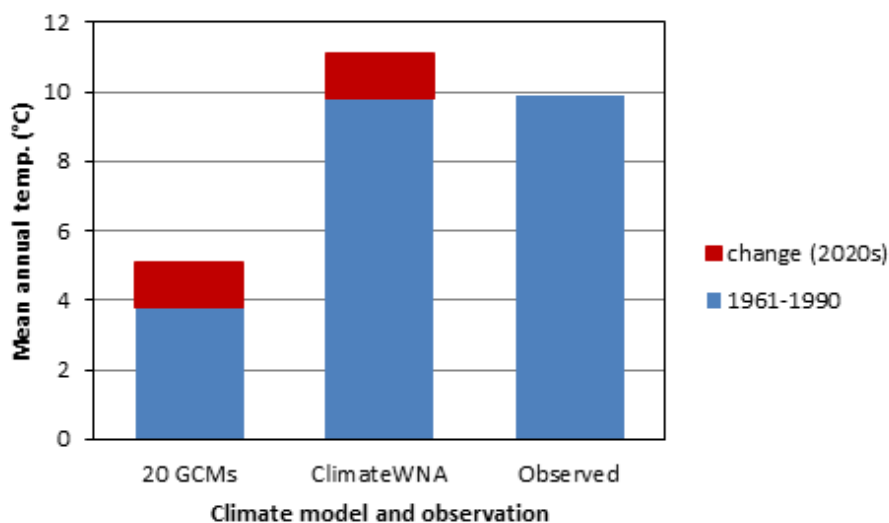


Figure 2.10 Illustration of ClimateAP downscaling method for GCM projections by removing errors in mean annual temperature associated with baseline climate data. Data shown are from a previous study using ClimateWNA that applied the same delta approach as ClimateAP.

USER GUIDE

Installation

The installation of ClimateAP is very simple because it does not require installation process. That is why we stick with Visual Basic 6 instead of the new version of VB.NET. Users need simply copy two files ("ClimateAP_v2.11.exe" and "Help.rtf") and three subfolders ("prismdat", "perioddat", "GCMdat") into the same location on your hard disk and double click the file ClimateAP_v2.11.exe". The program can run from USB drive, but it does not work properly on network drives.

Interactive mode

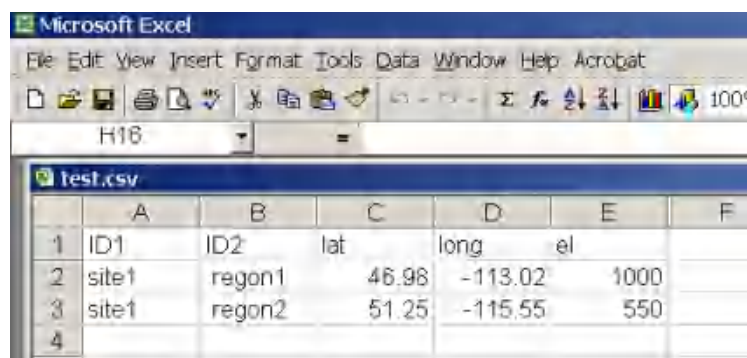
It is easier to use the interactive mode for a single location or a small number of locations. The users just need to input the latitude, longitude and elevation (optional), and click the “Start” button. Options are available for latitude and longitude input in either decimal degree or degree-minute-second. If elevation is missing, the elevation in the baseline data will be used and no elevational adjustment will be performed. A drop-down box is for choosing the targeted period.

By clicking the “Start” button, climate variables for all the three time scales (annual, seasonal and monthly) will be displayed on the screen. The output can be copy and passed to a file. It can also be saved to a Comma-separated-value (csv) file by clicking the “Save button”.

Multi-location mode

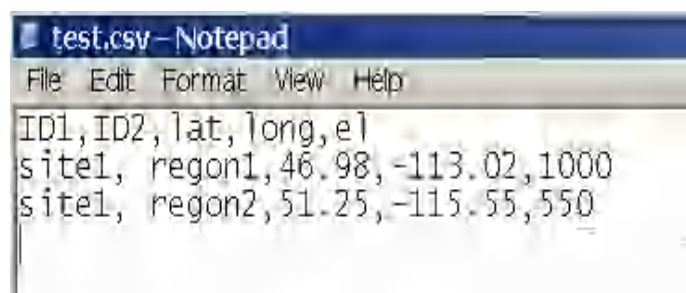
It is much more efficient to use the Multi-location mode to process multiple locations than to use the Interactive mode. The program does not have an upper limit for the number of locations to be processed. In order to use the Multi-location mode, a coordinate input file needs to be prepared.

The input file requires two columns of IDs, latitude and longitude in decimal degree, and elevation in meter. A header row is also required. It can be prepared in MS Excel,



	A	B	C	D	E	F
1	ID1	ID2	lat	long	el	
2	site1	regon1	46.98	-113.02	1000	
3	site1	regon2	51.25	-115.55	550	
4						

or in any text editor:



```
test.csv - Notepad
File Edit Format View Help
ID1,ID2,lat,long,el
site1,regon1,46.98,-113.02,1000
site1,regon2,51.25,-115.55,550
```

If the input file is prepared in Excel, it needs to be saved in CSV format. If it is prepared in a text editor, the columns have to be separated by commas.

When the input file is ready, users can select a target year or a period, then click on **Select input file** to read your spreadsheet and on **Specify output file** to specify your output file folder and file. By clicking the **Calculate** button, output climate variables will be generated.

Time-series functions

ClimateAP has two time-series functions, one for historical years and another for future years. The historical and future time-series functions in ClimateAP enable users to obtain climate data time-series for multiple locations by a few clicks (Figure 2.11).

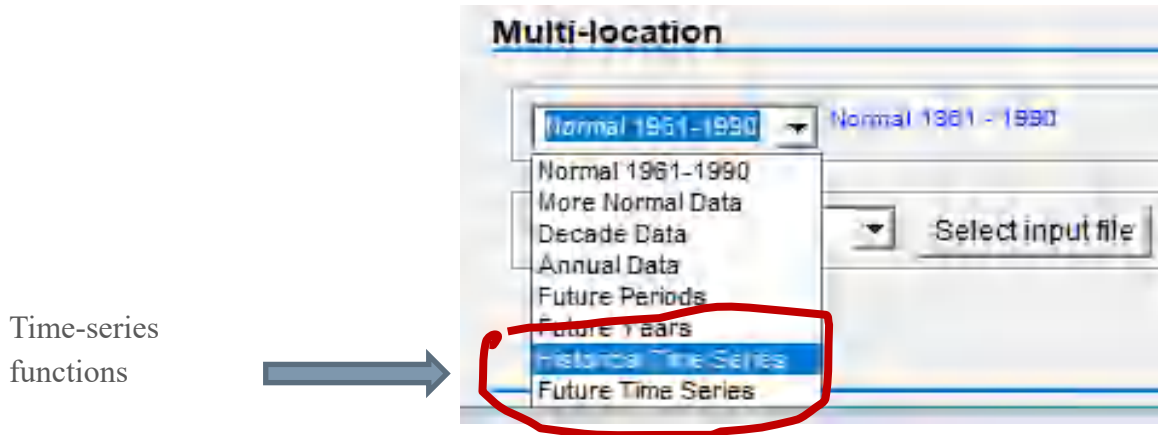


Figure 2.11 Time-series functions of ClimateAP.

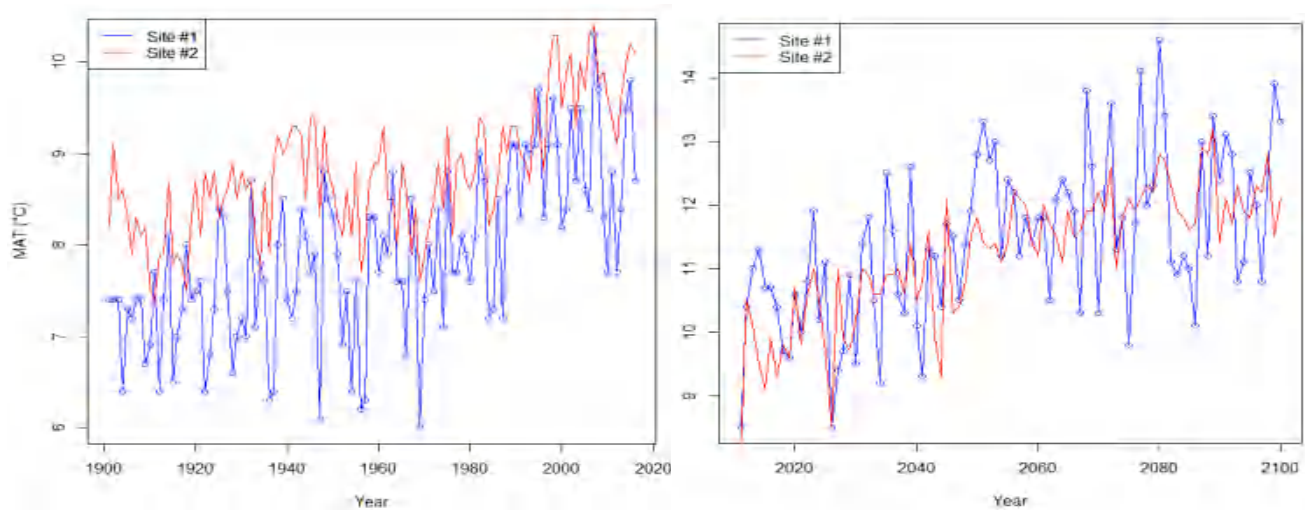


Figure 2.12 Climate time-series for a historical (left) and future (right) periods for two site locations.

APPLICATIONS

1. ClimateAP makes our access to climate variables as easy as to geographic variables. Climate is the primary factor regulating the geographic distributions of forest ecosystems and tree species (Woodward 1987, McKenney et al. 2007). It is also the main driver affecting the health and productivity of trees and other plants. Due to the difficulty in accessing climate data, research

scientists have been using geographic variables, such as latitude, longitudes and elevation, as substitutes to climate variables for experimental design and data analysis. However, results obtained from such studies are limited to specific locations. For example, a relationship developed between the performance of a plant and elevation gradient in Kunming, China will not be valid in Beijing. This is because the effect of elevation on climate is very different between the south and north. In contrast, a relationship between the performance of a plant and climate variables will be applicable to anywhere. In addition, a relationship with geographic variables will not be useful for predicting the impact of climate change.

Climatically based experiments are more effective than geographically based in most cases. This is because the effect of climate on tree health and productivity is more direct than that of geographic variables. A typical example is the experimental design of the Lodgepole pine provenance trial in British Columbia. It has 60 test sites in the province and well represents the geographic distribution of this species. However, when plot the test sites against the mean annual temperature (MAT), the most important climate variable for this species, we found that the majority of the tests are located in a very narrow range of MAT and are redundant (Figure 2.11). A climatically based experimental design would save 60-70% of the cost.

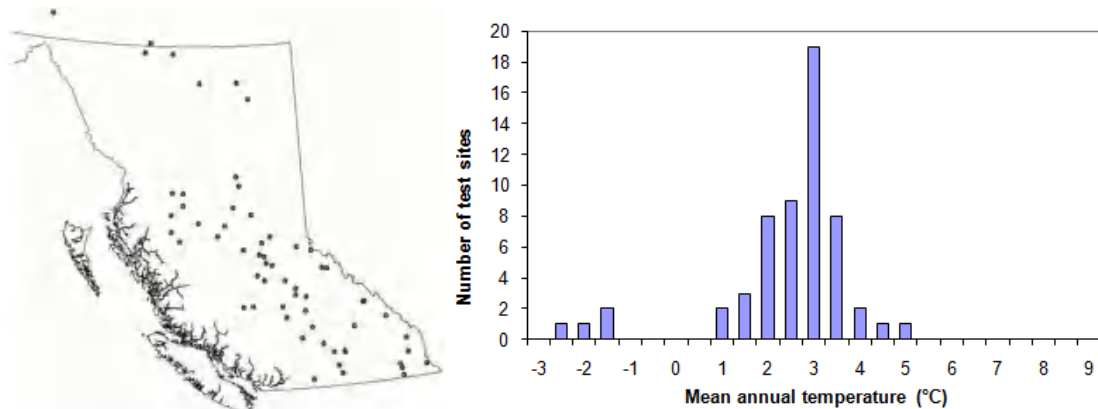


Figure 2.13 Geographic (left) and climatic (right) distributions of planting sites of the provenance test in British Columbia.

2. ClimateAP allows users to generate climate surfaces at any spatial resolutions. The output of ClimateAP is in the format of spreadsheet file. It can easily be imported to ArcGIS to generate maps. The resolution of the map depends on the resolution of the input file, which means that it is up to the user to determine the resolution of the climate surface.

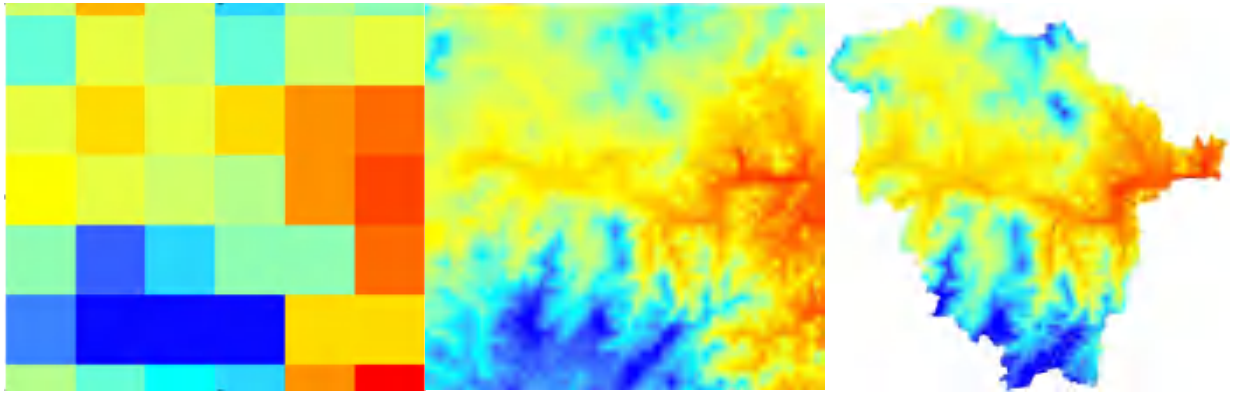


Figure 2.14 Illustration of ClimateAP output at three different spatial resolutions (4 x 4 km, 90 x 90 m and 25 x 25 m).

3. Modelling climate niches for ecosystems and species. Such modelling exercises require climate data to be as close as to the actual locations of the vegetation data. The scale-free climate data generated by ClimateAP can best meet this requirement than any of the currently available climate data sources. More details can be found in the next section.

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Chapter 3: Climate Niche Modelling for Forest Ecosystems and Tree Species

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AN OVERVIEW CLIMATE NICHE MODELLING

Unprecedented rapid climate change is causing a mismatch between the climate that a plant species is historically adapted to and the climate that the species will experience in the future. Such a mismatch may compromise productivity and increase vulnerability of the species and its residing ecosystems. Climate niche models, alternatively known as ecological niche models, bioclimate envelope models or species distribution models, have been widely used to predict the geographic distribution of climate niche (or the range of the suitable climate conditions) of a species for historical and future climates. This information can be used to assess the impact of climate change and to develop adaptive strategies for species and ecosystems including species selection and assisted migration. However, the credibility of a climate niche model depends on many factors including: 1) the accuracy of climate data; 2) the quality of species occurrence data; 3) modeling methodologies; and 4) the interpretation of the model predictions. For climate data in particular, using different sources climate data to build climate niche models may considerably affect the model accuracy.

A climate niche model can be built at species level or forest type (or forest ecosystem or vegetation type) level. There are pros and cons for a climate niche model built at each of these levels. Both of them are covered in this material.

BIOCLIMATIC MODELING FOR FOREST TREE SPECIES

When an individual tree species is concerned in term of adaptation and conservation under a changing climate, it is straightforward to build a climate niche model and make projections for the species. The general approach of building a climate niche model for a species requires the following three elements: 1) georeferenced localities for the species in question (i.e., localities where a species has been collected and for which latitude and longitude coordinates are available); 2) climatic variables at each site; and 3) algorithms that estimate the climatic niche envelope of these species on the basis of the distribution of climatic variables where they occur and do not occur within a region. The most widely used modeling algorithm is MaxEnt as it powerful and requires presence data only, while the most accurate one is Random Forest that requires both presence and absence data. Both of them are machine-learning based algorithms. We have been only using Random Forest for the best credibility of the model predictions. Still, if not well optimized, Random Forest models can also produce misleading predictions. I used Chinese fir as an example to demonstrate building a climate niche model using Random Forest.

Presence and absence data

Presence-absence observations for Chinese fir were obtained from the digital version of Vegetation Map of China. First, a shape file of the distribution for this species was generated from polygons with the species present. The shape file was then rasterized at the spatial resolution of 0.008333 arc minute (approximately 1 km). Each data point (i.e., a raster pixel) within a polygon of presence was assigned as presence of the species. Similarly, a data point within a polygon of absence was assigned as absence within the range of the species distribution and expanded by 200 km in each of the four directions if possible following Barbet-Massin et al. (2012). Due to a long history of anthropogenic disturbances to forests in China the current distributions of the species are likely to be underestimated. Thus, some of the absence data points were assumed to be false absences. An adjustment was applied to our modeling process to address this consideration (details in Wang et al. 2016).

Climate data

ClimateAP (version 2.11) (Wang et al. 2017) was used to generate climate data. An input file containing point location coordinates (latitude, longitude, and elevation) for each rasterized grid cell was queried by ClimateAP to generate 66 annual and seasonal climate variables for the point locations. Climate variables for the reference period 1961-1990 and future periods were obtained for each data points in the training datasets using ClimateAP.

Random Forest model building

We used the R version (Liaw and Wiener 2002) of Breiman's (2001) of the Random Forests (RF) algorithm to model relationships between climate for the reference period and the geographic distribution of forest types in China. RF produces many classification trees, collectively called a 'forest', and aggregates the results over all trees. Each of these decision trees in the forest is constructed using a bootstrap sample of the input data (i.e., a random sample with replacement) so that the resulting dataset ('bagged sample') contains about 64% of the original observations, and the remaining observations comprise the 'out-of-bag' (OOB) sample. Tree nodes (bifurcations in a branch) are created using the climate predictor variable that has the smallest classification error among a randomly selected subset of predictor variables. By default, the number of predictors randomly selected at each node is the square root of the total number of predictors. Using the trees grown with the bootstrap sample, each of the independent observations in the OOB sample is classified (assigned to an ecosystem) and a model prediction error, called the OOB error (% of incorrectly classed observations), is calculated.

To build a Random Forest niche model, it is better to keep the presence and absence samples balanced. By simply making the samples equal between these two categories do not work well in most cases because climate conditions in the areas for the absent category are more heterogeneous and need a larger sample to represent it. We applied a "multiple- forests" approach to solve this problem. With the multiple-forests approach, a balanced sample dataset was constructed for each of 10 Random Forests. Among the 10 training datasets, the *present* data points were identical, but the data points for the *absent* data points were randomly sampled. Using this approach, balanced datasets satisfy the Random Forest requirements, while the repeated random sampling of the area for absent improves the representation of the heterogeneous climate conditions

for this category. Predictions of the 10 Random Forest models (or sub-models) were aggregated for the final model output.

A backward optimization approach was applied to eliminate the least important climate variable through each model run as Random Forest provides an importance value for each climate variable. This process was iterated until the best fit of the model was achieved, from which the best combination of climate variables can be identified. The identified climate variables were then used in each of the 10 sub-models. The final model prediction was based on the consensus of among the 10 sub-models.

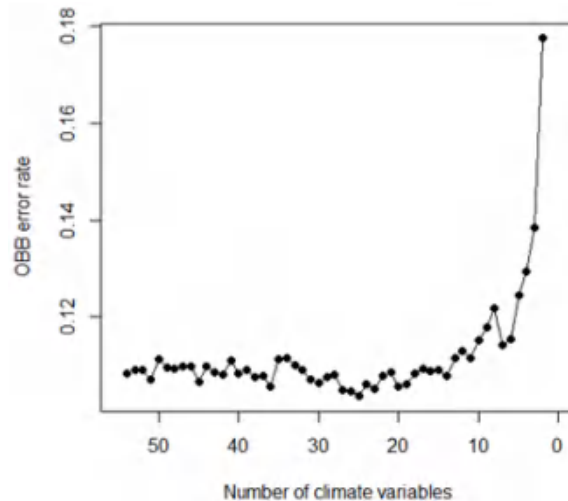


Figure 3.1 Changes in error rate of RF model prediction for out-of-box (OOB) samples with the least importance climate variable removed step by step.

Model prediction and projections

After the Random Forest model was built, it was used predict the current distribution and to compare with observed presence data (Figure 3.2a). For the future period, gridded climate data were generated using ClimateAP for 12 climate change scenarios including six AR5 GCMs and 2 emission scenarios (RCP4.5 and RCP8.5). The six GCMs include ACCESS1-3, BCC-CSM1, CanESM2, CNRM-CM5, CSIRO-Mk3-6-0, and HadGEM2-ES. A projection was generated using the species climate niche model for each of the 12 climate change scenario. A consensus projection was then produced using the 12 projections for each future period. Model predictions for current and the three future periods are shown in Figure 3.2.

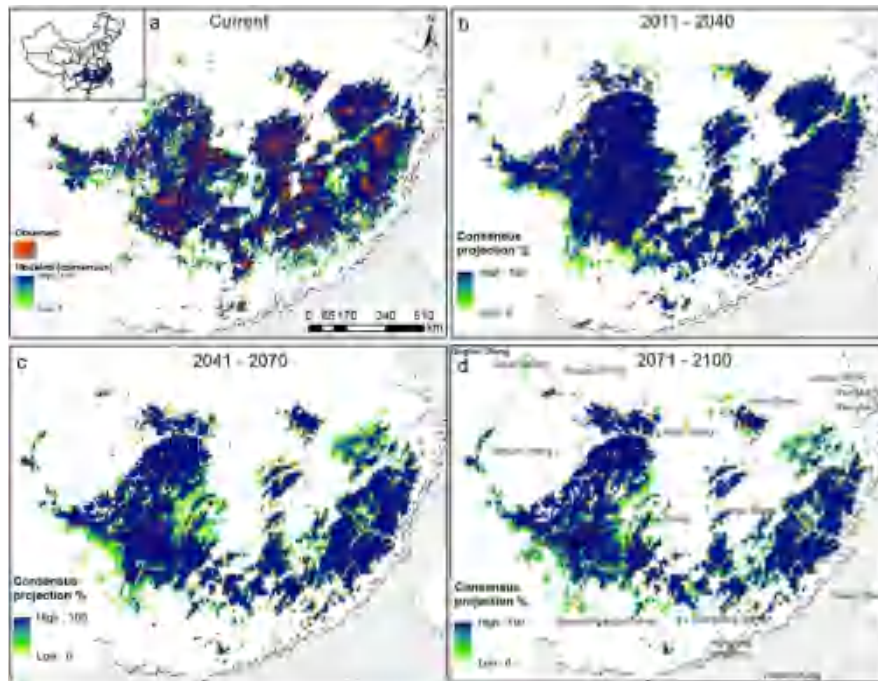


Figure 3.2 Projected shifts in climate niches for Chinese fir: a) current geographic distribution; b) projected climate niche suitable for this species in 2050s based consensus projections.

CLIMATE NICHE MODELLING FOR FOREST ECOSYSTEMS

Building a climate niche model is not always feasible or efficient in some cases. Presence-absence data are often not available for a tree species. Even there are such data for a species, it is still difficult to build a credible niche model if the species has a very limited the distribution. In tropical or sub-tropical regions, the number of tree species is large; it is not effective to develop climate niche models for individual species. In addition, ecological land classification systems are often used for natural resource management. For example, in British Columbia (BC), Canada, the ecosystem classification system, called Biogeoclimatic Ecosystem Classification (BEC) (Meidinger and Pojar 1991), has been served as a fundamental for resource management planning and decision-making in. A climate niche model and its projections for the BEC system have been widely used in forest resource management for adaptation to climate change (Wang et al. 2012).

When a climate niche model is built for a forest ecosystem, it is possible to associate the components (individual species) of a forest ecotype as a whole and make projections for future climates. Thus, building niche models at forest type or ecosystem level can be more feasible and effective for some occasions. In this project, we have developed climate niche models for forest types in China, Chinese Taipei, Malaysia and Myanmar. In this material, we used vegetation types in China to demonstrate the model building process. Figure 3.3 shows the 56 vegetation types and spatial climate data in China including Chinese Taipei.

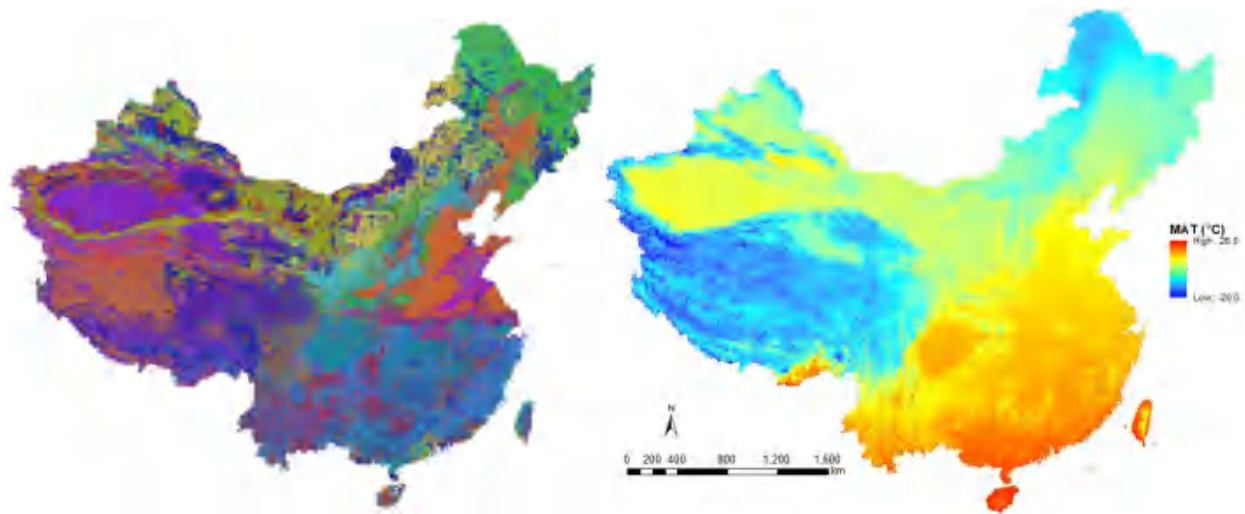


Figure 3.3 Maps of vegetation types (a) and spatial climate data (mean annual temperature) (b) in China.

Ecosystem data

The digital map (a shape file) of the vegetation types were obtained from the digital version of Vegetation Map of China. The shape file was rasterized to grid resolutions of 800 m in ArcGIS (version 10.2) for model building and model validation, respectively. Each grid was assigned to a forest type occurring at the center of each cell.

Climate data

ClimateAP (version 2.11) (Wang et al. 2017) was used to generate climate data as mentioned above. The climate data were generated for sample locations for model building and for all pixels across China to generate prediction maps. The spatial climate data were generated for the reference period (1961-1990) for modelled vegetation types and for the three future periods (2020s, 2050s and 2080s) to project for future climates.

Model building

We also used Random Forest to build climate niche model for vegetation ecotypes as we did for individual tree species. The only difference is that there are only two class for individual tree species, presence vs. absence, while there are multiple classes for vegetation types. Random Forest can handle a large number of classes.

As for individual tree species, each sample data point has the same contribution to the model. Therefore, the model is more weighted by the classes with a large number of sample data points. A sampling strategy is often needed to balance the sample size among the classes. We used a proportional sampling strategy to deal with this issue, in which larger proportions (or even all) of sample points are sampled for smaller classes and smaller proportions of sample points are used for larger classes. The sampling strategy applied in this modelling process is described in Wang et al. (2012).

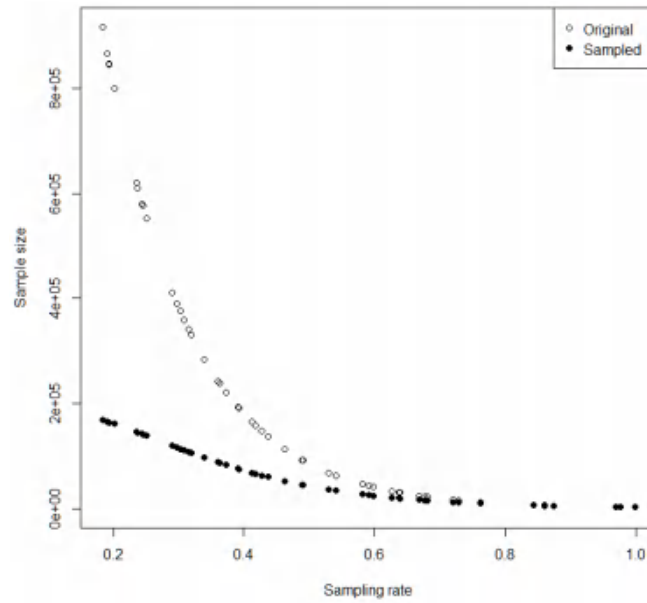


Figure 3.4 Illustration of the proportional sampling strategy. The sample size represents the number of sample points in a forest type class.

The final RF model was built with balanced sample dataset. The process for selection of climate variables and model optimization were the same as for individual species.

Model prediction

Model predictions were made for each pixel tiles across the entire country for the reference period 1961-1990 to represent the modeled distribution of forest types in China. The modeled spatial distributions were compared to the original map (Figure 3.5). Although the rate of mismatches was relatively large, the modeled spatial distributions of the forest types matched well to the original ones. Since the vegetation types are not well defined, our modelled ones might be more accurate in reflecting the reality than the currently mapped based on our experience.

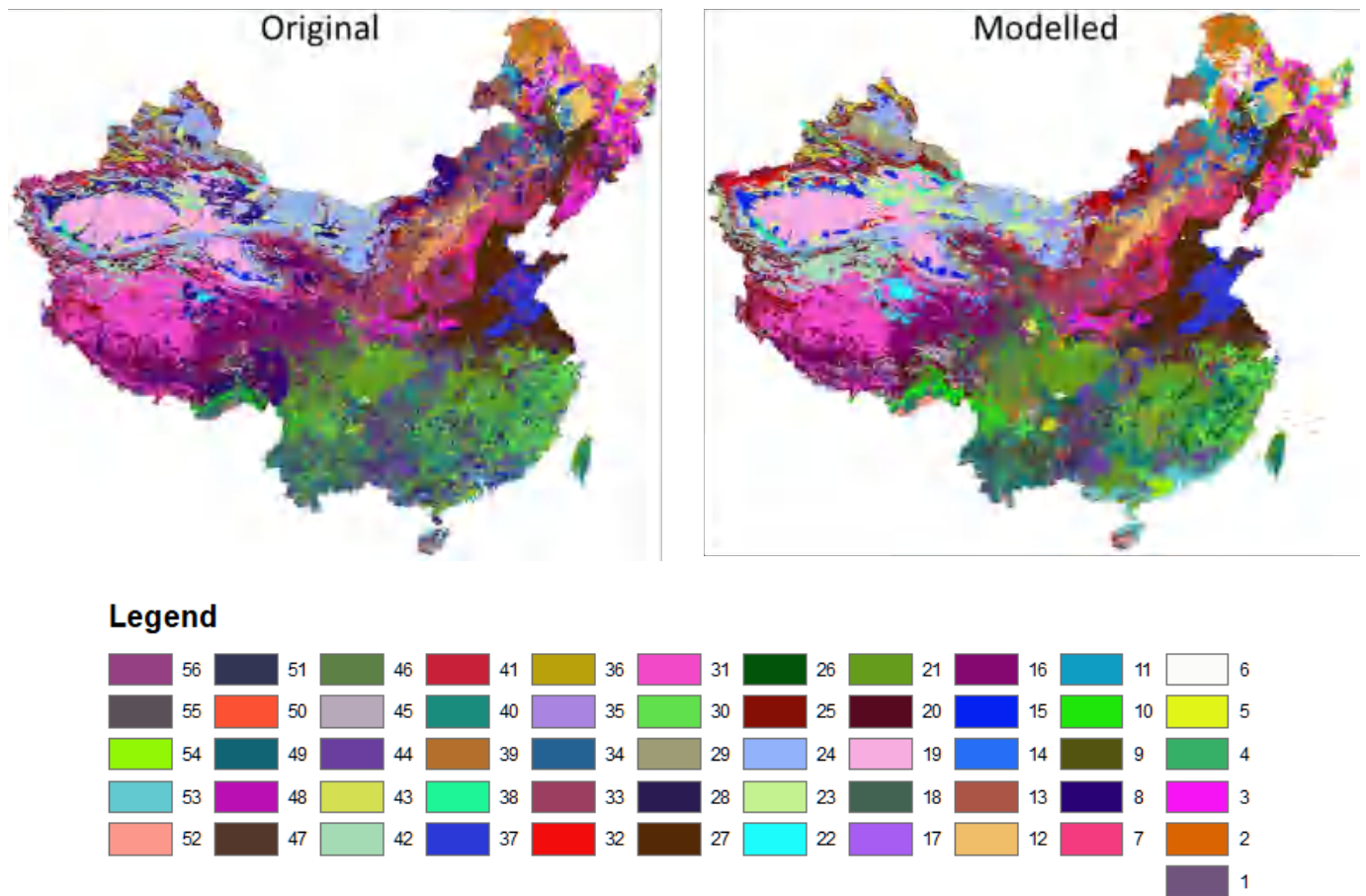


Figure 3.5 Comparisons between currently mapped vegetation types (left) and predicted ones (right) in China. Vegetation types are listed in Appendix I.

Future projections

We used the ensembles of 15 GCMs for RCP 4.5 (in agreement to the Paris Agreement) to represent the future climates for the three periods 2011-2040, 2041-2070 and 2071-2100. The procedure for the future projections was the same for the prediction for the reference period. The outputs of the projections were imported into ArcGIS (version 10.2) to produce the maps showing the shifts among the vegetation types in Figure 3.6.

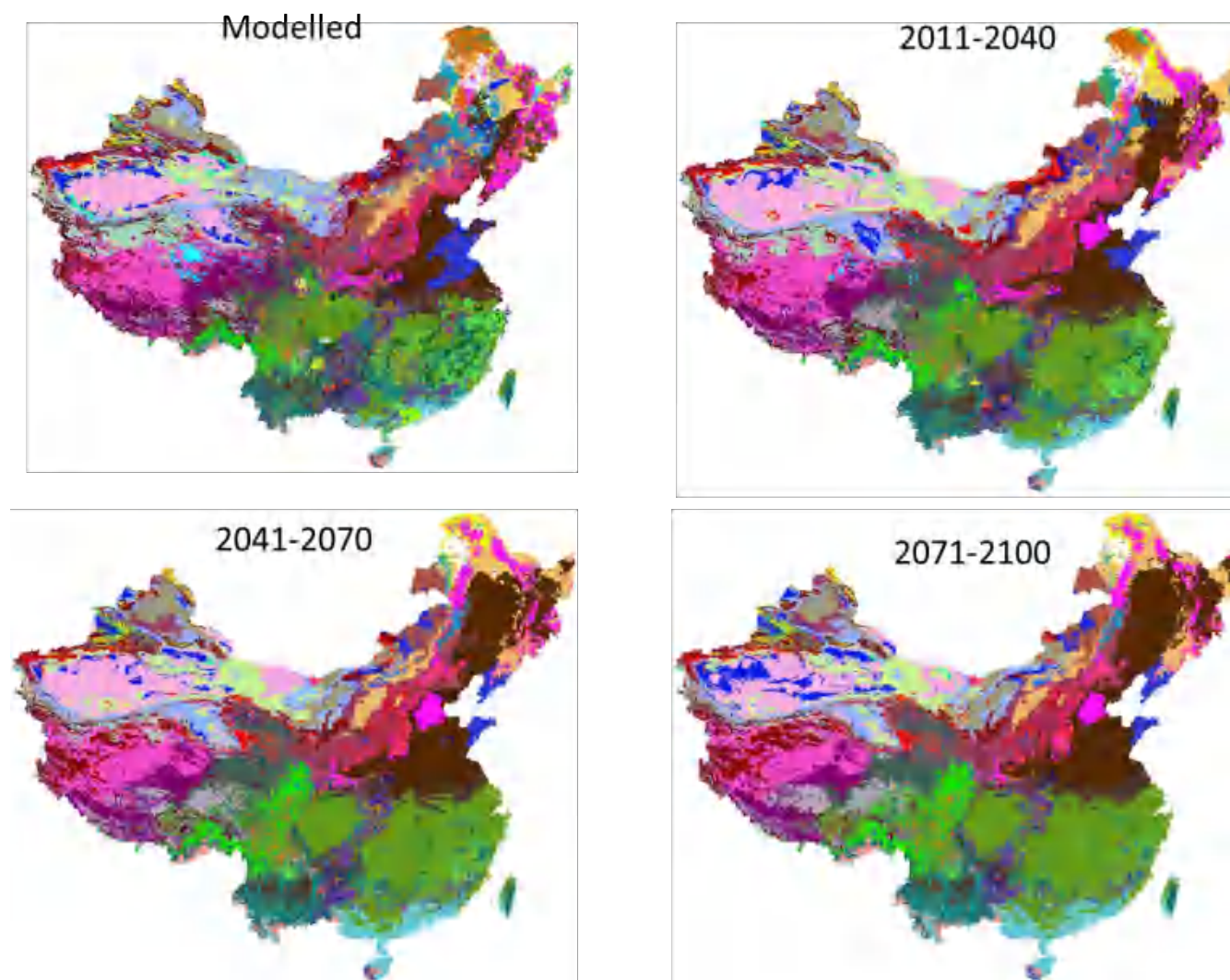


Figure 3.6 Predicted changes in temperature and precipitation for China including Chinese Taipei by 134 climate changes scenarios for 2050s. Color legend is the same as in Figure 3.5.

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Appendix I. List of forest ecotypes

ID	Forest ecotypes
1	One year one ripe fields with cold-tolerant crops of short growth duration
2	Needleleaf forests in cold-temperate zone and on mountains in temperate zone
3	Broadleaf deciduous forests in temperate zone
4	Grass, Carex and forb swamp meadows
5	Grass and forb meadows
6	Cold-temperate and temperate marshes
7	Deciduous scrubs in temperate zone
9	Needleleaf and deciduous broadleaf mixed forests in temperate zone
10	Needleleaf forests on mountains in subtropical an tropical zones
11	Temperate grass, forb meadow steppes
12	One year one ripe grain fields and cold-tolerant economic crop fields
13	Temperate tufted grass steppes
14	Microphyllous deciduous woodlands in temperate zone
15	Grass and forb halophytic meadows
16	Kobresia spp., forb high-cold meadows
17	Alpine tundra
18	Subalpine broadleaf deciduous scrubs
19	No vegetation
20	Alpine sparse vegetation
21	One year two ripes or three ripes grain fields; evergreen orchards and subtropical economic tree plantations
22	Alpine cushion vegetation
23	Shrub deserts

24	Semi-shrub and dwarf semi-shrub deserts
25	Temperate tufted low grass, nano-semi-shrub desert steppes
26	Bamboo forests and scrubs in subtropical and tropical zones
27	Two years three ripens or one year two ripens grain fields and deciduous orchards
28	Broadleaf deciduous forests in subtropical zone
29	Dwarf semi-arboreal deserts
30	Needleleaf forests in subtropical zone
31	Grass, Carex spp. high-cold steppes
32	Succulent halophytic dwarf semi-shrub deserts
33	One year one ripe grain fields and cold-tolerant economic crop fields; deciduous orchards
34	Needleleaf, evergreen and deciduous broadleaf mixed forests on mountains in subtropical zone
35	Steppe shrub deserts
36	Broadleaf evergreen and deciduous mixed forests in subtropical zone
37	Needleleaf forests in temperate zone
38	Annual herb deserts
39	Sclerophyllous broadleaf evergreen forests in subtropical zone
40	Subtropical and tropical grasslands
41	Temperate grasslands
42	Cushion nano-semi-shrub high-cold deserts
43	High-cold marshes
44	Broadleaf evergreen and deciduous scrubs in subtropical and tropical zones
45	Subalpine needleleaf evergreen scrubs
46	Subalpine sclerophyllous broadleaf evergreen scrubs

47	One year two ripens grain fields; evergreen and deciduous orchards; economic tree plantations
48	Subtropical and tropical marshes
49	Broadleaf evergreen forests in subtropical zone
50	Evergreen xeromorphic succulent thorny scrubs in subtropical and trpical zones
51	Needleleaf forests in tropical zone
52	Tropical rain forests
53	One year three ripens grain fields; tropical evergreen orchards and economic tree plantations
54	Tropical mangroves
55	Tropical monsoon forests
56	Broadleaf evergreen succulent scrub and dwarf forest on coral islands in tropical zone

Chapter 4: A process-based stand-level for evaluating multi-objective forest management in the context of changing climates

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Worldwide, forest health and productivity are being affected by anthropogenic climate change. The frequency and intensity of catastrophic natural disturbance agents, for example, are rising [1-4]. Moreover, evidence suggests that unusually severe drought events have triggered a significant rise in mortality rates in forested regions throughout the world (Allen et al. 2010; Van Mantgem et al. 2009). Climate change is expected to influence long-term forest productivity through its effect on moisture availability (Barber et al. 2000; Zhao and Running 2010), temperature-limited net photosynthetic rates (Nemani et al. 2003; McMahon et al. 2010) and nutrient cycling (Chung et al. 2013). After litter quality, temperature and soil moisture are the key determinants of heterotrophic respiration and nutrient mineralization rates in temperate forests (Trofymow et al. 2002; Prescott et al. 2004).

Climate change introduces considerable uncertainty into forest management planning and outcomes, potentially undermining efforts at achieving sustainable practices (Spittlehouse and Stewart 2003; Millar et al. 2007). There is a need for models capable of projecting the potential impact of climate change on long-term patterns of forest growth and development while being reasonably accessible to forest managers. Ideally, such models should: 1) be capable of representing the effects of climate change on forest productivity and drought-related mortality, 2) include the ability to simulate a variety of forest management options to allow for an evaluation of adaptive management strategies, 3) provide broad outputs relevant to multi-objective forest management, and 4) be relatively straightforward to calibrate.

The hybrid simulation model FORECAST Climate, developed at the University of British Columbia (Seely et al. 2015), has proven to be an effective tool for evaluating the potential long-term impact of alternative climate change scenarios on forest growth and development. The model has been applied in several forest types including a montane forest ecosystem in southwestern British Columbia, Canada (Seely et al. 2015), a Chinese fir ecosystem in Fujian Province, China (Kang et al. 2017), and a mixed pine-beech forest in the Pyrenees region of northern Spain (de Andres et al. 2016). The following sections contain a description of the model and its primary components.

Finally we provide an example of the application of FORECAST for evaluating management tradeoffs between economic fiber production and other ecosystem services in a Chinese-fir dominated forest plantation in Fujian province (after Kang et al. 2016).

FORWADY: THE FOREST HYDROLOGY SUBMODEL USED IN FORECAST CLIMATE

ForWaDy (Forest Water Dynamics; Seely et al. 1997; Seely et al. 2015) is a vegetation-oriented, forest hydrology model. A diagram illustrating the model structure and function is shown in Figure 4.1. The model can be used as a stand-alone application, and it is integrated within FORECAST Climate where it is coupled to the main tree growth engine and the tree ring model (Seely et al. 2015).

ForWaDy simulates potential evapotranspiration (PET) using an energy balance approach based on the Priestly-Taylor equation. Incoming radiation is partitioned among vertically stratified canopy layers (vegetation type) and the forest floor to drive actual evapotranspiration (AET) calculations. The model has a representation of soil physical properties dictating moisture availability, storage, and infiltration, and it simulates the relative impact of soil cover depth, minor vegetation competition and climate on the water availability for trees. A detailed description is provided in Seely et al. (1997, 2006).

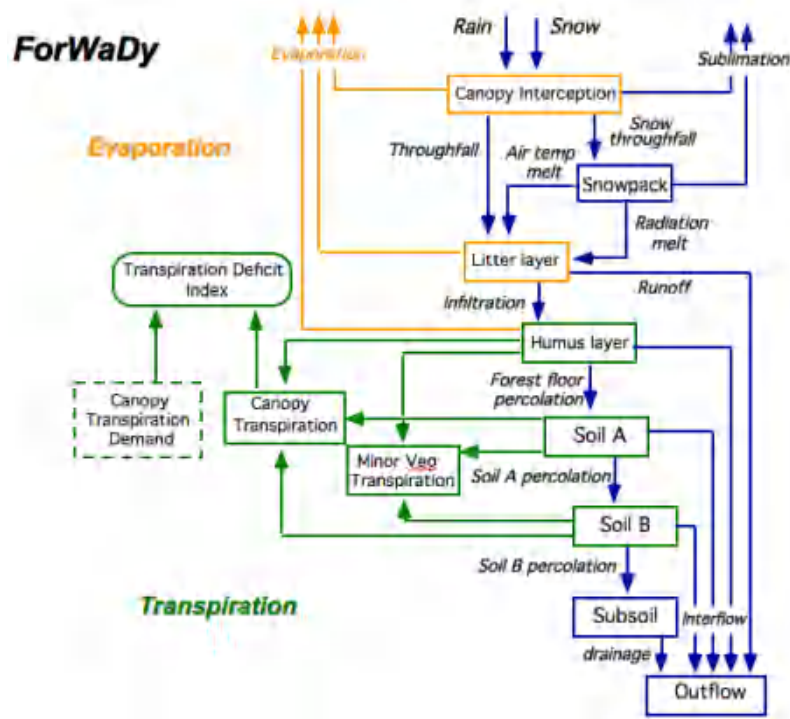


Figure 4.1 Schematic illustration of the structure of ForWaDy indicating the flow pathways and storage compartments represented in the model.

Water stress in ForWaDy is calculated as a transpiration deficit index (TDI). In essence, the TDI represents the difference between potential transpiration (as dictated by available energy) and actual transpiration (limited by available moisture), as follows:

$$TDI = (CanT_{Total} - CanT_{Actual}) / CanT_{Total}$$

where:

$CanT_{Total}$ = energy limited transpiration: f (leaf area index, intercepted short- wave radiation, canopy albedo, and canopy resistance)

$\text{CanT}_{\text{Actual}} = \text{actual tree transpiration: } f(\text{CanT}_{\text{Total}}, \text{root occupancy, available soil moisture})$

EXAMPLE CALIBRATION OF FORECAST CLIMATE FOR CHINESE-FIR IN FUJIAN PROVINCE

The following section describes the calibration data that have been assembled to drive the FORECAST Climate model for the Fujian Province project area. Table 4.1 provides a summary of the data used to calibrate the ForWaDy submodel of FORECAST Climate for Chinese-fir and two understory groups represented within the model.

Table 4.1 Species-specific parameter values used in the ForWaDy submodel that are specific to simulating evapotranspiration.

SOIL VARIABLES	EDAPHIC CLASS	SOIL TEXTURE CLASS	COARSE FRAGMENT (%)	MINERAL SOIL DEPTH (CM)	FIELD CAPACITY MOISTURE CONTENT (Θ)
	Mesic site	Silt loam	25	85	0.25

Soil Water Extraction and Transpiration	Species	Maximum LAI ¹	Canopy Parameters		Permanent Wilting Point ⁴ (%)		Maximum Root Depth ⁵ (cm)
			Albedo ²	Resistance ³	Humus	Mineral soil	
	Chinese fir	4.5	0.12	0.3	0.07	0.09	100
	Shrubs	NA	0.12	0.25	0.08	0.1	100
	Grass	NA	0.12	0.2	0.07	0.09	75

¹ Sets the upper limit for LAI by species. LAI is determined as a function of simulated foliage biomass. Not applicable (NA) for understory vegetation.

² Estimated values.

³ “Canopy resistance” represents a general measure of the resistance to water loss from foliage via stomata and cuticle. It is used to adjust the α value in the Priestley-Taylor equation to represent the amount of stomatal control on transpiration from a dry canopy based upon the relationship $R_{\text{Can}} = 1 - (\alpha/1.26)$ (Seely et al. 2015). An α value of 1.26 represents a freely evaporating surface, a canopy resistance value of 0.3 would reduce the α value to approximately 0.88. The value 0.3 for Chinese fir was estimated based upon the physical characteristics of its foliage and its known climate niche in comparison to other species for which values of canopy resistance have been measured (dry pine = 0.45, Douglas-fir = 0.33, non-sclerophyllic broad leaves 0.13, see Seely et al. (2015)).

⁴ Refers to the volumetric moisture content at which the species can no longer extract moisture from the soil. It is related to the soil texture class.

⁵ Indicates the maximum rooting depth within the total soil profile. Estimated values.

LINKING TREE GROWTH WITH FOREST HYDROLOGY

The linkage between the FORECAST and ForWaDy models underpins the operation of FORECAST Climate. This linkage is based upon the iterative sharing of information between models through the creation of feedback loops (see Figure 4.2). One challenge is the fact that the ForWaDy model operates on a daily time step (since this is the relevant interval for many hydrological processes), whereas FORECAST calculates productivity on a yearly time step. The latter model thus provides annual estimates of the key variables used by ForWaDy. These are listed in Table 4.2. ForWaDy output in turn is provided to FORECAST as a series of annual summaries of soil and forest floor moisture conditions, and cumulative measures of water stress for trees and plants.

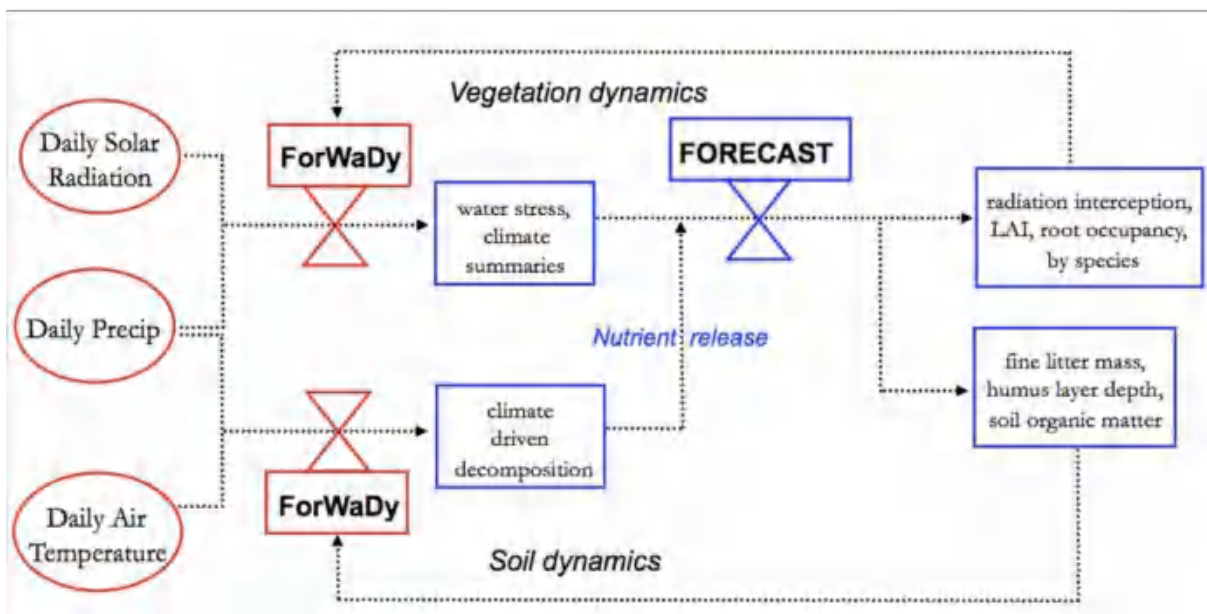


Figure 4.2 A schematic diagram illustrating the feedback loops established to facilitate the linkage of FORECAST and ForWaDy.

Table 4.2 A list of vegetation and soil condition variables passed from the forest growth model (FORECAST) to the hydrological model (ForWaDy). The function of each variable in ForWaDy is also described.

FORECAST	ForWaDy	
<i>Variable</i>	<i>Receiving variable</i>	<i>Function</i>
Canopy light interception	Canopy radiation interception	Drives species specific transpiration
Foliage biomass	LAI ¹	Canopy interception
Fine root biomass	Lateral root occupancy	Soil water uptake capacity within a specific soil layer
Tree age	Rooting depth	Soil water uptake capacity from vertical soil layers
Fine litter mass ²	Litter mass	Litter layer moisture content
Humus mass	Humus depth ³	Humus layer water holding capacity

¹ Leaf area index is estimated using a species-specific conversion factor.

² Fine litter mass includes foliage, bark, and fruit (cone) litter types.

³ Humus depth is estimated from humus mass, based on a parameter that defines the proportion of new humus transferred to non-surface layers and an estimate of surface humus bulk-density.

ACCOUNTING FOR CLIMATE IMPACTS ON TREE AND PLANT PRODUCTIVITY

The impact of climate on tree growth and ecosystem development in FORECAST Climate is focused, in part, on their relationship to temperature and water stress. These relationships are represented using curvilinear response functions, simulated on a daily time step and summarized annually. The temperature response function (see Figure 4.3A) encapsulates the multiple and complex physiological growth processes governing the response of trees growth to mean daily temperature. The relative effect of temperature as a limiting factor on tree growth is captured annually through the sum of daily values. The positive effect of a lengthening growing season can also be represented with this approach. Note, however, that increases in growing season temperatures may not necessarily have a positive impact on annual growth rates (Wilmking et al. 2004; see Figure 4.3A). The effect of moisture availability on plant growth rates in FORECAST Climate is simulated by ForWaDy and calculated as the Transpiration Deficit Index (TDI, see ForWaDy description above). The daily TDI value represents the degree to which a tree species was able to meet its energy-driven transpiration demands; a higher TDI value indicates more moisture stress. As the TDI increases, plants close their stomata to conserve water and there is an associated reduction in photosynthetic production (see McDowell et al. 2008). An extensive evaluation of TDI growth response curves using tree ring chronologies in combination with climate records (see Seely and Welham 2010) suggest that a negative exponential curve best reflects the effect of TDI on daily and annual productivity (Figure 4.3B).

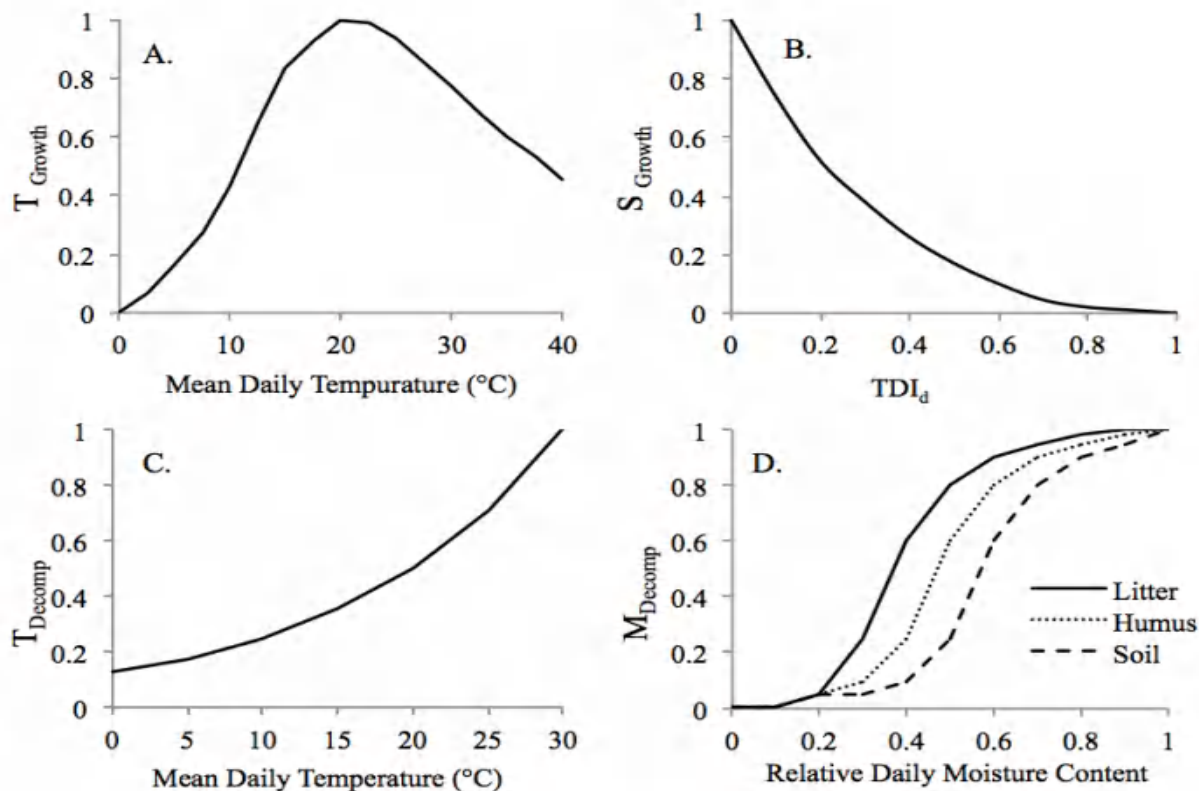


Figure 4.3. Climate response functions used in FORECAST Climate related to Chinese fir. These functions illustrate the relationship between daily growth rate for Chinese fir and A) mean daily temperature, B) daily water stress; and the response of decomposition rates to C) mean daily air temperature (based upon a Q_{10} of 2), and D) relative daily moisture content, for litter, humus and soil .

The temperature and moisture response functions are incorporated into FORECAST Climate through their inclusion in a climate response index function (CRI_{growth}). The CRI_{growth} function is first calculated daily as the product of the temperature multiplier (Figure 8.3) and the TDI multiplier (Figure 4.3A), and then summed over the year to create an annual index. Two types of CRI_{growth} values were calculated. First, a climate-normal growth value ($normal\_CRI_{growth}$) was determined using a 30-year (1975 to 2004) historical climate data set from a local weather station. The process of determining a ‘normal’ value for CRI_{growth} involves calculating a CRI_{growth} value for each year of the historical climate data set and then calculating an average value for the climate response index ($normal\ CRI_{growth}$) over the 30-year period. The second type of CRI_{growth} ($current\_CRI_{growth(i)}$) is calculated during an actual simulation, for each year, i . A weighted adjustment value is then derived using the $normal\_CRI_{growth}$ value as the comparative standard (see equation below). The potential growth rate (based on light and nutrient availability) in a given year is multiplied by the weighted climate response index to yield the actual annual growth rate in year, i :

Annual growth rate(i) = potential growth rate(i) * (current_CRI_{growth(i)} - normal_CRI_{growth}) / normal_CRI_{growth}

where:

potential growth rate(i) = expected growth based on light availability and site quality

current_CRI_{growth(i)} = the climate response index for a given year, *i*

normal_CRI_{growth(i)} = average climate response index based upon long-term historical climate data

REPRESENTATION OF DROUGHT MORTALITY

In addition to the changes in growth, climate variability can also induce mortality events (e.g. Daniels et al. 2011). A drought mortality function was developed and implemented within FORECAST Climate to represent these effects. The function, illustrated in Figure 4.4, simulates drought mortality using a response curve in which a two-year running average of species specific TDI is used as a predictor of annual mortality rates. The use of the 2-year running average TDI allows for a decrease in drought mortality when a dry year is preceded or followed by a wet year, but will cause greater mortality in consecutive dry years. An exponential sigmoidal function curve was selected as a good approximation of the significant increase in expected mortality associated with consecutive years with high levels of water stress. The shape of the curve takes into account evidence of enhanced vulnerability of stands to biotic disturbance agents (e.g. bark beetles) during extended periods of extreme moisture stress. The amplitude of the function curve was fit for each species using the historical climate data simulations for reference (to assure that historical climate data led to mortality rates that are consistent with past observations). Two different mortality curves (low and high) were simulated for each tree species to illustrate the sensitivity of the model to varying assumptions with respect to tree susceptibility to drought stress (Figure 4.4).

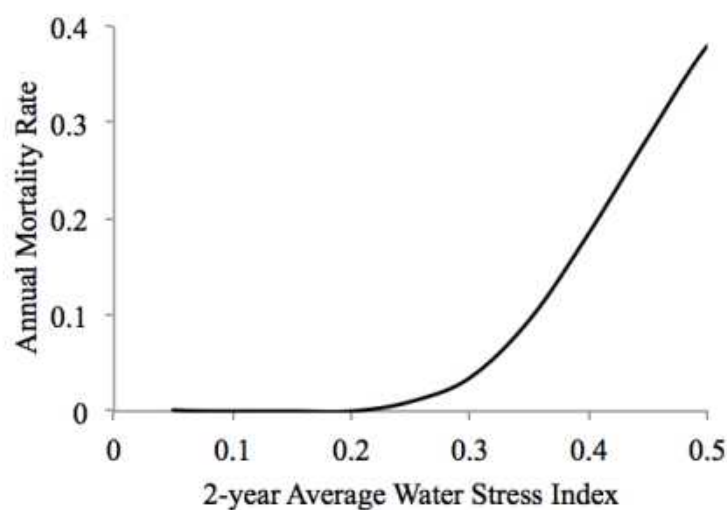


Figure 4.4 Drought-related mortality function showing the relationship between mortality and running 2-year average of the transpiration deficit index (TDI).

ACCOUNTING FOR CLIMATE IMPACTS ON DECOMPOSITION RATES

The decomposition of dead organic matter (litter and soil organic matter) in FORECAST is represented by grouping litter created through the death of specific biomass components into different litter types, each with defined mass loss rates (see Kimmins et al. 1999). In FORECAST Climate, these litter decomposition rates and their associated nutrient mineralization rates are adjusted based on soil moisture content and temperature (Fig 4.3 C&D). A base mass loss rate is provided for each litter and humus type (parameterized from field or literature values) that reflects both the quality of the litter and a 'normal' climate regime. These mass loss rates are then modified within the model to account for the effect of climate, as follows.

Temperature

A variety of techniques have been developed to quantify the effect of temperature on decomposition. The most common are simple calculations of weight loss using litterbags, field soil respiration measures (either by eddy covariance or gas chambers), and laboratory or ¹⁴C studies. Consumption of dead organic matter by heterotrophic microbes and fungi is generally faster in warmer environments (Chen et al. 2000, Gholz et al. 2000, and references therein). Many studies use the Q₁₀ equation to describe effect of temperature on organic matter decomposition rates:

$$Q_{10} = (R_2/R_1)^{10/(T_2-T_1)}$$

where:

R₁ = mass loss rate at temperature 1 (T₁ °C)

R₂ = mass loss rate at temperature 2 (T₂ °C)

In FORECAST Climate, the impact of temperature on the decomposition rates of litter and humus is simulated based on the Q₁₀ equation. A default value of 2 was selected for Q₁₀ based on published studies in similar forest types (Chen et al. 2000, Gholz et al. 2000, and references therein). The effect of this value on relative mass loss rates is illustrated in Figure 4.3C. A Q₁₀ value of 1.5 is recommended for forests located in tropical and subtropical regions.

PRECIPITATION AND LITTER MOISTURE CONTENT

Precipitation as a factor in decomposition rates has received much less attention than temperature despite the fact its importance has been clearly demonstrated (e.g., Chen et al. 2000, Ise and Moorcroft 2006, Prescott et al. 2004). A key feature of these studies is that decomposition rates are directly correlated to precipitation until a threshold is reached, after which there is little or no additional effect.

A daily relative mass loss rate is calculated within FORECAST Climate for each litter and humus type using a curvilinear function based upon simulated moisture content in the litter and humus layers (Figure 4.3D). Litter moisture content is used to drive mass loss rates for forest floor litter types while humus moisture content is used for any below-ground litter and humus.

FORECAST Climate employs a similar method for scaling decomposition rates to climate as was used for scaling annual growth rates (see above). The temperature-limited relative mass loss rate (Figure 4.3C) is multiplied by the daily moisture-limited rate (Figure 4.3D for each litter and humus type, *j*, to produce a daily

decomposition climate response index, CRI_{decomp} , that is then summed over the year to provide an annual index. A $normal\_CRI_{decomp}$ value is calculated for each litter and humus type based on historical climate data using the same approach described for adjusting tree growth above. A second type of CRI_{decomp} ($current\_CRI_{decomp(i)}$) is calculated during an actual simulation, for each year, i . A weighted adjustment value is then derived using the $normal\_CRI_{growth}$ value as the comparative standard (see equation below).

The base mass loss rate of a given litter or humus type, j , is multiplied by the weighted climate response index to yield the actual mass loss rate in year, i (Annual mass loss rate(i,j)):

$$Annual\ mass\ loss\ rate(i,j) = base\_rate(j) * (current\_CRI_{decomp(i,j)} - normal\_CRI_{decomp(j)}) / normal\_CRI_{decomp(j)}$$

where:

$base\_rate(j)$ = expected mass loss rate for each litter and humus type, j

$current\_CRI_{decomp(i,j)}$ = climate response index for each litter and humus type, j , for the current year, i

$normal\_CRI_{decomp(j)}$ = average response index for each litter and humus type, j , based upon long-term historical climate data

DEVELOPMENT OF CLIMATE CHANGE SCENARIOS FOR IMPACT ANALYSIS

To evaluate potential the long-term impact of climate change patterns of forest growth and development it is necessary to construct ‘realistic’ climate change scenarios. There are several approaches that may be taken in developing such scenarios. One approach is to develop scenarios designed to identify response thresholds with respect to ecosystem function. Under this approach, one may design an artificial trend in change to determine the degree of change required to elicit a fundamental change in equilibrium or imbalance forest growth and development such that it differs distinctly from that related to the reference climate. A second approach is to utilize output from scientifically credible global circulation models (GCMs) to generate specific climate change scenarios related to projected changes in greenhouse gas (GHG) emissions. An example of the latter approach employed for the Chinese-fir plantation in Fujian province (derived from Kang et al. 2017) is provided below.

Two general circulation models (HadGEM2 and CNRM-CM5) included as part of the International Panel on Climate Change Fifth Assessment Report (IPCC 2013) were selected in combination with two different emission scenarios to generate four alternative climate change projections for the study site location. The Climate models were selected to represent a general range in potential change patterns where HadGEM2 = “warm and wet”; CNRM = “cool and dry”. The two emission scenarios selected were RCP4.5 and RCP8.5, derived from the IPCC AR5 analysis (Meinshausen et al. 2011; Peters et al. 2012). Monthly outputs for the 2025, 2055 and 2085 from these models were downscaled to daily data and extrapolated for a 100-yr period (2013-2112) using a direct approach linked to the daily reference climate data. In other words, the variability present in the daily reference data was projected forward in the future scenarios with the daily temperatures and precipitation amounts adjusted according to the monthly trends from the GCM models. Time periods after 2080 were assumed to have no further change other than the inherent interannual variation. Projected patterns of change in mean temperature and precipitation for the four climate change scenarios are shown

in Figure 4.5. Each climate data set also includes projections for annual changes in atmospheric CO₂ concentrations that are consistent with the associated emissions scenarios.

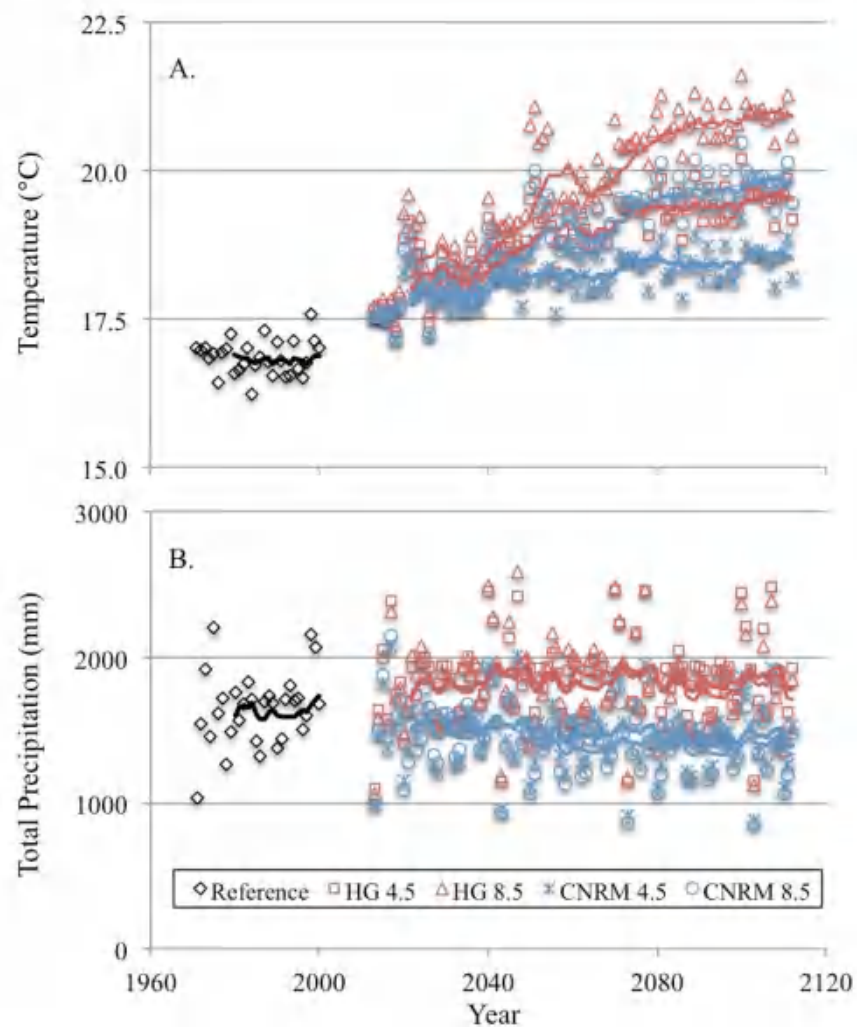


Figure 4.5. Historical reference climate data and projected pattern of change. Panel A and B show mean annual air temperature and total annual precipitation for the next 100 years based on four downscaled climate change projections, respectively. Lines represent the 10-year moving average for each series.

SIMULATED LONG-TERM EFFECTS OF CLIMATE CHANGE ON CHINESE FIR PRODUCTIVITY

Effects of Climate Change on Tree Growth

The influence of the alternative projected climate change scenarios on the simulated annual growth response index for Chinese fir is shown in Figure 4.6A. In general, the climate change scenarios showed modest increases in GRI_y relative to the reference scenario. The selection of climate model had a greater impact than the emission scenario with the HadGEM model showing the largest increase. Simulation results for stemwood biomass production followed a similar pattern (Figure 4.6B) with increases in productivity of 5.4% to 8.1%

by the end of the first rotation (years 1-30), 6.1% to 12.1% for the second rotation (years 31-60), and 4.5% to 17.1% for the third rotation (years 61-90).

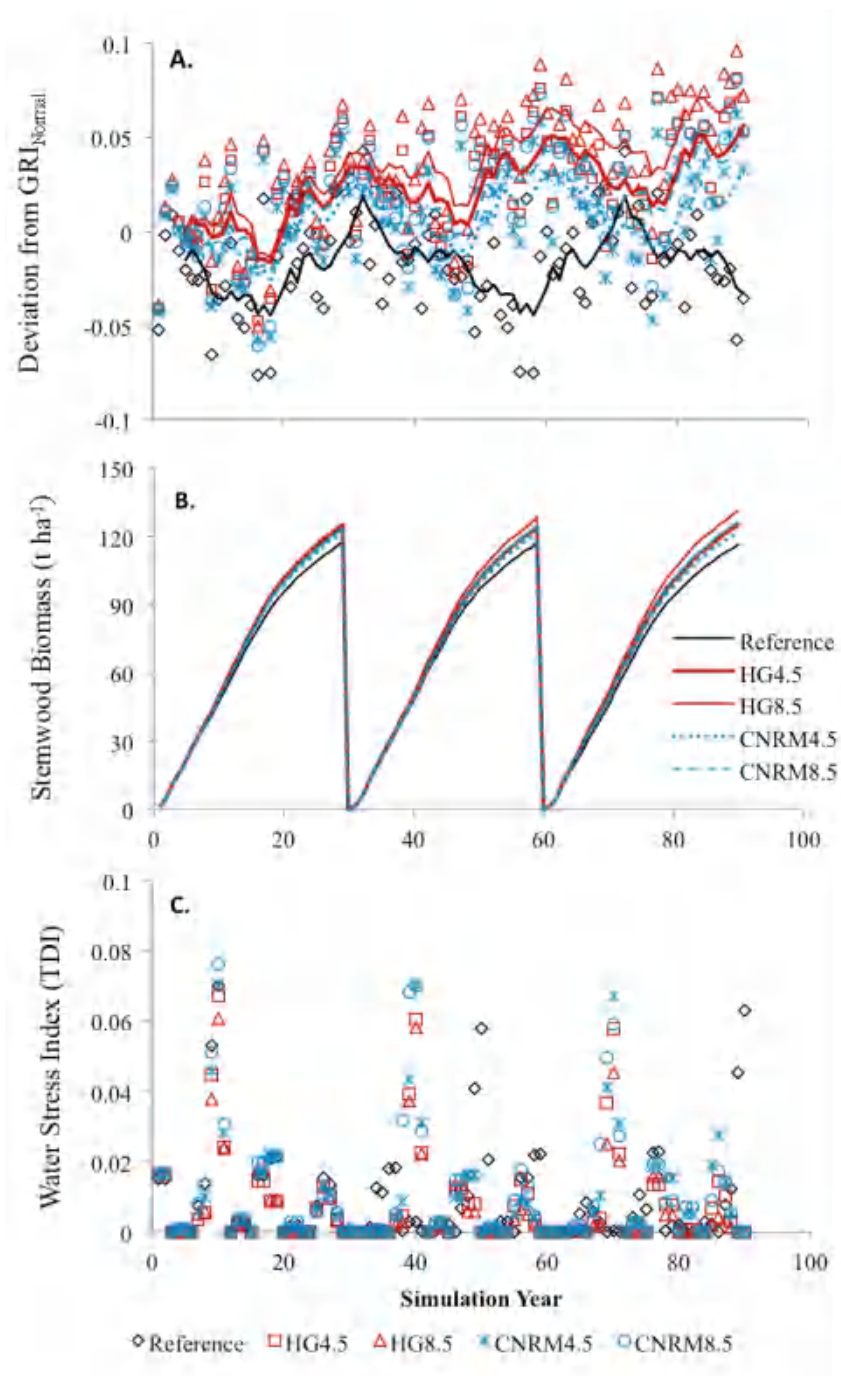


Figure 4.6. Simulation results showing the impacts of climate change on the growth of Chinese fir. A) The relative change in the annual growth response index (GRI_y) from the climate normal (GRI_{Normal}), lines represent 5-year moving averages. B) Stemwood biomass production, and C) the annual water stress index (TDI) for four climate change projections and the reference climate for Chinese fir on a medium site.

The projected impact of the different climate change scenarios on the annual water stress index is illustrated in Figure 4.6C. Water stress varies substantially year-to-year in all climate scenarios as a result of interannual variability inherent in the reference data. Scenarios based upon the CNRM-CM5 model show the highest water stress while those based upon the HadGEM2 model tend to be slightly lower than the reference climate. These results are consistent with projected rainfall trends shown in Figure 4.5. Consecutive years of elevated water stress were rare in all scenarios (Figure 4.6C) and, accordingly, the model projected low levels of drought-related mortality.

Effects of Climate Change on Daily Growth Response Index

To evaluate long-term trends in seasonal climate change impacts on forest growth rates, the 90-year simulations (2013-2102) were divided into three 30-year future periods (coinciding with each rotation) for each climate scenario. Model results showing the average daily growth response index of Chinese fir for the different periods and climate scenarios are provided in Figure 4.7. The daily growth response index (GRI_d) is the product of temperature response index and water stress response index. Increases in average GRI_d were greatest during the spring and fall for all climate change scenarios. In contrast, average GRI_d tended to show modest declines in the future climate periods relative to the reference period during mid to late summer due to higher-than-optimal temperatures and greater than normal moisture deficits. However, this negative impact was offset by a simulated lengthening of the growing season. For example, compared to reference climate, the average length of the growing season (determined as the number of calendar days in which $T_{Growth} \geq 0.25$) for the period from 2073-2102 increased by 26days and 34days under HG4.5 and HG8.5 scenarios, respectively.

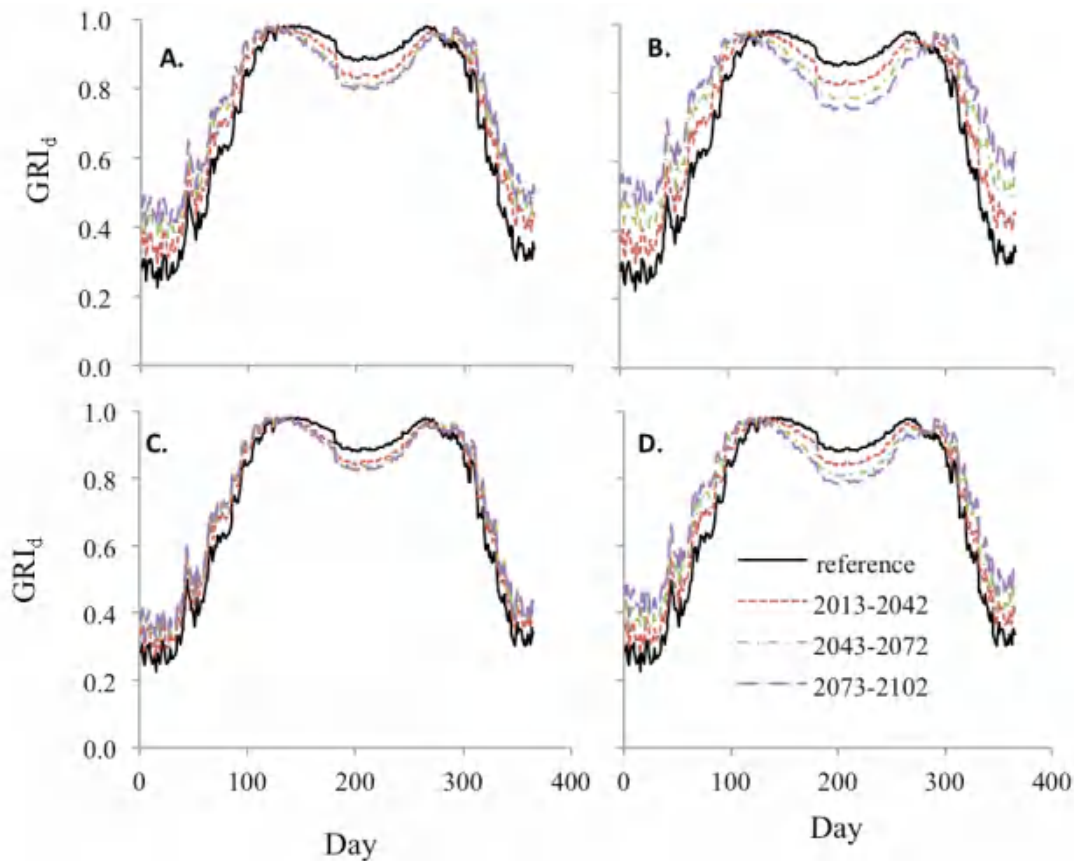


Figure 4.7. Simulation results showing the average daily growth response index. Based on three 30-year future time periods (coinciding with each rotation) relative to the reference period for the A) HG4.5 scenario, B) HG8.5 scenario, C) CNRM4.5 scenario and D) CNRM8.5 scenario.

Summary of Predicted Climate Change on Chinese-Fir Productivity

Model results suggest that Chinese-fir plantations developed in the subtropical climate of Fujian Province will show modest increases in productivity (6.1 to 12.1%) over the next 30 to 60 years due primarily to a lengthening of the growing season. These results are consistent with a recent study by Wang et al. (2014), who observed that productivity of Chinese fir in the Fujian region increased during a 10-year warming trend from 2000-2010. They suggested this pattern was linked to a prolonging of the photosynthetically active period. This conclusion is supported by a spatial-temporal climate analysis conducted by Liu et al. who reported an increase in the growing season in southeastern China of 6.9-8.7 days during the period from 1955-2000 (Liu et al. 2009).

While net annual growth rates are projected to increase, FORECAST Climate predicts variably reduced growth during the dry season as a result of increased water stress and greater-than-optimal daytime temperatures depending on the climate model selected (see Figure 4.5). Predicted elevations in peak summer temperatures will exceed optimal levels causing reductions in growth during these periods, but the net positive impacts of increased growing season length were greater. Wang found that the optimal temperature

and humidity required during the main period of the Chinese fir growing season were 18-20 °C and 80%, respectively. In addition, he observed that growth of Chinese fir was limited when daily temperature exceeded 28°C and/or monthly precipitation was less than 50 mm (Wang 2006).

EXAMPLE OF MODEL APPLICATION FOR TRADEOFF ANALYSIS

The following example is a summary of a model-based tradeoff analysis conducted using FORECAST calibrated for a Chinese-fir plantation in Fujian Province as presented in Kang et al. (2016).

Chinese fir (*Cunninghamia lanceolata*) is not only a valuable timber species, but also plays an important role in the provision of ecosystem services. Forest management decisions to increase the production of fiber for economic gain may have negative impacts on the long-term flow of ecosystem services from forest resources. Such tradeoffs should be taken into account to fulfill the requirements of sustainable forest management. We employed the stand-level model (FORECAST) in combination with a simplified harvest-scheduling model to evaluate the potential tradeoffs among indicators of provisional, regulating and supporting ecosystem services in a Chinese-fir-dominated landscape located in Fujian Province (Fig. 4.8) as a case study. Indicators included: merchantable volume harvested, biomass harvested, ecosystem carbon storage, CO₂ fixation, O₂ released, biomass nitrogen content, pollutant absorption, and soil fertility. A series of alternative management scenarios, representing different combinations of rotation length and harvest intensity, were simulated to facilitate the analysis.

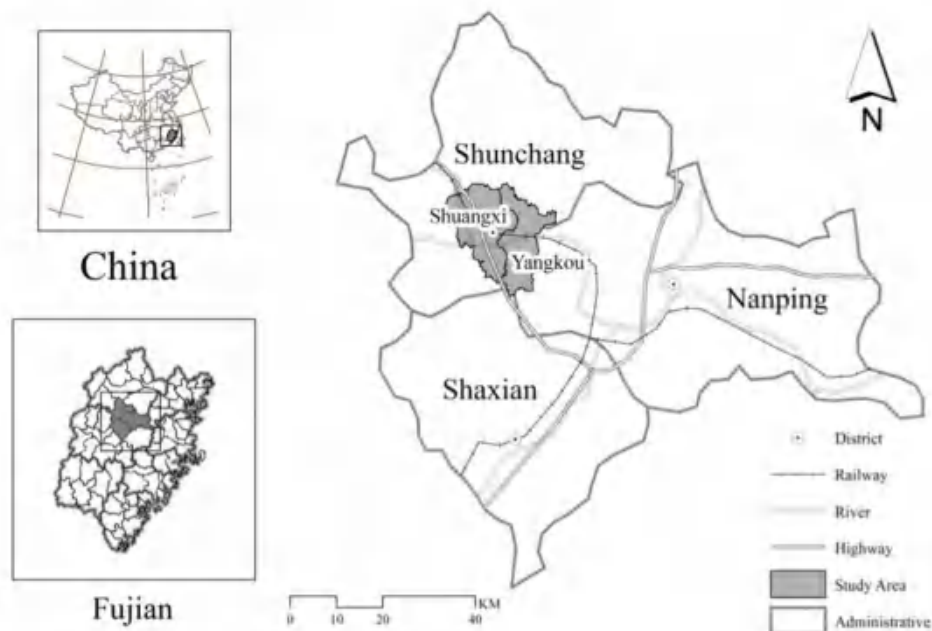


Figure 4.8. A map showing the location of Shunchang county and the study area.

The stand level FORECAST model was applied to simulate the growth and development of a variety of stand types or analysis units representing a combination of species composition, productivity, and silviculture objectives (Table 4.3).

Table 4.3. Analysis units representing the Fujian study area.

ID	AU	Area (ha)	Species	Productivity Class	Management Purpose
101	CF_P_LD	203.1	Chinese fir	Poor	Large diameter timber
102	CF_P_MD	1805.5	Chinese fir	Poor	Medium diameter timber
103	CF_P_SD	686.5	Chinese fir	Poor	Small diameter timber
104	CF_P_EF	127.7	Chinese fir	Poor	Ecological forest
105	CF_M_LD	268.9	Chinese fir	Medium	Large diameter timber
106	CF_M_MD	3177.5	Chinese fir	Medium	Medium diameter timber
107	CF_M_SD	1662.6	Chinese fir	Medium	Small diameter timber
108	CF_M_EF	308.9	Chinese fir	Medium	Ecological forest
109	CF_G_LD	116.9	Chinese fir	Good	Large diameter timber
110	CF_G_MD	935.2	Chinese fir	Good	Medium diameter timber
111	CF_G_SD	811.9	Chinese fir	Good	Small diameter timber
112	CF_G_EF	75.4	Chinese fir	Good	Ecological forest
201	MP_M_MD	2860.5	Masson pine	Medium	Medium diameter timber
301	BL_M_EF	5993.8	Broadleaf	Medium	Ecological forest
Total		19034.4			

A stand attribute database was developed using output from FORECAST to construct stand attribute tables directly related to specific ecosystem services. In addition, we developed a Landscape Summary Tool (LST) by employing the stand-level, ecosystem-based FORECAST model (Kimmins et al., 1999) in conjunction with a simplified harvest scheduling model to facilitate the trade-off analysis. The LST model was used to project the impact of alternative management scenarios on both wood production and the development of biophysical forest attributes in a managed landscape dominated by Chinese fir plantations. A diverse suite of indicators of ecosystem services was derived from a similar Chinese study (Wang et al., 2008). These indicators were linked to modeled stand attributes and utilized as the basis for the analysis presented here. An example of the stand attributes and the spatially linked modelling framework is shown in Figure 4.9.

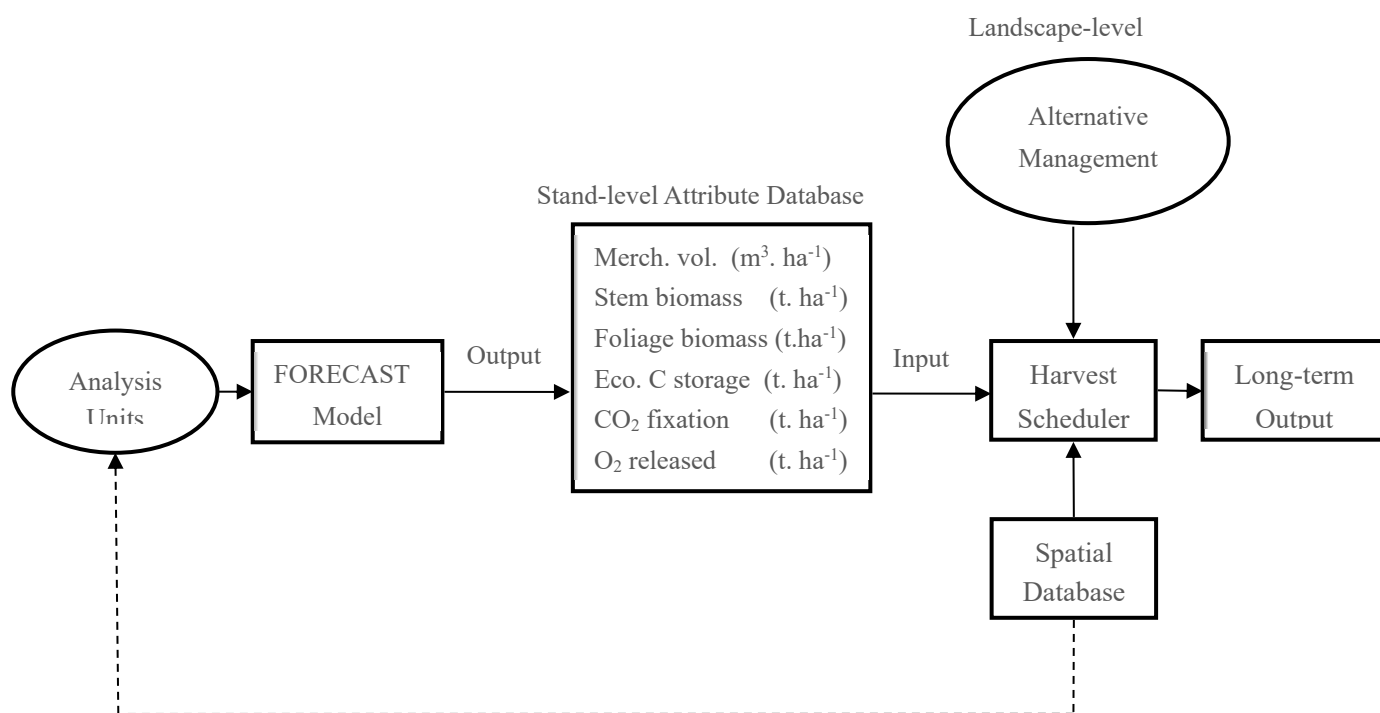


Figure 4.9. A schematic diagram illustrating the framework and data transfer pathways in the LST model.

Trade-off Analysis Using the LST Model

To facilitate a trade-off analysis, a series of alternative management scenarios were developed to explore the impact of varying rotation length and harvest intensity (retention of live trees) on the flow of ecosystem services at the stand and landscape scale. Nine alternative management scenarios were developed using a factorial analysis approach based upon 3 rotation length options * 3 harvest intensity options.

Employing the LST model, all 9 scenarios were simulated by projecting the development of the inventory polygons for a 50-year time period. If a polygon was designated for full harvest, its age was reset to zero in the next time step. In scenarios where stands were partially harvested, the polygon was split into two parts based upon the percent area harvested. The age of the harvested portion was reset to zero while the portion with retained trees continued to age. The absolute output values calculated for each of the indicators were converted to relative values (scaled from 0 to 1 by dividing by the maximum value for all simulated AUs and ages) to facilitate direct comparisons among indicators. We included a variable weighting decision approach to allow the users to determine the importance of each indicator. Through this, a total score based on the weighted sum of the indicators is calculated for each scenario to allow for a ranking of management options. Finally, a decision matrix output table was produced to illustrate the trade-off analysis results.

Stand-level Results

An example of the temporal pattern of development of individual indicators of ecosystem services at the stand level is shown for two analysis units in Figure 4.10. Indicators of provisional services increased with stand age in all analysis units. However, total stem biomass accumulated more quickly than merchantable volume approaching 55% of its maximum value by year 31, for example, in a medium-productivity Chinese fir stand (AU 105, Fig. 4.10A1). In contrast, merchantable volume in the same stand type had reached only 20% of its maximum by year 31.

Among the indicators of regulating and supporting services, a few general patterns were evident. Indicators of atmospheric regulation (CO_2 fixation and O_2 release) showed the highest values in young stands, peaking around age 5-15y and declining in conjunction with net annual primary productivity. Pollution absorption potential reached relatively high levels (>80% of maximum) around age 10y and remained at high levels for the remainder of the simulation period (Fig. 4.10). Lastly, total ecosystem C and N content increased slowly but steadily with stand age. These patterns were reasonably consistent for all analysis units. The general impact of thinning on most indicators was small and short-lived as the thinned canopies tended to recover within 3-5 years of thinning (Fig. 4.10A1).

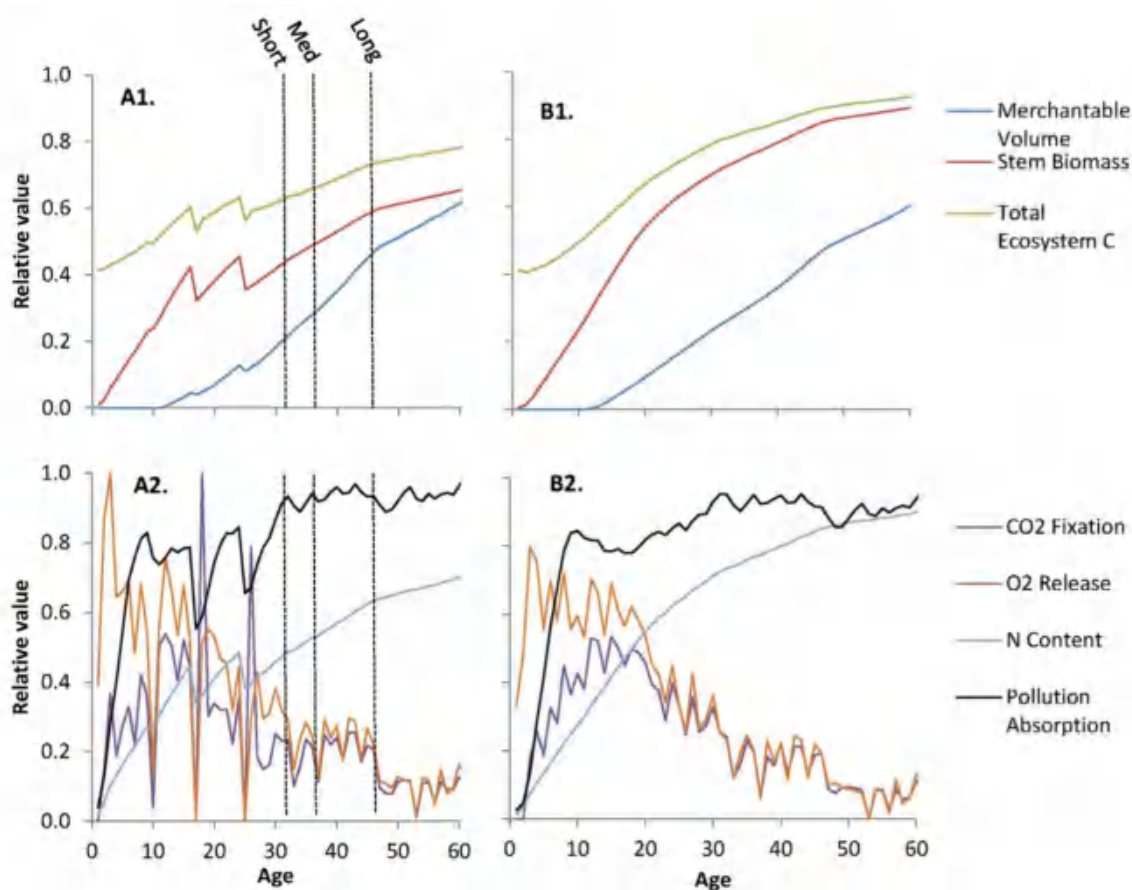


Figure 4.10. An example of the development of indicators at the stand-level for two different analysis units. Panels A1 & A2 show output for the medium site quality where the plantation is managed to produce large-diameter timber (AU 105). The dashed lines show the different rotation lengths used for this analysis unit in the landscape management scenarios. Panels B1 & B2 show output for the medium site ecological forest unit (no harvesting or thinning). Output for merchantable volume, stem biomass and ecosystem C storage are shown in panels A1&B1, while panels A2 & B2 show output for CO₂ fixation, O₂ release, biomass N content and pollution absorption potential. Only the first 60 years of the simulations are shown.

Landscape-level Trade-off Analysis Results

The landscape-scale impacts of the different management scenarios for the study area are summarized for the whole 50-year simulation period in the indicator output matrix generated by the LST (Table 4.4). A total of eight indicators were calculated for each alternative management scenario and used to calculate a score based on the weighting factors assigned in the top row. The matrix illustrates tradeoffs associated with specific management options. For example, short rotations with low levels of live-tree retention scored highest for harvested stemwood biomass but lowest for soil fertility. In contrast increasing the level of live-

tree retention was best for several regulating and supporting indicators (Ecosystem C storage, N content, Pollution absorption, and soil fertility) but had negative impacts on both provisional indicators as well as indicators of atmospheric regulation (CO₂ fixation and O₂ release). Long rotations with low levels of retention were ranked best overall with the weighting factors provided.

Table 4.4. Output from the LST model in the form of an indicator matrix with example weighting factors provided for each indicator. The value shown for each indicator represents the average value during the 50-year simulation period. The color scale ranges from green representing the highest ranking scenario to red, representing the lowest ranking scenario.

Weight (0-1)			0.5	0.5	0.7	1	1	0.5	1	1		
Scenario			Vol_	Bio_	Eco_	CO ₂ _	O ₂ _	N_	Pol_	Soil_	Rank	Score
ID	Rotation Length	Retention	Harv	Harv	C	Fix	Rel	Cont	Abs	Fert		
S1	short	0%	0.77	1.00	0.87	1.00	1.00	0.78	0.87	0.56	4	5.30
S2	short	25%	0.58	0.75	0.92	0.93	0.89	0.86	0.91	0.74	6	5.21
S3	short	50%	0.39	0.50	0.97	0.86	0.78	0.94	0.96	0.91	9	5.11
M1	med	0%	0.91	0.93	0.89	1.00	0.96	0.82	0.90	0.61	2	5.41
M2	med	25%	0.68	0.70	0.93	0.93	0.86	0.89	0.94	0.77	5	5.29
M3	med	50%	0.46	0.47	0.98	0.86	0.76	0.96	0.98	0.94	8	5.16
L1	long	0%	1.00	0.77	0.93	0.96	0.86	0.89	0.95	0.73	1	5.47
L2	long	25%	0.74	0.57	0.97	0.90	0.79	0.94	0.97	0.86	3	5.33
L3	long	50%	0.50	0.38	1.00	0.84	0.71	1.00	1.00	1.00	7	5.19

Summary

The study focuses on evaluating tradeoffs between economic fiber production and ecosystem services. We illustrate the utility of an ecosystem-based, stand-level model and a harvest scheduler to evaluate the potential impacts of alternative management strategies on the tradeoffs between fiber production and ecosystem services. The work presented here demonstrates the value of using modelling tools to assist forest managers in developing comprehensive plans for sustainable plantation management. The decision matrix

method for displaying results provides users with the capability to easily calculate a score to allow for a ranking of management options through the weighted sum of the indicators for each scenario based on their own determination of the importance of each indicator according to the forest management purpose.

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APPENDIX A: Climatic niche models and their consensus projections for future climates for four major forest tree species in the Asia-Pacific region

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ABSTRACT

Modeling and mapping the climatic niches of forest tree species and projecting their potential shift in geographic distribution under future climates are essential steps in assessing the impact of climate change on forests and in developing adaptive forest management strategies. It is particularly important for selecting suitable tree species to match future climates for afforestation and restoration of forest ecosystems. Large scale afforestation and reforestation projects have occurred or planned in Asia-Pacific region; however, the direct impact of climate change has not been widely considered. This has been at least partially due to the lack of availability of robust inventory data on forest vegetation and lack of access to appropriate climate data. In this study, we used our recently developed model, ClimateAP, to generate a large number of climate variables for point locations and used an ensemble modeling approach with Random Forest to overcome some limitations that exist with vegetation data. Uncertainty in future climates was incorporated into the analysis through consensus based projections using 12 climate change scenarios. We modelled the climatic niches for four economically and ecologically important forest tree species in the region and projected their shift in geographical distribution under climate change. Unusual patterns in the shift of geographic distributions of climatic niches were found in two species in Southern China. The implications of the projections in forest management for adaptation to climate change are discussed.

INTRODUCTION

Climate is the primary factor regulating geographic distributions of plant species (Woodward and Williams, 1987; Davis and Shaw, 2001; McKenney and Pedlar, 2003). Most forest tree species are adapted to a range of climatic conditions, which is referred to as their climatic niche (Peterson et al., 1999; Pearson and Dawson, 2003). Due to the long lifecycle and slow rate of migration of forest trees, unprecedented rapid climate change will likely result in a mismatch between the climate that trees are historically adapted to and the climate that trees will experience in the future (Aitken et al., 2008). Individuals or populations exposed to climate

conditions outside their climatic niches will likely be maladapted, resulting in compromised productivity and increased vulnerability of species to disturbance such as insects and pathogens (Hamann and Wang, 2006; Kurz et al., 2008; Fettig et al., 2013). Therefore, understanding the climatic niches of forest tree species and projecting their potential shift in spatial distributions for the future are important to assess the vulnerability of tree species and to develop adaptive forest resources management strategies under a rapidly changing climate, including assisted migration (Huntley et al., 2010; Alfaro et al., 2014; Rehfeldt et al., 2014a).

Climatic niches can be defined as constituting the climatic component of Hutchinson's (1957) fundamental niche (Pearson and Dawson, 2003). As they are often built based on the observed distribution of the target species, these models thus reflect a realized climatic niche (i.e., resulting from climatic and biotic constraints, such as interspecific competition) (Pearson and Dawson, 2003; Holt, 2009) as opposed to the fundamental niche (i.e., solely based on the species' environmental requirements) (Hutchinson, 1957). As models of this form involves biological and ecological components, thus they are typically referred to as climatic niche models, bioclimatic envelope models or ecological niche models. We used these terms interchangeably in this study.

The volume of literature using climatic niche models has been rapidly growing in recent years, while debate about the usefulness of the approach has also followed. A recent review suggests that the criticism has often been misplaced in regard to the objectives of the climatic niche models (Araujo and Peterson, 2012). A climatic niche model defines and predicts the suitable climatic habitat rather than the actual distribution of a species, which involves a series of evolutionary and ecological processes (Aitken et al., 2008). Therefore, a climatic niche model is technically not a species distribution model (SDM) but a habitat suitability model (Keith et al., 2008; Anderson et al., 2009). Confusion between these two kinds of models has led to unrealistic expectations about the outcomes from climatic niche models (Araujo and Peterson, 2012). As a result, many now feel that these so-called SDMs cannot meet users' expectation in adaptation decision making or species conservation strategies (Keenan, 2015).

The distribution and potential shift of climatically suitable habitats are the target of many ecosystem management activities. This information allows users to assess the vulnerability and climate change impact for species or ecosystems for adaptation and conservation (Schueler et al., 2014; Keenan, 2015). Bioclimatic envelope models are reasonably suited for informing species selection and assisted migration in reforestation or afforestation (McLane and Aitken, 2012; Gray and Hamann, 2013; Alfaro et al., 2014). Using the species that best match both current and future climates, regenerating stands will have a better chance of remaining healthy, productive and able to maximize their ecological and/ or economic value under a changing climate. This is particularly important given the stated policy aim of planting 20 million hectares of forests in the Asia Pacific over the coming years (Rozelle et al., 2000). Climatic niche models, if properly established and interpreted, can provide valuable, first-order assessments of the potential impacts of climate change and provide a scientific basis for developing adaptive strategies in forest management (Huntley et al., 2010; Fettig et al., 2013; Alfaro et al., 2014; Rehfeldt et al., 2014b).

Bioclimatic envelope models have widely been used in North America (Hamann and Wang, 2006; Rehfeldt et al., 2006; McKenney et al., 2007; Wang et al., 2012a) and Europe (Araujo and New, 2007; Buisson et al., 2010; Lindner et al., 2014). However, related studies in Asia Pacific are lagging behind. This is partially due to the lack of vegetation data and limited access to high quality climate data and to a large number of

projections for future climates. In this study, we chose three major forest tree species in China including Chinese fir (*Cunninghamia lanceolata* (Lamb.) Hook), Masson Pine (*Pinus massoniana*) and Chinese pine (*Pinus tabulaeformis* Carr.). We also chose a major plantation tree species in Australia, blue gum (*Eucalyptus globulus* Labill.). Chinese fir and Masson pine are the two most important subtropical coniferous species in China. Chinese fir occupies about 30% of all plantations in China accounts 25% of China's national commercial timber production, thus it plays a major role in environment, timber supply, and human society (FAO, 2006). Chinese pine is the most widely distributed conifer in North China, with a natural range that stretches from northeastern to northwestern China, between latitudes 31°00' and 44°00' N and longitudes 101°30' and 124°25' E (Xu 1993). Within this range it grows as discrete populations in mountain areas at elevations from 100 to 2700 m (Xu et al., 1993). Blue gum, an evergreen broadleaved tree species, is one of the most widely cultivated trees native to Australia (Booth, 2013). It has four subspecies distributed across southeast Australia. The main objectives of our study is to 1) develop climatic niche models for each of the four major forest tree species in the Asia Pacific considering the limitation of vegetation data; 2) identify climate variables that are important in determining the climatic niche for each species; and 3) project climatic niches for future periods addressing the uncertainty in future climates.

DATA AND METHODS

Vegetation data

Presence-absence observations for Chinese fir, Masson pine and Chinese pine were obtained from the digital version of Vegetation Map of China (1:1000,000) provided by "Environmental & Ecological Science Data Center for West China, National Natural Science Foundation of China"(link: <http://westdc.westgis.ac.cn>). A shape file of the distribution for each species was generated from polygons with the species present. The shape file was then rasterized at the spatial resolution of 0.008333 arc minute (approximately 1 km). Each data point (i.e., a raster pixel) within a polygon of presence was assigned as presence of the species. Similarly, a data point within a polygon of absence was assigned as absence within the range of the species distribution and expanded by 200 km in each of the four directions if possible following Barbet-Massin et al. (2012). Due to a long history of anthropogenic disturbances to forests in China the current distributions of the species are likely to be underestimated. Thus, some of the absence data points were assumed to be false absences. An adjustment was applied to our modeling process to address this consideration (see below).

For blue gum, 7, 172 presence observations were obtained from the Atlas of Living Australia (Atlas) (<http://www.ala.org.au>). These observations were aggregated from a wide range of data providers including museums, herbaria, community groups, government departments, individuals and universities. As there were no absences demarcated in the observations, pseudo-absence data points (Elith and Leathwick, 2007; Barbet-Massin et al., 2012) were generated with the following steps: 1) generation of grid locations at the spatial resolution of 0.008333 arc minute for areas within the range of the species distribution and extended by 200 km in each of the four directions if possible; 2) randomly sampling 50,000 pseudo-absence data points from the grid locations; and, 3) elimination of false-absence data points in the modeling process as described below. After the presence-absence datasets were constructed, the elevation for each data point was extracted, based on its geographic coordinates, from a 90 × 90 m digital elevation model (DEM) obtained from the

Shuttle Radar Topography Mission (SRTM). The latitude, longitude and elevation of the datasets were then used to extract climate data.

Climate data

The availability of a climate data for the Asia Pacific was achieved through the development of a high-resolution climate model, ClimateAP. This model was used to generate climate data across the region. ClimateAP is a climate data downscaling tool developed for the Asia-Pacific region using the same downscaling algorithms used in ClimateWNA (Wang et al., 2012b) which extracts and downscales PRISM (Daly et al., 2008) and WorldClim (Hijmans et al., 2005) 1961-1990 monthly normal data (2.5 x 2.5 arcmin) to produce seasonal and annual climate variables for specific locations (scale-free) based on latitude, longitude and elevation. The program uses the scale-free data as a baseline, in combination with monthly anomaly data (relative to the 1961-1990 normals) from IPCC AR5 general circulation models (GCMs) to calculate and downscale (i.e., a delta downscaling approach) monthly, seasonal and annual climate variables for future periods. The output of the program includes both directly calculated and derived climate variables. For this study, we generated 66 annual and seasonal climate variables for the point locations with presence and absence of the species for the reference normal period 1961-1990. Monthly climate variables were not considered due to the large number of annual and seasonal climate variables. For the predictions and projections of the geographic distribution of each species for the reference period (1961-1990 normal) and three future periods (2020s, 2050s and 2080s), gridded climate data were generated at the spatial resolution of 4 x 4 km for each of these periods for China and Australia. For future projections, the gridded climate data were generated for 12 climate change scenarios including six AR5 GCMs and 2 emission scenarios (RCP4.5 and RCP8.5) (Taylor et al., 2012). The six GCMs include: ACCESS1-3, BCC-CSM1, CanESM2, CNRM-CM5, CSIRO-Mk3-6-0, and HadGEM2-ES (<http://cmip-pcmdi.llnl.gov/cmip5/availability.html>).

Statistical analysis

We used the R version (Liaw and Wiener, 2002) of (Breiman, 2001) of the Random Forests (RF) algorithm to model relationships between climate variables for the reference period and the presence and absence of each of the four species. RF produces many classification trees, collectively called a 'forest', and aggregates the results over all trees. Each of these decision trees in the forest is constructed using a bootstrap sample of the input data (i.e., a random sample with replacement) so that the resulting dataset ('bagged sample') contains about 64% of the original observations, and the remaining observations comprise the 'out-of-bag' (OOB) sample. Using the trees grown from a bootstrap sample, each of the independent observations in the OOB sample is classified (assigned to either presence or absence) and a model prediction error, called the OOB error (% of incorrectly classed observations), is calculated. RF is designed for overcoming collinearity and over-fitting problems (Breiman, 2001; Dormann et al., 2013) and considered as one of the most credible statistical methods for climatic niche model building (Rehfeldt et al., 2006; Elith et al., 2008; Wang et al., 2012a).

RF works best if the samples are relatively balanced between classes (Breiman, 2001; Rehfeldt et al., 2006; Barbet-Massin et al., 2012). Our sample data were unbalanced with the number of locations for absence much greater than that for presence. One way to balance the samples was to randomly sample the data points for absence to match the number of samples for presence. However, this can lead to a poor representation of the areas for the absence of the species. We applied a multiple "forests" approach to build

an ensemble of RF models; each RF model was built with randomly sampled data points for absence while the data points for presence remained the same. The final prediction was based on the ensemble of the 10 individual model predictions. This also is a recommended method when using machine-learning based modeling approaches (Barbet-Massin et al., 2012).

To remove the false-absence samples from the absence data points for the three species in China, we eliminated absence samples with an absence probability of less than 0.20 in each RF model, which removed about 10% of the absence data points. To maintain the balance in sample size between presence and absence, 10% more absence samples were taken at the initial sampling step as mentioned above. The same approach was also used to eliminate the false-absence samples from the pseudo-absence data points for blue gum in Australia. However, we increased the threshold probability from 0.20 to 0.25 based on the assumption that there were more false-absence samples in the pseudo-absence data. This also removed about 10% of the pseudo-absence samples.

RF generates importance values for each of the predictors. We used the importance values to optimize the model and to identify the climate variables that were important for determining the climatic niche of each species. All 66 climate variables were included in the initial RF model. The least important climate variables were iteratively removed until only two climate variables remained in the model (i.e., the least possible number of predictors for RF). By comparing the accuracies of different RF models composed of a different number of climate variables the best RF model was identified and selected. The final RF models were therefore built using the optimal combination of climate variables for each of the four species.

The models were also optimized for the number of trees in each forest and the number of predictors selected at each node. We used 300 trees, which was more than adequate, for all species. The effect of the number of predictors selected at each node was minor, so we used the default square-root of the number of climate variables (Breiman, 2001).

The final RF models were then fed with climate variables for the gridded data points to generate spatial distributions of the climatic niche for each species for the reference period (1961-1990 normal period) and future periods (2020s, 2050s and 2080s). For the reference period, the ensemble predictions for presence of a species was determined from 10 forests generated for each gridded pixel. For future periods, the frequency was calculated at two levels; the first was among the 10 forests and the second was among the 12 climate change scenarios. We set it as “presence” if the number of predictions for presence was equal or larger than five (i.e., 50%), so that we only needed to count predictions for “presence” among the climate change scenarios to determine the consensus of the projections. Since blue gum was modeled at the subspecies level, we could not count the frequency for multiple categories. Instead, we used the mode of predictions as the final outputs. The final outputs were then imported into ArcGIS (v10.2.1) to generate maps.

RESULTS

Climatic niches of the species and important climate variables

The overall accuracies of the models were high (> 90%) for all species modelled (Table A.1). The climatic niche for each species in terms of the most commonly used climatic variables (mean annual temperature and precipitation) were defined by the models (Table A.1). The OOB error rate was higher for absence than for

presence except for blue gum. This was expected as the sampling rate for absences was much smaller for blue gum which in turn affects the error rate.

Table A.1 Model error rate and major climate profiles for the climatic niches of the four major forest tree species.

Species	Model error rate (%)			Mean annual temperature (°C)	Mean annual precipitation (mm)
	Presence	Absence	Overall		
Chinese fir	5.4	11.8	8.6	16.9 (9.2–22.6)	1637 (834–3062)
Masson pine	3.0	9.7	6.4	17.6 (6.4–23.5)	1553 (650–3199)
Chinese pine	7.1	12.4	9.8	7.3 (0.4–14.7)	620 (228–1122)
Blue gum	9.7	6.8	8.1	12.0 (4.6–18.4)	887 (455–2928)

Through the removal of the least important climate variables from the RF model each time, we identified the best combination of climate variables for the RF model for each species. The change in the OOB error rate with various number of climate variables is illustrated for Chinese fir in Figure A.1. The level of the change was not substantial when the number of climate variables was greater than 20. The 10 most important climate variables for each species are listed in Table A.2.

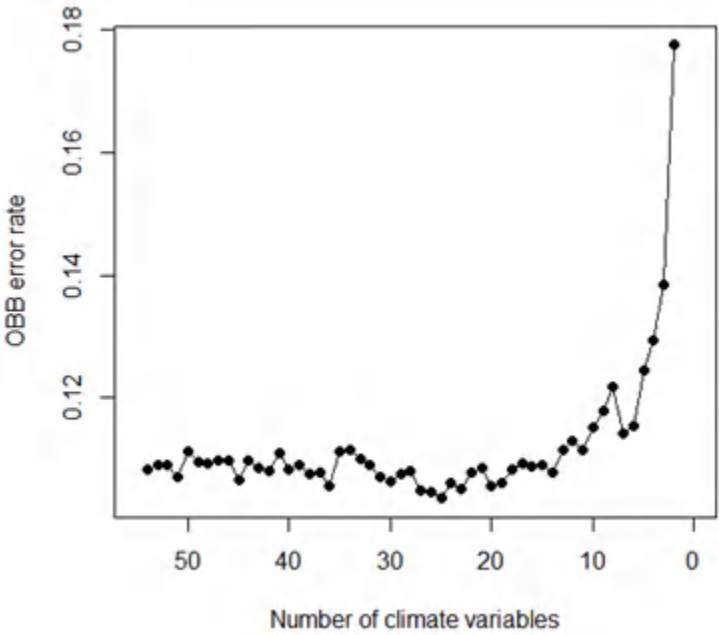


Figure A.1 Changes in error rate of RF model prediction for out-of-box (OOB) samples with the least importance climate variable removed step by step.

Table A.2 The 10 most important climate variables for each of the four forest species based on the importance values (Imp. value) generated from the Random Forest models.

Chinese fir		Masson pine		Chinese pine		Blue gum	
Climate variable	Imp. value	Climate variable	Imp. value	Climate variable	Imp. value	Climate variable	Imp. value
PPT_MAM	40.6	TD	33.8	CMD_JJA	39.9	PPT_DJF	41.1
TD	35.6	PPT_MAM	32.8	PPT_JJA	37.8	Eref_MAM	32.1
Tmin_JJA	34.6	CMD_DJF	31.4	Tmin_JJA	32.6	PPT_JJA	39.3
PPT_SON	30.4	PPT_JJA	26.9	TD	31.1	Eref_JJA	26.6
Tmin_DJF	29.6	PPT_DJF	22.9	DD5_SON	25.4	TD	30.7
Eref_MAM	29.1	DD5_JJA	22.2	MAP	24.0	CMD_DJF	27.7
PPT_JJA	28.9	Tmax_MAM	22.0	MWMT	23.8	DD5_DJF	26.6
CMD_SON	27.8	CMD_SON	20.5	CMD_SON	23.7	EXT	28.7
Tmin_SON	27.7	Eref_JJA	19.8	DD5_JJA	23.1	PPT_SON	26.5
DD5_JJA	27.6	Tmin_JJA	19.2	CMD	22.8	Tmin_MAM	27.5

PPT = precipitation; Tmin = mean minimum temperature; Tmax = mean maximum temperature; MAP = mean annual precipitation; EXT = extreme maximum temperature over 30 years; Eref = Hargreaves reference evaporation; CMD = Hargreaves climatic moisture deficit; MWMT = mean warmest month temperature; MCMT mean coldest month temperature; TD = the difference between MWMT and MCMT, also referred to as continentality; DD5 = degree-days above 5°C, growing degree-days; MAM = March-May; JJA = June-August; SON = September-November; DJF = December-February.

The ensemble predictions of the geographic distribution of the climatic niche for each species are illustrated in Figures A.2a, A.3a, A.4a and A.5a. The predictions of the 10 RF models using random samples for absence agreed for vast majority of the areas, while the disagreement only occurred at margins of the climatic niches for all the four species. The predicted geographic distribution of each species climatic niche was larger but congruent with its current distribution. This was particularly the case for Chinese fir.

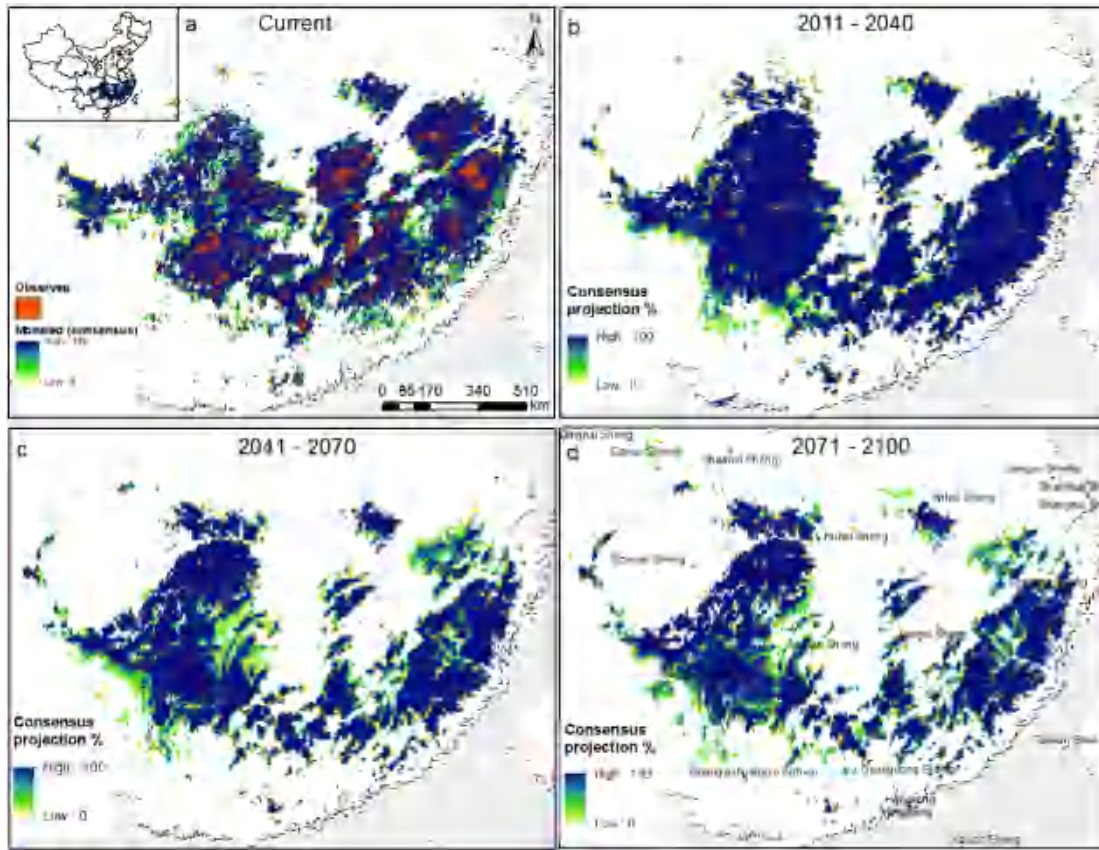


Figure A.2 Geographic distributions of current and potential climatic niches for Chinese fir based on ensemble predictions for the current (1961-1990) and consensus projections for the three future periods 2020s, 2050s and 2080s.

Consensus projections of the geographic distribution of the climatic niches for future periods

Consensus based projections of the future geographic distribution of the climatic niches among the four species shared some common features (Figure A.2, A.3, A.4 and A.5). The projections were highly consistent among the 12 different climate change scenarios for the 2020s, suggesting that the uncertainty in projections of the change in species geographic distribution is relatively low for the near future. However, the consistency declined in the 2050s and 2080s scenarios. Another common feature, was the upward shift in elevation of the projected distribution for each species. The magnitude of the shift was substantial (up to 1100m by the 2050s). Interestingly, no clear shift in latitude was projected as commonly expected for species with the exception of blue gum, which showed a slight southward shift. The size of the climatic niches were projected to contract for most of the species (3 out of 4) and ranged between 24 – 34% by the 2050s.

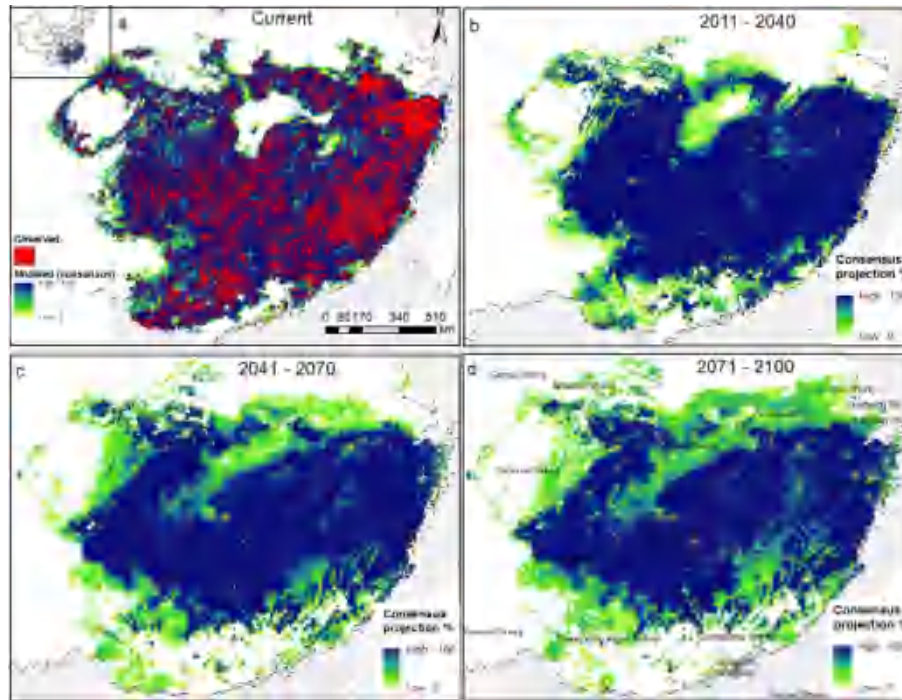


Figure A.3 Geographic distributions of current and potential climatic niches for Masson pine based on ensemble predictions for the current (1961-1990) and consensus projections for the three future periods 2020s, 2050s and 2080s.

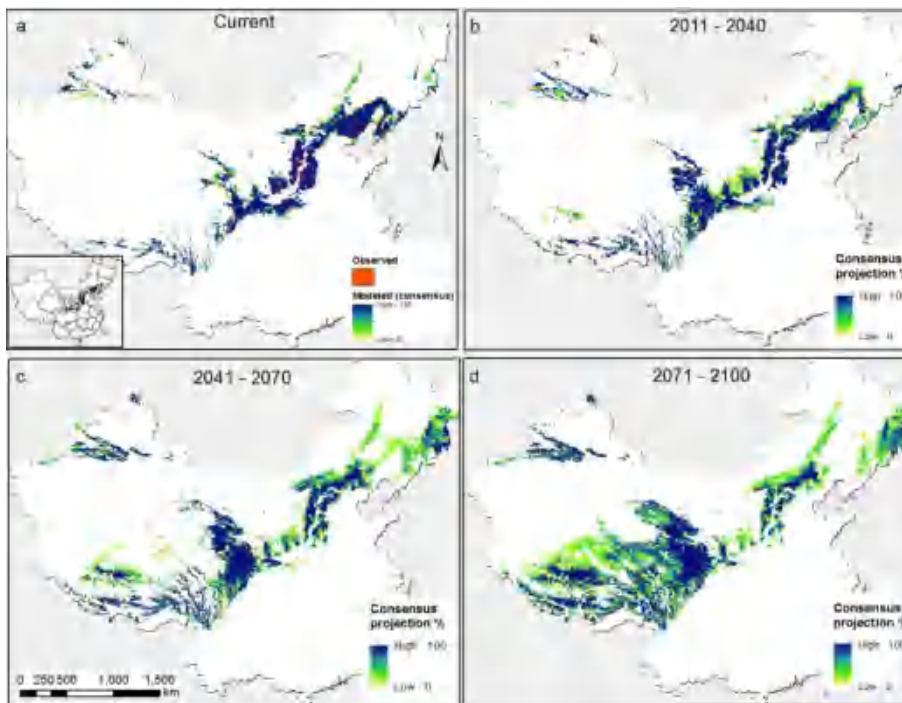


Figure A.4 Geographic distributions of current and potential climatic niches for Chinese pine based on ensemble predictions for the current (1961-1990) and consensus projections for the three future periods 2020s, 2050s and 2080s.

For Chinese fir and Masson pine, contractions along the trailing edge of their climatic niches were projected (Figure A.2 and A.3). Surprisingly, the expansion of their climatic niche along the leading edges was not predicted. For Chinese pine (Figure A.4), the expansion of its climatic niche was substantial (47% by the 2050s) (Table A.3). Interestingly, the expansion was predicted to occur westward instead of northward. For blue gum, the projected shift under future climates was southward towards the edge of the continent, resulting in a considerable contraction of its geographic distribution (-24% by the 2050s) (Figure A.5 and Table A.3). Projected changes in the area of the climatic niches varied considerably among subspecies (Table A.4). The distribution of the climatic niche of *E. globulus ssp. pseudoglobulus* was projected to nearly disappear by 2050s. In contrast, the size of projected climatic niche for *E. globulus ssp. globulus* remained almost the same. The contraction for *E. globulus ssp. bicostata* was also substantial (-50%).

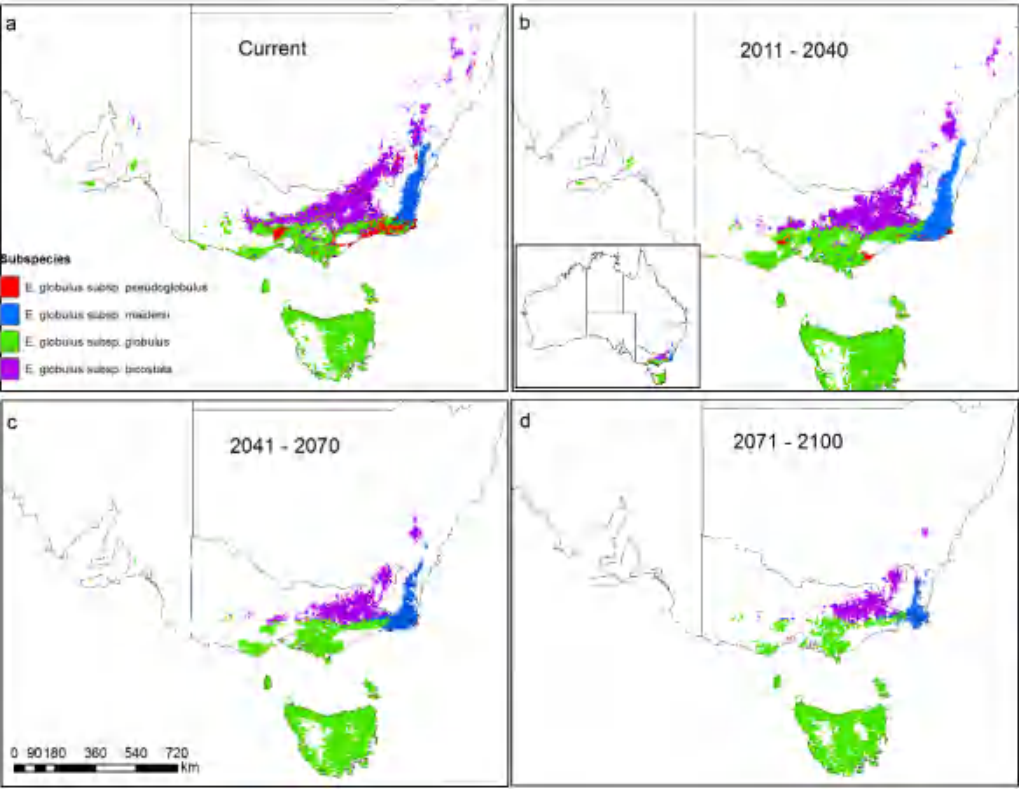


Figure A.5 Geographic distributions of current and potential climatic niches for the four subspecies of blue gum based on ensemble predictions for the current (1961-1990) and consensus projections for the three future periods 2020s, 2050s and 2080s.

Table A.3 Changes in average latitude, longitude, elevation and areas of climatic niches for each species by 2050s relative to the reference period 1970s.

Species	Latitude (°)	Longitude (°)	Elevation (m)	Area (%)
Chinese fir	0.1	-0.7	244	-34.2
Masson pine	0.4	0.5	61	-17.0
Chinese pine	-0.7	-5.6	1129	46.8
Blue gum	-1.2	-0.1	3	-24.3

Table A.4 Changes in average latitude, longitude, elevation and areas of climatic niches for subspecies of blue gum by 2050s relative to the reference period 1970s.

Subspecies	Latitude (°)	Longitude (°)	Elevation (m)	Area (%)
<i>bicostata</i>	-6.8	-9.6	230	-50.7
<i>maidenii</i>	-0.9	-0.4	3	-10.9
<i>globulus</i>	-0.6	0.3	-1	-1.4
<i>speudoglobulus</i>	-0.2	-2.1	-224	-99.0

DISCUSSION

Climatic niches of the species

Our results suggest that the climatic niches of the major forest species in the Asia-Pacific region can be modeled with a combination of climate variables at an accuracy consistent with other regions (Rehfeldt et al., 2006; Gray et al., 2011; Rehfeldt et al., 2014a). The application of following approaches in this study contributed to the low error rates observed in the climatic niche models for the four tree species. These approaches included: 1) the removal of false-absence samples; 2) the optimization of the combination of climate variables; and 3) the use of multiple forests to address the issue of an unbalanced dataset. The developed climatic niche models thereby produced credible predictions of the current geographic distributions for four important tree species in the Asia Pacific (Figure A.2a, A.3a, A.4a, and A.5a). The predicted distribution of the climatic niche included both the areas where the species are currently occupied and areas where the climatic conditions are suitable for the species, but where they may not be present due to various factors including physical barriers, adaptational lag and/or human interference. The models do not consider the role of soil properties and the incidences of disease, insects or fire regimes that may limit a species occurrence/ expansion into climatically suitable areas.

Consensus projections for the future

Uncertainty in future climate is probably the greatest challenge in assessment of the impact of climate change on forest ecosystems and tree species and therefore in developing adaptive strategies in forest management for the future. There are four greenhouse gas emission scenarios and over 20 general circulation models (GCMs) in the latest IPCC report (IPCC, 2014). For a given period, there are over 80 (4 scenarios x 20 GCMs climate change scenarios) different projections of climate conditions. From a modeler's point of view, projections for a large number of climate change scenarios are resource demanding and time consuming as the spatial datasets are usually huge. Therefore, most of the future projections involve only a small number of climate change scenarios. Some studies used ensembles by averaging over GCMs or emission scenarios. However, such ensembles may cancel out the spatial and seasonal patterns of specific GCMs as discussed in Wang et al. (2012a). From a practitioner's point of view, the large range of scenarios makes it almost impossible to develop multiple adaptive options to accommodate a range of potential futures. Consensus projections that aggregate multiple individual projections provide an effective option for practical applications (Wang et al., 2012a). We believe that the consensus projections provide a solid basis for the assessment of climate change impacts on species and for the development of adaptive strategies in forest resources management under a changing climate. Specific characteristics of the consensus projections for each species are described below.

Chinese fir

Our results suggest that the geographic distribution for Chinese fir may substantially contract under predicted climate change. The contraction in its current distribution, particularly in the south, was not a surprise as warmer climate conditions are projected to occur in the southern parts of its current distribution (Figure A.2). What was a surprise was the lack of a predicted northward shift for this wide spread species. The northward expansion of trees in response to climate change is commonly predicted in other studies (Hamann and Wang, 2006; McKenney et al., 2007; Rehfeldt et al., 2014a). The limited northward expansion is likely attributable to the spatial pattern of precipitation in China. Current species distribution and its predicted current climatic niche occur in areas with a mean annual precipitation (MAP) above 830 mm. Under future climates, the geographic distribution of temperatures suitable for this species is projected to move northward; however, the geographic distribution of mean annual precipitation is projected to remain about the same as for the reference period (Figure A.6). The areas with MAP above 830 mm are mostly south of the Yangzi River. The sharp contrast in precipitation between northern and southern China appears to play an important role in the direction of future projections and may limit the northward expansion of this species. In addition, the new combinations of temperature and precipitation may represent some novel climates (Williams and Jackson, 2007) in the region and impose new challenges to model predictions.

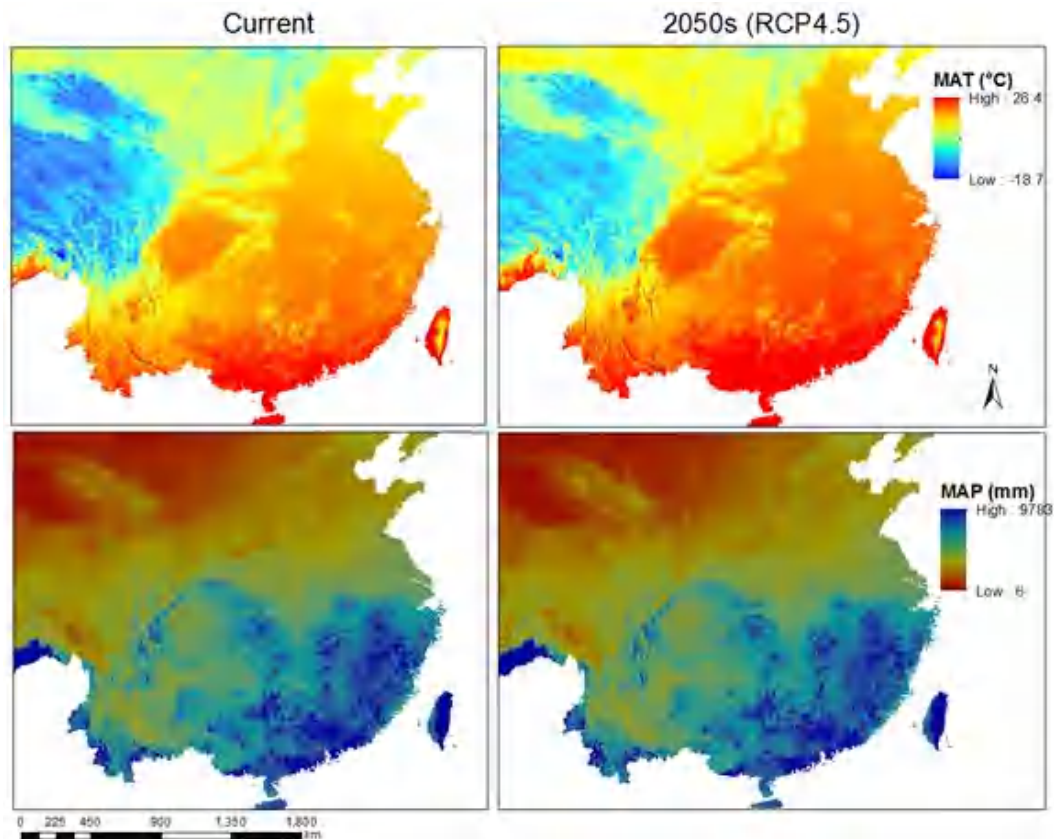


Figure A.6 Distribution of mean annual precipitation (MAP) for 1961-1990 (left) and 2080s (right) projected by one of the AR5 GCM: HadGEM2.

It is worth noting however that the climatic niche modelled in this study (or in the vast majority of other studies) is a realized climatic niche. It reflects the climate conditions currently occupied by the species. Whether or not Chinese fir can grow outside of the current climatic niche is unknown and needs to be further explored through field experiments, such as provenance tests. A recent study using a process-based model 3-PG (Physiological Principles to Predict Growth) reported a northward expansion for this species, but the projected growth potential was extremely low (Lu et al., 2015). The limiting factor appeared to be the soil water content. The findings of Lu et al. (2015) are therefore in agreement with our realized niche-based projections.

The dramatic decline in the area suitable for Chinese fir projected in this study is concerning as this species is one of the most important forest species in China in term of both its economic value and role in ecosystem functioning (FAO, 2006; Jiang et al., 2011). Our results should provide an early warning for policy makers and practitioners to develop adaptive strategies in species selection and forest management practices in order to adapt the management of Chinese fir forests/plantations to future climate. Managing this species within its current geographical distribution will become increasingly problematic as its current climatic niche becomes fragmented which may lead to a loss in economic value of plantations and impair forest ecosystem functioning.

Masson pine

The climatic niche of Masson pine almost entirely overlaps that of Chinese fir, but it has a broader range in term of both temperature and precipitation (Table A.1 and Figure A.3). Projected contraction in its current distributions was much less (-17%) than that of its counterpart Chinese fir (-34%). Like Chinese fir, Masson pine exhibited no substantial northward expansion under future climate conditions. The contraction of its geographic distribution was projected to mostly occur along the trailing end of its current distribution in the south of China. This is in contrast to the projections for Chinese fir, for which a contraction was also projected to occur in the central areas of its distribution. This is probably attributable to the broader climatic niche of this species compared to Chinese fir. Masson pine may therefore provide a good alternative to Chinese fir for reforestation and afforestation under a future climate in these regions of China.

Chinese pine

The consensus projections for Chinese pine falls into line with our expectations of species response to climate change. This species' distribution was modelled to contract along the trailing edges and expanded along the leading edges of its range. Instead of shifting northward, our projected distribution for this species showed a westward expansion. This is not a surprise as the topography in China is characterized by an increase in elevation as one moves from the east to the west. A dramatic increase in elevation (+1100 m) was projected for the distribution of this species' climatic niche by the 2050s. The potential distribution of the climatic niche for this species is projected to increase substantially (~ 50%). Chinese pine is a drought tolerant forest tree species with a relatively fast growth rate (Farjon, 2013). Drought is projected to be more frequent in northern and western China under climate change (IPCC Fifth report (<http://www.ipcc.ch/report/ar5/>)). These trends, together with our projected increase in areas suitable for Chinese pine, suggest that Chinese pine could play an important role in afforestation/ reforestation in north and western China in the future. Assisted migration to help the species expand westward to new locations in the future could be an option in adaptive forest resource management.

Blue gum

As a whole species, the geographic distribution of climatic niche for blue gum is projected to shift southward towards cooler conditions. The shift pole ward will be constrained by the Tasman Sea at the leading edge and likely result in a contraction of its total distribution under future climates (by 24% in 2050s, Table A3). The level of the contraction varied considerably among subspecies. The most impacted subspecies were *E. globulus ssp. pseudoglobulus* and *E. globulus ssp. bicostata*. The climatic niches of these two subspecies are predicted to almost completely disappear and contract by 50% by the 2050s, respectively (Table A.4). This clearly indicates that climate change could bring in new challenges in maintaining the current level of genetic diversity within this species. However, *E. globulus ssp. bicostata* is regarded as being better adaptive to drought than other subspecies (Wang et al., 1988). It will be interesting to observe the response of this subspecies to the impact. In contrast, the total distribution of the climatic niche for the major subspecies *E. globulus ssp. globulus* is projected to exhibit little change in overall area; however, contraction is predicted to occur on the mainland with expansion in Tasmania compensating for this loss.

The contraction in the overall climatic niche of blue gum on the mainland of southeast Australia could have negative implications for the productivity and vitality of blue gum plantations into the future but positive outcomes for plantation and forest managers in Tasmania. However, the adaptive capacity of eucalypt plantations is considered high with many eucalypts grown on short rotations (< ten years). This provides managers with opportunities to adapt their silvicultural practices and/ or plant different genotypes or species to match changing climatic conditions with relative ease (Booth, 2013).

It is important to keep in mind that climatic niche models predict the realized climatic niche rather than the fundamental climatic niche or the actual distribution of a species. The realized climatic niche represents a range of climate conditions currently occupied by a species within its fundamental niche. It is a result of a long term evolutionary and ecological processes of the species involving migration, local adaptation and its interactions with other species and perturbations (Rosenzweig, 1995; Wiens and Graham, 2005). The process is complicated and remains a challenge to be fully understood. However, the objective of climatic niche models is to model a range of climate conditions rather than to model the process and to predict the actual species distributions as is done by species distribution models (Elith and Leathwick, 2009). The projected expansion in the geographic distribution of a species climatic niche at the leading edges of its distribution is therefore a conservative estimate of its potential distribution based on climate, not other factors. It provides baseline information to aid in decision making around assisted migration for a given species (Gray et al., 2011; McLane and Aitken, 2012; Gray and Hamann, 2013). It is up to the forest managers to consider other factors such as soil and disturbance agents that can constraint the predicted climatic niche. Compared to a changing climate, the factors can be static (i.e. soil) and so simple to consider or stochastic (i.e, insects, disease, fire) and therefore difficult to consider.

An additional utility of the climatic niche approach is the identification of areas of a species distribution where they are more vulnerable to climate change. For example, the predicted changes at the trailing edge of a species distribution suggests that there may be populations that will occur outside their climatic niche which lead to maladaptation. Under these conditions the productivity, resilience and competitive advantage of a species may be compromised, which in turn will increase the species vulnerability to abiotic and biotic disturbances (Fettig et al., 2013; Gray and Hamann, 2013). Monitoring and genetic conservation (Hamann

and Aitken, 2013) should be a priority for these areas. However, if these populations are still within their fundamental niches, which were not modeled, these problems related to their survival or even productivity may not eventuate.

In this study, the climatic niches of four economically and ecologically important tree species in the Asia Pacific were modelled and their geographic distributions estimated with a high level of accuracy. This was achieved despite a paucity of vegetation and climate data highlighting that the methodology developed for this study is robust and useful for assessing the impacts of climate change on forests in other regions of the Asia Pacific where similar data issues exist. Understanding how the climatic niches and future distributions of these tree species may change should be useful for informing managers undertaking afforestation and ecosystem restoration in the studied regions. The consensus based projection approach for aggregating multiple climate change projections in this study provides a solid basis for the assessment of climate change impact on tree species and for developing adaptive strategies around species selection in consideration of the uncertainty of future climates.

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APPENDIX B: ClimateAP: an application for dynamic local downscaling of historical and future climate data in Asia Pacific

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ABSTRACT

While low-to-moderate resolution gridded climate data are suitable for climate-impact modeling at global and ecosystems levels, spatial analyses conducted at local scales require climate data with increased spatial accuracy. This is particularly true for research focused on the evaluation of adaptive forest management strategies. In this study, we developed an application, ClimateAP, to generate scale-free (i.e., specific to point locations) climate data for historical (1901–2015) and future (2011–2100) years and periods. ClimateAP uses the best available interpolated climate data for the reference period 1961–1990 as baseline data. It downscales the baseline data from a moderate spatial resolution to scale-free point data through dynamic local elevation adjustments. It also integrates and downscales the historical and future climate data using a delta approach. In the case of future climate data, two greenhouse gas representative concentration pathways (RCP 4.5 and 8.5) and 15 general circulation models are included to allow for the assessment of alternative climate scenarios. In addition, ClimateAP generates a large number of biologically relevant climate variables derived from primary monthly variables. The effectiveness of the local downscaling was determined based on the strength of the local linear regression for the estimate of lapse rate. The accuracy of the ClimateAP output was evaluated through comparisons of ClimateAP output against observations from 1805 weather stations in the Asia Pacific region. The local linear regression explained 70% to 80% and 0% to 50% of the total variation in monthly temperatures and precipitation, respectively, in most cases. ClimateAP reduced prediction error by up to 27% and 60% for monthly temperature and precipitation, respectively, relative to the original baselines data. The improvements for baseline portions of historical and future were more substantial. Applications and limitations of the software are discussed.

1 INTRODUCTION

High-quality climate data are essential for conducting climate change impact analyses. Accordingly, a large volume of climate data has become available through various sources [1–4] in recent years. However, these data sets are mostly in grid format with low-to-moderate spatial resolutions. While such data are suitable for climate impact modeling and analyses conducted at global and ecosystems scales, modeling studies are

increasingly shifting toward local scales often with the goal of developing practical and effective adaptive management strategies. Considering the high levels of heterogeneity in climate in mountainous areas, such gridded climate data are often not adequate to meet the requirements for such studies. Thus, the demand for high-resolution and high-quality spatial climate data are rapidly increasing [5].

Historical climate data, often from a specific reference period (e.g., 1961–1990), are widely utilized to support a wide range of research focused on understanding the relationships between climate variables and plant health and productivity. They are also essential for building climate niche models for examining the distribution of specific ecosystems and their components[6,7] and for testing mechanistic models designed to predict plant growth response to climate[8,9]. Further, the veracity of analyses of plant-climate relationships is dependent on the degree to which the climate conditions reflected in historical data match the actual climate conditions where the plants or ecosystems reside[10,11]. For example, when conducting research with a climate component, it is desirable that climate data are derived from a nearby weather station(s) as such data would be the most accurate and reliable. However, as the number of weather stations is limited, the locations for research projects are often far away and have considerably different climate conditions from weather stations [2, 12]. Spatial interpolation techniques are often used to predict climate conditions for these locations or for developing spatial climate data sets to cover large areas. Statistical methodologies applied to interpolate climate data, including kriging, bilinear and spline interpolations, are primarily based on distances from nearby weather stations. Yet, considering the degree to which topography variations and other factors can influence local climates over relatively short distances, the accuracy of interpolated climate data obtained through these methods is often not adequate.

A number of algorithms and software packages have been developed to facilitate the spatial interpolation of climate data. The ANUSPLIN software developed at the Australian National University employs thin plate smoothing splines to improve on distance-based interpolation, and has been widely used. For example, WorldClim hosts gridded climate data for the entire globe using this approach [2]. The algorithm used in ANUSPLIN is a purely statistical approach and its accuracy often limited for the areas with sharp changes in elevation [1]. Another widely used interpolation method is the Parameter-elevation Regressions on Independent Slopes Model (PRISM) [13] developed at the Oregon State University. PRISM uses a combination of statistical techniques and knowledge-based methods to make adjustments to account for the effect of factors including rain shadows, coastal proximity, and temperature inversions on climate interpolations. PRISM climate data are generally regarded as the highest quality spatial climate data sets currently available. Interpolated climate data are available for the United States and some other regions, including China, at moderate resolutions.

Spatialized historical climate data sets are essential for supporting research geared toward understanding the response of plants, communities and ecosystems to past and ongoing climate change. The most widely used historical climate data are from the Climate Research Unit in the UK, which provides global time series for monthly climate data at the spatial resolution of 30 arcmin (about 50 km × 50 km) available from 1901 to 2015[3].

Although the availability of climate data has improved considerably during the last decade, some challenges remain for non-meteorological users. For example, the process required to obtain climate data for locations of interest can be onerous. Specific software and knowledge of geographic information systems are

typically required to process the data. This is particularly true when climate data for historical and future periods are derived from different sources and with different formats, variables and resolutions. In addition, climate data generated by meteorologists often lack climate variables that are relevant for biological applications.

Several climate databases and tools have been developed to address these needs including those created by McKenney et al.[7] and Rehfeldt et al.[14] using ANUSPLIN for North America. With these tools, users must submit coordinates files for specific locations to request climate data. The web-based Climate Wizard Tool [15] covers the entire world and allows users to obtain climate data for a location. However, there is no downscaling involved and it can be time consuming to assemble climate data for multiple locations. ClimateBC represents another tool that has been widely used for its effectiveness in downscaling, inclusion of both historical and future data, and its user-friendly interface [16]. ClimateBC was initially developed for western Canada and was subsequently expanded to cover the western North America (ClimateWNA) [17] and finally encompassed the whole of North America (ClimateNA) [18]. Along with expansion in coverage, its functionality has also been enhanced, particularly by shifting the downscaling algorithm from a partial-derivative-function based approach [16] to a dynamic-local-regression approach [18].

Using the dynamic-local-regression approach designed for ClimateNA, we developed a climate model to represent the eastern Asia Pacific region called ClimateAP. While the fundamental approach is similar to that employed in ClimateNA, ClimateAP differs considerably in terms of the baseline data, the fact that it covers distinct terrains and topography, and the fact that it crosses an equatorial region. Considering these differences, the effectiveness of the downscaling algorithms and the accuracy of the output of ClimateAP need to be evaluated to provide confidence for its use in supporting climate change research in the Asia Pacific region. Accordingly, the primary objective of the work presented here is to describe the key algorithms employed in the model and to evaluate the accuracy of its output through comparisons against historical climate data. The evaluation includes detailed assessments of derived biologically relevant climate variables, the performance of regionally specific functions, and the efficacy of methods to incorporate daily weather station data in estimating these climate variables.

2 DATA AND METHODS

2.1 Baseline data

Baseline gridded climate data for the reference period 1961–1990 are required to drive the ClimateAP. PRISM data represent the highest quality data but were only available for China and Mongolia. Consequently, it was necessary to use monthly climate data from WorldClim [2] for other countries within the AP region (Fig. 1). Since the WorldClim data set had a complete coverage for the region, it was used as the base data set, with the PRISM data substituted for China and Mongolia. To avoid steps at the contact points between the data sets, inverse-distance-weighted averages were applied to a 20 km overlapping zone of the two data sets. The baseline climate data were provided at the resolution of 0.25×0.25 arcmin (about 4 km $\times$ 4 km). The climate variables obtained from these data sources included three primary climate variables: monthly minimum temperatures (Tmin01–Tmin12), monthly maximum temperatures (Tmax01–Tmax12) and monthly precipitation (Pre01–Pre12). The mean elevation of each grid cell was also included.

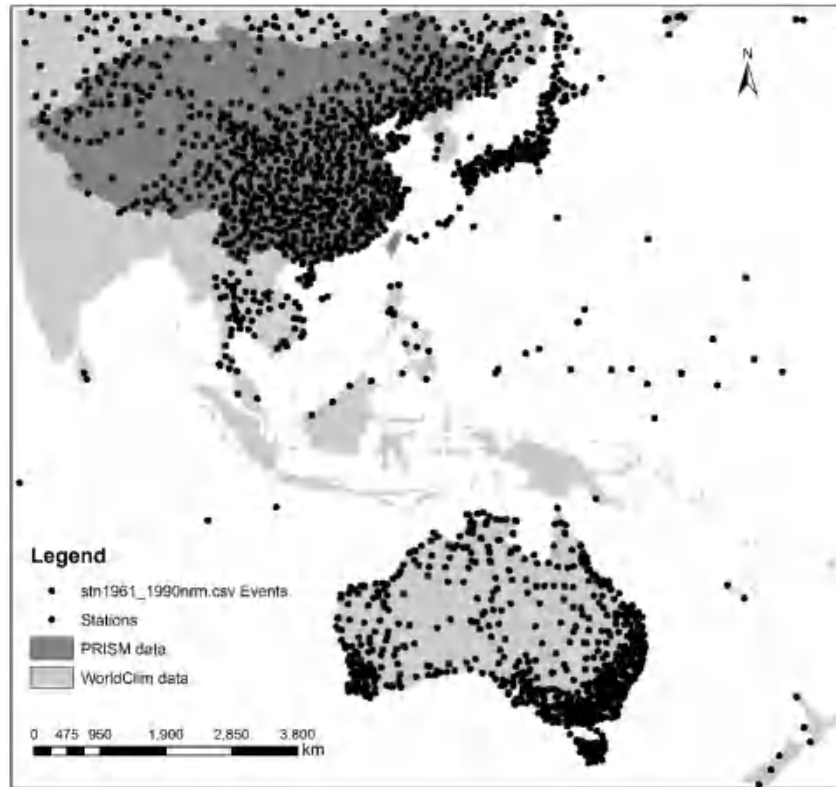


Figure 1 The distribution of the baseline climate data (from PRISM and WorldClim) and weather stations that were used to derive biologically relevant climate variables and to evaluate the output of ClimateAP.

2.2 Historical climate data

Monthly temperature and precipitation data for 1901–2015 (version CRU TS 3.24) generated by the Climatic Research Unit (CRU) at the University of East Anglia [3, 19] were used to represent the historical climate data. According to Mitchell and Jones [19], the original data were developed based on anomalies relative to the reference period 1961–1990, although absolute values were delivered for each individual year at the resolution of $0.5^\circ \times 0.5^\circ$. To facilitate the delta downscaling approach (described below) in ClimateAP, the data were converted back to anomalies for each year by subtracting 1961–1990 normals.

2.3 Future climate data

The climate data for future periods and years were derived from a variety of general circulation models (GCM) included in the CMIP5 project in the IPCC Fifth Assessment Report [20] and downloaded from <http://cmip-pcmdi.llnl.gov/cmip5>. GCM data are available at various spatial resolutions, ranging from $0.75^\circ \times 0.75^\circ$ to $2.85^\circ \times 2.85^\circ$. The GCM data were converted to a resolution of $1^\circ \times 1^\circ$ using bilinear interpolation to simplify the process of integration into ClimateAP. Monthly climate data from two emission scenarios (RCP 4.5 and 8.5) and 15 GCMs [21] were included in ClimateAP for three normal periods 2011–2040, 2041–2070 and 2071–2100. An ensemble data set based on all the 15 GCMs was generated for each of the two RCPs and the three periods. In addition, future monthly data were included for individual years 2011–2100 from three GCMs for the two RCPs. As for the historical data, future monthly values were converted into anomalies relative to the 1961–1990 normals for the purpose of downscaling using the delta approach described below.

2.4 Downscaling of the baseline climate data

The downscaling algorithm in ClimateAP was adopted from ClimateNA [18]. It uses a combination of bilinear interpolation and local regression approaches to downscale the baseline monthly grid data (4 km × 4 km) to scale-free point data. The bilinear interpolation functions to interpolate values for locations between midpoints of the four neighbor grids, while the local linear regression is used to estimate lapse rates for the location of interest to account for elevation effects. In the case of the local regression, ClimateAP retrieves monthly climate data and elevation values from nine closest neighbors of the location of interest and calculates differences in climate variables and elevation between all 36 possible unique pairs of the nine data points. A simple linear regression of the differences in a climate variable on the difference in elevation is performed and the slope of the regression is used as the lapse rate for the climate variable at that specific location. A lapse rate is estimated for each of the 36 monthly primary climate variables at each location of enquiry. Given that the local linear regressions are dynamically performed for every location of interest, the process is called dynamic local regression or dynamic local downscaling. To avoid over-adjustment due to a weak local regression, the adjusted amount is weighted by the r^2 value of the regression.

2.5 Integration and downscaling of historical and future climate data

Both historical and future monthly climate data were integrated and downscaled using a delta method following Wang et al. [18]. With this approach, the historical data (and future projections) are split into two sections: one section for the reference period (i.e., 1961–1990 normal period) and another section for the anomaly period (e.g., the period between the reference period and 2015). For the anomaly section, historical and future monthly climate anomaly grids are interpolated to continuous surfaces using bilinear interpolation at runtime. For the reference-period section, the scale-free baseline monthly climate normal data generated by ClimateAP are used to replace the original historical and future climate data. After adding the interpolated anomaly section to the scale-free reference section, ClimateAP produces scale-free climate data for historical and future years or periods. Since the baseline data downscaled by ClimateAP are at much higher accuracy than that of the historical and future projections, this process is designed to improve the prediction accuracies for both historical and future climate data over their original values.

2.6 Calculated and derived climate variables

The baseline data contain 36 primary monthly climate variables including monthly maximum ($T_{\max 01}$ – $T_{\max 12}$) and minimum ($T_{\min 01}$ – $T_{\min 12}$) temperatures and precipitation (PPT01–PPT12). ClimateAP generates many additional biologically relevant climate variables based on these primary climate variables (Table 1). Some of these variables, such as mean annual temperature (MAT) and mean annual precipitation, can be directly calculated using the primary monthly climate variables. Others, such as degree-days (DD) above 5°C ($DD > 5$) and number of frost-free days, require daily climate data. Since daily data are not available in ClimateAP, daily climate data from weather stations in the region were used to calculate these climate variables and then related back to monthly climate data. The functions reflecting such relationships were used in ClimateAP to estimate those climate variables. Specifically, these relationships were modeled using daily climate data from 1,805 weather stations located throughout the Asia Pacific region from the Daily Global Historical Climatology Network. The distribution of the weather stations is shown in Fig. 1.

Table 1 Climate variables directly calculated (Calculated) using the primary climate variables included in the baseline data and functionally derived (Derived) based on the relationships between the climate variables calculated using daily climate data and monthly climate variables from the 1805 weather stations shown in Fig. 1

Category	Variable name	short	Variable long name	Availability at monthly and seasonal levels
Calculated	MAT		Mean annual temperature	Yes
	MWMT		Mean warmest month temperature	Yes
	MCMT		Mean coldest month temperature	Yes
	TD		Continental, temperature difference between MWMT and MCMT	No
	MAP		Mean annual precipitation	Yes
	AHM		Annual heat-moisture index $(MAT + 10)/(MAP/1000)$	No
Derived	DD < 0 (°C)		Degree-days below 0°C	Yes
	DD > 5 (°C)		Degree-days above 5°C	Yes
	DD < 18 (°C)		Degree-days below 18°C	Yes
	DD > 18 (°C)		Degree-days above 18°C	Yes
	NFFD (day)		Number of frost-free days	Yes
	EMT (°C)		Extreme minimum temperature over a 30-year period	Yes
	EXT (°C)		Extreme maximum temperature over a 30-year period	Yes
	PAS (mm)		Precipitation as snow	Yes
	Eref		Hargreaves reference evaporation	Yes
	CMD		Climatic moisture deficit	Yes

Due to the wide range of variation in climate variables in the Asia Pacific region, no single linear, polynomial or nonlinear function could adequately reflect the relationships between DD and monthly climate variables. Thus, piecewise functions constructed using combinations of linear and nonlinear functions were applied to model these relationships [18]. The DD variables included DD < 0, > 5, < 18 and > 18. The general form of the DD piecewise functions (DD_m) is:

$$DD_m = \begin{cases} \text{if } T_m > k, \frac{a}{1 + e^{-\left(\frac{T_m - T_0}{b}\right)}} \\ \text{if } T_m \leq k, c + \beta T_m \end{cases} \quad (1)$$

where T_m is the monthly mean temperature for the m month; and k , a , b , T_0 , c and β are the six parameters to be optimized. The annual values of the DD variables were calculated by summing up the monthly values. The same approach was applied to other derived monthly climate variables described below.

For the number of frost-free days ($NFFD$) and precipitation as snow (PAS), a sigmoid function was used to model the relationship between these monthly variables and monthly temperatures:

$$NFFD_m(\text{or } PAS) = \frac{a}{1 + e^{-\left(\frac{T_m - T_0}{b}\right)}} \quad (2)$$

where T_m is the monthly minimum temperature for the m month; and a , b and T_0 are the three parameters to be optimized.

For extreme minimum (EMT) and maximum (EXT) temperature over a 30-year period, polynomial functions were used as follows:

$$EMT = a + bTmin01 + cTmin01^2 + dTmin12^2 + eTD^2 \quad (3)$$

$$EXT = a + bTmax07 + cTmax07^2 + dTmax08 + eTmax08^2 + fTD \quad (4)$$

where a , b , c , d , e and f are the parameters to be optimized; $Tmin01$ and $Tmin12$ are monthly minimum temperature for January and December; $Tmax07$ and $Tmax08$ are monthly maximum temperature for July and August, respectively; and TD is continentality.

The other two derived climate variables, Hargreaves reference evaporation and a climatic moisture deficit were directly adopted from Wang et al.^[18] due to a lack of observations to evaluate these variables and the fact that the methods used to estimate them are rather generic^[22].

2.7 Statistical evaluations of ClimateAP outputs

The accuracies of the climate variables generated by ClimateAP were evaluated against observations from weather stations. Observed monthly normals of the primary climate variables for the reference period 1961–1990 were calculated based on the daily climate data from the 1805 weather stations across the entire study area shown in Fig. 1. The amount of variance explained by the ClimateAP outputs and prediction errors, defined as the mean absolute error, were used to evaluate the accuracy of the climate variables generated by ClimateAP for the baseline data.

For the evaluations of the historical data downscaled with the delta approach, we compared the predicted values using CRU, GCMs and ClimateAP against observations for the three primary monthly variables for the baseline normal period 1961–1990. As in the delta approach, the baseline part of the historical and future climate data was replaced by the scale-free baseline data generated by ClimateAP. The amount of improvement in the scale-free baseline data relative to the baseline part of the historical and future climate data provides a conservative evaluation of the predictions of historical and future climate data.

3 RESULTS

3.1 Effectiveness of the local downscaling

The dynamic local linear regressions explained 70% to 80% of the total variation in monthly maximum and minimum temperatures, and 0% to 50% in monthly precipitation variables among the nine neighboring pixels in most cases (i.e., medians) (Fig. 2). These results suggest the local downscaling algorithm is effective for temperature and moderate for precipitation variables. An assessment of seasonal results shows that the downscaling was more effective for warmer months than for cooler months. Spatially, the downscaling was more effective in mountainous areas ($r^2 > 0.85$ in most cases), where elevation adjustment is critical, than in

flat areas. The seasonal and spatial patterns were similar for areas both north and south of the equator (Fig. 2).

The local regression showed a negative linear relationship between the changes in elevation and the changes in monthly minimum and maximum temperatures in most cases. However, positive relationships were also found in winter months associated with temperature inversions that often occur in mountainous areas during the winter. The relationship between precipitation and elevation was mostly positive. The benefit of downscaling for refining gridded climate data in mountainous regions is illustrated in Fig. 3. When considered for the whole AP region, the effect of downscaling applied in ClimateAP was relatively small in terms of the amount of total variance explained for temperatures (less than 1%) and precipitation (0% to 12%) due to the large amount of total variation in the region. However, the improvement was substantial on prediction errors (Fig. 4). The downscaling reduced prediction errors by 16% to 27% for monthly maximum temperatures and up to 60% for monthly precipitation. The improvement on monthly minimum temperatures was relatively small (1% to 6%).

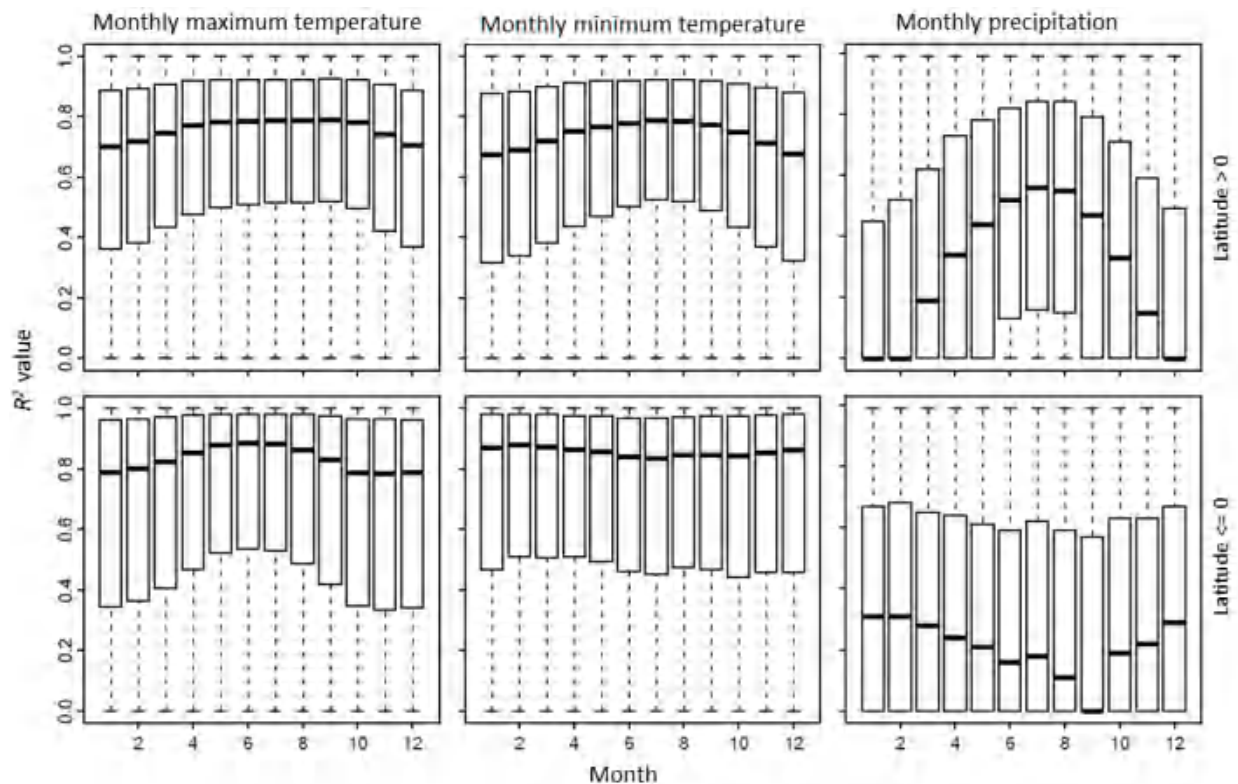


Figure 2 Proportions of variance explained by local linear regressions in total variation among the nine neighboring pixels for the three primary monthly climate variables separated by the equator. The extent of the box indicates the 25th and 75th percentiles. The horizontal solid lines inside the boxes indicate the medians.

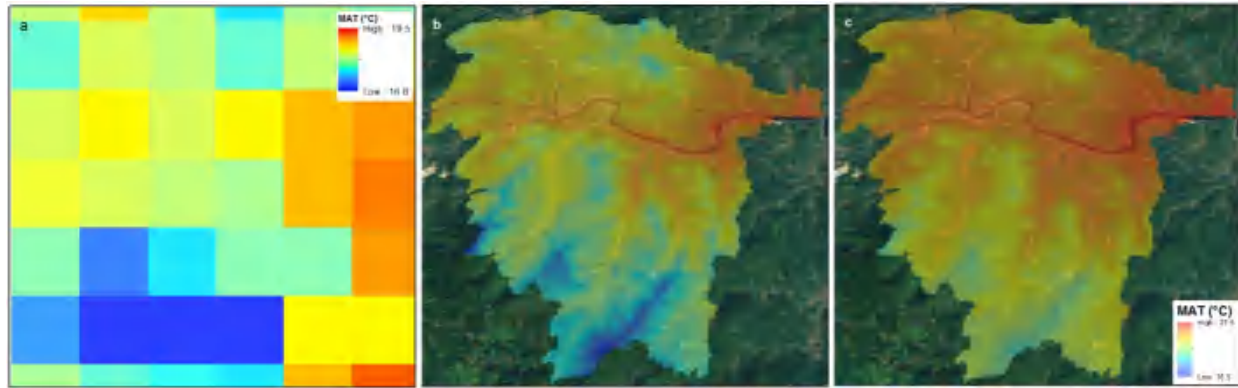


Figure 3 Illustration of the effectiveness of the local downscaling applied in ClimateAP shown in a mountainous area in Fujian Province (117.50°E and 26.52°N). (a) mean annual temperature (MAT) of the baseline data at 4 km × 4 km; (b) downscaled MAT (90 m × 90 m) by ClimateAP and overlaid on a satellite geographic image for the reference period; and (c) downscaled future MAT for the period of 2041–2070 based on the 15 GCMs' ensemble for the RCP 4.5.

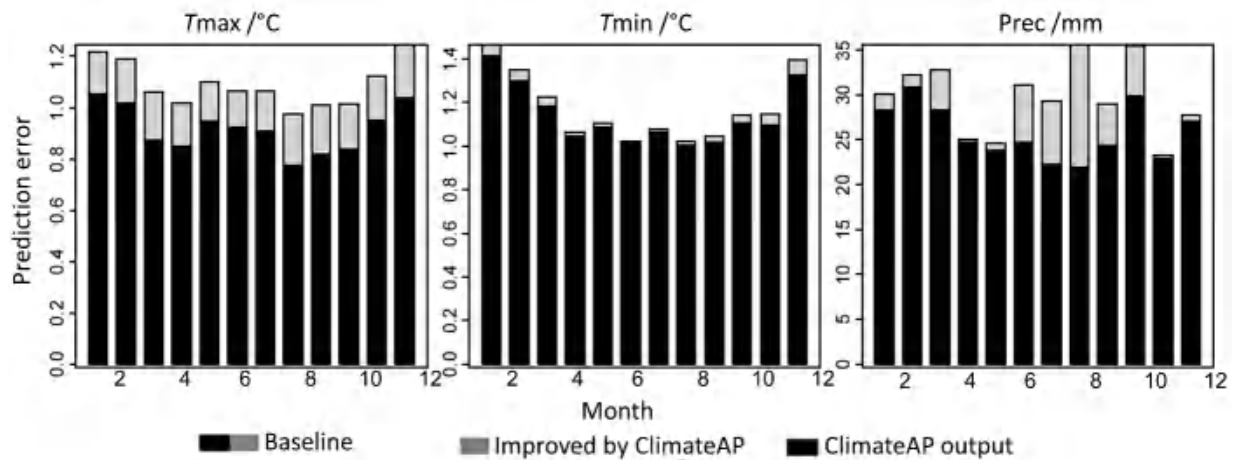


Figure 4 Comparisons in prediction errors between baseline data (i.e., directly from PRISM and WorldClim) and ClimateAP output for monthly maximum temperature ($T_{\max 01}$ – $T_{\max 12}$), monthly minimum temperature ($T_{\min 01}$ – $T_{\min 12}$) and monthly precipitation ($Prec_{01}$ – $Prec_{12}$).

The amount of variance in observed climate variables explained by ClimateAP predictions were high, between 97.3% and 99.3% for monthly minimum temperatures, between 97.7% and 99.6% for monthly maximum temperatures, and between 81.6% and 93.9% for monthly precipitation (Table 2). The prediction errors were between 1.0 and 1.4°C for monthly minimum, between 0.7 and 1.0°C for maximum temperatures, and between 22 and 30 mm for monthly precipitation.

Table 2 The amount of variance in observed climate variables explained by ClimateAP predictions and their prediction errors

Variable	Variance explained/%*	Prediction error/°C	Variable	Variance explained/%	Prediction error/°C	Variable	Variance explained/%	Prediction error/mm
Tmin01	99.2	1.4	Tmax01	99.6	1.0	Pre01	88.2	28
Tmin02	99.3	1.3	Tmax02	99.5	1.0	Pre02	85.2	30
Tmin03	99.0	1.2	Tmax03	99.4	0.9	Pre03	88.4	28
Tmin04	98.3	1.0	Tmax04	98.8	0.8	Pre04	84.8	24
Tmin05	97.3	1.1	Tmax05	97.7	0.9	Pre05	89.1	23
Tmin06	97.9	1.0	Tmax06	98.2	0.9	Pre06	92.4	24
Tmin07	98.2	1.1	Tmax07	98.6	0.9	Pre07	93.7	22
Tmin08	98.3	1.0	Tmax08	98.9	0.7	Pre08	93.9	22
Tmin09	97.8	1.0	Tmax09	98.4	0.8	Pre09	91.9	24
Tmin10	98.0	1.1	Tmax10	98.8	0.8	Pre10	86.5	29
Tmin11	99.0	1.1	Tmax11	99.3	0.9	Pre11	85.6	23
Tmin12	98.6	1.3	Tmax12	99.3	1.0	Pre12	81.6	27

Note: * ClimateAP predictions all exceeded the significance level of $P < 0.0001$.

3.2 Accuracies of derived climate variables

The fits of the piecewise and nonlinear functions were strong for all derived climate variables. Comparisons between the derived climate variables that were estimated from monthly climate variables and those that were calculated from observed daily climate data indicated that the derived climate variables were highly accurate based on the amount of variance explained (mostly over 99%) and the prediction errors listed in Table 3.

Table 3 The amount of variance in observed climate variables explained by monthly climate variables and their prediction standard errors

Variable	Variance explained/%		Prediction standard error	
	Monthly	Annual	Monthly	Annual
DD < 0 (°C)	94.4 – 99.9	99.8	0.5 – 8.2	21.7
DD > 5 (°C)	98.7 – 100.0	99.8	3.2 – 27.2	97.9
DD < 18 (°C)	99.3 – 100.0	99.8	5.2 – 13.9	73.4
DD > 18 (°C)	99.2 – 99.8	99.9	5.0 – 10.8	41.5
NFFD (day)	90.5 – 99.8	98.5	0.5 – 1.6	7.1
EMT (°C)		99.3		2.1
EXT (°C)		86.5		1.5

Note: *All derived climate variables exceeded the significance level of $P < 0.0001$.

3.3 Improvements of historical and future climate data

ClimateAP output showed substantial improvements for historical and future climate data relative to the original CRU and GCM data for the baseline period (1961–1990 normal) (Fig. 5). On average, the prediction errors for CRU data were reduced by 0.5°C (31%) for monthly minimum temperatures, 0.8°C (47%) for monthly maximum temperatures, 21 mm (44%) for monthly precipitation. The relative improvement for

GCM output was even greater as prediction errors were reduced by 2°C (67%) for monthly temperatures and 35 mm (56%) for monthly precipitation on average.

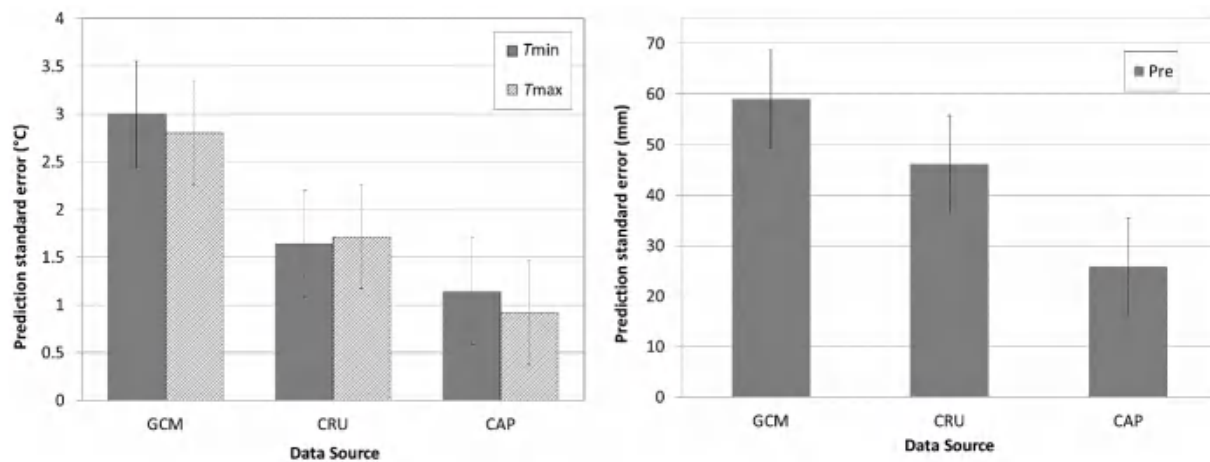


Figure 5 Comparisons in prediction errors among three data sources for the reference normal period 1961–1990: IPCC GCM predictions (GCM), Climate Research Unit (CRU) and ClimateAP (CAP) output. The error bars are standard errors indicating the variation among the 12 months.

4 DISCUSSION

High-quality and high-resolution climate data are essential for facilitating climate impact studies and applications. ClimateAP allows users to extract and downscale gridded climate data to scale-free climate data for specific point locations through a dynamic local downscaling approach. It also generates a diverse series of biologically relevant derived climate variables at monthly, seasonal and annual time steps. Evaluations of the downscaling process and comparisons of output against observations suggest that the dynamic local downscaling approach implemented in ClimateAP is effective for reducing interpolation error in baseline data. The level of improvement in prediction accuracy is comparable to that determined for ClimateNA^[18]. Historical monthly climate data from CRU and future monthly climate data from GCMs for individual years or normal periods can also be effectively downscaled using the delta method by taking advantage of the scale-free climate data for the reference period generated by ClimateAP.

4.1 Downscaling and prediction accuracy for the reference period

The baseline data used in ClimateAP from PRISM^[23] and WorldClim^[2] are at relatively high spatial resolution (4 km × 4 km) in comparison to historical climate data from CRU^[3] (50 km × 50 km) and projected future climate data from GCMs^[20] (up to 250 km × 250 km). Elevation has been identified as the dominant factor driving the local variation in climate within each pixel of the baseline climate data^[1]. Results of this study have confirmed this. Thus, the effectiveness of the downscaling depends largely on the accuracy of the estimated lapse rate, which varies with latitude at a large scale and local site factors at a fine scale. Although partial derivative functions have been used successfully for elevation-related temperatures adjustment, they are not feasible for precipitation^[24]. In this study, a dynamic local linear regression approach developed for ClimateNA^[18] was applied to ClimateAP. Results of the analyses show that the lapse rates estimated through

local linear regressions were able to capture such variation in monthly temperature and precipitation variables among the neighboring pixels, including temperature inversion in winter months, which is considered difficult to model [7, 25].

The accuracy of ClimateAP predictions for temperatures were high based on the amount of variance explained (97% to 99%) and prediction errors (0.7–1.4°C) (Table 2). The prediction accuracy was considerably lower for precipitation than for temperatures in terms of both the amount of variance explained (82% to 94%) and prediction errors (22–30 mm). The accuracy of ClimateAP predictions was slightly lower than those observed for ClimateNA [18], despite the fact that the relative improvement over the baseline data by elevation adjustment was comparable or even greater in ClimateAP. This suggests that the quality of the baseline data in ClimateNA is better, as would be expected. PRISM data have been updated for the USA, but not for China. In addition, the number of weather stations used for developing these baseline data was much greater in North America than in the Asia Pacific region.

4.2 Calculated and derived climate variables

The baseline climate data used in ClimateAP have 36 primary monthly climate variables (T_{min01} – T_{min12} , T_{max01} – T_{max12} and $Pre01$ – $Pre12$). ClimateAP calculates and derives many additional biologically relevant climate variables at monthly, seasonal and annual time steps (Table 1). These additional climate variables have been widely used in modeling forest ecosystem and species climate niches [6, 10, 26], population response to climate [8, 27, 28] and evolutionary genomics [29]. The most frequently used climate variables include MAT, annual heat-moisture index, continentality or temperature difference, cooling and growing DD (< 0 and > 5 , respectively), and precipitation as snow. The ability to generate these biologically relevant climate variables significantly expands the utility of ClimateAP.

4.3 Integration and downscaling of historical and future climate variables

ClimateAP integrates both historical and future climate data through a delta method. While the delta method is relatively simple, it appears to perform as well as sophisticated downscaling methods in producing mean characteristics [30]. With this method, the baseline portion of the historical and future climate data are replaced by the scale-free data generated by ClimateAP. As the accuracy of the scale-free baseline data are much higher than that in the historical or future climate data, this replacement not only increase the spatial resolution, but also considerably improves the accuracy of the historical (31% to 47% for temperatures and 44% for precipitation) and future climate data (67% for temperatures and 56% for precipitation).

For the anomaly section of the historical and future climate data, ClimateAP bilinearly interpolates the gridded data into point data at runtime. Although this process is not likely to improve the accuracy of the predictions, it smoothens steps across the original grid cells. Moreover, errors associated with the anomalies are typically small as they are less sensitive to topography and their spatial variations are relatively easy to model in comparison to absolute values for historical climate data [19]. The same applies for projections of future climate data. Through a combination of the replacement of the baseline section and the bilinear interpolation to the anomaly section, ClimateAP is able to generate seamless climate surfaces (Fig. 3c). This makes it possible to develop adaptive forest management strategies at the local scale for a changing climate.

4.4 Applications and limitations

Modeling climate niches for ecosystems and species requires climate data that are consistent with the actual locations of the vegetation in question^[31, 32]. The scale-free climate data generated by ClimateAP allows it to meet this requirement. In addition, the availability of a large number of calculated and derived biologically relevant climate variables will considerably increase the flexibility of models to address such objectives. ClimateAP has been used to model the climate niche for four major forest tree species in Asia Pacific^[33].

Due to the difficulty in accessing climate data in the past, scientists have been using geographic variables, such as latitude, longitudes and elevation as substitutes for climate variables in experimental design and data analysis. However, results obtained from such studies are limited to specific locations. In contrast, a relationship between plant performance and specific climate variables should theoretically remain consistent at different locations. ClimateAP significantly improves access to spatially distributed, climate variables for use in a wide range of applications including climate based experimental design, modeling climate niches for ecosystems and species, and population responses to climate. In particular, the time-series function in ClimateAP allows users to generate monthly climate time series for multiple locations and multiple years for historical and future years between 1901 and 2100. In the absence of such a tool, it may take several months to obtain and process the same amount of data. ClimateAP can be used to generate climate surfaces. ClimateAP produces output in a comma-separated-values format that can be imported easily to ArcGIS to generate maps. The resolution of the map depends on the resolution of the input file. It is particularly useful to generate high-resolution climate maps for specific areas to develop management strategies accounting for locally variable climate conditions.

ClimateAP predictions can account for more than 97% of the total variation in temperatures and more than 82% in precipitation for the 1961–1990 normals. However, the standard prediction errors in term of absolute values are still considerably large, that is 0.7–1.4°C for temperatures and 22–30 mm for monthly precipitation. This can be much greater when it comes to specific locations and specific years (instead of the 30-year normal periods). The prediction errors are expected to be smaller in the regions with more weather stations than the regions where weather stations are lacking. The dynamic local elevation adjustment is effective to downscaling the baseline data. However, it is not able to correct all the errors associated with the baseline data or the anomalies of the historical and future climate data. In addition, although ClimateAP can generate spatial climate surface at very fine resolution or for specific locations, the microclimate affected by aspect, slope and vegetation types at micro-scale are not reflected in the predictions. Therefore, caution is required when interpreting the climate data at very fine spatial resolution.

5 CONCLUSIONS

ClimateAP uses the best available climate data as baseline climate data and downscales it to a scale-free format with improved prediction accuracy using a dynamic local downscaling approach. It incorporates historical and future climate data into a single package and improves prediction accuracy using a delta approach by taking advantage of the high-quality scale-free baseline data generated by the application. Additions of calculated and derived biologically relevant climate variables make the application more useful for a variety of applications in forest modeling. In addition, ClimateAP allows users to generate climate data at any spatial resolution, which is particularly important for development of adaptive forest management

strategies at local scales. However, it should be noted that errors inherent in the original baseline and anomaly climate data cannot be totally corrected by the application. The desktop version (intensive users) and a Google Map based web version (occasional users) of ClimateAP can be accessed at <http://asiapacific.forestry.ubc.ca/research-approaches/climate-modeling>.

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APPENDIX C: Modelling forest ecosystem net primary production: the hybrid simulation approach used in FORECAST

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ABSTRACT

In order to evaluate the impacts of alternative stand-level management scenarios on long-term site productivity, forest resource managers need ecologically based forest growth models. The FORECAST forest ecosystem management simulation model combines the traditional bioassay modelling approach with process-based simulation modelling to provide a method of projecting future forest biomass yield as well as a variety of other ecosystem variables and social values under a range of management conditions. A review of the hybrid simulation approach to modelling forest ecosystems is provided, and the representation of stand-level net primary production and nutrient cycling in FORECAST is described. The major driving function in the model (shade-corrected foliage nitrogen efficiency), the concept of site quality, and the simulation of site quality change are discussed. The value of an accurate definition of the state of the simulated ecosystem at the start of a run is emphasized, and the use of the ECOSTATE (STATE of the ECOSystem, as generated by FORECAST) file in this process is described. Limitations of the FORECAST modelling approach are reviewed.

1. INTRODUCTION

With the steady increase in the demand for both traditional timber and non-timber forest values from a shrinking land base and the global commitment to the concept of sustainability, the need for credible forecasts of the probable consequences of alternative forest management strategies has never been greater. For nearly two centuries, volume-age curves, height-age curves, and yield tables have been the basis on which foresters have predicted future yields. This "historical bioassay" method is valid for the species involved and the particular set of biotic and abiotic growth conditions that pertained over the period of growth. However, if changes in future management regimes, human impacts on the environment (e.g. climate change, atmospheric chemistry), and/or changes in soil fertility significantly alter future growth conditions, the predictions of the bioassay are unlikely to be accurate (Kimmins, 1988, 1990; Korzukhin et al., 1996). In addition, these empirically based growth and yield models were not designed to project the effects of management on future trends of a wide variety of wood and non-wood forest products and values. They do

not provide an adequate basis for comparing the impacts of different forest management strategies for multiple resource values, nor are they suitable for stand-level analysis of various measures of sustainability.

Because of the inflexibility of this traditional growth and yield approach, a great deal of interest and research has been focused recently on mechanistic models. These process-based models consist of empirically derived relationships between a series of independent variables and the dependent variable, tree (stand) growth. Examples of such models developed for forests and other ecosystems can be found throughout the literature (e.g. Sollins et al., 1979; Running, 1984; Running and Coughlan, 1988; Barclay and Hall, 1986; Parton et al., 1987; Bossel and Schäfer, 1989; Dixon et al., 1990). While process-based models have great heuristic value, most of them are not ecosystem-level models and they are rarely used in practical applications in forestry. This is primarily because we do not know enough about the key ecosystem processes and their interactions to combine them for the purpose of making accurate predictions of forest growth (Mohren and Burkehart, 1994).

A third, 'hybrid' approach to yield prediction has been developed which attempts to combine the strengths of the other two approaches and thereby compensate for their individual weaknesses. The most developed models in this category, designed for the assessment of harvesting impacts on long-term site productivity, include LINKAGES (Pastor and Post, 1985), FORCYTE-11 (Sachs, 1991, Kimmins, 1993), and FORECAST (the successor to FORCYTE-11; e.g. Kimmins and Scoullar, 1994; Comeau et al. 1995; Wang et al. 1995; Morris et al., 1997). These models take the yield (production) predictions from a historical-bioassay model (or from raw field data), and modify these predictions according to a simulation of the temporal variation in competition for light and in the availability of one or more nutrients. Nutrient availability is the focus of the process simulation because it is often the factor which most limits forest growth at the stand level, and it is the site factor that is most subject to change as the type and/or intensity of forest stand management changes. Light competition is also a central component of the simulation of stand development. Moisture limitations and moisture competition are not well represented in these models, which are, therefore, restricted in their application to sites that do not have severe site moisture deficits or severe soil moisture competition. A moisture and temperature submodel, based on an extension of Arp and Oja (1996a,b) and Arp and Yin (1992), is being added to Forecast to address this shortcoming (Seely et al., 1997).

The objective of this paper is to provide a description of the simulation algorithms controlling ecosystem net primary production in the FORCYTE-FORECAST series of hybrid-simulation, forest ecosystem models. Future papers will describe other aspects of the model, evaluate its performance, and report on its applications. For discussions of the predecessor model, FORCYTE, and some preliminary evaluations of FORECAST, see: Comeau and Kimmins (1986); Kimmins et al. (1986); Sachs and Sollins (1986); Yarie (1986); Kellomäki and Seppala (1987); Kimmins (1988, 1990); Kimmins et al. (1990); Sachs and Trofymow (1991); Kimmins and Scoullar (1994); Comeau et al. (1995); Wang et al. (1995); and Morris et al. (1997).

2. FORECAST: GENERAL DESCRIPTION

2.1 Model structure

Figure B1 depicts a flowchart of the files and programs that are contained within the Forecast ecosystem management model. Kimmins (1993) has provided an in-depth review of the scientific foundations and

programming logic used in the development of FORCYTE-11, which is conceptually and structurally similar to FORECAST. Basic empirical data (TREEDATA, PLANTDATA, BRYODATA, and SOILDATA) are fed into the 'setup' programs (TREEGROW, PLNTGROW, BRYOGROW, and SOILS) which use the information to derive a set of simulation rules and values for various process rates that are used in the ECOSYSTEM program to simulate the management of the ecosystem (see Figure B.1). The algorithms in FORECAST's setup process are analogous to the curve fitting procedures that produce the coefficients defining the shape of mathematical relationships in conventional process-based models. The characteristics of the simulation rules and rate estimates, contained in the *TRND output files, may be evaluated with diagnostic graphs produced as output from each setup program. The SOILDATA 'setup' also produces an INITSTAT file, which, used in conjunction with a special run of ECOSYSTEM, results in a description of the initial values for organic matter and nutrient inventories for the start of future runs (the ECOSTATE file). The ecosystem simulation performed by ECOSYSTEM is under the control of the ECODATA file. This file is analogous to the 'scheduler' files in other models; it defines the starting site quality, plant community species composition, and run conditions: it prescribes the various management options and duration of the runs imposed on the ecosystem. Output files are then fed into the NAVIGATOR output management program for viewing and printing the results generated from the ECOSYSTEM runs. The entire user-model interaction is conducted through the FORECAST NAVIGATOR software which facilitates entry and editing of calibration data, program running, scenario generation, and tabular and graphical output analysis.

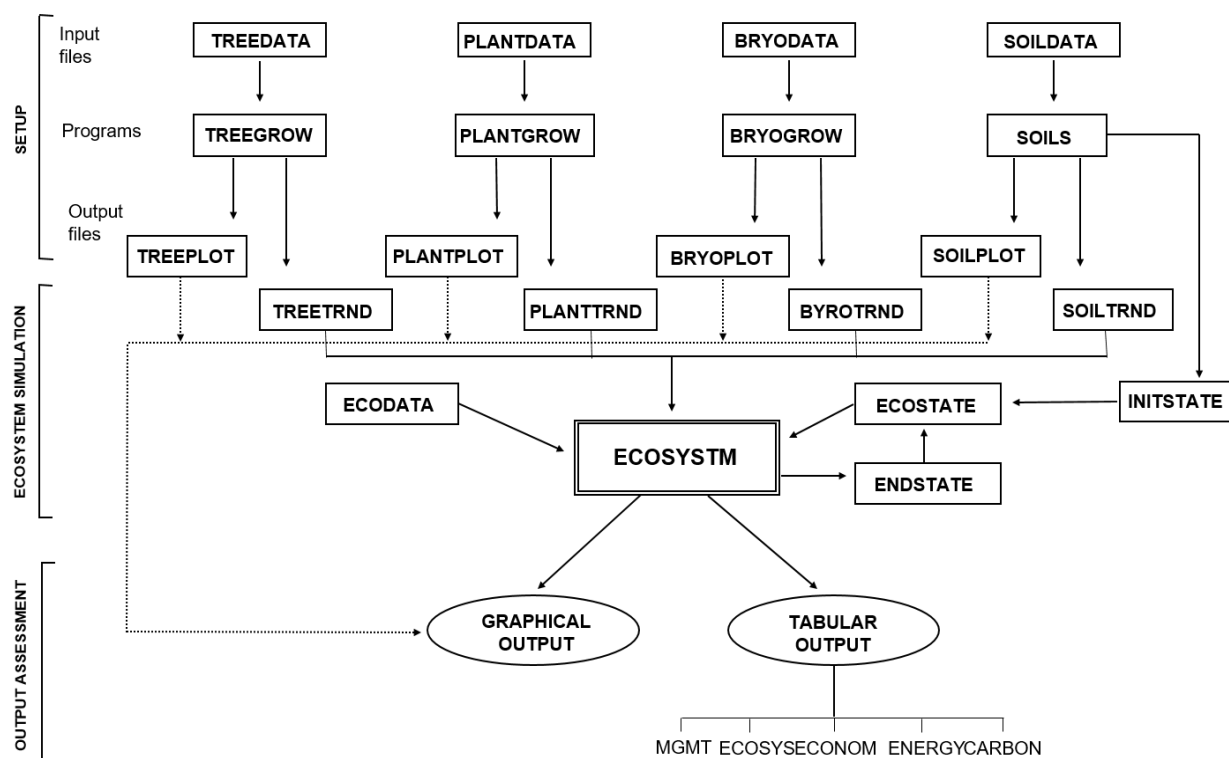


Figure B.1 A flowchart of the setup programs, data files, and management files that are contained within the FORECAST modelling structure.

2.2 Data requirements

The complete data requirements for the calibration of FORECAST are specified in Appendices A-D. Because the development of indices or coefficients for the various ecosystem processes is conducted within the model itself, and because the model represents, or has the capability to represent, a variety of ecosystem processes and management activities (Figure B.2), the input data requirements to run the model are substantial. They are much larger than in comparable 'gap' models (e.g. LINKAGES, Pastor and Post, 1985), because in such models this preparatory 'setup' work has been done external to the model, and the average model user never actually works with the data that calibrate the model. However, if the full data requirements for the estimation of all the coefficients, simulation rules and other data requirements of gap models are compared for similar simulation capabilities, the difference between gap models and FORECAST is much less than it appears to be. Data are required on height, stand density, stem size frequencies, biomass accumulation, nutrient concentrations in the various biomass components, atmospheric nutrient inputs, foliar leaching (optional), biomass to litterfall transfer rates, photosynthetic adaptations of foliage (e.g. photosynthetic light saturation curves for sun and shade foliage), and a variety of other stand and soil (physical and chemical properties) information from a chronosequence of stands on sites that vary in nutritional site quality. By providing empirical data that describe different process rates and growth strategies in response to varying nutrient availability (i.e. data from sites varying in nutritional site quality), the model is able to establish simulation rules that permit the simulation of shifts in production and carbon allocation in response to management-induced changes in soil resource availability.

FORECAST was designed to be used at various levels of ecosystem representation. The lower the level of representation, the lower the associated input requirements. For example, the user may switch off the representation of nutrient feedback and site quality change and reduce the data requirements substantially. However, the light-limited population or community model that results is incapable of addressing soil-related sustainability issues. Thus, the wider the range of questions the user wishes to explore, greater the data requirements. This flexible approach permits the analysis of the prediction implications of including or omitting various key ecosystem processes.

3. DERIVATION OF TOTAL NET PRIMARY PRODUCTION (TNPP) FROM THE HISTORICAL BIOASSAY

The setup plant growth programs (TREEGROW, PLNTGROW, BRYOGROW) derive, for each plant species for which historical bioassay data are provided, the total net primary production that occurred for each annual time step (TNPP_t) based upon the following equation:

$$\text{TNPP}_t = \Delta \text{biomass}_t + \text{ephemeral litterfall}_t + \text{mortality}_t \quad (1)$$

where:

$\Delta \text{biomass}_t$ = the sum of the change in mass of all the biomass components of the particular species in time step t ,

litterfall_t = the sum of the mass of all ephemeral tissues that are lost in time step t (e.g. leaf, branch, bark and reproductive litterfall, and root death),

mortality_t = the mass of individual plants that die in time step t .

This estimation of past, net ecosystem production is used as the basis to predict potential growth in the ecosystem simulation module of FORECAST (ECOSYSTEM). The simulation algorithms used for estimating $\Delta \text{biomass}_t$, litterfall_t , and mortality_t are explained below. FORECAST calculates Total Net Primary Production (TNPP), rather than only Aboveground (ANPP) or Stemwood Net Primary Production (SNPP). This total ecosystem approach allows for a representation of the important effects of belowground biomass allocation (Keyes and Grier, 1981, Comeau and Kimmins, 1989, Kurz, 1989) in the simulation of management-induced changes in aboveground production. It also permits a more complete representation of soil organic matter dynamics (Morris et al., 1997).

3.1 Change in biomass

Change in biomass ($\Delta \text{biomass}_t$) in each time step is derived from a series of age-biomass data pairs in the input file using an interpolation (data-smoothing) algorithm that functions as follows: 1) the individual setup programs calculate the rate of change in biomass (the slope of the rate-lines) between successive biomass/age data pairs for each biomass component; 2) the slopes of the lines joining the age midpoints of these rate-lines are estimated by linear interpolation and subsequently used to reconstruct a change-of-biomass-over-age-curve with a yearly time step; 3) this curve is forced through the origin and through the maximum value given in the input data file; 4) the smoothed curve becomes the basis for calculating the change in mass for each biomass component ($\Delta \text{biomass}$) in each simulation time step. When the program has created a smoothed biomass/age array, it selects 30 biomass/age pairs from the array (the model assumes that the user will want to be able to run the model for at least 30 time steps) and saves these as a data base. The "ages-for-saving" are defined by the user and should be concentrated over the sections of the biomass/age curve at which there is rapid change in the accumulated biomass; fewer data pairs are assigned to other portions of the curve that are changing more slowly. Reduced array sizes are used to economize on memory. The program uses linear interpolation to generate points between the saved data ages. The same "ages-for-data-saving" array is used for all biomass components of a species.

The smoothing/interpolation algorithm described above produces curves that track the input data quite closely. Most mathematical equations have their own "character" or shape that may not fit a particular

biomass/age curve well. While it may be appropriate to use such equations for monotonically-increasing functions (e.g. most examples of stem wood accumulation), the smoothing technique accommodates variables such as foliage biomass and fine-root biomass, which may have a variety of characteristic temporal patterns, including a bimodal pattern or a single early peak followed by decreasing values. It also allows for cases in which stem biomass accumulation may be bimodal (e.g. *Abies balsamea* in central Newfoundland, Dr. Bill Meades, Canadian Forestry Service, unpublished data). Since the algorithm tracks the input data quite faithfully, the user is responsible for editing the field data to exclude or adjust any data points that might deviate from the expected "normal" biomass/age relationship for that species on that site. The problem of "spurious" or questionable data points in a chronosequence data set [i.e. data that violate the assumption of the chronosequence method, that the only variable that differentiates the sites is time (Dyck and Mees, 1989; Dyck and Cole, 1994)], can be avoided by using averages of data from several or many replicates of a particular site, or output from a well-calibrated and reliable historical bioassay model based on a large data set. Where this solution is not available, the user should exercise judgment concerning unexpected trends in biomass/age data, and hand-smooth the data appropriately.

3.2 Ephemeral litterfall

For the calculation of annual TNPP (Eq. 1) the growth setup programs use input data to define the proportions of roots of various sizes and of bark that die and become "litterfall" in each time step. The number of years of leaf and dead-branch retention must also be given; the reciprocals of these values give the proportions of the foliage and dead-branch biomass that fall as litter each year. These proportions are applied to the existing mass of each of these biomass components at the end of each time step, and the result is an estimate of the ephemeral litterfall in that time step (litterfall_t).

3.3 Mortality

3.3.1 Changes in stand density

The growth setup programs treat input data on tree stand density, in self-thinning stands, as a function of stand age in much the same manner as the biomass/age input data. The rate of change between successive stand density-age input data pairs is calculated and the slope of the lines joining the median age of each of these rate-lines is used to produce a smoothed density-age curve, forced through the origin and the maximum value in the input data. This smoothed density curve then becomes the basis for the array of mortality rate/age data pairs used to simulate mortality (mortality_t). Thirty data pairs from this array are saved. As was the case for the biomass/age data, it is the responsibility of the user to ensure that the input data on stand density represent the best available estimate of the characteristic temporal pattern of stand self-thinning for a normally-stocked stand for that site. Where data from self-thinning stands are not available, best estimates of stand density time trends can be obtained from stand density diagrams (Drew and Flewelling 1979).

3.3.2 Calculation of individual tree size

In conjunction with the natural tree mortality simulated in each time step (mortality_t), the model also uses a simulation of individual tree size to define the biomass transfers associated with mortality. TREEGROW (the tree growth setup module) simulates the stemwood biomass of individual trees using an index of individual tree size differentiation calibrated with data contained in the TREEDATA file that describe stem biomass size

frequencies for a given stand age. This data may be derived from DBH class distributions obtained from the remeasurement of even-aged permanent plots or from chronosequence data from unthinned stands. Tree size distribution data may be presented for as many as ten stand ages, but the model will simulate tree size variation even if size distribution data are given for one age only. In this case, it is simply assumed that the shape of the stem size frequency distribution given for one age remains constant over all stand ages.

The simulation algorithm works by using the stem biomass class distribution data at the specified stand ages to calculate the rate of size increase in each time step for the median tree in each distribution. Individual trees are divided into as many as 10 biomass classes according to the distributions specified in the input data. The rates of growth of all trees at a particular stand age are expressed relative to the growth rate of the median tree (set to 1.0) at that age and the annual net stand stemwood biomass production is allocated to individual trees (Eq. 2). It then calculates the rate of growth of trees in: a) the largest size classes, b) trees in the smallest size class that remain alive over the time period (it is assumed that the smallest trees will die first), and c) trees distributed into the intermediate size classes (Figure B.3).

$$\text{Growth of tree } i = \frac{\text{RGR tree}_i}{\sum_{i=1}^n \text{RGR tree}_i} \cdot \text{Net stand stemwood production} \quad (2)$$

where:

Growth of tree_i = the proportion of total stand stemwood production allocated to tree_i,

RGR tree_i = growth rate of tree_i relative to the median tree in the distribution

Net stand stemwood production = total stand stemwood biomass production for an annual time step (kg ha⁻¹).

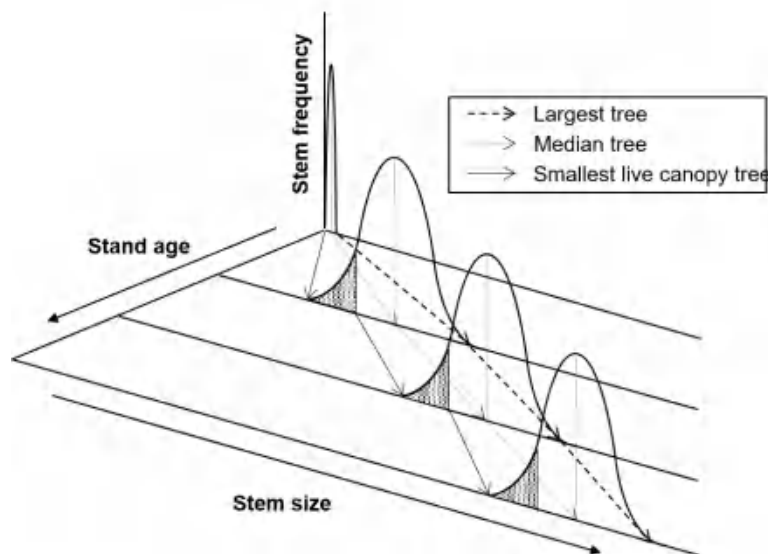


Figure B.3 A diagram of FORECAST's representation of individual tree size of a group of cohorts through time.

When mortality occurs, the transfer of biomass to the litter pool is based on the stem biomass of the dying trees. The mass of other components of the dying trees is estimated by multiplying the mass of total mortality stemwood by the ratio of stemwood to the other individual tree components obtained from the biomass input data adjusted for stand age. There is no individual plant mortality or stand self-thinning component in the net primary production calculation for life forms other than trees, because these understory plants are not represented as individuals. For herbs, shrubs, and bryophytes, all biomass losses, including both litterfall and mortality, are represented as ephemeral litterfall. Height growth is determined for individual trees using a similar method bounded by data-defined shortest-live tree and canopy top height for a series of stand ages.

4. CALCULATION OF ANNUAL POTENTIAL GROWTH (APG) IN THE ECOSYSTEM SIMULATION MODULE (ECOSYSTEM)

Annual potential growth (APG) of vegetation in the ecosystem simulation module of FORECAST is driven by the photosynthetic production of the foliage biomass (Figure B.4). The productive capacity of a given quantity of foliage biomass is assumed to be dependent on its nitrogen content, corrected for shading. Photosynthetic rates are expressed per kilogram of foliage nitrogen (FN) rather than per kilogram of foliage biomass because N content is believed to be a better measure of the function of the photosynthetic "apparatus" (Brix, 1971, and H. Brix, personal communication). The production efficiency of foliar nitrogen (FNE) is derived in the plant setup programs by dividing the annual TNPP for a particular species by the total quantity of foliar nitrogen present in a given time step (Eq. 3). However, FNE, by itself, is not suitable for use as a driving function as it has been shown to vary as a function of foliage biomass (due to self shading; Ågren, 1983), and of the degree to which a plant can alter its foliage morphology and physiology as light intensity changes. While the latter factor is a fixed characteristic of a species, the first requires either: a) an equation describing how FNE varies as a function of foliage biomass, or b) an explicit simulation of the effect of shading on photosynthetic activity.

$$FNE_t = TNPP_t / FN_t \quad (3)$$

$$FN_t = \text{foliage biomass}_t \times \text{foliar N concentration} \quad (4)$$

where:

FN_t = total foliar N content of a given species at time t (kg ha^{-1}).

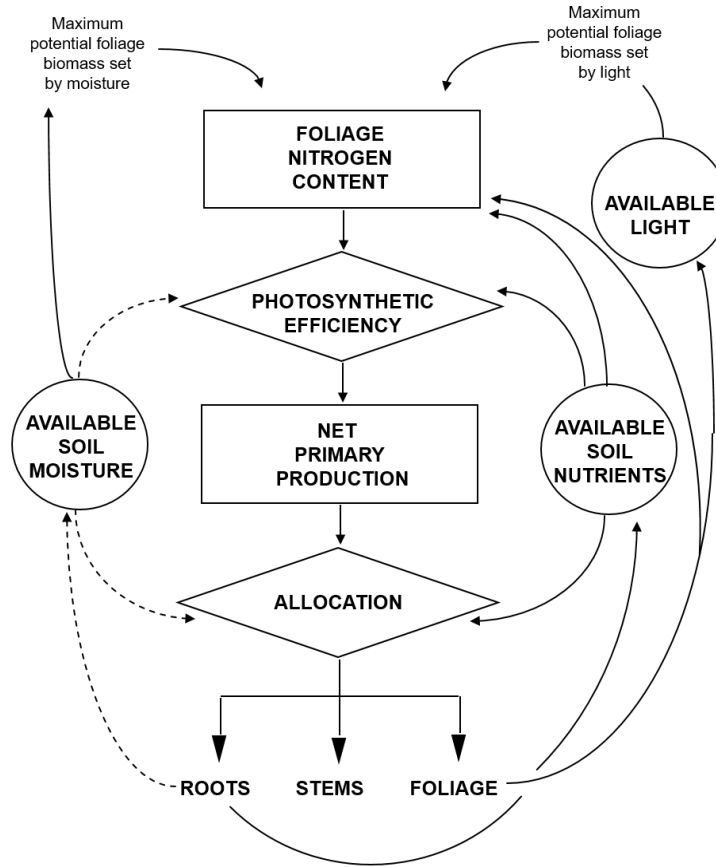


Figure B.4 A diagrammatic representation of the structure and function of the ecosystem simulation module in FORECAST. The dashed arrows indicate connections that will be facilitated by linkage to the hydrology submodel.

The major difference between these two approaches is whether the calculations are performed externally to, or internally in the model. The FORECAST model adopts the latter approach because it permits greater flexibility in the simulation of events such as thinning, pruning, and defoliation. This choice of modelling strategy also reflects the philosophy that the user should be responsible for the quality of all the calibration data. Thus, instead of using foliage nitrogen efficiency estimated for different values of foliage biomass and associated foliar N content, the ecosystem simulation module of FORECAST calculates APG as a function of shade-corrected foliar nitrogen efficiency (SCFNE) (Eq. 5). APG is calculated separately for each plant species represented in the model. The actual annual growth achieved by vegetation is subsequently determined based on the availability of nutrients (described in Section 5).

$$APG_{(t+1)} = SCFN_t \times SCFNE_t \quad (5)$$

where:

$APG_{(t+1)}$ = annual potential growth (kg ha^{-1}) for a given species in the next time step ($t = t+1$),

$SCFN_t$ = shade-corrected foliar N content at time t (kg ha^{-1}), defined below,

$SCFNE_t$ = shade-corrected foliar N efficiency at time t (kg ha^{-1}), defined below.

4.1 Shade-Corrected Foliar Nitrogen Efficiency (SCFNE)

4.1.1 Canopy representation

To account for the effect of shading on photosynthesis, the TREEGROW setup program uses a simulation of the distribution of foliage biomass within the canopy to estimate the degree of self-shading associated with specific quantities of foliage biomass. Input data define the average relative intensity of photosynthetically active radiation (PAR, as a percentage of that above the canopy) beneath stands that cover a range of canopy biomass values. These data can be obtained in the same stands that were used for the input data on stand biomass (including canopy biomass). Alternatively, data could be obtained using Beer's Law with published light extinction coefficients. The canopy is represented as an "opaque blanket" with foliage distributed uniformly over a simulated hectare, and uniformly with height in the canopy. The setup program establishes a relationship between relative PAR and the amount of foliage biomass (comparable to using a Beer's Law equation), and uses this as a basis to simulate canopy light profiles. For each time step, the foliage biomass is distributed uniformly into quarter-metre canopy height increments between the top and bottom of the live canopy (defined in input data). The percentage of above canopy light (PAR) reaching each quarter-metre canopy level is calculated based on the total amount of foliage biomass above it (Figure B.5).

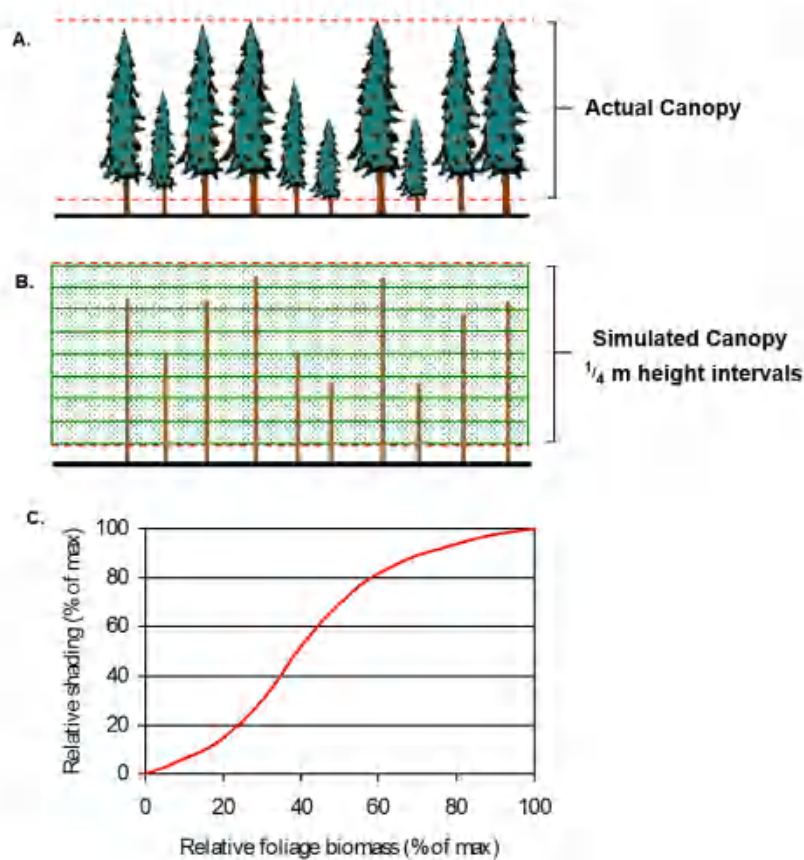


Figure B.5 (A) The representation of an actual canopy in FORCAST with (B) foliage biomass distributed evenly into 0.25 m thick layers, and (C) the relative shading estimated for each canopy layer.

Species-specific photosynthetic light saturation curves (PLSC), based on a proportion of the maximum photosynthesis rate determined as a function of PAR levels, are used to define the extent of the photosynthetic activity associated with the foliage N content of each quarter-metre height increment in the canopy. Since sun-adapted foliage has higher absolute rates of photosynthesis at high PAR, and lower rates at low PAR, in comparison with shade-adapted foliage, the PLSC curves defined in the input data for sun and shade-adapted foliage characteristically cross (Figure B.6). The TREEGROW setup program uses this cross-over point to determine whether shade or sun-adapted foliage should be produced in each canopy level. Thus, at canopy levels where PAR is less than the PAR at the cross-over point for the PLSC graphs, shade foliage is produced; at higher PAR levels new foliage is defined as sun foliage. When there is no difference in the PLSC for foliage in the upper and lower canopy, a single set of PLSC values will be given. The model does not simulate the acclimation of a given foliage type to changes in light intensity, nor does it directly simulate changes in photosynthetic activity as a function of foliage age, both of which can occur in real foliage. It does however, allow for a representation of the different productive capacities of young and old foliage in evergreen species. This achieved by providing input data for N concentration values for each foliage type as well as data specifying the number of time steps each foliage type is retained. The reduced N concentration typically observed in old foliage renders it less productive per unit of foliage mass relative to new foliage.

The canopy of understorey species (herbs and shrubs) is represented using a similar but simplified approach in which only a canopy top and bottom height are specified. Foliage is distributed evenly throughout.

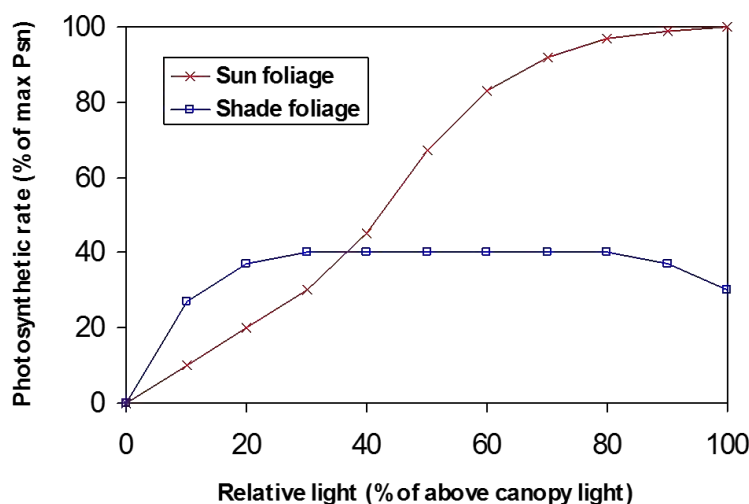


Figure B.6 An example of the photosynthetic light saturation curves used in FORECAST to represent the relative photosynthetic efficiency of sun and shade foliage.

4.1.2 Calculation of Shade-corrected Foliar N content (SCFN)

Once an estimation of self-shading has been completed for a particular time step using the canopy representation method described above, the setup program calculates a foliar N content value adjusted for the effects of self-shading (Eq. 6). This shade-corrected foliage N content (SCFN) represents the amount of fully illuminated foliage N (in sun foliage) that would be required to produce the same TNPP as is produced by the current sun and shade foliage at the simulated levels of illumination. The mean photosynthetic rate of

the foliage in canopy level i is calculated by combining simulated light intensities in canopy level i with input data that define photosynthetic light saturation curves for the foliage type in question. These calculations are repeated for every time step (t), spanning the time from the seedling stage ($t=1$) to the maximum tree age ($t=\text{max age}$) to be simulated, thus producing a species-specific time series curve of SCFN values. A plot of SCFN and FN over a stand development time sequence illustrates the relationship between total foliage biomass and self-shading (Figure B.7).

$$\text{SCFN}_t = \sum_{i=1}^n (\text{FN}_i \times \text{PLSC}_i) \quad (6)$$

where:

FN_i = mass of foliage nitrogen in the i th quarter-metre height increment in the live canopy,

PLSC_i = Photosynthetic light saturation curve value for the associated light level in the i th quarter-metre height increment in the live canopy,

n = number of quarter-metre height increments in the live canopy.

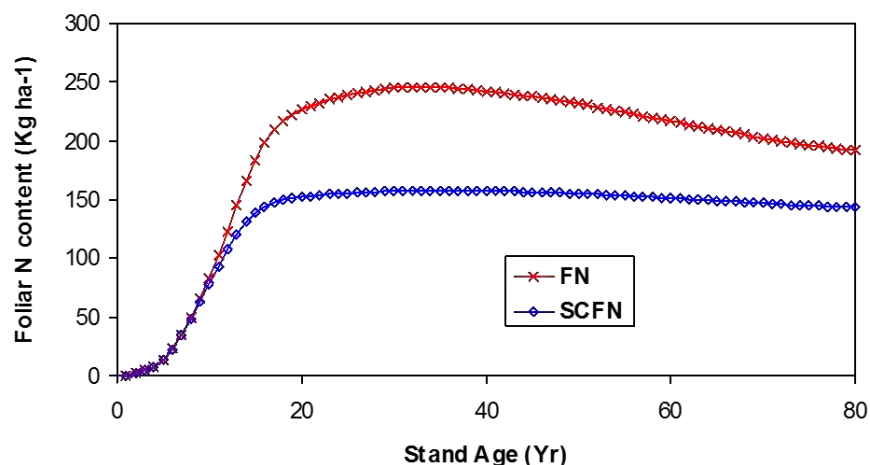


Figure B.7 An example plot of shade-corrected foliar nitrogen content (SCFN) vs. total foliar nitrogen (FN) over a stand development time sequence in FORECAST.

4.2 Use of SCFNE as the driving function in ECOSYSTEM

The driving function curve for potential growth of a given species in the ecosystem simulation module of FORECAST is obtained by dividing TNPP_t by SCFN_t to yield SCFNE_t for each annual simulation time step (as described for SCFN above) (Eq. 7). Wherever self-shading within the canopy reduces photosynthesis, SCFNE will have a higher value than FNE. When data describing the growth of a species on more than one site quality are provided, SCFNE function curves will be generated in the setup program for each site quality. The ecosystem simulation module interpolates between these curves when simulated site quality change occurs (see below).

$$\text{SCFNE}_t = \frac{\text{TNPP}_t}{\text{SCFN}_t} \quad (7)$$

Calibration of FORECAST with several different data sets has resulted in SCFNE curves that are highest during the seedling stage and decline with time to reach a level that remains fairly constant over the rotation (Kimmins et al., 1986). The consistency of the pattern among species suggests that the decline represents, in part, an increasing respiration tax as the ratio of photosynthetic biomass to respiring nonphotosynthetic biomass decreases as the stand ages. The pattern of initial decline in SCFNE is not a precise mirror image of the increase in the total quantity of nonphotosynthetic live biomass, however. Nonphotosynthetic live biomass is dominated by sapwood and large root biomass, which have lower respiration rates than fine and medium roots (Szaniawski, 1981, Amthor, 1984), and branches. Interestingly, these biomass components show a pattern of increase in biomass that mirrors the decline in SCFNE more closely than does the biomass of stem sapwood and large roots. The higher early SCFNE values could also reflect the higher nutrient availability early in the life of a plantation as a result of the "assart flush" (Kimmins, 1997 p. 119).

5. SIMULATION OF NUTRIENT CYCLING IN ECOSYSTEM

While the annual potential growth (APG) of vegetation in ECOSYSTEM is determined as a function of SCFNE, the actual annual growth (AAG) achieved in a given time step will depend upon whether the nutrient uptake demand created by this potential growth can be satisfied by the available nutrient resources. The quantity of available nutrient resources in a given time step is a function of: a) the simulated internal translocation of nutrients within the plants (based on input data on nutrient concentration and specific gravity changes with tissue death), b) simulated net canopy uptake / leaching losses, and c) the simulated level of available nutrients in the soil that is accessible to the plants.

Nutrient cycling in the ECOSYSTEM module is based on a mass balance approach where nutrients can exist in three distinct pools: 1) The plant biomass pool, 2) the available soil nutrient pool, and 3) the soil organic matter / forest floor pool (see Figure B2). The storage of nutrients in the available soil nutrient pool from one time step to the next is limited by the nutrient-specific ion exchange capacities defined for the soil in the SOILDATA file. The size of these exchange capacities can be defined to change as a function of simulated site quality. Nutrients exceeding the capacity of the exchange sites are assumed to be lost from the system (see below).

5.1 The geochemical cycle

The imports and exports from the geochemical cycle are represented as part of the annual mass balance calculations performed for each nutrient simulated the ECOSYSTEM module.

5.1.1 Geochemical inputs

Input data are provided on rates of inputs of nutrients in precipitation, mineral weathering, and slope seepage for each of the nutrients to be simulated for sites representing the range of nutritional qualities associated with the growth data. These defined input rates are assumed to be determined by a site's location in the landscape, its soil physical characteristics, and its surficial and bedrock geology, and thus do not change with simulated site quality during a simulation run. However, the proportion of these available nutrients in a

given ionic form (e.g. nitrate/ammonium ratios for N) is assumed to be related to the simulated site quality, and therefore will change with site quality as specified in the input data. The user can also specify rates of nutrient additions in the form of fertilizer.

In addition to the mineral inputs, the user has the option to provide rates of N fixation by symbiotic N-fixing plant species that are being simulated or by free-living N-fixing microbes. The former is determined by a user-provided rate that is a function of the amount of foliage (kilograms of N fixed per kilogram of shade-corrected foliage-N carried by the N-fixing plant) derived from published data on N-fixation rates for N-fixing plants of known foliage biomass. This approach is based on the assumption that N fixation is an energy-requiring process, and that the best single estimate of energy-availability in FORECAST is SCFN. Symbiotically fixed N is assumed to be captured directly by the N-fixing plants, where it is used to satisfy their N demand for new growth prior to their simulated uptake of N from the soil. The fixed N eventually reaches the soil via litterfall, plant death, foliar leaching, or defoliation from the N-fixing plants. Free-living N fixation by bacteria or other soil organisms living nonsymbiotically can be specified as a constant annual input rate directly to the available soil nutrients compartment. Alternatively, substrate-specific N-fixation rates may be specified for decomposing litter types (e.g. foliage, decomposing wood). The geochemical inputs are either incorporated directly into plants (symbiotic N fixation or uptake by foliage from precipitation) or into the available soil nutrient pool (see Figure B.2). Many of the geochemical input data are optional (see Appendix A), and the user is not required to address each of the inputs described above. However, the user then accepts the responsibility for the omission of an input that may have an important effect on the overall nutrient budget for a site.

5.1.2 Geochemical outputs

The FORECAST model represents the geochemical losses of nutrients from the available soil nutrient pool by volatilization of fertilizer N and leaching. The percentage of fertilizer N that is lost to volatilization is described as part of the management data in the ECODATA file. This loss will occur prior to any simulated uptake of nutrients by plants. Following the simulation of geochemical inputs, volatilization, immobilization, and plant uptake, any nutrients remaining in the available nutrient pool in excess of the defined ion exchange capacities of a site (cation exchange capacity [CEC] or anion exchange capacity [AEC]) are assumed to be lost from the ecosystem via leaching. Leaching is thus likely to occur with various combinations of reduced plant uptake (e.g. following clearcutting), or accelerated input of nutrients into the available soil pool. Leaching of nitrate-N is more accurately defined as the "disappearance" of nitrate-N because the model does not explicitly simulate the process of microbial denitrification. Loss of soil nitrate is assumed to represent the combination of both leaching and denitrification. Most of the simulated leaching in FORECAST will be of nitrate-N rather than ammonium-N because the simulated soil will normally have a higher CEC than AEC. The failure to deal explicitly with denitrification, which can be a major source of post-harvest N loss in some types of forest (Davidson et al., 1990; Struwe and Kj  ller, 1990), is a limitation of FORECAST's representation of the geochemical cycle.

Nutrients may also be lost from the other two pools represented in FORECAST (see Figure B.2). Nutrient loss from the soil organic matter pool (other than via mineralization) can occur by simulated wildfire or a management-controlled slash burn. Loss of forest floor nutrients can also be simulated as loss due to litter raking, or mechanical removal of logging slash. Removals by fire include losses of fly ash and volatilization

during simulated burning. The model can simulate various types of fire (wildfire, crown, surface, or ground; slash burning; or stand underburning), with nutrient loss being predicted on the basis of user-provided input data on the percent loss of each nutrient being simulated from material that is converted to ash. Harvest removals from the biomass nutrient pool are simulated by accounting for the nutrient content of each of the biomass components removed from the site during any intermediate or final harvest (e.g., a clear-cut). The model predicts the long-term site nutrient budget as the balance of the geochemical inputs and outputs, and simulates consequences of this balance on the circulation of nutrients and plant nutrition within the ecosystem.

5.2 The biogeochemical or within-ecosystem cycle

5.2.1 *Decomposition: mineralization/immobilization*

The simulation of litter decomposition in FORECAST is driven by empirical input data describing the following: a) weight loss rates as a function of the type of decomposing material and its age (since litterfall), b) the concentrations of nutrients in fresh litter and in humus, and c) the temporal pattern of change in nutrient concentration between fresh litter and humus. These data are combined to calculate the change in the total content of nutrients in a cohort of decomposing material in each time step from fresh litter to humus. An increase in content is interpreted as microbial immobilization; a decrease as mineralization. This approach is applied to annual cohorts of all the different types of litterfall simulated by the model, or the user can opt to combine different litterfall types that have similar decomposition characteristics into a few generalized decomposition types. Decomposition rates given in the input file may be modified by a set of exposure factors provided by the user in the soils input file. These control the simulation of the response of humus and litter decomposition rates to the removal of vegetation by harvest or other disturbance. Empirical data on decomposition rates must be provided for each climate region in which the model is to be used because the present version of FORECAST lacks any representation of the effects of temperature and moisture on decomposition processes.

5.2.2 *Competition for and uptake of available nutrients by plants*

Within the ECOSYSTEM module of FORECAST, plants can take up nutrients from precipitation inputs, throughfall inputs (understory plants), symbiotic N fixation (if applicable) or from the available soil nutrient pool. Uptake from precipitation (net canopy uptake) or throughfall is defined by input data on the difference in the nutrient content of precipitation or throughfall above and below the plant canopy. Mosses are assumed to be able to withdraw from throughfall as much nutrient as is required to support their expected new growth. In FORECAST, mosses are assumed to be of the feather moss type, which obtain their nutrients from throughfall or precipitation (Tamm, 1953) and do not take up nutrients from the available soil nutrient pool.

Competition for nutrient resources among simulated plant species is represented in the ECOSYSTEM module as a function of simulated nutrient uptake demand, the size of the available nutrient pool, and the relative occupancy of the soil by fine roots of each species. The annual uptake demand (UD) for a given species is determined using a mass balance approach driven by the potential growth in which the nutrient demands to meet potential growth are calculated while accounting for internal cycling, canopy uptake and foliar leaching (Eq. 8).

$$UD_i = (APG_i \times EC_i) - (IC_i + CU_i) + L_i \quad (8)$$

where:

UD_i = annual uptake demand for species i (kg ha^{-1}),

APG_i = annual potential growth for species i (kg ha^{-1}),

EC_i = average expected nutrient concentration for new biomass of species i (%),

IC_i = annual net nutrient gain from internal cycling for species i (kg ha^{-1}),

CU_i = annual direct canopy uptake from precipitation or throughfall for species i (kg ha^{-1}),

L_i = total annual foliar leaching from species i (kg ha^{-1}).

Once the nutrient demand for each species has been calculated, the actual uptake for a given species from the available soil nutrient pool is simulated. The size of the available pool at the start of a simulation time step depends on the quantity of nutrients held on exchange sites at the end of the last simulation time step, plus precipitation, weathering, seepage, nonsymbiotic N-fixation, and fertilization inputs in the current time step. Nutrients are then added or removed from this pool depending on the outcome of the decomposition subroutine (see above). The quantity of available nutrients accessible to plants of a given species is dependent on the proportion of the soil occupied by the fine roots of that species (RO) (Eq. 9). This proportion is derived from the ratio of the current biomass of fine roots to the site maximum biomass of fine roots. The site maximum fine-root biomass is assumed to be equal to the maximum value observed over time for a particular species in a fully stocked stand on the site, as specified in the input data file. (Eq. 10).

$$NAP_i = TAN \times RO_i \quad (9)$$

$$RO_i = FRB_i / MFRB_i \quad (10)$$

where:

NAP_i = quantity of available nutrients accessible to species i (kg ha^{-1}),

TAN = total size of the available nutrient pool in the current time step (kg ha^{-1}),

FRB_i = the fine root biomass of species i for the current time step (kg ha^{-1}),

$MFRB_i$ = the maximum fine root biomass for species i on a given site quality (kg ha^{-1}).

When the total combined uptake demand by all species is less than the total available nutrient pool, nutrient uptake by different plant species occurs simply in response to the individual species uptake demand according to equation 11.

$$AU_i = \min (UD_i, NAP_i) \quad (11)$$

$$AU_i = \min \left(\frac{UD_i}{\sum UD_{\text{total}}}, NAP_i \right) \quad (12)$$

where:

AU_i = annual actual nutrient uptake for species i (kg ha^{-1}),

UD_{total} = annual total uptake demand for all species (kg ha^{-1}).

However, when the combined total uptake demand is greater than the available nutrient supply, competition occurs. In this situation, the available supply of nutrients is divided between species according to their relative uptake demands and root occupancies (Eq 12). There is no representation of the vertical distribution of fine roots, and they are assumed to be distributed uniformly across the site. This lack of spatial representation is also true for the available soil nutrients and the decomposing litter.

5.2.2 Distribution of nutrients within plants

Nutrients taken up by plants and internally cycled nutrients are allocated to new growth of different biomass components according to the relative magnitude of new biomass multiplied by the expected concentration, calculated separately for each biomass component. Where there are insufficient nutrients from internal cycling and uptake, this "new growth demand" is limited to that which can be provided with sufficient nutrients to achieve the expected concentrations. The ratios of the different biomass components in the new growth, and thus the distribution of nutrients among different new biomass components, are defined by input data on biomass ratios for different site qualities given in the setup data files, and are not affected directly by the difference between "new growth demand" and supply (uptake + internal cycling). The FORECAST model cannot simulate changes in internal cycling or the internal distribution of nutrients within plants as a function of changing competition due to stand density effects. These changes are limited in the model to site quality, and site quality is determined by the total availability of nutrients on the site. There is no simulation of change in site quality due to between-species competition or changes in stand density.

5.2.3 Internal cycling and nutrient losses from plants

It is impractical to simulate the biochemistry of internal cycling in rotation-length modeling of entire stands. Instead, FORECAST adopts the empirical approach of requiring data on the concentrations of nutrients in plant tissues of various ages or condition, and on weight change at the time of tissue senescence. If a representation of the effects of site quality change on internal cycling is desired, such data are required for sites that vary in their nutritional quality. As the model simulates nutritional site quality change within a run, it interpolates between the input data for various site qualities to find the concentrations and weight loss appropriate for the current site quality. It then calculates the quantity of nutrients retranslocated at the time of senescence, or during tissue aging, from the appropriate concentration and weight change data.

Nutrient loss from plants as ephemeral litterfall is determined by the mass of litterfall and the concentration of nutrients in dead tissue relative to the associated live biomass component. The mass of ephemeral litterfall that occurs during each timestep is defined in the data set as a proportion of the dead tissue produced by the senescence of each biomass component. With the exception of fine roots, litterfall mass in any time step cannot exceed the mass of the biomass subcompartment from which it came. For fine roots, the user can simulate litterfall within a single time step that exceeds the biomass of that component at the start of that time step. For example, the biomass of fine roots that die in the time step might be 150% of

the quantity of fine roots at the start of that time step because of death, regrowth, and death of this size class of roots within the time step.

Foliar leaching loss is simulated on the basis of the difference in the nutrient content of precipitation and throughfall above and below the foliage canopy of a given species. Input values for these nutrient contents are given in the input setup plant growth modules, in conjunction with estimates of the foliage biomass associated with the measured difference in content. This permits a simulation of leaching per kilogram of foliage (this also applies to the estimates of uptake from precipitation or throughfall), and thereby a simulation of the change in the amount of nutrients transferred by foliar leaching as the biomass of foliage changes (e.g. by a thinning). Simulation of these throughfall processes, and the data to calibrate them, are optional unless simulating bryophytes that depend on throughfall for their nutrition. Defoliation-related losses of nutrients are simulated on the basis of the user-defined removal of foliage biomass by defoliation and the current concentration of nutrients in that foliage biomass (i.e., there is no internal cycling before the foliage is lost by defoliation).

6. SITE QUALITY CHANGE IN FORECAST

Site quality evaluation is an important part of silviculture and forest management because silvicultural and management prescriptions must be site-specific. Traditional historical-bioassay yield predictors have always been tied to some system of site quality evaluation. Since such yield predictors are not able to predict site quality improvement or deterioration in response to management, foresters have relied on independent assessments of site quality to suggest the need to switch to a new yield table class or site index curve when sites are degraded or improved. Process-simulation growth and yield models have generally not addressed this deficiency. The JABOWA class models, and models such as Mohren's (1987) model and ecophysiological canopy models do not simulate changing site quality during a run. The lack of site quality simulation in community succession and most ecosystem-level models is understandable. There is still disagreement on many of the details of both the ecology of site quality change, and of the physiological response of plants to such change. However, it has been demonstrated that change in crop yield in response to changing resource availability is as much or more a function of changing allocation of photosynthates as it is of absolute changes in net primary production (e.g. Keyes and Grier, 1981; Kurz, 1989). Tissue chemistry, internal cycling, foliage leaching losses, decomposition rates, nitrate-ammonium ratios, and a variety of other important processes and site characteristics may also change as a function of nutritional site quality change. In FORECAST, the user has the option to simulate the changes in these variables when nutritional site quality is either improved or degraded during a simulation run.

6.1 Representation of ecosystem response to site quality change

The FORECAST model adopts an empirical approach to the representation of site quality change. Site quality in FORECAST is defined in the input data files by entering data for both plant growth and a number of plant and ecosystem processes for several sites that vary in nutritional site quality. Each of these site quality data sets is given a number on some user-specified scale of site quality. This can be a conventional site index value (height at a given age), a yield table site quality class, or an arbitrary scale set by the user. The choice of scale is not important, as long it is kept consistent throughout the data set. The specified site quality scale is used to reference the nutritional data that define the site quality (discussed below). FORECAST uses linear

interpolations between different site quality reference values to define changes in variables in response to simulated site quality change.

6.2 Estimation of the relative nutrient abundance associated with site quality

In each of the plant growth setup programs, the nutrient uptake that is estimated to have been associated with the historical pattern of growth and biomass accumulation by the species in question is calculated for each site quality class. For each of the nutrients that are defined in the data input files, the setup growth programs estimate the total level of the nutrient that was available in the soil to support such a level of uptake, accounting for the degree of soil occupancy by fine roots. For example, if trees of species 'x', whose growth is nutrient limited, are calculated to have taken up 20 kg/ha of nutrient 1 in time step t , but to have only had 50% of the maximum observed fine-root biomass in that year, the model assumes that the total amount of nutrient 1 available on the site in that time step must have been 40 kg/ha. Using this approach, the setup programs estimate the temporal pattern of nutrient availability that probably occurred on each of the various site qualities to have supported the observed pattern of growth on each of those sites. For each site, the program then takes the highest value in this temporal pattern as the definition of the availability of that nutrient for a specified site quality. If the availability of a particular nutrient is indeed limiting plant growth, it is expected that the availability of that nutrient will increase as site quality (and consequently tree growth) increases. Where setup program output does not confirm this expectation, the input data are in error, or the assumption that the nutrient is limiting growth must be wrong. In such a case, input data and the assumptions made about the role of the nutrient in regulating growth must be reexamined. If only one nutrient is being simulated as growth limiting in an ECOSYSTEM run, then nutritional site quality will be defined in that run by comparing simulated total availability of that nutrient on the site with the defined maximum value for nutrient availability for each of the site qualities defined in the setup modules. If two or more limiting nutrients are simulated in a single run, the model defines site quality in terms of the nutrient that is most limiting.

6.3 Site quality for plant versus site quality for soil processes

Two types of site quality are defined in FORECAST: 1) nutritional site quality as perceived by individual plant species, and 2) site quality for soil processes. Forest soils have a considerable "nutritional inertia" that reflects the characteristically large mass of high C/N ratio organic matter in the forest floor, the prevailing soil fauna and flora, and the prevailing understory vegetation and litterfall quality. Several years of sustained alterations of litterfall quality and nutrient availability are required to cause the fundamental changes in soil processes that result in significant changes in site quality. Representation of this inertia is achieved by having the site quality for soil processes follow site quality for trees and plants, but with a user-defined damping function defined as the proportion of the change in site quality for the trees and other plants that can occur for soil site quality in each time step. However, individual tree and plant species can define the nutrient availability on a given site differently in terms of site quality; consequently, the user must specify a weighted average of the site qualities defined by the various simulated trees and plants. It is this average that the soil site quality follows.

Plant growth response to changing soil nutrient availability will normally be much faster than changes in soil processes; consequently, the basis for the site quality change damping function is different for plant growth versus soil processes. A second damping function for site quality change in plants must be specified

as a percentage of the change possible in one time step, based on the plant's annual potential growth (APG). In contrast, the site quality change damping function for soils is specified as a percentage of the actual achieved change in plant-defined site quality in one time step based on the nutrient-limited achieved growth. As noted, both percentages are defined by the user in the ECODATA input file.

A shortcoming of the definition of site quality used in FORECAST is that the setup input data used to represent sites of different nutrient status may also reflect variations in environmental variables not explicitly represented in the model. For example, differences in nutrient site quality are frequently accompanied by differences in moisture availability. When nutrient site quality change on a given site is simulated in ECOSYSTEM, it is based on input data from sites that may differ in moisture conditions as well as nutrient conditions. This problem is partly rectified by putting user-defined constraints on certain variables (e.g., maximum foliage biomass that can be carried on the site). The value of these variables is fixed at the start of the run by the definition of starting site quality and remain unaltered even if nutritional site quality changes during a run.

7. INITIAL ECOSYSTEM CONDITION: THE ECOSTATE FILE

The response of a given ecosystem to a particular set of management activities or other types of disturbance depends to a large degree on its condition at the time of disturbance. Levels of organic matter resources and competing vegetation are typically altered by silvicultural treatments or natural disturbance events. Thus, the condition of an ecosystem at any given time reflects past treatments, harvests and natural disturbance, stand growth, and stand development. The effects of past management and natural disturbance events on ecosystem condition and future productivity are dealt with in FORECAST through the use of the ECOSTATE file. The function of the ECOSTATE file is to initialize values for all of the types and ages of decomposing organic matter in the forest floor and the levels of soil humus at the start of the run including: total mass, nutrient content and stage of decomposition. The file also defines the existing populations of each of the tree and other plant species to be represented in the simulation. It considers, for example, whether one is starting with a clear-cut devoid of living mosses, herbs, shrubs, and trees, or if there is an established community with both aboveground and below ground live biomass, or below ground live biomass only. In the latter case, whether this below ground biomass constitutes a budbank that will sprout or sucker at the start of the new rotation is considered. Rather than attempting to define an ecosystem starting condition through the measurement of hundreds of state variable for a given site, an initial ecosystem state is established by running the ecosystem module without nutrient feedback to force the vegetation to grow as it has historically and to allow the ecosystem to accumulate soil organic matter, forest floor litter and coarse woody debris as expected under a defined historical scenario. The output of this run is saved as an ECOSTATE file for future use.

Experience with FORECAST to date indicates that the model's predictions are very sensitive to the initial ecosystem state as defined by ECOSTATE (Morris et al. 1998). This is particularly evident in the first simulated rotation of tree crops, or the first 100 or more time steps. Careful preparation of an appropriate ECOSTATE file can be just as important a modeling activity as getting accurate calibration data. It is, in fact, one aspect of model calibration, and a major component of the setup activity of FORECAST.

8. OTHER PROCESSES IN FORECAST

A detailed description of the algorithms used to represent the various ecosystem compartments and processes in FORECAST is beyond the scope of this paper. The reader is referred to Kimmins (1993) for more information on the following simulation processes: regeneration, representation of understorey growth dynamics, coppice resprouting or root suckering, tree mortality, height growth, nutrient cycling and competition for nutrients, nutrient availability in the soil, and light competition among species.

9. SOME LIMITATIONS OF THE FORECAST APPROACH

As is the case with all models, FORECAST has a number of limitations in its application that should be considered by the user. For example, many of the representations of soil processes in FORECAST are relatively simplistic. The lack of representation of soil horizons, soil mixing, and root distribution limits the ability of FORECAST to address issues of soil compaction and soil erosion. The model's approach for estimating ephemeral litterfall (see Section 3.2) may result in an overestimate of litterfall in the first few time steps of the simulation, and this may contribute to the higher values of shade corrected foliage nitrogen efficiency (SCFNE) early in the simulation. The early overestimates of litterfall rates, however, are applied to a very small biomass, so in terms of rotation-length simulations, the error involved should be very small. The representation of the tree canopy in FORECAST as an "opaque blanket" also poses some difficulties for the simulation of individual tree growth, thinning response, agroforestry, shelterwood, and mixed-age stand management. Modifications have been made to the simulation of the canopy to improve the model in this respect. A detailed description of these modifications will be reported in a subsequent paper. There is no representation of seasonality in FORECAST. This places a limitation on the use of time steps of less than 1 year in climatic regions that have seasonally variable climatic conditions. The model does account for winter photosynthesis by evergreens while deciduous competitors are leafless, and it can simulate mortality and regrowth of fine roots on time steps shorter than one year. There is, however, no detailed representation of the variation of the other ecosystem processes between seasons.

In spite of these limitations, experience to date suggests that, within the limits of model design, FORECAST performs predictably and that it is able to address most of its design objectives. The following works summarize different evaluations to date of FORCYTE-11 and FORECAST: Chan and Peterson (1987), Apps et al. (1988), Peterson et al. (1988), Apps and MacIsaac (1989), Grewal et al. (1989), Peterson and Apps (1989), Pike and Meades (1989), Sachs et al. (1989), Grewal et al. (1990), Sachs and Trofymow (1991), Trofymow and Sachs (1991), Wang et al. (1995) and Morris et al. (1997).

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Appendix A

Data resources necessary for the calibration of FORECAST's TREEDATA file

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application ^a	Relative sensitivity of model to data ^b	General function in FORECAST
Stemwood biomass	(mg ha ⁻¹)	Y	N/A	Required	***	Biomass accumulation
Stembark biomass	(mg ha ⁻¹)	Y	N/A	Optional	*	Biomass accumulation
Branch biomass	(mg ha ⁻¹)	Y	N/A	Optional	**	Biomass accumulation
Foliage biomass	(mg ha ⁻¹)	Y	N/A	Required	****	Driving function, light competition, biomass accumulation
Maximum stand foliage biomass	(mg ha ⁻¹)	Y	N/A	Required	**	Moisture limited maxi- mum
Maximum foliage biomass for an individual tree	(kg tree ⁻¹)	N	N/A	Required	*	Limit individual tree foliage
Tree age associated individual tree biomass maximum	(year)	N	N/A	Optional	*	Limit individual tree maximum
Stand age at canopy closure	(year)	N	N/A	Required	**	Light competition
Large root biomass (arbitrary definition)	(mg ha ⁻¹)	Y	N/A	Optional	**	Biomass accumulation
Medium root biomass (arbitrary definition)	(mg ha ⁻¹)	Y	N/A	Optional	**	Biomass accumulation
Small root biomass (<5 mm diameter)	(mg ha ⁻¹)	Y	N/A	Required	****	Nutrient competition
Fruit biomass	(mg ha ⁻¹)	Y	N/A	Optional	*	Biomass accumulation
Stand density	(stems ha ⁻¹)	Y	N/A	Required	****	Mortality calculations
Proportion of mortal- ity density indepen- dent	(None)	Y	N/A	Required	**	Mortality calculations
Canopy reduction to stop shade mortality	(%)	Y	N/A	Optional	*	Light competition
Average top height	(m)	Y	N/A	Required	****	Light competition
Top height of shortest live canopy tree	(m)	Y	N/A	Required	***	Light competition, canopy representation
Average height of canopy bottom	(m)	Y	N/A	Required	***	Light competition, canopy representation
Photosynthetic light saturation curve (PLSC) for sun foliage	(% of max. rate)	N	N/A	Required	***	Used in calculation of driving function

Appendix A (Continued)

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application ^a	Relative sensitivity of model to data ^b	General function in FORECAST
Photosynthetic light sat- uration curve (PLSC) for shade foliage	(% of max. rate)	N	N/A	Optional	**	Used in calculation of driving function
Shading by maximum foliage biomass	(% of full light)	N	N/A	Required	***	Light competition
Curve defining shading as % of maximum foliage biomass	(% of max.)	N	N/A	Required	***	Light competition
Amount of photosynthe- sis that occurs when competitors are leafless	(%)	N	N/A	Optional	**	Winter photosynthesis in conifers
Amount of reduction in stemwood biomass production at which stunted height growth occurs	(%)	N	50%	Optional	*	Height growth in low light
Soil volume occupied at maximum small root biomass	(%)	N	100%	Optional	***	Nutrient competition
Efficiency of root cap- ture for each nutrient	(%)	N	100%	Optional	***	Nutrient competition
Proportion of trees in stem biomass classes (for up to ten stand ages but only one required)	(% in each class)	N	N/A	Required	**	Individual tree size dis- tribution in an age co- hort
Mean stemwood biomass for each size class above	(kg tree ⁻¹)	Y	N/A	Required	**	See above
Nutrient concentration in all simulated biomass components, live and dead (up to five nutrients)	(%)	N	N/A	Optional	***	Uptake demand, inter- nal cycling, litter nutri- ent concentration
Nutrient concentration in young foliage	(%)	N	N/A	Required	****	Uptake demand, driving function
Nutrient concentration in old foliage	(%)	N	N/A	Optional	****	Internal cycling, driving function

Appendix A (Continued)

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application ^a	Relative sensitivity of model to data ^b	General function in FORECAST
Nutrient concentration in dead foliage	(%)	N	N/A	Required	***	Nutrient concentration in foliage litter
Annual atmospheric deposition to canopy surface	(kg ha ⁻¹)	N	0	Optional	**	Net canopy uptake
Annual throughfall below canopy	(kg ha ⁻¹)	N	0	Optional	**	Net canopy uptake
Foliage biomass associ- ated with throughfall data	(mg ha ⁻¹)	N	0	Optional	**	Net canopy uptake
Symbiotic N-fixation per kg foliage biomass	(kg N)	N	0	Optional	***	Symbiotic N-fixation
Annual transfer of stemwood to sapwood	(%)	N	5%	Optional	**	Internal cycling
Annual transfer of live to dead tissue for branches, large and medium roots	(%)	N	10, 4, 5, 5%, respec- tively	Optional	***	Internal cycling
Annual transfer of dead tissue to litterfall for bark, large, medium and small roots, and fruit	(%)	N	3, 0.1, 2, 1, 50, 100%, respectively	Optional	***	Ephemeral litterfall
Retention time for dead branches, young fo- liage and old foliage	(year)	N	N/A	Young foliage required; branches Optional	***	Biomass accumulation, branch litterfall and fo- liage productivity
Change in mass at death: all biomass components	(%)	N	0%	Optional	*	Internal cycling
Change in mass with fo- liage aging and death	(%)	N	0%	Optional	*	Internal cycling

^a The data are specified as optional or required for each tree species to be simulated in FORECAST. A simulation of the effect of site quality change on any variables related to these data requires input data from two or more sites varying in nutritional quality.

^b * = Low sensitivity, **** = high sensitivity.

Appendix B

Data resources necessary for the calibration of FORECAST's PLANTDATA file

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application ^a	Relative sensitivity of model to data ^b	General function in FORECAST
Stem biomass	(kg ha ⁻¹)	Y	N/A	Optional	***	Biomass accumulation
Rhizome biomass	(kg ha ⁻¹)	Y	N/A	Optional	**	Biomass accumulation
Root biomass	(kg ha ⁻¹)	Y	N/A	Optional	****	Biomass accumulation
Fruit biomass	(kg ha ⁻¹)	Y	N/A	Optional	*	Fruit production
Foliage biomass	(kg ha ⁻¹)	Y	N/A	Required	****	Driving function, light competition, biomass ac- cumulation
Maximum site foliage biomass	(kg ha ⁻¹)	Y	N/A	Required	**	Moisture limited maxi- mum
Average top height of plants	(m)	Y	N/A	Required	****	Light competition
Average height of canopy	(m)	Y	N/A	Required	***	Light competition, canopy representation
Photosynthetic light saturation curve (PLSC) for sun foliage	(% of max. rate)	N	N/A	Required	***	Used in calculation of driving function
Photosynthetic light saturation curve (PLSC) for shade foliage	(% of max. rate)	N	N/A	Optional	**	Used in calculation of driving function
Shading by maximum foliage biomass	(% of full light)	N	N/A	Required	***	Light competition
Curve defining shading as % of maximum foliage biomass	(% of max. shading)	N	N/A	Required	***	Light competition
Amount of photosyn- thesis that occurs when competitors are leafless	(%)	N	N/A	Optional	**	Winter photosynthesis
Amount of reduction in stem biomass pro- duction at which stunted height growth occurs	(%)	N	50%	Optional	*	Height growth in low light
Soil volume occupied at maximum small root biomass	(%)	N	100%	Optional	***	Nutrient competition

Appendix B (Continued)

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application ^a	Relative sensitivity of model to data ^b	General function in FORECAST
Efficiency of root capture for each nutrient	(%)	N	100%	Optional	***	Nutrient competition
Nutrient concentration in all simulated biomass components, live and dead (up to five nutri- ents)	(%)	N	N/A	Optional	***	Uptake demand, internal cycling, litter nutrient concentration
Nutrient concentration in foliage, live and dead	(%)	N	N/A	Required	****	Uptake demand, driving function
Annual atmospheric deposition to canopy surface	(kg ha ⁻¹)	N	0	Optional	**	Net canopy uptake
Annual throughfall below canopy	(kg ha ⁻¹)	N	0	Optional	**	Net canopy uptake
Foliage biomass associ- ated with throughfall data	(kg ha ⁻¹)	N	0	Optional	**	Net canopy uptake
Symbiotic N-fixation per kg foliage biomass	(kg N)	N	0	Optional	***	Symbiotic N-fixation
Annual transfer of live tissue to dead litterfall for stem, rhizomes, roots, and fruit	(%)	N	N/A	Roots required; others optional	***	Ephemeral litterfall
Retention time for foliage	(year)	N	N/A	Required	***	Foliage litterfall
Change in mass at death: all biomass components	(%)	N	0%	Optional	*	Internal cycling
Growth from seed in first year: stem, foliage, rhizome, root, and fruit	(kg ha ⁻¹)	N	N/A	Optional	**	Growth from seed
Remaining biomass after cutting back: stem foliage, rhizome, root, and fruit	(kg ha ⁻¹)	N	N/A	Optional	*	Growth from sprouts fol- lowing cutting
Growth from sprouting in first year: stem, foliage, rhizome, root, and fruit	(kg ha ⁻¹)	N	N/A	Optional	**	See above

Appendix B (Continued)

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application ^a	Relative sensitivity of model to data ^b	General function in FORECAST
Mortality after cutting: root, rhizome	(%)	N	N/A	Optional	*	See above
Loss of vigor at each successive cut	(%)	N	N/A	Optional	*	See above

^a The data are specified as optional or required for each plant species to be simulated in FORECAST. A simulation of the effect of site quality change on any variables related to these data requires input data from two or more sites varying in nutritional quality.

^b * = Low sensitivity, **** = high sensitivity.

Appendix C

Data resources necessary for the simulation of a moss complex in FORECAST

Data type	Units ()	Data from chrono- sequence required	Default value	Data required for sim- plified application	Relative sensitivity of model to data ^a	General function in FORECAST
Moss complex biomass	(kg ha ⁻¹)	Y	N/A	Required	***	Biomass accumulation, driving function
Photosynthetic light- saturation curve (PLSC)	(% of max. rate)	N	N/A	Required	***	Used in calculation of driving function
Amount of photosyn- thesis that occurs when competitors are leafless	(%)	N	N/A	Optional	*	Winter photosynthesis
Nutrient concentration in biomass, live and dead (up to five nu- trients)	(%)	N	N/A	Required	****	Uptake demand, driving function
Symbiotic N-fixation per kg foliage biomass	(kg N)	N	0	Optional	**	Symbiotic N-fixation
Retention time of live and dead biomass	(year)	N	5, 10 years, respectively	Required	***	Ephemeral litterfall
Change in mass at death; biomass	(%)	N	0%	Optional	*	Internal cycling

A simulation of the effect of site quality change on any variables related to these data requires input data from two or more sites varying in nutritional quality.

^a * = Low sensitivity, **** = high sensitivity.

Appendix D

Data are specified as optional or required for the simulation of soil process in FORECAST

Data type	Units ()	Data from chronosequence required	Default value	Data required for sim- plified application	Relative sensitivity of model to data*	General function in FORECAST
Define litter types: each biomass component is assigned a litter type (up to 40)	(None)	N	N/A	Required	N/A	Each litter type can have unique decomposition characteristics
Define humus types: each litter type is assigned a humus type (up to 40)	(None)	N	N/A	Required	N/A	Each humus type can have unique decomposition characteristics
Curves describing relative change in nutrient in concentration for each litter type during decomposition from fresh litter to humus (for each nutrient)	(Proportion)	Y	Linear curve	Required	***	Controls mineralization and immobilization rates
Total annual nutrient input to site in precipitation	(kg ha ⁻¹)	N	N/A	Optional	**	Geochemical cycle input
Annual upslope seepage nutrient input to site	(kg ha ⁻¹)	N	0	Optional	**	Geochemical cycle input
Annual nutrient input from weathering	(kg ha ⁻¹)	N	0	Optional	**	Geochemical cycle input
Annual non-symbiotic N-fixation	(kg ha ⁻¹)	N	0	Optional	**	Geochemical cycle input
Proportion of each nutrient in anionic form	(Proportion)	N	N/A	Optional	*	Effects leaching
CEC of mineral soil (for each nutrient)	(kg ha ⁻¹)	N	N/A	Optional	***	Controls storage of available nutrients in soil
CEC per ton of humus (for each nutrient)	(kg)	N	0.1	Optional	*	See above
AEC of mineral (for each nutrient)	(kg ha ⁻¹)	N	N/A	Optional	**	See above
AEC per tone of humus (for each nutrient)	(kg)	N	0.1	Optional	*	See above

Appendix D (Continued)

Data type	Units ()	Data from chronosequence re- quired	Default value	Data required for sim- plified application	Relative sensitivity of model to data ^a	General function in FORECAST
Concentration of nutri- ents in each humus type	(%)	N	N/A	Required	****	Controls mineralization and immobilization rates
Decomposition rate for each Humus type	(% year ⁻¹)	N	N/A	Required	***	Humus accumulation and see above
Concentration of nutri- ents in ashed material	(%)	N	N/A	Optional	**	Nutrient release following burn
Ash produced per kg of burned material	(kg)	N	0.015	Optional	**	Nutrient release following burn
Mass loss rate over time for each litter type	(proportion)	Y	N/A	Required	****	Controls mineralization and immobilization rates
Total time to become humus for each litter type	(year)	N	N/A	Required	**	See above
Delay in conversion of total fresh tree heart- wood to decomposing matter (enter values for log from trees in an age series)	(years)	Y	N/A	Optional	**	Log persistence
Measured N-fixation rates in specific litter types	(nmol C ₂ H ₄ g litter mass ⁻¹ day ⁻¹)	Y	0	Optional	**	N-fixation associated with coarse woody debris

A simulation of the effect of site quality change on any variables related to these data requires input data from two or more sites varying in nutritional quality.

** = Low sensitivity, **** = high sensitivity.

APPENDIX D: Application of a hybrid forest growth model to evaluate climate change impacts on productivity, nutrient cycling and mortality in a montane forest ecosystem

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ABSTRACT

Climate change introduces considerable uncertainty in forest management planning and outcomes, potentially undermining efforts at achieving sustainable practices. Here, we describe the development and application of the FORECAST Climate model. Constructed using a hybrid simulation approach, the model includes an explicit representation of the effect of temperature and moisture availability on tree growth and survival, litter decomposition, and nutrient cycling. The model also includes a representation of the impact of increasing atmospheric CO₂ on water use efficiency, but no direct CO₂ fertilization effect. FORECAST Climate was evaluated for its ability to reproduce the effects of historical climate on Douglas-fir and lodgepole pine growth in a montane forest in southern British Columbia, Canada, as measured using tree ring analysis. The model was subsequently used to project the long-term impacts of alternative future climate change scenarios on forest productivity in young and established stands. There was a close association between predicted sapwood production and measured tree ring chronologies, providing confidence that model is able to predict the relative impact of annual climate variability on tree productivity. Simulations of future climate change suggest a modest increase in productivity in young stands of both species related to an increase in growing season length. In contrast, results showed a negative impact on stemwood biomass production (particularly in the case of lodgepole pine) for established stands due to increased moisture stress mortality.

INTRODUCTION

Worldwide, forest health and productivity are being affected by anthropogenic climate change. The frequency and intensity of catastrophic natural disturbance agents, for example, are rising [1-4]. Moreover, evidence suggests that unusually severe drought events have triggered a significant rise in mortality rates in forested regions throughout the world [5, 6]. Climate change is expected to influence long-term forest productivity through its effect on moisture availability [7, 8], temperature-limited net photosynthetic rates [9, 10] and nutrient cycling [11]. After litter quality, temperature and soil moisture are the key determinants of heterotrophic respiration and nutrient mineralization rates in temperate forests [12, 13].

Efforts at modeling the impact of climate on forests can be divided into three broad categories: dynamic global vegetation models (DGVMs), statistical models derived from climate envelope analysis, and stand-level, process-based models. The overall objective of DGVMs is to evaluate the influence of climate on the biogeochemical and hydrological processes regulating vegetation growth dynamics [14]. Although they can be detailed with respect to process simulation, these models are designed to predict general patterns of vegetation development over large spatial and temporal scales [15] and have limited application for evaluating alternative forest adaptation strategies (see, for example, [16]). In general, DGVMs may be best suited to evaluating the impact of changing climate regimes on regional patterns of forest productivity and hydrology.

Models based on the climate envelope approach rely on detailed statistical analyses of historical climate data collected from a species' observed range. Deviations from climate normals are calculated for future climate scenarios and then used to project changes in growth rates, mortality, and species distributions. Examples include a modified version of the Forest Vegetation Simulator (FVS) model [17], and adjustments to site index based on anticipated changes in growing-degree days [18]. The strength of this approach is that it provides a method for predicting climate change impacts with relatively small calibration data requirements. Challenges with the approach include, 1) limited insight with respect to the underlying mechanisms of response, 2) an assumption that current species distributions are dictated exclusively by climate, and 3) the issue that if the range of variation in future climate exceeds the historical climate regime then applications of the model are beyond the scope of its statistical foundations.

The third category of model is the stand-level, process-based models. These models employ physiological and physical principles in conjunction with simulated edaphic conditions to project forest development and productivity under a changing climate. They vary widely in their complexity and application, from comprehensive, research-oriented ecosystem models (e.g. Ecosys; [19]) to less complex, management-oriented models such as CABALA [20] to relatively simplified models designed for broad application such as 3PG [21]. The more complex models can be difficult to calibrate because they usually comprise many site and species-specific parameters. This can necessitate expensive, multi-year field research programs to support their application (e.g. [20]). Highly simplified process models usually have lower calibration requirements but they often cannot adequately address the complexity of forest management in the face of climate change. A compromise approach is embodied in 'hybrid' process-based models, in which empirical data inputted to the model are used to 'self-calibrate' at least some of the algorithm parameters associated with ecosystem processes (see [22]). This makes it possible to retain adequate model complexity while minimizing the calibration load [23].

Climate change introduces considerable uncertainty into forest management planning and outcomes, potentially undermining efforts at achieving sustainable practices [24, 25]. There is a need for models capable of projecting the potential impact of climate change on long-term patterns of forest growth and development while being reasonably accessible to forest managers. Ideally, such models should: 1) be capable of representing the effects of climate change on forest productivity and drought-related mortality, 2) include the ability to simulate a variety of forest management options to allow for an evaluation of adaptive management strategies, 3) provide broad outputs relevant to multi-objective forest management, and 4) be relatively straightforward to calibrate.

Here we describe the development and application of the hybrid simulation model FORECAST Climate. The model is evaluated with respect to its ability to reproduce the effects of historic annual climate variability on the annual variation of Douglas-fir and lodgepole pine growth in a montane forest located in southern British Columbia, Canada as measured using tree ring analysis. Simulations of the long-term impacts of alternative future climate change scenarios on forest productivity in young and established stands were conducted with the verified model.

METHODS

2.1 Model Description

FORECAST Climate was developed as an extension of FORECAST [26] which is a stand-level, management-oriented forest growth simulator. FORECAST was designed to accommodate a wide variety of harvesting and silvicultural systems in order to compare and contrast their effect upon forest productivity, stand dynamics and a series of biophysical indicators of non-timber stand values. The model has been used in a wide variety of applications and has been evaluated against field data for growth, yield, ecophysiological and soil variables [27-30].

FORECAST is a 'hybrid' model and many of its parameters are calibrated using historical bioassay data inputted to the model. As with any model of this type, a fundamental assumption with respect to its successful calibration and application is that the past climate regime constitutes a faithful representation of future climate conditions. The validity of this assumption is now questionable given anticipated trends in greenhouse gas emissions and their associated impacts on future temperature and precipitation patterns [31]. The FORECAST model simulates the effect of light and nutrient availability on forest productivity but it has no explicit representation of moisture or temperature on ecosystem processes. Thus, the rationale in developing FORECAST Climate was to incorporate these two factors. The foundation for FORECAST Climate was established through the creation of a dynamic linkage with a forest hydrology model including direct feedback to the core processes driving forest ecosystem production.

2.1.1 The basic FORECAST model

In FORECAST, the rates of key ecosystem processes are combined with data describing rates of decomposition, nutrient cycling, light competition, and other ecosystem properties to simulate annual changes in forest growth (Figure C.1). Plant populations can be initiated from seed and/or vegetatively, and stand development can occur with or without competition from non-target tree species and understory populations. Decomposition and dead organic matter dynamics are simulated using a method in which specific biomass components (eg. foliage, fine roots, branches, etc.) are transferred at the time of tissue death to one of a series of independent litter types. Residual litter mass and its associated nutrient content are transferred to active and passive humus pools when the mass remaining is within 15 - 20% of the original litter mass. Typically, mean residence times for active and passive humus types are 50 and 600 years, respectively. See [26] for further details.

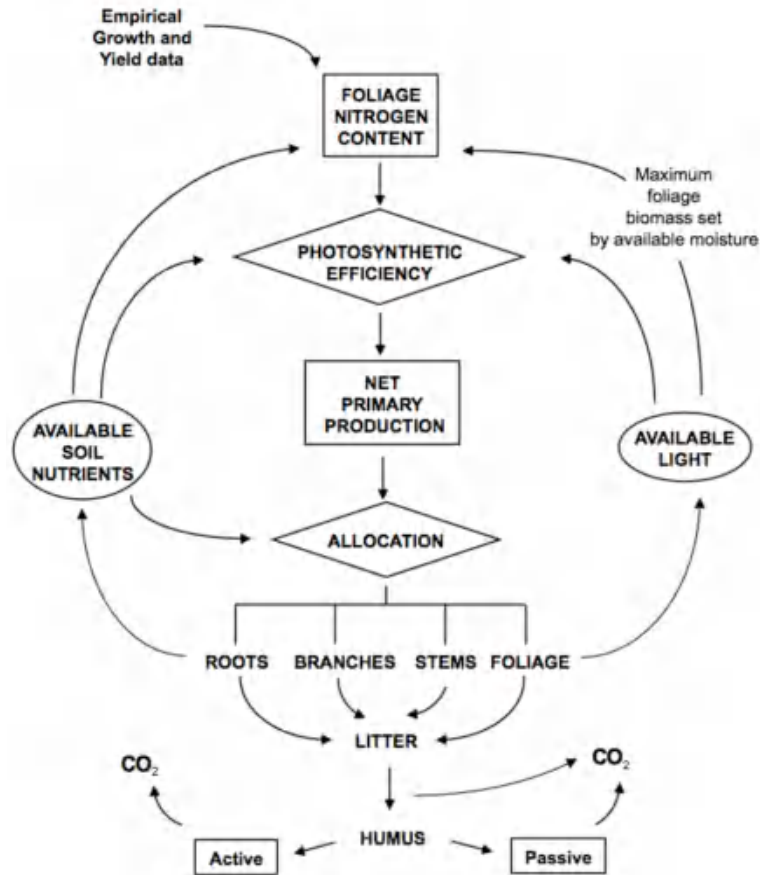


Figure C.1 Schematic illustration of the key ecosystem processes and flows represented in FORECAST (after [30]).

2.1.2 The ForWaDy Model

The Forest Water Dynamics (ForWaDy; [32]) model simulates the hydrologic dynamics of a forest stand on a daily time step for a given set of climatic and vegetation conditions. The model was specifically designed with a structure to facilitate its linkage to FORECAST [32]. It has been shown to perform well for predicting the effect of forest management on evapotranspiration [33] and temporal patterns in soil moisture content under field conditions [33, 34]. The model represents potential evapotranspiration (PET) using an energy balance approach based on a modified version of the Priestly-Taylor equation [35]. This equation is effective in predicting evapotranspiration under a wide variety of forest types and conditions [36-39]. Net shortwave solar radiation interception is used to drive the PET calculations. It is calculated for each tree and plant species from a light competition submodel built into FORECAST (see [26]) and surface albedo. ForWaDy includes a representation of the vertical flow of water through canopy and soil layer compartments (Figure C.2). Movement of water through each soil layer is regulated by its physical properties that dictate moisture holding capacity, permanent wilting point moisture content, and infiltration rate.

Water stress is calculated for each species separately on a daily time step and is expressed as a transpiration deficit index (TDI). The TDI is the relative difference between potential energy-limited transpiration demand and actual transpiration:

$$TDI_{i,d} = (CanT_{Demand,i,d} - CanT_{Actual,i,d}) / CanT_{Demand,i,d} \quad (1)$$

where:

$CanT_{Demand,i,d}$ = energy-driven transpiration demand for species i (mm) on day d , as a function of leaf area index, intercepted short-wave radiation, canopy albedo, and canopy resistance,

$CanT_{Actual,i,d}$ = actual tree transpiration for species i (mm) on day d , as a function of $CanT_{Demand,i,d}$, root occupancy, and available soil moisture.

A detailed description of the ForWaDy model is provided in the Supplementary Material S1 (at the end of this paper). Its general data requirements are listed in Table C.1.

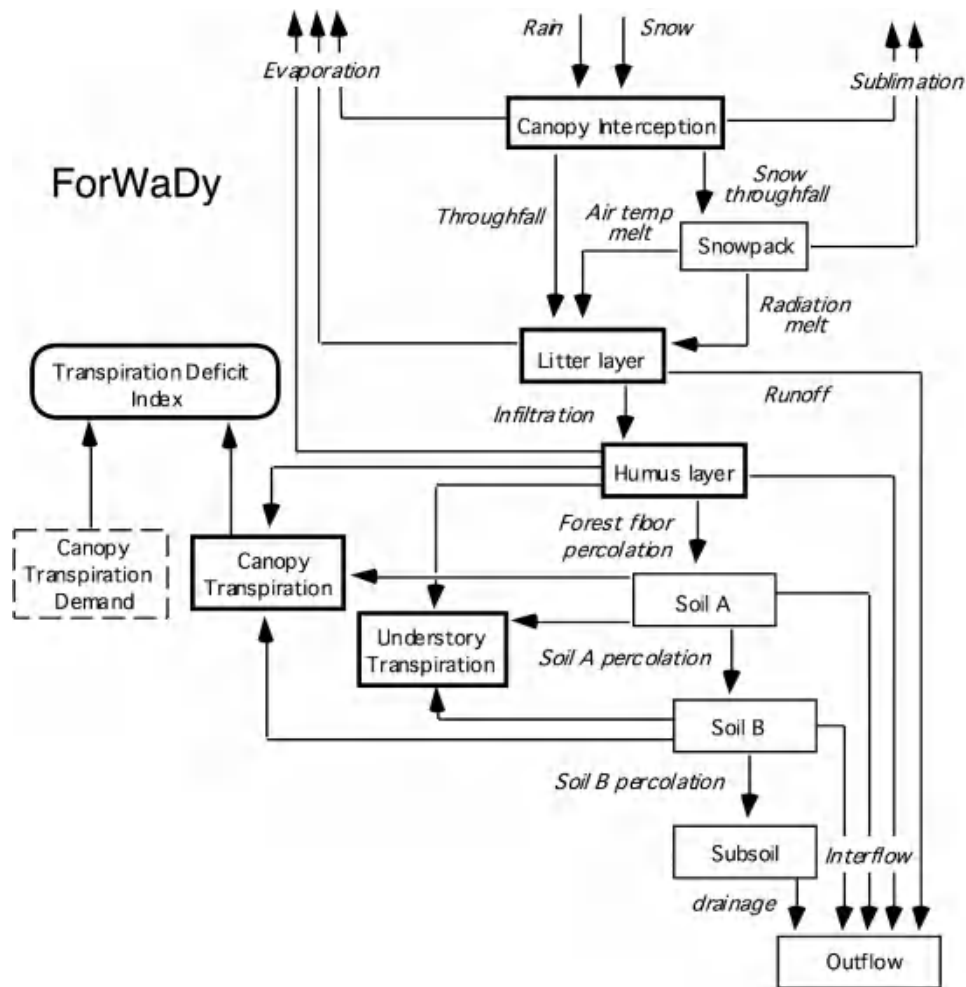


Figure C.2 Schematic diagram of the ForWaDy model indicating water flow pathways and storage compartments.

Table C.1 General data requirements for the ForWaDy model.

Climate data (daily)	Vegetation data	Forest floor & soil data
mean, max and min air temperature (°C)	seasonal conifer and hardwood LAI	fine litter mass (kg/ha)
solar radiation ¹ (MJ/m ²)	seasonal understory % cover	humus layer depth (cm) and bulk density (g/cm ³)
total precipitation (mm)	rooting depths for trees (cm)	depth of mineral soil layers (cm)
snow fraction	rooting depths for understory (cm)	soil texture ³ (by layer)
atmospheric [CO ₂] ²	canopy resistance and albedo (by species)	coarse fragment content (% by layer)

¹ Solar radiation may be estimated from max and min air temperature, elevation, latitude, slope and aspect using published radiation models.

² Only annual data required.

³ Standard texture classes used to estimate clay content.

2.1.3 Simulating the effect of increasing CO₂ on forest growth

Higher atmospheric CO₂ concentrations (c_a) are associated with lower stomatal water vapour conductance [40, 41] and greater water use efficiency [42, 43]. These processes are represented in ForWaDy using a function that modifies canopy resistance in each species in relation to projected changes in c_a [44]. The functional curve is derived from the physiological relationship between relative net assimilation rate and changes in c_a relative to a reference atmospheric CO₂ concentration (Eq. 2A). The impact of c_a on stomatal conductance is given in Equation 2B [44], and stomatal conductance in relation to canopy resistance in Equation 3 (see Figure C.3B, for an example).

$$A_{n(\text{rel})} = [(c_a - r') * (c_{a0} + 2r')] / [(c_a + 2r') * (c_{a0} - r')] \quad (2A)$$

where:

$A_{n(\text{rel})}$ = relative net assimilation rate

c_a = current atmospheric CO₂ concentration (ppm)

c_{a0} = reference atmospheric CO₂ concentration (determined from reference climate data, ppm)

r' = CO₂ compensation point = 40 ppm

and the relative stomatal conductance for water vapour ($g_{w(\text{rel})}$; dimensionless) is

$$g_{w(\text{rel})} = A_{n(\text{rel})} / c_{a(\text{rel})} \quad (2B)$$

where:

$c_{a(\text{rel})}$ = relative atmospheric CO₂ conc = c_a/c_{a0} (dimensionless)

Adjusted canopy resistance ($R_{\text{Can,adj}}$; dimensionless) is

$$R_{\text{Can,adj}} = R_{\text{Can,ref}} + R_{\text{Can,ref}} * (1 - g_{w(\text{rel})}) \quad (3)$$

where:

$R_{\text{Can,ref}}$ = reference canopy resistance (dimensionless)

Many models incorporate a representation of the direct effect of CO₂ fertilization on tree growth [45] based on evidence from short-term studies [46, 47]. There is little evidence, however, supporting the long-term impacts of CO₂ fertilization on forest growth [48, 49]. As such, the FORECAST Climate model does not presently include this as a control on growth.

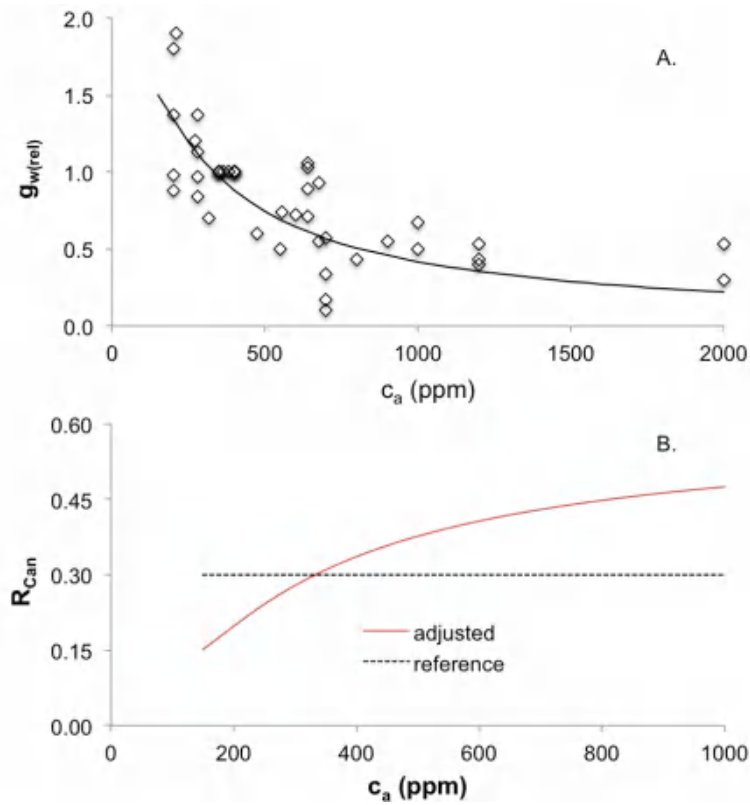


Figure C.3 Relationships between atmospheric CO₂ concentration (c_a) and (A) relative stomatal conductance and (B) canopy resistance. (A) Observations of relative stomatal conductance of water vapour ($g_{w(\text{rel})}$) under changing atmospheric CO₂ concentrations (c_a ; data from [44] re-plotted). The solid line is derived from Eq. 2B where $c_{a(\text{rel})} = c_a/c_{a0}$, c_{a0} is 360 ppm, and $A_{n(\text{rel})}$ is obtained from Eq. 2A. (B) An example of the calculation of adjusted canopy resistance ($R_{\text{Can,adj}}$) as a function of c_a , using a reference canopy resistance ($R_{\text{Can,ref}}$) value of 0.3.

2.1.4 Linkage of FORECAST and ForWaDy

The ForWaDy - FORECAST linkage couples forest water availability directly with ecosystem process simulation. Furthermore, this linkage is dynamic in that the respective functions from each model are continuously updated in response to the iterative sharing of information encoded within a series of feedback loops (see Figure C.4). One aspect of this linkage is reconciling FORECAST's annual time step with the daily time step used in ForWaDy, the latter of which is required to properly capture short-term moisture limitations. This was accomplished by aggregating the daily ForWaDy output into an annual index that was then used as input to FORECAST (Figure C.4). FORECAST, in turn, supplies input to ForWaDy at the beginning of each growing season with respect to vegetation and forest floor conditions (Figure C.4).

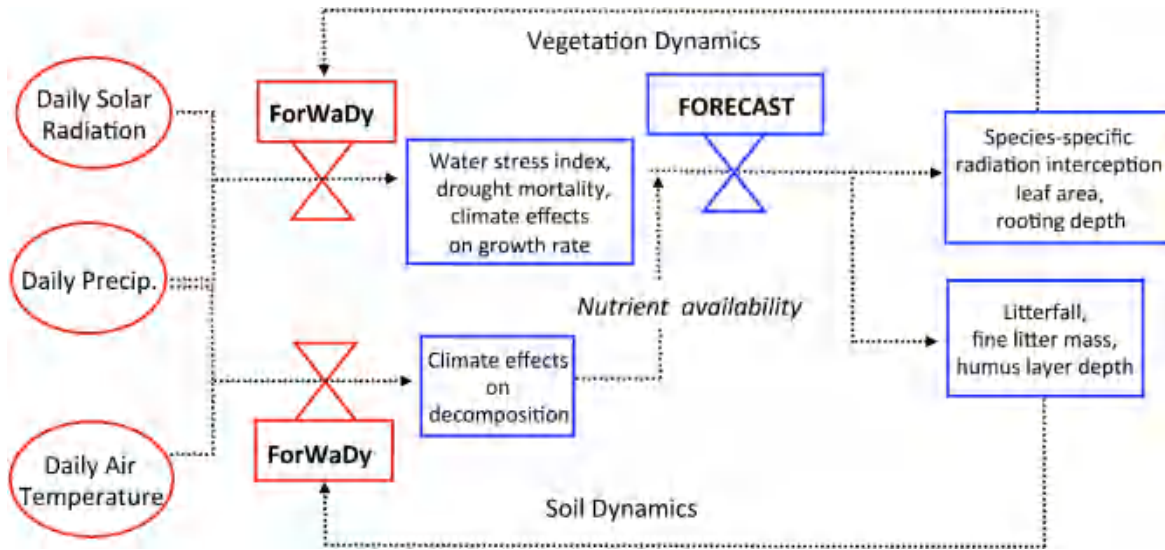


Figure C.4 A schematic diagram illustrating feedback loops and data transfer pathways between FORECAST and ForWaDy.

2.1.5 Accounting for climate impacts on productivity

The impact of climate on tree and plant growth in FORECAST Climate is focused primarily on the relationships between growth rate, temperature and water stress. These relationships are represented using species-specific, curvilinear response functions simulated on a daily time step. The net daily growth response index of species i on day d ($GRI_{Day,i,d}$) is derived as the product of two indices, calculated as temperature and water stress response functions:

$$GRI_{Day,i,d} = T_{Growth,i,d} * S_{Growth,i,d} \quad (4)$$

where:

$T_{Growth,i,d}$ = The temperature response index (range 0-1; dimensionless) for species i on day d . Specified in the model as a user-defined graphical function of daily mean air temperature (see Section 2.2.3).

$S_{Growth,i,d}$ = The water stress response index (range 0-1; dimensionless) for species i on day d . Specified in the model as a user-defined graphical function of the daily mean water stress index (see Section 2.2.3).

The temperature response index is designed to encapsulate the complex physiological growth processes governing tree and understory response to variations in mean daily temperature. It is intended to represent net effect of variations in temperature on primary productivity (NPP) by accounting for the impact of temperature on both photosynthesis and respiration. Data for calibrating the index can be derived from greenhouse studies and/or in situ measurements of seasonal primary productivity (eddy covariance, for example; see [50]).

The water stress response index is calculated from TDI (see Section 2.1.2). The daily TDI value represents the degree to which a species was able to meet its energy-driven transpiration demands (a higher TDI value indicates greater moisture stress). Plants typically respond to water stress by closing stomata to conserve water, leading to an associated reduction in photosynthetic production (see [51]). A negative relationship between S_{Growth} and TDI is therefore expected.

The net daily growth response index is summed to calculate an annual growth response index for year, y ($\text{GRI}_{\text{Year}, i, y}$; Eq. 5).

$$\text{GRI}_{\text{Year}, i, y} = \sum_{d=1}^{365} \text{GRI}_{\text{Day}, i, d} \quad (5)$$

This index is used as a weighting factor that reflects the ‘quality’ of a given climate year relative to an expected growth rate (further details below).

The climate response functions within FORECAST Climate are calibrated using historical daily climate data. A ‘reference’ daily climate series must be compiled with data derived from a climate station near the forest area to be modeled, and should span a minimum 20-year time period. A summary of the climate data required is provided in Table C.1.

Using the reference data set, a calibration run is conducted from which the annual growth response index is calculated (Eq. 5). By averaging the annual values for the length of the reference climate period, a normalized growth response index is derived for each species (Eq. 6) that reflects growth conditions in an average historical climate year. This index is used in subsequent calculations.

$$\text{NGRI}_i = \left(\sum_{y=1}^n \text{GRI}_{\text{Year}, i, y} \right) / n \quad (6)$$

where:

NGRI_i is the normalized growth rate index for species i derived from the reference climate data set (dimensionless)

$\text{GRI}_{\text{Year}, i, y}$ is the annual growth response index for species i (Eq. 5).

n = the number of years in the historical climate data set

Simulation of growth response to climate in FORECAST Climate is achieved by modifying base growth rates (as determined in the underlying FORECAST model – section 2.1.1) according to the climate relationships described in section 2.1.4. A climate-limited growth rate is calculated by multiplying the base growth rate (Eq. 7A) by a climate response factor (Eq. 7B).

$$CGR_{i,y} = BGR_{i,y} * CRF_{i,y} \quad (7A)$$

$$CRF_{i,y} = (GRI_{Year,i,y} - NGRI_i) / NGRI_i \quad (7B)$$

where:

$CGR_{i,y}$ is the climate-limited growth rate for species i in year y (tons ha⁻¹),

$BGR_{i,y}$ = the base growth rate for species i and year y determined in FORECAST as the light and nutrient-limited growth rate (tons ha⁻¹),

$CRF_{i,y}$ is the climate response factor for species i in year y (dimensionless), and $GRI_{year,i,y}$ and $NGRI_i$ are as defined in Equations 5 and 6, respectively.

2.1.6 Climate and decomposition rates

The decomposition of dead organic matter in FORECAST is represented based upon user-defined mass loss rates associated with litter quality and derived from field incubation experiments. A maximum of 40 dead organic matter types may be defined and simulated within the model [26]. In FORECAST Climate, decomposition rates are modified by soil moisture content and air temperature with the calculation of a daily decomposition response index (Eq. 8). The model does not include any representation of the potential effects of mixing different litter types on mass loss rates.

$$DRI_{Day,l,d} = T_{Decomp,d} * M_{Decomp,l,d} \quad (8)$$

where:

$DRI_{Day,l,d}$ = daily decomposition response index (range 0-1; dimensionless) for soil layer l on day d

$T_{Decomp,d}$ = Temperature decomposition response (range 0-1; dimensionless). Specified in the model as a user-defined graphical function of daily mean air temperature (see Figure C.5A).

$M_{Decomp,l,d}$ = Moisture decomposition response (range 0-1; dimensionless). Specified in the model as a user-defined graphical function of daily moisture content (see Figure C.5B).

Assuming moisture is not a limiting factor, the decomposition rate of dead organic matter is generally faster in warmer environments [52, 53]. The default temperature response function is shown in Figure C.5A, and is based upon a Q₁₀ factor of 2 [52, 54]. The moisture response functions for litter, humus, and soil, are shown in Figure C.5B.

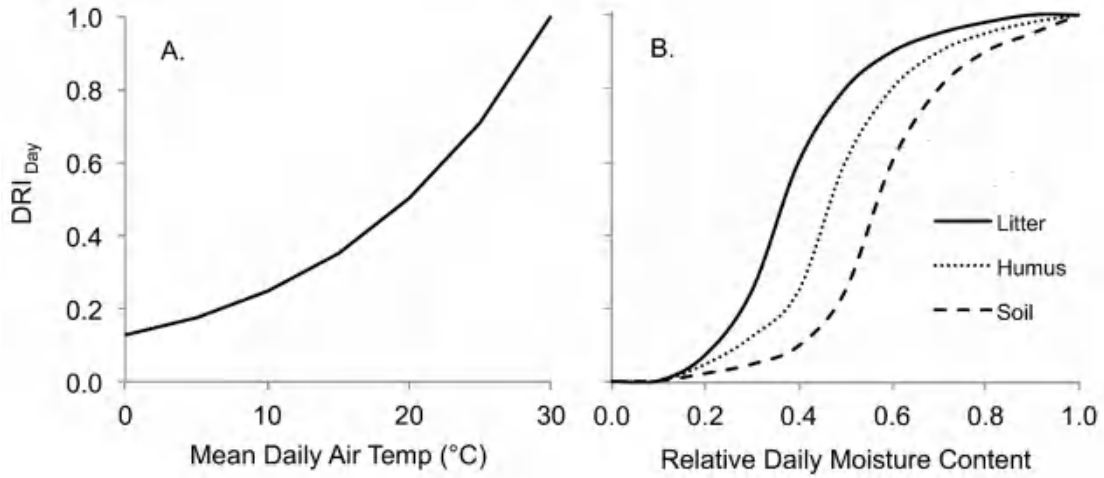


Figure C.5 Daily decomposition index in relation to (A) daily air temperature, and (B) relative daily moisture content. (A) The relationship with mean daily air temperature is based upon a Q_{10} function where $Q_{10} = 2$. (B) Moisture content relationships are shown for litter, humus, and mineral soil (see text for details).

The climate impact on decomposition rates is represented using the same procedure as the growth response index calculation (Section 2.1.5). First, a normalized decomposition response index (NDRI) is calculated for each soil layer l using the reference climate series:

$$NDRI_{l,i} = \left(\sum_{y=1}^n DRI_{Year,l,y} \right) / n \quad (9)$$

where:

$NDRI_{l,i}$ is the normalized decomposition response index for layer l derived from the climate calibration data (dimensionless)

$DRI_{Year,l,y}$ is the annual decomposition response index for each soil layer l

n = the number of years in the reference climate data set

A climate decomposition factor ($CDF_{x,y}$; Eq. 10A) is then calculated as the relative difference between the current and normalized decomposition response indices (Eq. 9). Climate feedback is represented by a climate decomposition rate index ($CDR_{l,y}$) for each soil layer l and year y (Eq. 10B).

$$CDF_{x,y} = (DRI_{Year,l,y} - NDRI_{l,i}) / NDRI_{l,i} \quad (10A)$$

$$CDR_{x,y} = BDR_{x,y} * CDF_{x,y} \quad (10B)$$

where:

$CDF_{x,y}$ is the climate decomposition factor for litter type x in year y (dimensionless)

$DRI_{Year,l,y}$ and $NDRI_{l,i}$ are as defined above (Eq. 9),

$CDR_{x,y}$ is the expected climate decomposition rate for litter type x and year y (tons ha⁻¹)

$BDR_{x,y}$ is the base decomposition rate for litter type x in year y determined as a function of litter quality (tons ha^{-1})

2.1.7 Representation of drought-related mortality

Extended periods of drought can lead to plant mortality, either directly or by increasing vulnerability to biotic disturbance agents [5, 55]. FORECAST Climate includes a drought mortality function in which a two-year running-average TDI is used to predict annual mortality. The two-year running average reflects the negative impact of consecutive years of drought (see, for example, [56]). The drought mortality relationship is specified in the model as a user-defined graphical function of species-specific, two-year running average TDI (see Section 2.2.3).

2.2 Evaluating model performance using tree-ring analysis

FORECAST Climate was calibrated for a montane forest in south central British Columbia. The model was used to predict annual sapwood production (a proxy measure of tree ring growth), which was then compared against measured 30-year ring chronologies.

2.2.1 Study area

The study area was located in south central British Columbia, Canada near the city of Kamloops ($50^{\circ}40'00''$ N, $120^{\circ}20'00''$ W), and is classified as a dry cool subzone of the Interior Douglas-fir biogeoclimatic zone [57]. The site, located in crown-owned forest land, is dominated by stands of interior Douglas-fir (*Pseudotsuga menziesii* var. *glauca*) and lodgepole pine (*Pinus contorta*). These species are common in montane regions in the southern interior of British Columbia, ranging from 900 to 1400m in elevation. The closest local climate station with a complete climate record (Red Lake: Elevation = 1162m, $50^{\circ}56'06''$ N, $120^{\circ}48'00''$ W) was selected from which 30 years of daily data (spanning the years 1975-2004) were obtained. Average monthly temperature and precipitation for Red Lake are shown in Figure C.6.

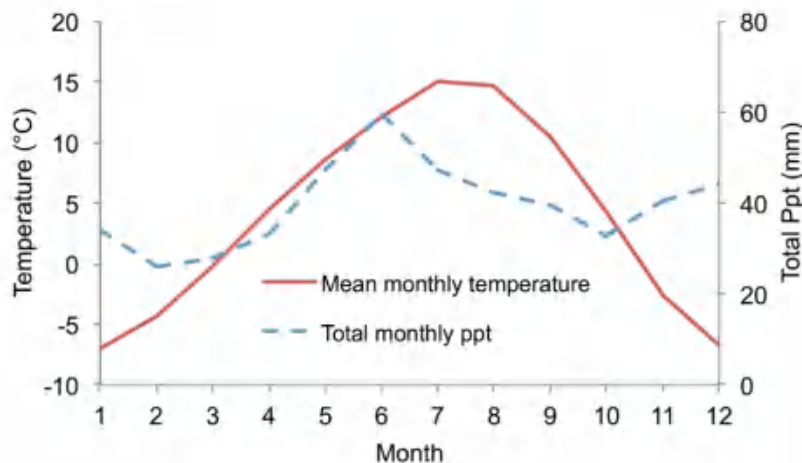


Figure C.6 Average monthly temperature and precipitation from the Red Lake climate station (1975-2004).

2.2.2 Tree-ring analysis

A total of 5 plots were randomly selected from a series of candidate stands identified using forest inventory data from the study site. Plots were split with 3 Douglas-fir and 2 lodgepole pine-dominated stands. Stands

with clear signs of fire scars or damage from biotic agents that could have masked a climate signal were avoided. Plot centers were established using a variable radius to define plot area such that a total of 20 dominant and/or co-dominant trees were identified within the plot area. Species, elevation, slope, aspect, and slope position were recorded for each plot. The stands ranged in age from 36 to 150 years (Table C.2).

Within each plot, a total of 20 dominant or co-dominant trees were cut down and a slice (cookie) approximately 4 cm thick removed from the base of each stem, within 20 cm of the soil surface. The cookies were prepared for analysis in the Tree-Ring Laboratory at the University of Northern British Columbia, using standard procedures [58]. Annual tree ring width was measured to the nearest 0.01mm using a Windendro system. The ARSTAN software [59] was used to prepare and cross-date the final chronologies. All series were de-trended by fitting a spline of 50% frequency response across 67% of the series length to remove the low frequency age trend. Slight modifications were made to spline stiffness for two of the series to improve their fit to the data. De-trended data were used to isolate the impacts of year-to-year climate variability on relative tree productivity. Chronologies for each plot were constructed using the final ARSTAN tree ring index. Each chronology was restricted to the 1975-2004 period and normalized by dividing by the average ring index. Typically, tree rings are compared against two consecutive years of climate data (current and previous year) [23, 60]. This is because early season wood growth is partly a function of climate suitability in the previous year and its impact on carbohydrate reserves [61].

Table C.2 Characteristics of sample plot locations from which trees were harvested for tree-ring analysis and choronology statistics.

Plot ID	Species	Average Age (y)	Elevation (m)	Slope (%)	Aspect (deg.)	Slope Position	Mean sensitivity	Serial correlation
4	Fd	54	1250	25	295	mid	0.288	0.836
9	Fd	67	978	20	50	mid	0.275	0.812
14	Fd	36	1125	18	64	mid	0.244	0.812
34	Pl	60	1300	8	26	low	0.124	0.946
71	Pl	150	1356	2	322	flat	0.159	0.846

A total of 20 trees per plot were sampled. Fd = Douglas fir, Pl = lodgepole pine

2.2.3 FORECAST Climate calibration

Detailed descriptions of FORECAST calibration data requirements are provided in [26] and [62]. The base FORECAST model was calibrated with an existing data set from the Interior Douglas-fir dry cool subzone [63]. The data set includes both Douglas-fir and lodgepole pine, and two minor vegetation functional groups (grasses and shrubs) common to the area. Calibration of the climate response functions in FORECAST Climate is described in the following sections.

The hydrological submodel requires data describing characteristics of the soil profile (Table C.3) and characteristics of simulated trees and minor vegetation with respect to the calculation of daily

evapotranspiration and water stress (Table C.4). Average soil characteristics were inferred from soil pits dug in each of the plots.

Table C.3 Parameter values in the hydrological submodel specific to the simulation of plant-available water within soil layers.

Soil layer	Soil Texture Class	Coarse Fragment Content (%)	Soil Depth ¹ (cm)	Field Capacity Moisture Content ²
Humus	N/A	0	12.5	0.32
Mineral A	Silt loam	25	40	0.25
Mineral B	Silt loam	25	45	0.25
Mineral C	Silt loam	25	50	0.25

¹ The starting humus depth is shown, but humus depth can change over time depending on rates production and decomposition.

² Volumetric water content above which drainage occurs.

Table C.4 Parameter values in the hydrological submodel specific to the simulation of evapotranspiration and water stress for trees and minor vegetation.

Species	Canopy Parameters		Permanent Wilting Point ³		Maximum Root Depth (cm)
	Albedo ¹	Resistance ²	Humus	Mineral Soil	
<i>Trees</i>					
Douglas-fir	0.12	0.3	0.08	0.12	100
Lodgepole pine	0.12	0.24	0.1	0.13	100
<i>Minor vegetation</i>					
<i>Calamagrostis grass</i>	0.12	0.15	0.09	0.11	75
<i>Vaccinium shrub</i>	0.12	0.10	0.10	0.11	75

¹ Estimated values.

² Reference relative canopy resistance to water loss through stomata ($R_{Can,i}$) [64]. Higher values indicate greater resistance.

³ Relative volumetric moisture content (proportion of total volume) at which soil water uptake is suspended [65, 66].

Calibration of climate response functions was completed as follows. Daily temperature and water-stress growth response curves were developed for Douglas-fir [67,68] and lodgepole pine [69, 70] based upon

literature reviews of climate-growth relationships (Figure C.7A-B). The sharp increase in growth beginning around 5°C for both species is indicative of the heat sum required to break dormancy. Each curve varies with respect to the optimal temperature range for growth and the relative rate of decline beyond the optimum, depending on a plant's tolerance characteristics. The decline at higher temperatures represents the increase in respiration associated with elevated temperatures [50].

A relative drought mortality curve was developed for each tree species based on its ecological characteristics within the subzone (Figure C.7C). Douglas-fir was assumed to be slightly more tolerant of drought stress relative to lodgepole pine. Each species-specific mortality function was evaluated using provincial forest health survey data (not shown) to verify that it produced realistic mortality projections when the model was run with the historical reference climate data.

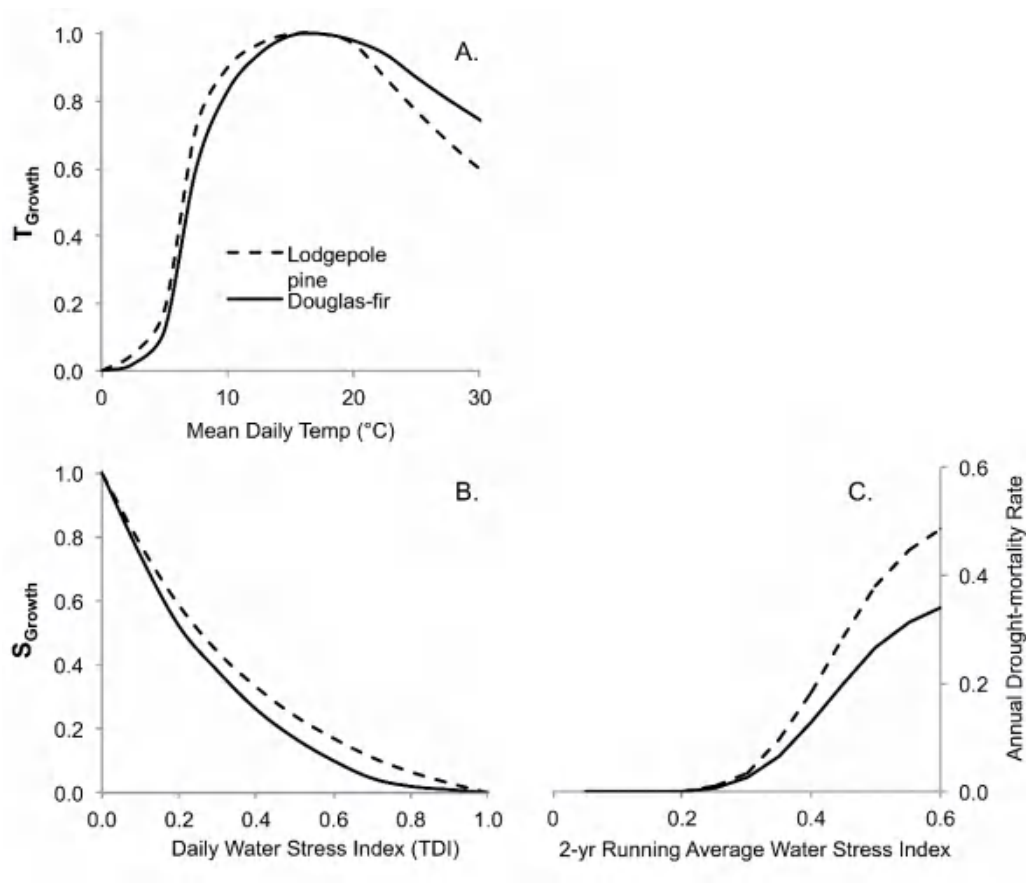


Figure C.7 Climate response functions showing the effect of temperature and water stress on growth (A,B) and mortality (C). (A) Relationships between mean daily temperature and the T_{growth} parameter, and (B) daily water stress and S_{growth} parameter used in Eq. 4. (C) The drought-related mortality rate as a function of the 2-year running average water stress index.

2.2.4 Growth simulation using historical climate data

To evaluate the capability of FORECAST Climate to reproduce the measured, climate-related annual variation in tree ring growth, the model was run using the historical climate data from the period of 1975 – 2004. The 30-year climate data set was cycled 5 times to generate 150 years of daily data. Model projections of annual

sapwood production were subsequently compared against the normalized tree ring indices for the corresponding climate years using regression analysis. However, because annual ring growth is fueled both by carbohydrates stored from the previous year and the current year's production, each ring index was compared against a normalized average of the previous and current year's simulated sapwood production.

2.3 Simulation of long-term climate change impacts

2.3.1 Development of climate change scenarios

To illustrate the potential of FORECAST Climate to simulate the impacts of climate on the growth and development of forests within the study area, climate change projections were derived from two established general circulation models (GCMs) included as part of the Intergovernmental Panel on Climate Change AR5 analysis [31], HadGem2 (www.enes.org/models/earthsystem-models/metoffice-hadley-centre/hadgem2-es) and CanESM2 (www.cccma.ec.gc.ca/data/cgcm4/CanESM2/rcp45/index.shtml). A medium range emissions pathway was selected for the two models (Figure C.8A). It is based on a representative CO₂ concentration pathway that generates a radiative forcing of 4.5 Wm⁻² (RCP 4.5, [71]). These models and scenario were selected to be representative of the middle of the range of potential climate change scenarios. It should be noted that other scenarios could generate different results. Atmospheric CO₂ concentration for the reference climate scenario was constrained to 2005 values (380 ppm). The regional monthly output from the GCMs for the 2020s, 2050s and 2080s was downscaled to daily data using a direct approach based upon the Red Lake daily climate data series from the years 1975-2004. The resulting data set spanned a 100-year period (2012-2111). Projected changes in mean growing season temperature and precipitation are shown in Figure C.8B-C. Mean growing season temperature is predicted to increase from approximately 12.5°C in 2013 to 16-17°C by 2111. In contrast, both GCMs predicted only a very gradual declining trend in growing season precipitation during the same period. It should be noted that the interannual variability in temperature and precipitation characteristic of the base reference data is retained as a result of the direct downscaling process.

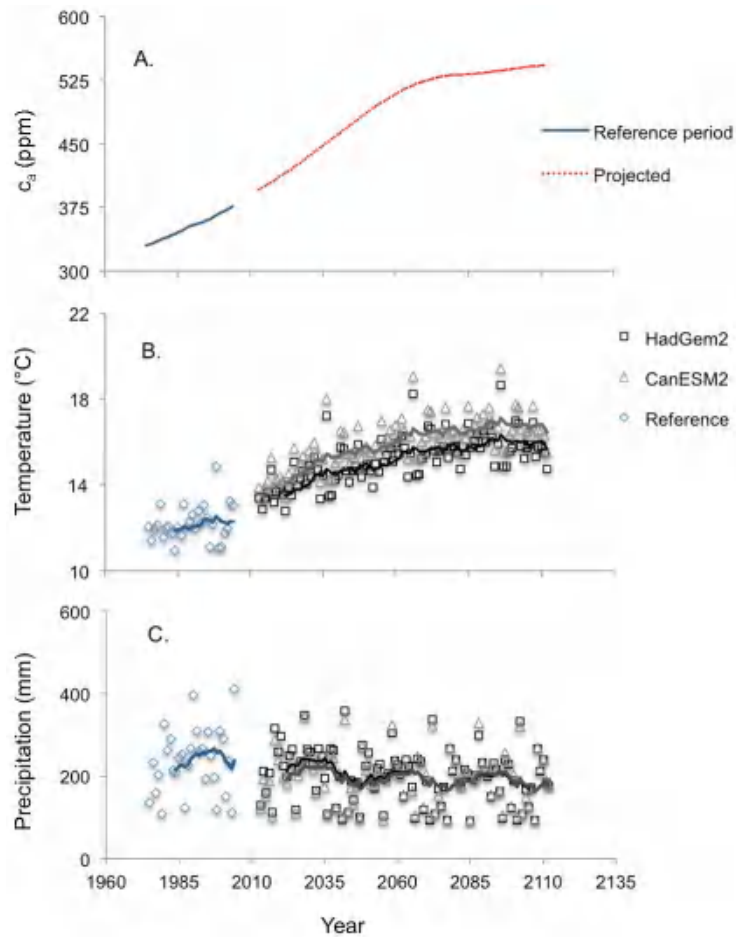


Figure C.8 Reference climate data and projected atmospheric [CO₂] (A), growing season temperature (B), and precipitation (C). (A) Projected increase in atmospheric [CO₂] (c_a) for the RCP 4.5 emissions scenario, (B) projected growing season (MAY – SEP) mean daily air temperature, and (C) projected total growing season precipitation for the next 100 years based on two downscaled climate change projections (see text). Lines represent the 10-year moving average for each series in panels B and C.

2.3.2 Model application for climate change simulation

FORECAST Climate was used to simulate the long-term impact of climate change on stand growth and development for both Douglas-fir-dominated and lodgepole pine-dominated stand types. Growth in newly planted (age = 1 year) and established stands (starting age = 60 years) was simulated for a 100-year period. In the newly planted stands, the climate began to change immediately (see Figure C.8). For established stands, however, the 30-year historical climate data were copied and appended to create 60 years of data before the climate change period began at age 61. A total of eight runs were completed (2 climate scenarios * 2 species * 2 age classes).

RESULTS

3.1 Model evaluation against tree ring data

Sapwood production predictions were concordant with 48% to 73% of the variation in measured annual ring widths in 4 of the 5 plots (Figure C.9). One Douglas-fir plot (Plot #9) showed no significant correlation with the other plots suggesting that annual variation in tree growth in this plots was likely a consequence of factors other than climate. This plot was therefore excluded from subsequent analysis. The average slopes of the regression lines were 1.04 and 1.05, for the remaining Douglas-fir (#4 & #14) and pine (#71 & #34) plots, respectively.

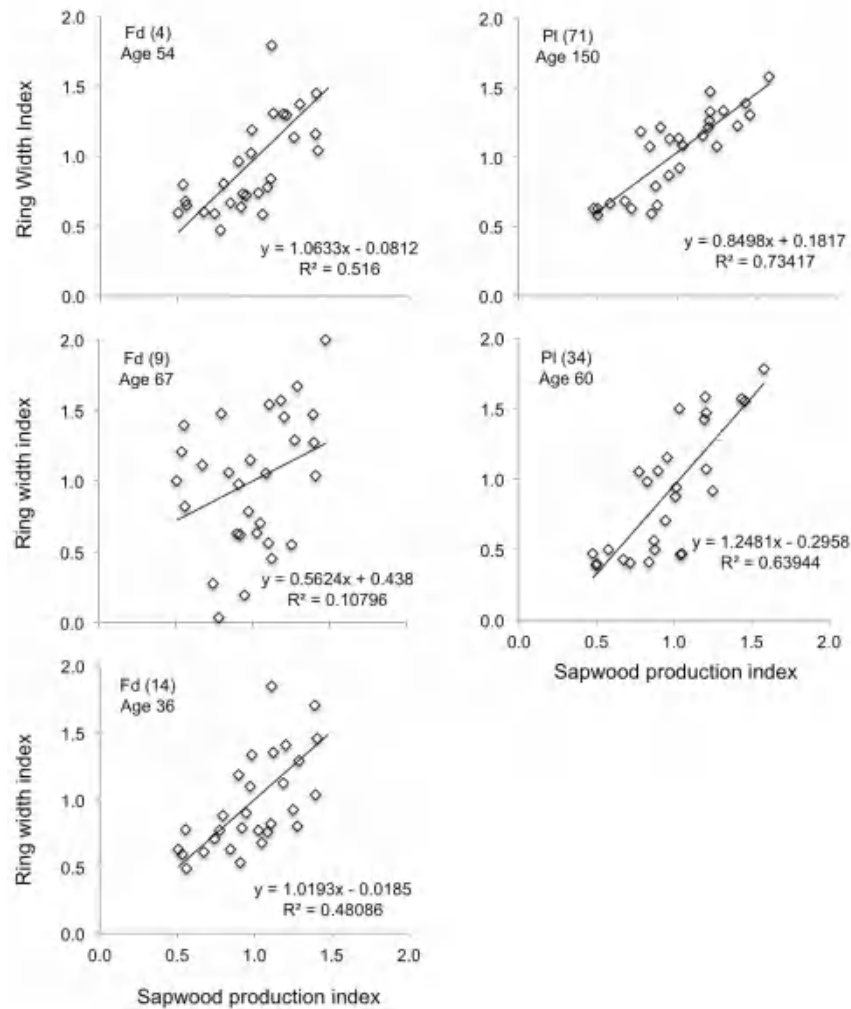


Figure C.9 Comparison of the simulated sapwood production index with the measured ring width index. Data are shown for Douglas-fir (Fd) and lodgepole pine (Pl) plots for the 30-year climate reference period. Average tree age is shown for each plot.

3.2 Climate change impacts on tree growth

Both climate change scenarios had a net positive impact on growth rates for newly planted stands, as indicated by the climate response factor (CRF, Eq. 7; Figure C.10A). Ten-year running averages show that the

CRF values under the historical (reference) climate oscillate around zero, while those for the climate change scenarios are consistently higher. The impact of climate change on stemwood biomass was generally positive for both tree species, except in pine stands 85 years and older (Figure C.10B). In Douglas-fir, stemwood biomass was 11 to 17% higher at rotation age (80 years), and 4 to 7% higher in pine. Climate change triggered more drought-related mortality (Figure C.10C), which was associated with an increase in both the frequency and intensity of water stress (Figure C.11B-C). The increase in water stress in the climate change scenarios occurred despite an increase in canopy resistance associated with higher CO₂ concentrations (Figure C.11A).

In established (60 year-old) stands, the impact of climate change was projected to be positive in terms of the CRF (Figure C.12A). This was not the case for stemwood biomass, however. For Douglas-fir, there was little difference among the historical and climate change scenarios, though biomass under the latter was lower when stands were very old (Figure C.12B). In pine, however, climate change reduced stemwood biomass early in the simulation. This discrepancy became more pronounced over time. Lower stemwood biomass was associated with elevated drought-related mortality in both species but more so in pine (Figure C.12C).

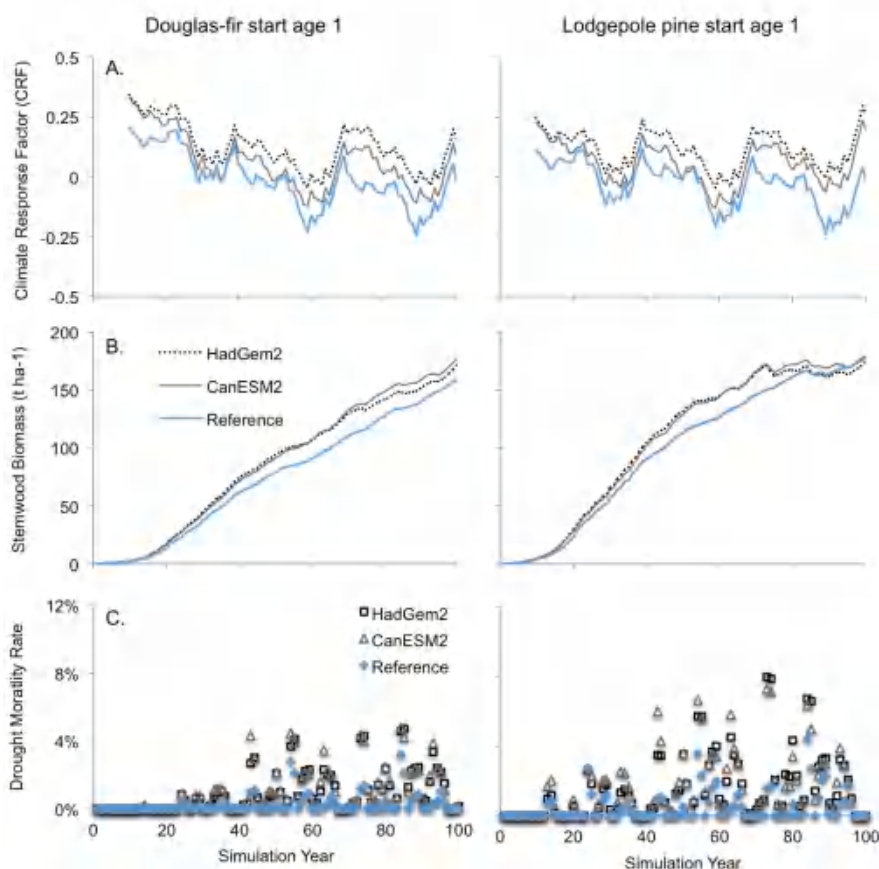


Figure C.10 Impact of climate change on: (A) growth response (CRF), (B) stemwood biomass, and (C) drought-related mortality. Simulations results for newly planted stands of Douglas-fir are shown on the left and for lodgepole pine on the right. Climate change simulation was initiated at year 1 of the simulation. Lines represent 10-year running averages of annual values. A CRF value near zero indicates that the simulated climate year was similar to the historical average year.

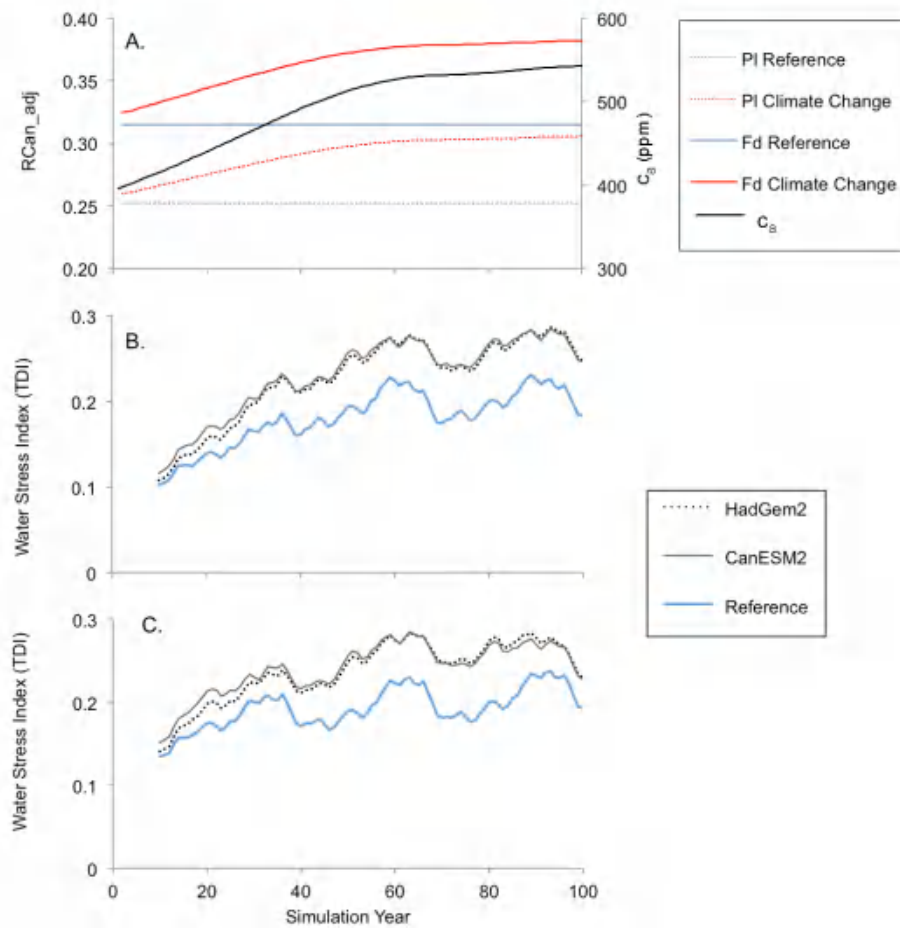


Figure C.11 Simulated effect of c_a on canopy resistance (A) and of climate change on tree water stress (B-C). (A) Projected atmospheric [CO₂] (c_a) for the climate change scenarios is based on the RCP 4.5 emissions scenario while reference scenario levels were constrained at 2005 values (380 ppm). The impact of c_a on canopy resistance (R_{Can_adj}) is shown for both species and for both climate scenarios (see Eq. 3). Lower panels show simulated water stress for newly planted stands of (B) Douglas-fir and (C) lodgepole pine. Water stress results represent the 10-year running averages of annual transpiration deficit index (TDI) values.

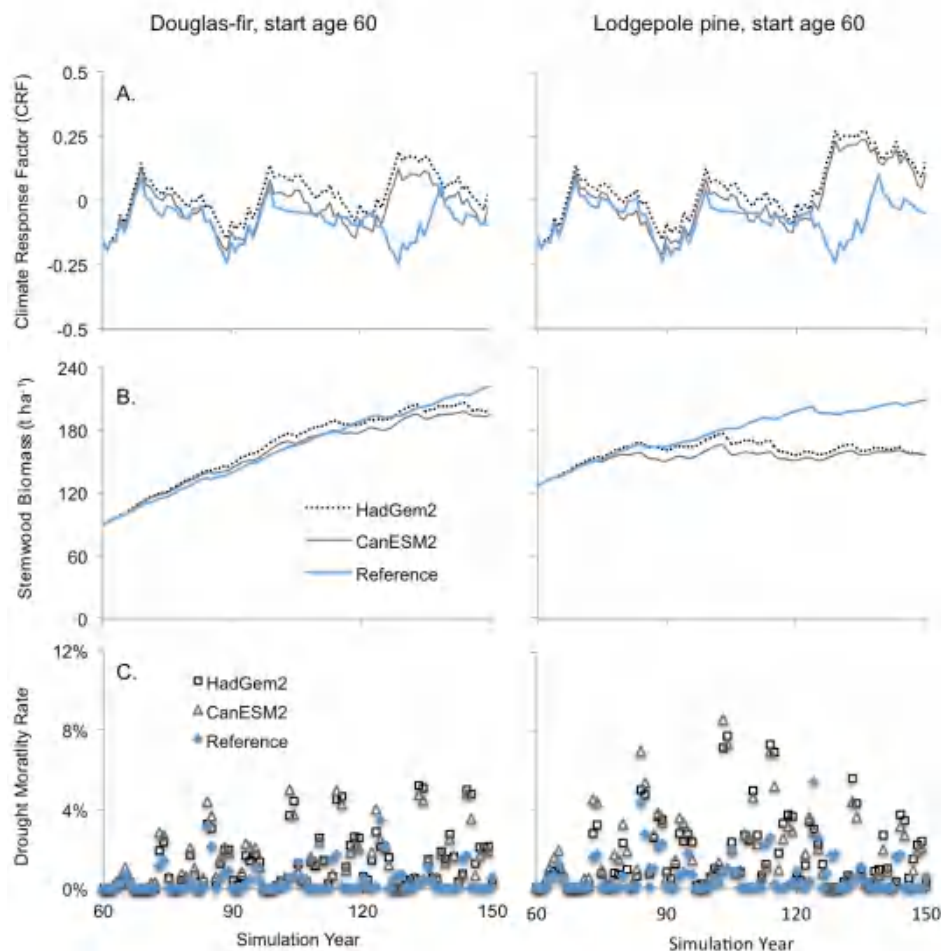


Figure C.12 The impact of climate change for on: (A) growth response (CRF), (B) stemwood biomass, and (C) drought-related mortality. Simulation results for established (60 years old) stands of Douglas-fir are shown on the left and for lodgepole pine on the right. Climate change simulation was initiated at year 60 of the simulation. Lines represent 10-year running averages of annual values. A CRF value near zero indicates that the simulated climate year was similar to the historical average year.

Projected impacts in newly planted stands of the reference climate and climate change (CanESM2) scenarios on the daily growth response index are shown for three future climate periods (Figure C.13). The daily growth response index (GRI_{Day}) is determined as the product of the daily growth response to temperature (T_{Growth}) and water stress (S_{Growth}) (Eq. 4) and is summed for the year to determine the annual growth response index (GRI_{Year}). The model predicts a considerable lengthening of the temperature-limited growing season, as approximated by the number of calendar days where the value of $T_{Growth} \geq 0.25$ (data not shown). The average length of the temperature-limited growing season for both species increased by 42 days in the period from 2073-2102 relative to the reference period (1975-2004). The increase, however, was also accompanied by higher daily drought stress during the growing season leading to a mid-summer decline in average GRI_{Day} (Figure C.13).

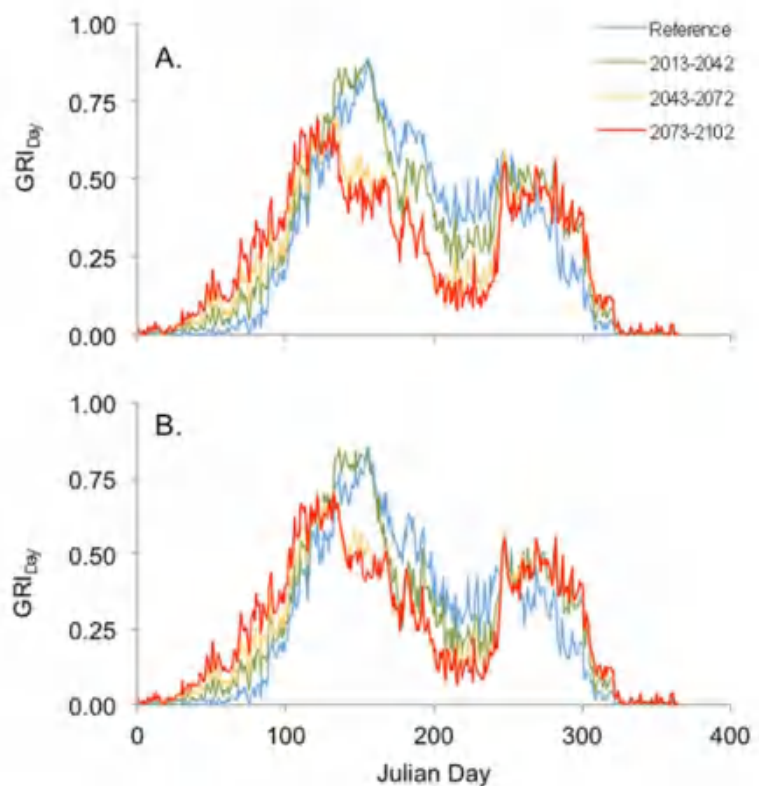


Figure C.13 Simulated impact of climate change on GRI_{Day} for Douglas-fir (A) and lodgepole pine (B). Results for mean daily growth response index (GRI_{Day}) are shown for newly planted stands and reflect data from the 30-year historical time period (reference), and three sequential 30-year future climate periods (2013-2042, 2043-2072, and 2073-2102) based upon the CanESM2 climate scenario.

Over the first 30 years of the simulation, climate change led to reduced levels of litter mass due to increased mass loss rates (Figure C.14A). Thereafter, total litter mass in the climate change scenarios increased to levels above that of the reference climate. Nitrogen (N) release was consistently higher under both climate change scenarios (Figure C.14B).

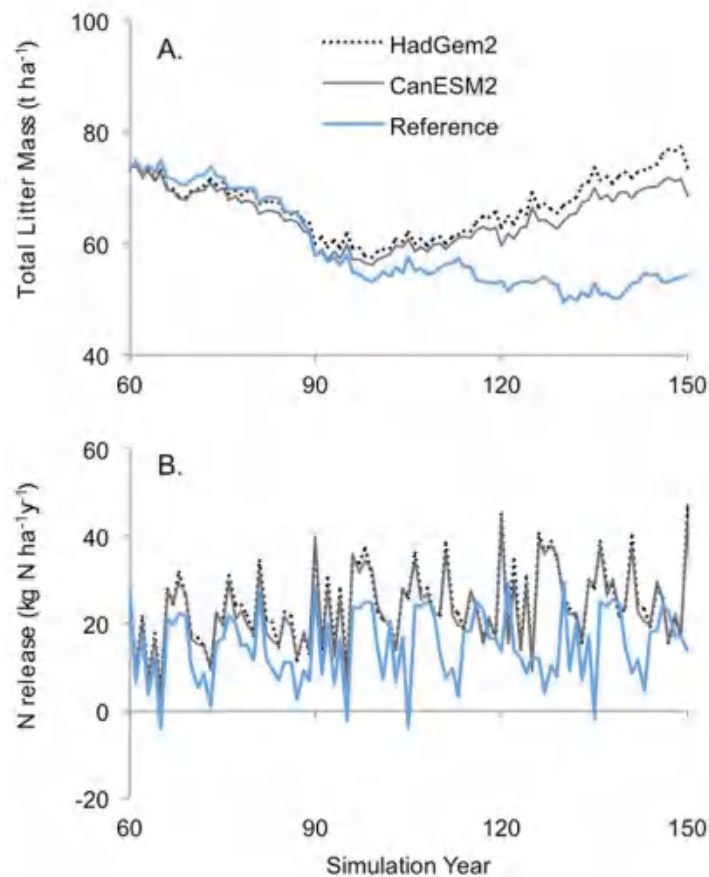


Figure C.14 Simulated impact of climate change on (A) total litter mass, and (B) net N release. Results are shown for established (60 years old at the start of the climate change simulation) Douglas-fir stands.

DISCUSSION

4.1 Model evaluation using tree-ring analysis

A variety of metrics have been useful in establishing the relationship between climate and plant productivity (see [72]). One metric used extensively is dendrochronology, in which changes in ring width are linked to annual variation in climate, particularly temperature and moisture [73]. Dendrochronology thus provides a means of assessing how well a forest model can project the impact of climate on plant performance (i.e., annual ring growth). If a model can successfully reproduce ring chronologies as a function of historical climate conditions, it should be reasonable to use these same relationships to predict the future growth response to a changing climate regime (see, for example, [74, 23, 60, 75]).

Dendrochronological records indicate that, in general, annual tree growth in temperate regions tends to be more sensitive to variations in water stress than temperature [76, 77]. FORECAST Climate performed well in capturing the historical effect of climate on ring width indices in 4 of the 5 measured plots. Model output was consistent with years when measured radial growth rates were reduced due to water stress as well as years in which growth was above average.

The positive impacts of temperature on ring width were captured directly by FORECAST Climate as a lengthening of the growing season, and indirectly through the positive influence of enhanced nitrogen mineralization on site productivity.

One of the challenges in using tree ring data is that climate signals can be obscured by other factors that influence growth, such as abiotic and biotic disturbance agents, and competition for site resources from neighboring trees and/or other vegetation types [73]. In our case, one of the two plots with lower R² values (Douglas-fir, plot #9; see Table C.2) displayed unusual patterns whereby ring widths declined to near zero for a three-year period before returning to 'normal' levels (data not shown). The other Douglas-fir plots showed no such pattern suggesting that the decline was not climate related. Abrupt disruption and subsequent recovery in tree radial growth is indicative of insect attack. In Douglas-fir that might be from budworm or bark beetle [78]. Regardless of its source, the ring pattern was sufficiently skewed that it effectively obscured the climate signal.

4.2 Effects of climate change on productivity and mortality

FORECAST Climate predicted an overall increases in annual growth rates under future climate conditions in both Douglas-fir and lodgepole pine (Figures C.10 & C.12). An increase in growing season length was the dominant factor in this regard and served to counteract an increase in the frequency and intensity of summer moisture stress, the latter of which represented a downward pressure on growth (Figure C.11). Summer moisture stress trended upwards under climate change despite simulated increases in canopy resistance associated with elevated atmospheric CO₂ concentrations (see Figure C.11). [23] also reported an antagonistic effect of growing season length and moisture stress on forest productivity in the boreal forest. [79] found that Douglas-fir growth rates in warm-dry regions correlated well with annual precipitation while growth in populations from cooler and wetter regions was better correlated with temperature and other climatic variables. Summer moisture deficit was the key climatic factor limiting interior Douglas-fir growth rates in montane ecosystems in the northwestern US [77]. In the Cascade Range, Washington, USA, [80] observed that growing season precipitation was the climate variable most strongly correlated with growth rates in mid-elevation lodgepole pine stands, indicating that summer water stress was a key limiting factor. They noted that temperature-regulated growing season length was the most important factor influencing growth rates in high elevation stands.

Higher drought-related mortality was predicted by FORECAST Climate in all climate change scenarios. This resulted in lower biomass production except for newly planted Douglas-fir stands. Established stands were vulnerable to the warmer and drier climate conditions due to a high leaf area. This is because older stands originated and developed under historical climate conditions, which can support a greater leaf area. The latter, however, is poorly adapted to an increasingly water-limited future environment. High evapotranspirational demand in older stands thus triggered widespread mortality during drought and a significant loss of live biomass. Although newly planted stands also incurred elevated mortality, the impact on long-term productivity was relatively low and surviving trees developed canopies with a lower leaf area. Finally, it should be noted that the intensity of predicted water stress declined after a mortality event. This was because mortality reduced stand leaf area (data not shown) resulting in a lower canopy water demand.

Evidence of increased drought-related mortality has been documented in forest ecosystems around the world [5, 81, 14]. Moreover, [82] observed widespread growth decline despite increases in water use efficiency in temperate and boreal forests in a study combining standard dendrochronological techniques with isotopic analysis. The complex physiological response of vegetation to water stress, however, has made it difficult to represent accurately within forest ecosystem models [78]. Prolonged moisture stress increases mortality generally [5, 83] and both hydraulic failure and carbon starvation have been implicated as direct causal factors [84, 51]. Trees suffering from water stress are also more vulnerable to abiotic and biotic disturbance, including fire and insect attack [6, 83]. The water-stress mortality function employed in FORECAST Climate was designed to encapsulate both the direct and indirect aspects of drought-related mortality. It can be parameterized through an iterative process whereby modeled mortality derived using historical reference climate data is adjusted to achieve a reasonable match to measured rates.

It should be noted that the projections of the impact of climate change on long-term growth and productivity in these ecosystems do not include any impacts from extreme climate events nor the effect of climate on population dynamics of natural disturbance agents. Both of these factors have the potential to substantially impact forest productivity as the climate continues to change.

4.3 Climate effects on decomposition and nutrient cycling

FORECAST Climate predicted a net increase in mass loss associated with litter decomposition over most years in the climate change scenarios and there was an increase in simulated litter mass over the long-term (Figure C.14A). The latter was a result of the higher mortality rates that occurred under climate change relative to historical conditions (see Figures C.10C & C.12C). Though warmer temperatures had a positive impact on decomposition rates there were periods when litter water content was low, which exerted a downward pressure on rates. Nevertheless, the net increase in decomposition led to an associated increase in N mineralization and thus a positive benefit to tree productivity. [11] provided evidence that soil warming leads to pronounced increases in litter mass loss and net N mineralization rates. In an experimental manipulation of soil warming over 7-years, [85] showed enhanced biomass production relative to controls, which they attributed largely to increased N availability. The representation of such feedback loops in models is thus paramount to improving their capability to capture climate change impacts on forest growth and development.

4.4 Hybrid modelling approach

FORECAST Climate employs a series of climate response functions to represent the impact of temperature and moisture stress on plant growth. The benefits of this approach are: 1) it represents a relatively simple and transparent approach to predicting the independent and combined effects of temperature and moisture stress on growth, 2) the shape of the response functions can be easily established and evaluated empirically, 3) it provides a convenient means of summarizing daily responses into annual indices, and 4) is easily calibrated using historical reference climate data. Further potential improvements to the model include a representation of the phenological responses of plants to climate, such as bud break or the onset of dormancy, and frost events.

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Supporting Information for *Application of a hybrid forest growth model to evaluate climate change impacts on productivity, nutrient cycling and mortality in a montane forest ecosystem*

1. FORWADY DESCRIPTION

The ForWaDy (Forest Water Dynamics) model was constructed around the foundation of FORHYM, a general water balance model designed by [2] for the simulation of water fluxes through temperate forest ecosystems. It includes a representation of the vertical flow of water through canopy and soil layer compartments (Figure S.1). Movement of water through each soil layer is regulated by its physical properties that dictate moisture holding capacity, permanent wilting point moisture content, and infiltration rate.

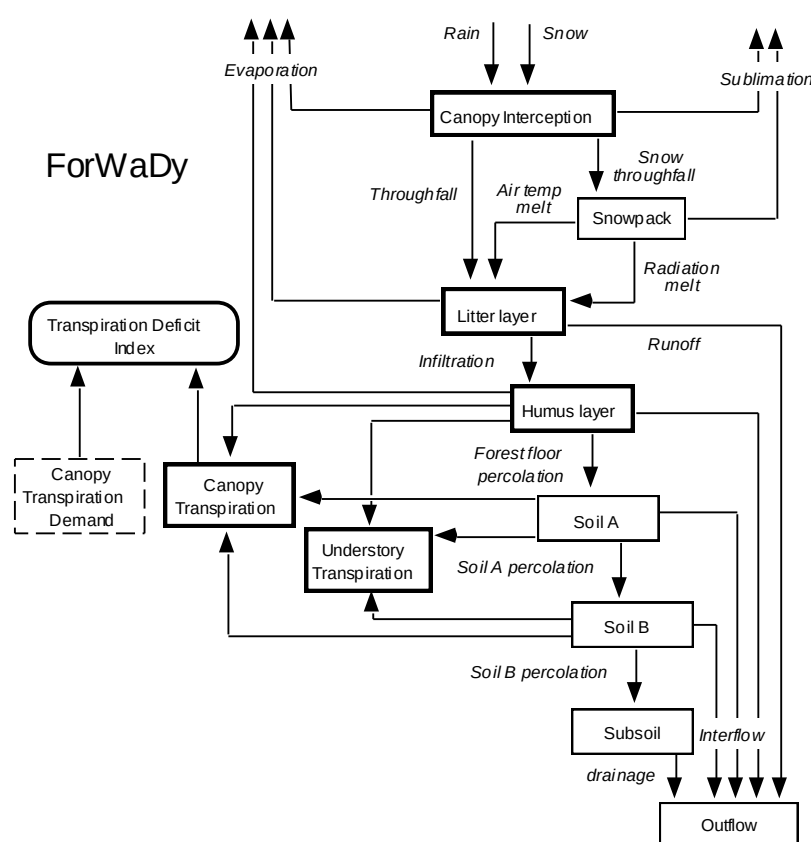


Figure S.1. Schematic diagram of the ForWaDy model indicating water flow pathways and storage compartments.

The daily energy available for evapotranspiration is divided among canopy trees, understory plants and the forest floor based on the proportional interception of incoming solar radiation by each layer adjusted for reflection depending on surface albedos. Subsequently, a passive competition for available soil moisture is simulated through the use of an algorithm that combines species-specific root occupancy information with energy-limited transpiration and evaporation demands. Canopy water stress is determined as a function of energy-limited canopy transpiration demand and soil-limited actual canopy transpiration through the

calculation of a cumulative water stress index. This index represents a dynamic measure of tree water stress over a given time period and may be used as a parameter to limit tree growth rates based on light and nutrient availability in models such as FORECAST and FORCEE. The simulation of snowfall and snowpack dynamics in ForWaDy is based on the RHYSSys Snow Model [4].

All equations describing water flow within the model are solved using a simulation dt of 0.25 days. The use of a dt less than one day enables the model to divide the flux of water from a particular soil reservoir among competing outflows.

S1.1. Data Requirements

One of the goals in model development was to produce a model that is portable and suitable for use in forest management; thus, climate and site-specific soil and vegetation data requirements were kept to a minimum. The use of parameters that must be calibrated for each site was also avoided when possible. Data requirements are shown in Table S.1.

Table S.1 Data requirements for ForWaDy

Climate data (daily)	Vegetation data	Forest floor & soil data
mean, max and min air temperature	seasonal conifer and hardwood LAI	fine litter mass (kg/ha)
solar radiation ¹	seasonal understory % cover	humus layer depth and bulk density
total precipitation	rooting depths for trees	depth of mineral soil layers
snow fraction	rooting depths for understory	soil texture (by layer)
atmospheric [CO ₂] ²	canopy resistance and albedo (by species)	coarse fragment content (by layer)

¹ Solar radiation may be estimated from max and min air temperature, elevation, latitude, slope and aspect using published radiation models.

² Only annual data required.

S1.2 Radiation interception

Radiation interception in ForWaDy may be estimated from a host model as is the case with FORECAST Climate or it may be done using the default equations within ForWaDy as follows. The energy available for driving evapotranspiration is estimated separately for the canopy, understory, and forest floor based upon the proportion of adjusted total daily solar radiation intercepted by each layer. The interception and extinction of radiation as it passes through the canopy and subsequently through the understory is calculated as a function of LAI using a simple formulation of Beer's Law with an extinction coefficient of 0.4 (Figure S.2). Forest floor radiation is calculated as the total remaining radiation following simulated canopy and understory interception. For simplification purposes, the transmittance of net radiation (S_n) is assumed to

be equal to that of shortwave radiation [10] following the reflection of a portion of total incident shortwave radiation according to a surface albedo (a) (Eq. S1). The default albedo (a) for the canopy and understory is set at 0.12 which is representative of typical values reported for forests [18, 9] and should be used as a reasonable approximation in the absence of a measured value. The forest floor albedo is determined as a function of solar zenith angle and moisture content according to [22].

$$S_n = Rad * (1 - a) \quad (S1)$$

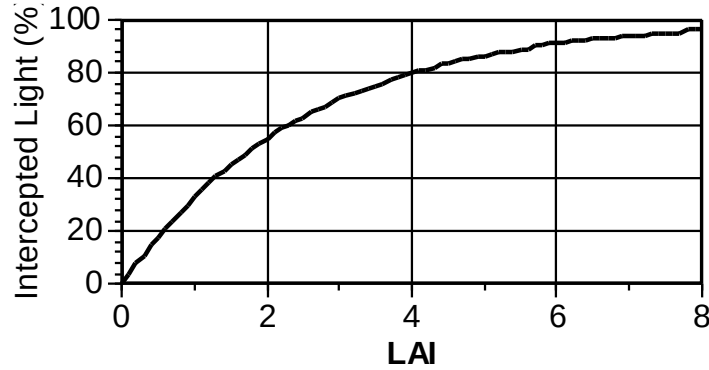


Figure S.2 The relationship between leaf area index (LAI) and intercepted light as a percent of total above canopy light according to Beer's Law with an extinction coefficient of 0.4.

S1.3 Energy-limited evapotranspiration

Energy-limited or potential evapotranspiration (PET) is calculated for each layer represented in the model based on the following simplification of the Penman-Monteith equation proposed by [16]:

$$PET = \alpha \frac{s}{s + \gamma} (S_n - G - M) \left(\frac{1}{L} \right) \quad (S2)$$

where α is an experimentally determined coefficient, s , γ , and L are respectively, the slope of the saturation vapor pressure curve, the psychrometric constant, and the latent heat of vaporization of water each evaluated at the daily average air temperature and S_n , G and M represent the daily (24-hour) values of net radiation, soil heat flux and energy storage in the canopy. The daily value of M is ignored in this model as it generally represents less than 5% of S_n in coniferous forests [13]. Thus, using the S_n values calculated for each layer according to the radiation interception submodel, PET is calculated separately for the canopy, understory and forest floor using equations (S3-S5), respectively.

$$PET_{Can} = \alpha \frac{s}{s + \gamma} S_{nCan} \left(\frac{1}{L} \right) \quad (S3)$$

$$PET_{US} = \alpha \frac{s}{s + \gamma} S_{nUS} \left(\frac{1}{L} \right) \quad (S4)$$

$$PET_{FF} = \alpha \frac{s}{s + \gamma} (Sn_{FF} - G) \left(\frac{1}{L} \right) \quad (S5)$$

In (Eq. S5) soil heat flux is estimated as a function of Sn_{FF} (Eq. S6) [7]. The default values for the a and b parameters are -43.1 and 0.335, respectively but may be adjusted the soil heat flux parameters if necessary.

$$G = a + b * Sn_{FF} \quad (S6)$$

Typically, the use of (Eq. S2) has been limited by the fact that, for dry canopy conditions, α must be calibrated against actual evapotranspiration rates for a particular site using Bowen ratio / energy balance techniques [19] which can be prohibitively expensive. For a range of dry forest conditions, α has been shown to vary from 0.6 to 1.1 [7]. However, for a wide range of relatively smooth, freely evaporating (wet) surfaces α is generally equal to 1.26 [16, 20, 5]. Values of α less than 1.26, typical in most forests with dry canopies, are thought to be the result of surface control of evaporation through stomatal resistance [11]. In an effort to eliminate the need for α to be experimentally determined for each new site, we suggest the use of a canopy resistance term (R_{Can}) based on mean literature values of α for dry canopies of various forest types (Table S.2). Using this method α is set at 1.26 for wet canopy conditions and adjusted under dry canopy conditions (where evaporated water must pass through stomata) through the use of R_{Can} . The use of an approximated R_{Can} will undoubtedly lead to some error in the calculation of canopy PET, but it should provide a reasonable estimate suitable for the intended use of the model.

Table S.2 Estimated canopy resistance (R_{Can}) for three forest types based on reported literature values of α' .

Forest Type	α'	$R_{Can} = 1 - (\alpha' / 1.26)$	References
Dry Pine	0.7*	0.45	* Estimation based on reported range [19]
Douglas-fir	0.84	0.33	[3, 8, 19]
Broadleaf / understory	1.1*	0.13	[14, 19] * Estimation based on reported range

S1.4 Canopy water, throughfall and canopy evaporation

The amount of water held in the canopy at time t ($C_{Wat(t)}$) is calculated as the difference between incoming rainfall (P) and the sum of throughfall (TF) and canopy evaporation (E_{Can}) evaluated at each time step (dt) (Eq. S7). The fraction of rainfall intercepted by the canopy is determined as a function of canopy vegetation area index (VAI), where a maximum canopy storage term is calculated based on the assumption that at saturation the upper surface of leaves and branches can hold a film of water 0.2 mm in depth (Rutter, 1975), thus $C_{Max} = 0.2 * VAI$.

$$C_{Wat(t+dt)} = C_{Wat(t)} + (P_{(t)} - TF_{(t)} - E_{Can(t)}) * dt \quad (S7)$$

Throughfall and canopy evaporation are calculated as follows:

$$\begin{aligned}
TF &= 0 & C_{Wat} < C_{Max} \\
TF &= C_{Wat} - C_{Max} & C_{Wat} \geq C_{Max}
\end{aligned}
\tag{S8}$$

$$E_{Can} = \min(C_{Max}, C_{Wat}, PET_{Can}) \tag{S9}$$

Stemflow is assumed to be included as part of throughfall.

S1.5 Soil water storage and drainage

Hydrologic dynamics in the forest floor and rooting zone are simulated using a multi-layered approach in which inflows and outflows are estimated sequentially for each soil layer (Figure S.1). Water storage in and vertical movement through the mineral soil layers are simulated using a “tipping bucket” type algorithm based on total porosity adjusted for coarse fragment content, field capacity and permanent wilting point boundaries (inputs to the model). Water stored in the humus and soil layers between field capacity and permanent wilting point boundaries is considered to be available for plant uptake. Water storage in the litter layer is calculated as a function of fine litter mass (i.e. not including coarse woody debris) per area and is assumed to be unavailable for plant uptake. Lateral flow or interflow of water from soil layers into stream channels is only allowed to occur when the water content of a given soil layer is greater than its estimated field capacity and is based on a coefficient related to slope.

S1.6 Soil-limited evapotranspiration

As the forest floor and soil layers begin to dry, evapotranspiration rates are limited by the availability of soil water. Transpiration loss is calculated separately from each layer for both the canopy and understory. Rooting depths of canopy and understory species are used to determine the layers from which water may be extracted. In order to represent the limited capacity of a drying soil to supply water to roots, particularly during periods of high PET, the daily, energy-limited transpiration rate is scaled back through the use of a relative transpiration rate (RTR) term. RTR is estimated as an empirical function of the percent of available water in each layer and PET [6] (Fig. S.3). A root fraction term is also introduced for both the canopy (RF_{Can}) and understory (RF_{Us}) as a scalar to account for the fraction of each layer occupied by roots.

This term is calculated from root depth occupancy data as well as soil layer depths provided by the user.

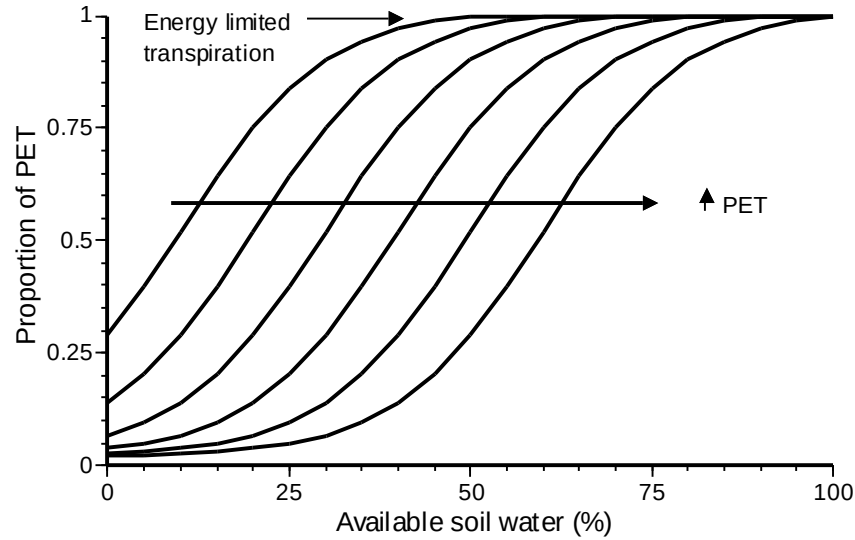


Figure S.3 The relative rate of transpiration determined as a function of available soil water and energy-limited evapotranspiration (PET). The function curve shifts to the right as PET increases.

The daily extraction of water from the various layers via transpiration occurs sequentially from the top downward, beginning with the humus layer and continuing down through the soil B layer. The total amount of energy available for canopy transpiration ($CanT_{(total)}$) is estimated after accounting for the canopy PET energy consumed by canopy evaporation and canopy resistance (Eqs. S10-S11). $CanT_{(total)}$ is then used to drive transpiration loss from each of the soil layers using an energy budget approach, moving from the humus layer downward as the amount of extractable soil water is depleted in each soil layer (Eqs. S12-S14). The daily extractable fraction of available water in a given layer is largely a function of the estimated RTR value and is generally less than the total plant available water in that layer. The transpiration algorithm continues until either all layers have been depleted of extractable water or the energy available for daily transpiration is depleted. Understory transpiration is calculated simultaneously using the same method.

$$GCanT = (PET_{Can} - E_{Can}) \quad (S10)$$

where: $GCanT$ = gross canopy transpiration ($mm\ day^{-1}$)

$$CanT_{(total)} = GCanT * (1 - R_{Can}) \quad (S11)$$

$$CanT_{(humus)} = CanT_{(total)} * RTR_{(humus)} * RF_{Can(humus)} \quad (S12)$$

$$CanT_{(soilA)} = (CanT_{(total)} - CanT_{(humus)}) * RTR_{(soilA)} * RF_{Can(soilA)} \quad (S13)$$

$$CanT_{(soilB)} = (CanT_{(total)} - (CanT_{(humus)} + CanT_{(soilA)})) * RTR_{(soilB)} * RF_{Can(soilB)} \quad (S14)$$

Energy-limited surface evaporation from the LF layer and humus compartments is also regulated as a function of water content through the use of a relative evaporation rate term (RER) estimated using a simple empirical function of available soil moisture. Drying proceeds from the top downwards (Eqs. S15 & S16) and evaporation from the humus layer is only allowed to occur when the litter layer has dried out.

$$E_{\text{Litter}} = PET_{\text{FF}} * RER_{(\text{litter})} \quad (\text{S15})$$

$$E_{\text{Humus}} = (PET_{\text{FF}} - E_{\text{Litter}}) * RER_{(\text{humus})} \quad (\text{S16})$$

S1.7 Canopy water stress

Typically, models of forest growth which include water stress as a feedback to forest growth have quantified tree water stress using a summed measure of soil water deficit. One of the problems in using a summed water deficit for a measure of water stress is that it frequently fails to capture the dynamic interactions between different components of the hydrological cycle and net effect of such interactions on tree water stress. For example, as part of the Biology of Forest Growth Study near Canberra, Australia, [12] demonstrated that cumulative soil water deficit may not be well correlated with tree water stress as defined by pre-dawn xylem potential, a commonly used physiological indicator of tree water stress. The weakness of the technique is even greater when monthly summaries of climate data are used to calculate the water deficit.

In order to evaluate tree water stress more dynamically we propose the use of a cumulative index termed the transpiration deficit index (TDI) (Eq. S17-S18). TDI provides a means of summarizing the net effect of several factors including canopy evaporation, understory transpiration and surface evaporation on actual tree transpiration. Furthermore the index is calculated on a daily timestep to better capture the cumulative effect of short term water stress events.

$$TDI = \sum_{i=0}^{i=t} \frac{CanT_{(\text{total})i} - CanT_{(\text{actual})i}}{CanT_{(\text{total})i}} \quad (\text{S17})$$

$$CanT_{(\text{actual})} = CanT_{(\text{humus})} + CanT_{(\text{soilA})} + CanT_{(\text{soilB})} \quad (\text{S18})$$

In (Eq. S17) the difference between total canopy transpiration demand ($CanT_{(\text{total})}$) and actual canopy transpiration ($CanT_{(\text{actual})}$) is divided by $CanT_{(\text{total})}$ to normalize the effect of leaf area index on the relative canopy transpiration deficit. This adjustment effectively converts the total canopy water deficit to a per unit leaf area measure of water deficit which should be more representative of the water stress of individual trees.

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Workshop schedule

Date	Time	Activity	Activity leader(s)
July 4	Whole day	Arrival of Participants, check in to hotel and registration for workshop	
July 5	7:30 – 8:00	BREAKFAST	
	9:00 – 10:00	Opening Ceremony	Dr. Li Xiao Chuan President Guangdong Academy of Forestry Dr. John Innes, Dean, Faculty of Forestry, UBC Dr. Guangyu Wang, Associate Dean, Faculty of Forestry, UBC
	10:00 – 10:30	Group photo/Tea Break	
	10:30 – 11:00	Introduction to programs, activities, instructors, and participants	Dr. Guangyu Wang, Associate Dean, Faculty of Forestry, UBC
	11:00-12:00	Introduction to climate and ecological modeling for forest adaptation to climate change	Dr. Tongli Wang, Faculty of Forestry, UBC
	12:00-13:00	LUNCH BREAK	
	13:00-15:00	Introduction to ClimateAP Working with ClimateAP Local application in Chinese Taipei Future development of ClimateAP	Dr. Tongli Wang, Faculty of Forestry, UBC Dr. Huanyu Lin, Taiwan Forest Research Institute, Chinese Taipei
	15:00-15:15	TEA BREAK	

	15:15-17:50	Introduction to climate niche models for forest tree species and forest ecosystems Applications of climate niche model in Chinese Taipei Working with climate niche model predictions on ClimateAP maps Where to go next?	Dr. Tongli Wang, Associate Dearn, Faculty of Forestry, UBC Dr. Huanyu Lin, Taiwan Forest Research Institute
	17:50	DINNER	
June 6	7:30-8:45	BREAKFAST	
	8:45-9:00	Recap from participants	
	9:00-10:15	Review of climate impacts on forest growth dynamics Overview of the application of FORECAST/FORECAST Climate as decision support tools	Dr. Brad Seely, Faculty of Forestry, UBC
	10:15-10:30	TEA BREAK	
	10:30-12:00	Evaluating management alternatives in teak/ bamboo ecosystems in Myanmar: Model calibration, field work, simulation of stand management	Dr. Brad Seely, Faculty of Forestry, UBC Ms. Lianzhen Xu, Faculty of Forestry, UBC
	12:00-13:00	LUNCH BREAK	
	13:00-13:30	Regional forest observations for sustainable forest management	Mr. Pang Yong, Chinese Academy of Science
	13:30-14:30	Simulating climate change impacts on long-term teak productivity and health	Dr. Brad Seely, Faculty of Forestry, UBC Ms. Lianzhen Xu, Faculty of Forestry, UBC
	14:30-15:00	TEA BREAK	

	15:00-16:45	Landscape-scale evaluation of alternative management strategies in the Yedashae Township region of Myanmar	Dr. Brad Seely, Faculty of Forestry, UBC Ms. Lianzhen Xu, Faculty of Forestry, UBC
	16:45-17:15	Review and Discussion	Dr. Brad Seely, Faculty of Forestry, UBC
	17:50	DINNER	
June 7	7:30-8:45	BREAKFAST	
	8:45-9:00	Recap from participants	
	9:00-10:30	Calibration and Application FORECAST climate to evaluate management of <i>Acacia mangium</i> plantations in Malaysia	Dr. Brad Seely, Faculty of Forestry, UBC Dr. Siti Nurhidayu Abu Bakar, Faculty of Forestry, Universiti Putra Malaysia
	10:30-10:45	TEA BREAK	
	10:45-12:00	Simulating climate change impacts on long-term Acacia productivity and health	Dr. Brad Seely, Faculty of Forestry, UBC
	12:00-13:00	LUNCH BREAK	
	13:00-14:30	Calibration and Application FORECAST climate to evaluate management of mangrove forests in Malaysia	Dr. Brad Seely, Faculty of Forestry, UBC
	14:30-14:45	TEA BREAK	
	14:45-15:15	Review and Future directions	Dr. Brad Seely, Faculty of Forestry, UBC
	15:15-16:00	Open discussion and Closing remarks	Dr. Guangyu Wang, Faculty of Forestry, UBC
June 8	7:30-9:00	BREAKFAST	
	FIELD TRIP TO DINGHU MOUNTAIN		
July 9	DEPARTURE		

Annex D10: Summary report on Pilot sites visit

Annex D 10.1: Site visits to Laos, Malaysia, and Myanmar

Dr. Brad Seeley and Ms. Lianzhen Xu

February 21st, 2017 to March 5th, 2017

Trip Summary

Dr. Brad Seely and Ms. Lianzhen Xu conducted site visits to Laos, Malaysia, and Myanmar in the spring of 2017 in order to collect information on selected plots and obtain information useful for the FORECAST model for selected regional key species. Six undergraduate students were trained in order to assist in field measurement and data collection in Myanmar, meanwhile 11 plots in Yedaeshe Township were established- covering an age series of teak plantation development, including private teak plantations and government owned teak plantations. Information regarding management of teak plantation were collected from local managers and farmers, meanwhile literature on teak was also reviewed from the library of the Forest Research Institute in Myanmar as supplementary data. Lastly, further climate data and vegetation mapping data were requested for FORECAST applications.

Schedule: Laos Trip

Date	Activity	Notes
February 23 rd	Meeting with Partners at NUOL	• Questions on the measurement of each plot: height, density difference, etc. • Historical management and disturbance of each plot: initial spacing, thinning, fertilization, management objectives, etc. • Information on study area: PSP dataset, maps, growth and yield table, etc. • Vegetation classification map • Additional teak plantations in the north
February 24 th	Visiting existing plots at Napo village in Vientiane	• 9 plots in total, but 1 missing coordinates: <i>Tectona grandis</i>, 3 plots; <i>Azadirachta indica</i>, 3 plots; <i>Pterocarpus macrocarpus</i>, 2 plots. • Re-measured sample trees to confirm the sites and made notes on each plot



Picture 1. Teak plantations (*Tectona grandis*) at Napo village*



Picture 2. Teak plantations (*Tectona grandis*) at Napo village*

* Pic.1 and Pic.2 are teak plantations. Established in 1998; Spacing: 3 by 3m; First year allowed rice planting no closer than 50 cm to teak tree, 3 weeding in the first 3 years, fertilized after first weeding; Thinned before measurement; Bamboo cut annually; Clumped bamboo; Termite attack.



Picture 3. *Afzelia xylocarpa* plantation Napo village. Established in 1998; spacing 3m by 2m; No thinning, but bamboo cutting annually. Less productive than teak.



Picture 4. *Pterocarpus macrocarpus*. Established in 1998; Spacing 3m by 2m.



Picture 5. Ms. Xu re-measured sample trees to confirm the sites and made notes on each plot



Picture 6. Dr. Seeley re-measured sample trees to confirm the sites and made notes on each plot

Myanmar

Schedule: Myanmar Trip

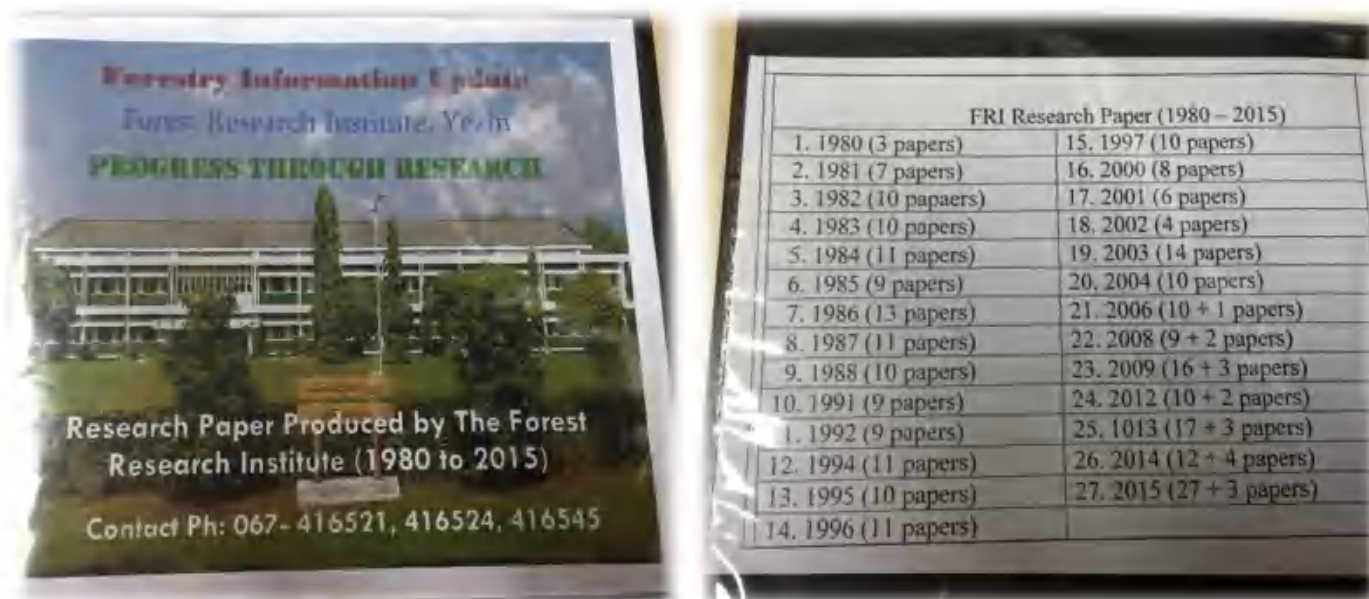
Date	Activity	Notes
February 26 th	Meeting with Mr. Thein Saung	• Memo • Invoice • Trip planning
February 27 th	FRI Visit: training students and visiting Yedaeshi Township	• Meeting with Director Me. Thuang Naing Oo • Training students for field work • Collected information from the FRI library • Pre-visited teak sites in Yedaeshi Township
February 28 th to March 3 rd	Eatbslihing 11 teak plots	• Establishment of 11 plots • Circle sample plots with different radius (10 to 30 meters) • Age chronoquence: from 1981 to 2010 • Ownership: 8 government and 3 private • Measurements: DBH, tree height • Data records: GPS, age, site conditions, disturbances, and other attributes



Picture 7. Meeting Mr. Thein Saung



Picture 8. Training students for the field work



Picture 9. Collecting information form FRI library

Plots in Myanmar

Plot 1_ 2000-01





Plot 2_ 1981



Plot 3_ 2010



Plot 4_ 2009



Plot 5_ 1992



Plot 6_ 2010



Plot 7_ 2001



Plot 8_ 2005



Plot 9_ 2004





Plot 10_ 2007-08



Plot 8_ 2005



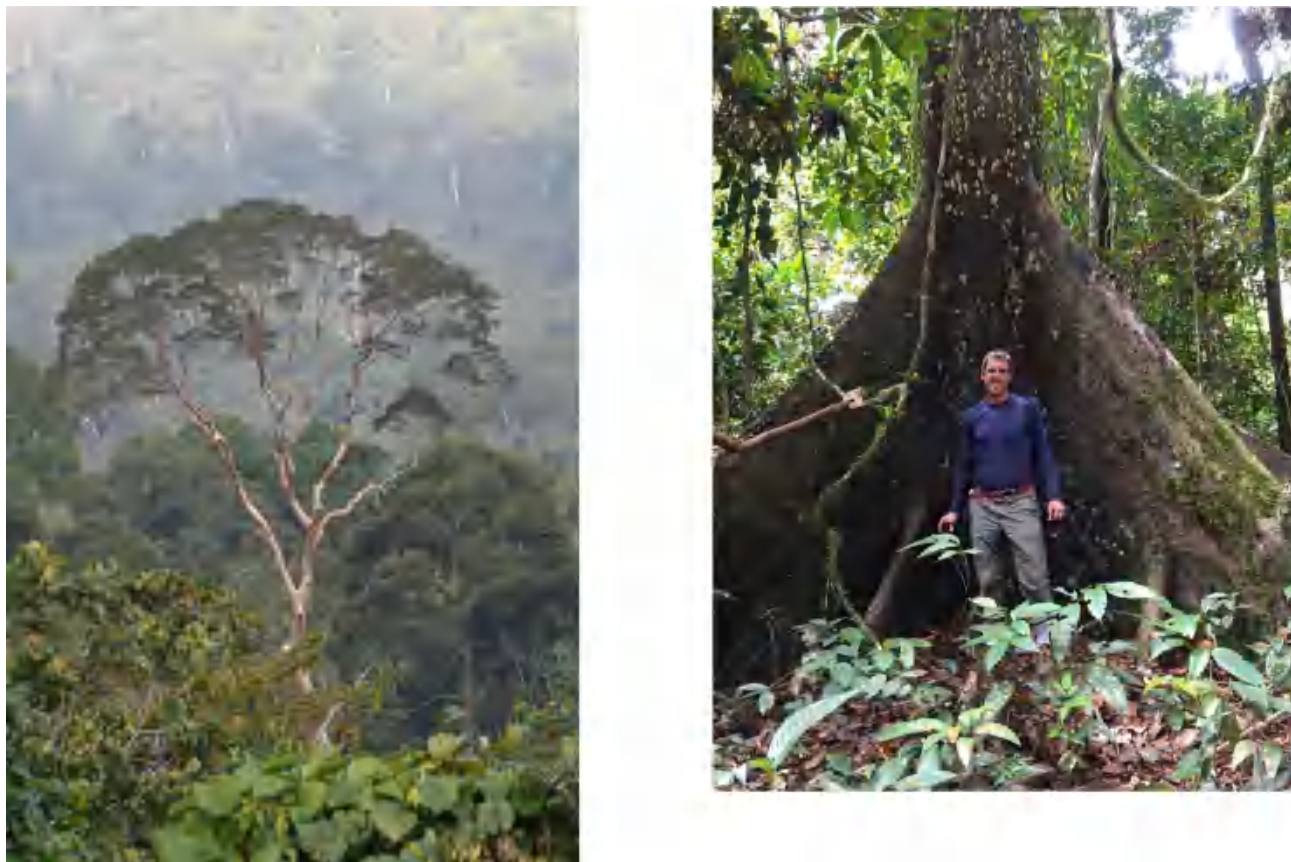
Plot 11_ 2007

Malaysia Visit

Dr. Brad Seeley conducted a visit to research plots in Malaysia prior to visits to Laos and Myanmar. With assistance and collaboration from Malaysia LP, Siti Nurhidayu Binti Abu Bakar from UPM. Together, project members visited an *Acacia mangium* plantation in the Sabah forest region in Borneo Malaysia. The plantation is owned and managed by SAFODA (Sabah Forestry Development Authority). The plantation was very productive with trees as young as 3 years old being 5-6 meters tall and more than 15cm in diameter. The SAFODA agreed to share their permanent sample plot data. Additionally, Dr. Seeley and Ayu visited the Danum Valley Research station to see if the forests would be suitable for the project. It was determined that the forests there were too complex to allow for the application of the FORECAST models. It was decided that instead we would focus on the Acacia plantations instead. Lastly, *Acacia mangium* plantations in peninsular Malaysia were also visited, which resulted in well-suitable data for the vegetation models.



Picture 10. *Acaica mangium* plots in Sabah Malaysia



Picture 11. Danum Valley

Trip Conclusions

Most teak plantation were established after 2000, and an increasing amount of private teak plantations have been established since 2010. Private teak plantations generally receive more management than government-owned plantations, and therefore were in better conditions. Fires are the most common disturbance in Laos and Myanmar, and are particularly common along the roadside. Additionally, termite infestation had occurred at the large majority of all sites.

Annex D 10.2: Summary Report-Site Visits in Myanmar and Malaysia and Training Workshop in Myanmar

Dr. Guangyu Wang, Dr. Brad Seeley and Ms. Lianzhen Xu

November 13-16, 2017

D.2.1: Filed Trip to Teak plantations and Training Workshop on FORECAST Climate Model

1. Introduction to the Trip

This trip to Myanmar was the follow-up visit to the last field trip conducted on February 21 to March 6, 2017. The objectives of this trip were to

- Collect more information on LAI, Bamboo competition and soil in the teak sample plots established in February 2017 to further calibrate FORECAST Climate Model
- Report the progress and results to date for application modelling tools developed in Project Phase I
- Introduce the models and tools developed in Phase I to the researchers and officials in the Forest Department (FD) and Forest Research Institute (FRI) of Myanmar to allow them effectively and accurately implement the research in their country
- Increase the capacity of participants in Myanmar to conduct research on forest adaptation to climate change
- Explore potentials for future cooperation with Myanmar

The trip lasted for 4 days and covered several activities including Field trip, meetings with officials in FRI and FD, and Training workshop on FORECAST Climate Modelling.

The field trip included following activities:

- Take understory canopy photos to estimate crown closure and light extinction rates
- Further document bamboo competition in each plot
- Soil sampling to estimate soil organic C, soil nutrient concentration, and soil texture to further calibrate FORECAST Model
- Repaint the plot trees

During the trip, our team got permissions to meet Director General, Dr. Nyi Nyi Kyaw, of Forest Department and his colleagues, including Dr. Thaung Naing Oo (FRI), Dr. U Kyaw Zaw, Dr. Su Mon and other researchers in FRI and FD. Topics of meetings with Officials in Forest Research Institute and Forest Department covered following aspects:

- Reviews of progress of application of APFNet modelling tools to Myanmar to date
- Introduction to the development and application of models used in Phase I including ClimateAP, climate niche modelling, and FORECAST Climate
- Discussion on further cooperation with Myanmar Forest Department

FORECAST Model training workshop attendance was higher than initially anticipated; present were 20 trainees including researchers from FRI and Forest Department. Training workshop Participants

received a comprehensive education on FORECAST Climate model so that they can independently use these models to contribute to the project's research. Based on the feedback from and discussion with the trainees, the training was well received and beneficial to participants.

Overall, the trip successfully achieved its objectives; we successfully increased the knowledge and capacity of participants to use the models and tools developed in Phase I that will be employed in Phase II which will enable them to help achieve the project's research objectives and help address climate change adaptation in Myanmar. A summary of each day's activities and presentation or lectures is provided in Section 2.

Schedule: Myanmar Trip

Date	Activity	Notes
November 13	Field trip to measure established plots (Measured 7 out of 11 plots)	• re-measured 7 established plots • Assembled Leaf Area Index • Assemble Soil Profile Data • Assemble data on bamboo competition
November 14	(1) FRI Visit and review of project progress and application (2) Visit Forest Department and review of project progress	• Meeting with Director Me. Thuang Naing Oo • Workshop presentation/sharing project progress, tools and models developed so far and its application (4 presentations in total) (Please see below for detail) • Meeting with Director General, Dr. Nyi Nyi Kyaw of Forest Department • Workshop presentation/sharing project progress, tools and models developed so far and its application (3 presentations in total) (please see below for detail) •
November 15	Conduct training workshop	• Hands on training on how to use FORECAST Climate Model; its application by Dr. Brad Seeley • 20 trainee from forest department and forest research institute participated/practiced in their computer (Please see detail for below)
November 16	Field trip to measure established plots (Measured remaining 4 plots of 11 plots)	• re-measured 4 established plots • Assembled Leaf Area Index • Assemble Soil Profile Data • Assemble data on bamboo competition

2. Summary of Trip Activities

2.1 Day 1: November 13, 2017

Activities: Field trip to 7 of the 11 established sample plots

Prior to visiting the plots, our team, Dr. Nobuya Mizoue, and Mr. Thein Saung met with the staff officers of Yedashe Township in the camp to discuss the logistics and plan of the field trip. We decided to visit 7 of the 11 established plots because of our tight schedule.



Photo1: Discussion on the logistics and plan of the fieldwork in the camp of Yedashe Township

We separated into three groups: soil sampling group, canopy and bamboo group, and repainting sample tree group. Soil sampling group was led by Dr. Billy Ne Win (FRI staff officer), including range officers, forestry students and local farmers. In each plot, soils in 3 depths including (0-10cm), (20-30cm), (40-50cm) of 3 locations were sampled in plastic bags and then taken back to FRI Lab to analyze the soil texture, soil nutrients content and soil organic C. The results from soil sample could help us further calibrate the model. Our team from UBC took understory canopy photos to estimate crown closure and light extinction rates and further document bamboo competition in each plot. Other range officers and farmers helped with repainting and renumbering the sample trees in the plots.



Photo: Plot 1 Teak trees with leaves



Photo: Soil sampling



Photo: Dr. Brad Seely is taking under canopy photos



Photo: Under canopy photo in Plot2 that is a thinned site established in 1981



Photo: Range Officer helps with repainting the plot trees

From revisiting the plots, we found that most of the plots were maintained very well that we were able to easily find the plot center and all the trees in the plot. However, Plot 2 (established in 1981), was recently repainted by some German researchers. Our tree numbers and paint on the DBH were covered by their paint that we were not able to identify the previous sampling trees in the plot. We also found our sampling tree in the center of plot 5 (established in 1992) was illegal logged by local farmers.



Photo: Plot trees in Plot 2 were repainted by German Researchers



Photo: Plot tree in Plot 5 was illegal logged by local people
2.2 Day 2: November 14, 2017

2.2.1 Meeting on review of Progress of application APFNet Modelling tools to Myanmar to date

Meeting with Dr. Thaung Naing Oo, Director of Forest Research Institute

Prior to the meeting, Dr. Guangyu Wang, Dr. Brad Seely, Dr. Nobuya Mizoue and Ms. Lianzhen Xu were invited to meet Dr. Thaung Naing Oo and Mr. Thein Saung in Dr. Thaung Naing Oo's office. During the meeting, Dr. Thaung Naing Oo welcomed our research team of APFNet climate change adaptation. He thanked us to offer them an opportunity to learn the modelling tools developed by the project, and to create potentials of future cooperation. By the end of the meeting, we finalized the schedule of the following review meeting in FRI and the meeting with Officials in FD.



Photo: Meeting with Dr. Thaung Naing Oo (Director of FRI)

Opening remarks of the review meeting

The meeting began with open remarks from Dr. Thaung Naing Oo (Director) from the Forest Research Institute of Myanmar, who is also a member of the Asia-Pacific Network for Sustainable Forest Management and Rehabilitation (APFNet). Dr. Thaung Naing Oo welcomed participants to the meeting and gave an introduction to their institution and involvement with the project. He then asked all the attendees from both FRI and FD to self-introduce themselves.



Photo: Opening remarks by Dr. Thaung Naing Oo

Presentation: Introduction to Faculty of Forestry at UBC by Dr. Guangyu Wang

Dr. Guangyu Wang opened the meeting by welcoming participants to the meeting and briefly introduced the programs, courses, and scholarships of Faculty of Forestry at UBC. Lastly, he welcomed students, researchers, and officers of Myanmar to come to UBC for studying, training and visiting.



Photo: Presentation by Dr. Guanyu Wang on introduction to Faculty of Forestry at UBC

Presentation: APFNet Modelling Tools for Forestry under Climate Change: Progress in Myanmar to date by Dr. Brad Seely

As Dr. Brad Seely was the only lecturer over the training workshop, he began with an overview of the agenda for meeting and training workshop and explained his objectives and what was expected from the participants both in the meeting and through the duration of the training workshop next day.

Firstly, Dr. Brad Seely introduced the participants to the climate model ClimateAP which Dr. Tongli Wang developed in Phase I, and reviewed the progress of application of ClimateAP to Myanmar to date. He explained how ClimateAP differs from other climate models and how these differences result in ClimateAP being more accurate than other available models. As well, Dr. Seely explained how to use both the GoogleMaps based version and desktop version of ClimateAP.

Secondly, Dr. Seely reviewed the progress of application of Climate Niche Model to Myanmar. He showed the map of 24 ecotypes of Myanmar, and presented the results of modelled ecotypes map and how climate change affects the distribution of different ecotypes in 2020s and 2050s. Dr. Thaung Naing Oo raised a question on how the original map of ecotypes of Myanmar was generated. Dr. Seely explained that the original map was from Chinese Forestry Academy. The map was generated from RS data and verified by field data from Myanmar. Dr. Thaung Naing Oo said the FD would have much better database for generating the map, and FD is working on One Map

Myanmar project. They would be able to provide the data to us, and in return, our team could help them generate much high resolution map under the context of climate change.

Lastly, Dr. Seely introduced the FORECAST model and calibration work have been done for teak plantation in Myanmar. Dr. Seely outlined the data requirements for the model and the ecosystem and management processes that it can represent. He discussed the application and outputs of the model. He presented that 11 plots were established in Yedashae Township in February to March this year and revisit to the plot during this trip.



Photo: Dr. Brad Seely overview the progress of application of ClimateAP, Climate Niche Model and FORECAST Climate Model to Myanmar to date

Presentation: FORECAST Model Application to Evaluate Impacts of Fire Frequency, Rotation Length, and Bamboo Competition on Teak Plantations by Ms Lianzhen Xu

Ms. Lianzhen Xu went through some example outputs using FORECAST Model to simulate the impacts of fire frequency, rotation length, and bamboo competition on teak plantation. She concluded that short rotation and frequency burnings would deteriorate the soil, resulted in declining yield and degraded soil fertility in the successive rotations; although Bamboos could lead to reduction in teak productivity, they can increase the humus mass thus improve the soil fertility. This presentation acted as a practice examples of FORECAST Climate Model training workshop that Dr. Brad Seely would give on November 15.



Photo: Ms. Lianzhen Xu presents some example outputs from FORECAST Model

Presentation: Review of climate change impacts on forest growth and development: toward the application of FORECAST Climate by Dr. Brad Seely

In Dr. Seely's second presentation, he gave an overview of FORECAST Climate Model, and then focused on some of the expected changes in climate that may impact forest productivity. He also touched on the importance of ENSO events and how they may be impacted by climate change. This is of particular importance, as El Niño events can result in severe drought in Southeast Asia, and the impacts of drought on forest productivity is one of the key research questions being explored in teak plantations in Myanmar. Dr. Seely conducted a comprehensive literature review on the analysis of teak rings in Myanmar forests shows impact of past climate on teak growth rates. He then presented the results of model validation by using tree ring data from Central Myanmar from period 1961-2006. Lastly, he presented the results of simulation of climate change impacts on teak plantations using FORECAST Climate with RCP 8.5 emission scenarios. The results showed that the stem biomass of teak increased in the future climate scenarios, which may be caused by increasing precipitation.



Photo: Group photo after the review meeting in FRI

2.2.2 Meeting with Myanmar Officials in FD: The progress of “Adaptation of Asia-Pacific Forests to Climate Change” project & Potentials for the future cooperation with Myanmar

Opening remarks of the meeting

The meeting began with open remarks from Dr. Thaung Naing Oo (Director) from the Forest Research Institute of Myanmar. He again welcomed our team’s visiting and overview the objectives of the meeting. Before presentation, he asked all the participants to make a self-introduction.

Presentation: Project Overview and Phase II Arrangement by Dr. Guangyu Wang

Dr. Wang opened the meeting with an overview of the evidence of climate change and how these changes are expected to impact forest ecosystems. He then stated goals of our research project which could help AP economies meet their Paris commitments by addressing gaps in technology and capacity, focusing on adaptation, providing locally-specific tools for economies to meet their NDCs, and helping to maintain forest ecosystems as an important carbon sink and reservoir into the future. He also reviewed the outcomes of Phase I and how Phase II will build upon them.



Photo: Dr. Guangyu Wang overview the project

Presentation: Introduction to APFNet Work Tools by Dr. Brad Seely

Firstly, Dr. Brad Seely reviewed the progress of application of ClimateAP and Climate Niche model to Myanmar to date. He explained how ClimateAP differs from other climate models and how these differences result in ClimateAP being more accurate than other available models. He showed the map of 24 ecotypes of Myanmar, and presented the results of modelled ecotypes map and how climate change affects the distribution of different ecotypes in 2020s and 2050s. Dr. Seely then introduced the FORECAST model and calibration work have been done for teak plantation in Myanmar. He discussed the application and outputs of the model. He presented two fieldwork that have been done this year. At the end of his presentation, he also presented how FORECAST output used to drive trade-off analysis on ecosystem services.



Photo: Dr. Brad Seely overview the progress of application of ecological and management tools to Myanmar to date

Presentation: Application from the project to Myanmar: Potential cooperation and contributions by Dr. Guangyu Wang

Dr. Guangyu Wang's second presentation focused on application from the project to Myanmar, what support needed from Forest Department, and future cooperation. He stated that our ecological and management model are best available tools for forest adaptation and mitigation strategies, which could help Myanmar meet Paris Commitment in the national level and generate regional adaptive forest management plans suitable for the given region's environmental, social and political conditions. He then asked for support from Forest Department for the research in Myanmar, including spatial data on forest type classification in national level and forest management in Yedashe Township, Forest inventory data, and teak forest management guidelines. Finally, he discussed potential future cooperation on the following field:

- forest management research in the context of climate change
- technical support for sustainable forest management
- Capacity building for Myanmar in terms of training program, visiting young scholars and professionals
- Student exchanges with Myanmar



Photo: Discussion on potential cooperation and contribution

In terms of future cooperation, Dr. Nyi Nyi Kyaw, Director General of Forest Department, agreed to sign the Memo. He said that Forest Department would be happy to support our research in Myanmar. He expected that we could strengthen our future cooperation not only on research, but also capacity building.



Photo: Group photo after meeting

2.4 Day 4: November 16, 2017

Activity: Field trip to 4 of the 11 established sample plots

For the full day field trip, as same as what we did in the first day, we separated into 3 groups to take the canopy photos, document the bamboo competition, and sampling soils. We found out that early bamboo cutting is very necessary, especially before the canopy closure. Bamboos can't compete with teak if teak grows to certain size. So, it is important to identify the competition between bamboos and teak along the stand development. During the field trip, we found that Plot 10 was recently thinned by the Township forestry station. The range officers told us that they did a mechanical thinning and bamboo cutting in this site. From the observation of the plot, we found that about 13 sample trees in the plot has been thinned. Dr. Brad Seely suggested that it is better to avoid future disturbances of management in the established plots.



Photo: Dr. Guangyu Wang asks questions on sources of income of local people on the way to the Plot



Photo: Soil sampling



Photo: Range Officer helps with repainting the trees in the plot



Photo: Teak tops left on the sites after thinning in Plot 10



Photo: Thinned logs piled up on the site

Field trip to Malaysia for data collection on *A. mangium* and sharing project progress (November 20-23, 2017)

Schedule

Date	Activity	Note
November 20	Meeting at UPM	-Review progress to date about the project and planning for field work
November 21-23	Conduct field work at Samarakan Plantation in Sarawak	-Established 5 plots and measuring top heights, DBH, Crown length estimate for all trees and Determination of Leaf Area Index

In Malaysia, Dr. Seely met with our local partners at UPM to review progress on the development of an *Acacia mangium* calibration dataset based upon the literature review. The team also discussed the availability of biomass and growth data from a mangrove study being conducted by researchers from UPM. It was determined that these data would be suitable to prepare a FORECAST calibration dataset representative of the Matang mangrove forests on the west coast of peninsular Malaysia. The team then traveled to the Samarakan plantation in the Sarawak region of Borneo and established 5 plots in plantations ranging in age and site quality. Plot measurements included top heights, DBH, and crown length estimates for all trees. In addition, under-canopy photos were taken for determination of leaf area index (LAI). All data of the collected during the fieldwork has been summarized and will be used for further calibration and verification of FORECAST Climate.



Photo: Measuring DBH of mature *A. mangium* tree in Samarakan Plantation in Sarawak



Photo: Seedlings of *A. mangium* in nursery.



Photo: Marking trees in Samarakan Plantation in Sarawak

Annex D: Project outputs

Trip Conclusions

Dr. Guangyu Wang, Dr. Brad Seely and Ms. Lianzhen Xu visited pilot sites in the fall of 2017 with objective to promote outreach of the project findings, tools and models among decision makers/forest managers, hold a training workshop, and re-measured previous plots and assemble more data on LAI, Soil profile and bamboo competition data for the FORECAST model. We successfully achieved our objectives of outreaching and sharing progress of project outcomes with decision makers/forest managers through series of discussions and workshops. Notably, we also extended our network and collaboration with Forest Department through signing MOU with DG. Such activities should be enhanced in future as they are important for building trust between us and promote capacity building of the regions. Our field measurement in the previously established plots along with additional data collection were successful and helpful for calibrating/advancing process based models. We conclude that this field trip was successful in achieving all the objectives that we aimed for promoting the project outcomes, networking, capacity building and field measurement.



D11 Poster: Adaptation of Asia-Pacific Forests to Climate Change

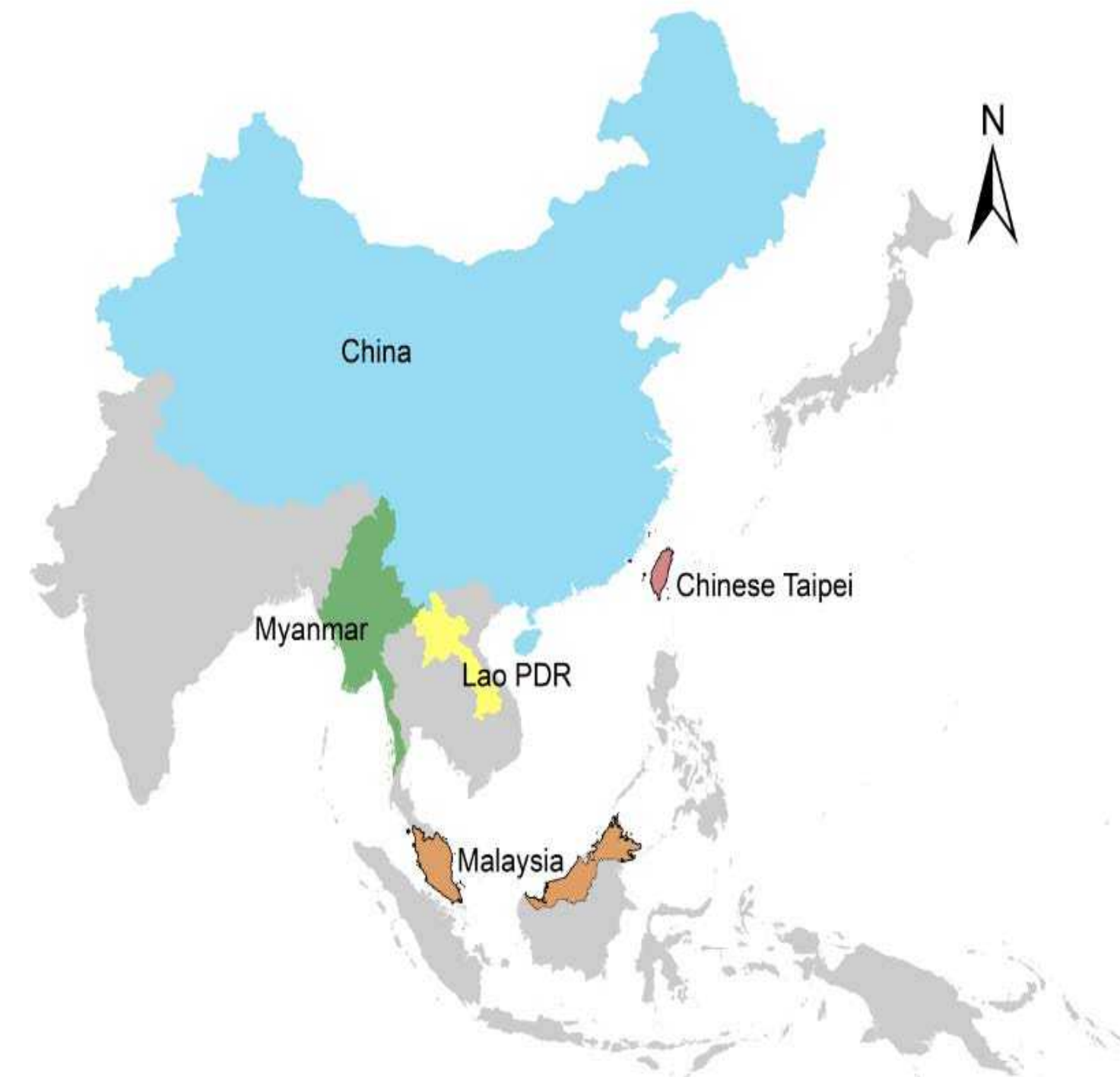


About the project

Climate change is a threat to the stability and productivity of the forest ecosystems in Asia-Pacific region. The project *Adaptation of Asia-Pacific Forests to Climate Change* aims to address this lack of knowledge and tools by developing :

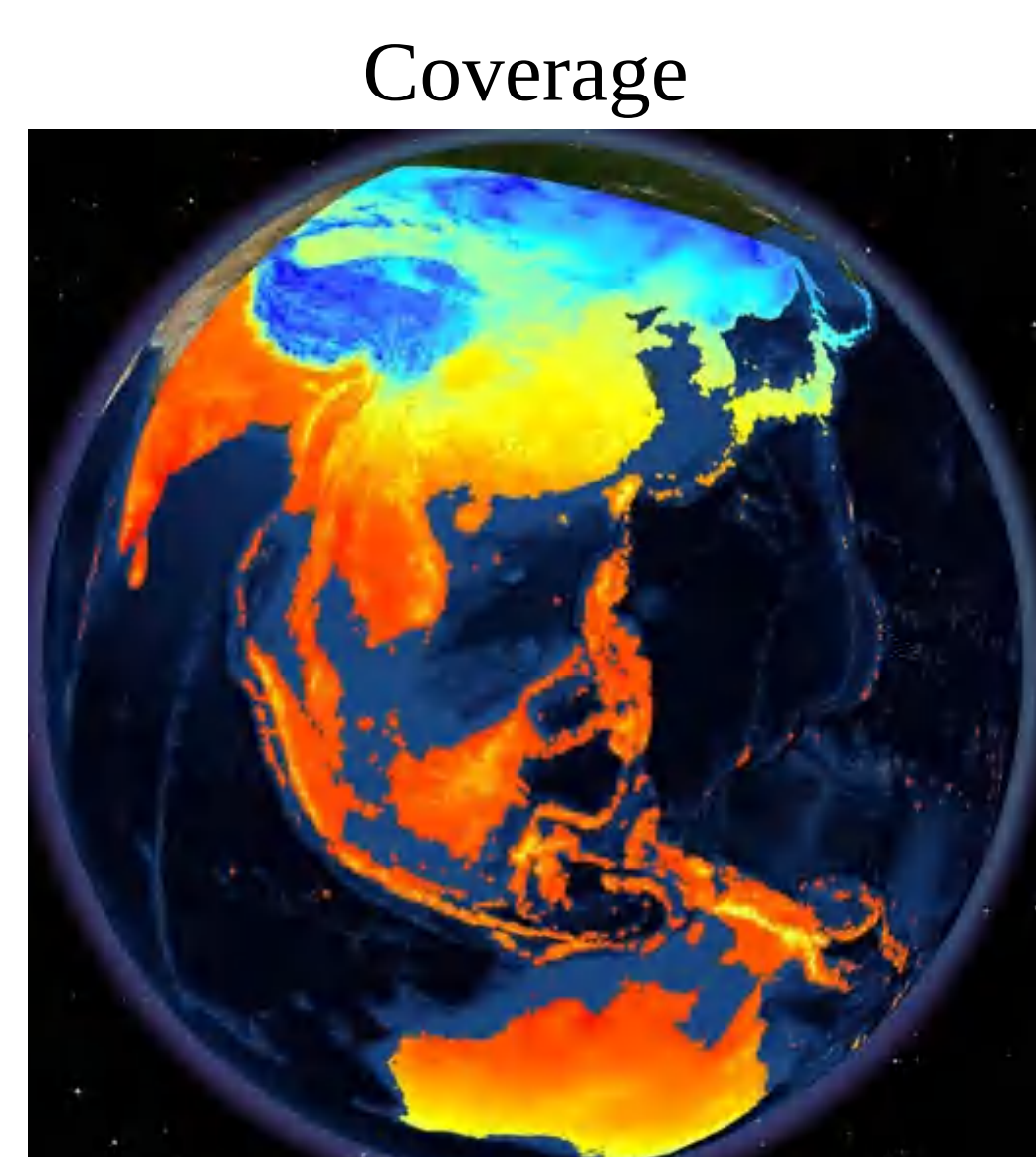
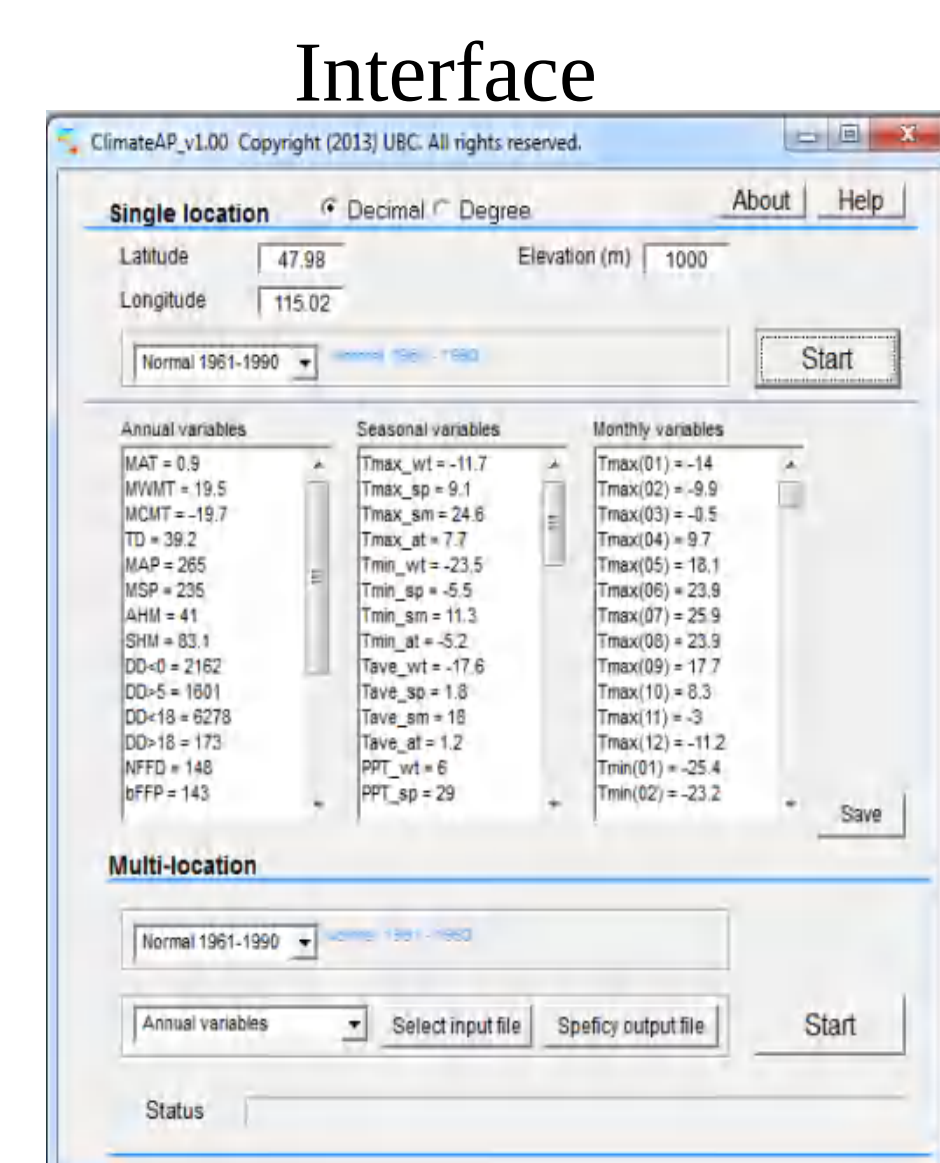
- (1) a high-resolution climate downscaling model, ClimateAP, applicable to any location in the region;
- (2) climate niche models to evaluate how climate change might affect the distribution of suitable climatic conditions for regionally important tree species and ecosystems;
- (3) development and application of forest models to assess alternative management strategies in the context of management objectives and the projected impacts of climate change;
- (4) Capacity building of policy makers, researcher and forest managers of our partner economies

Map of partner economies: China, Chinese Taipei, Laos, Myanmar and Malaysia.



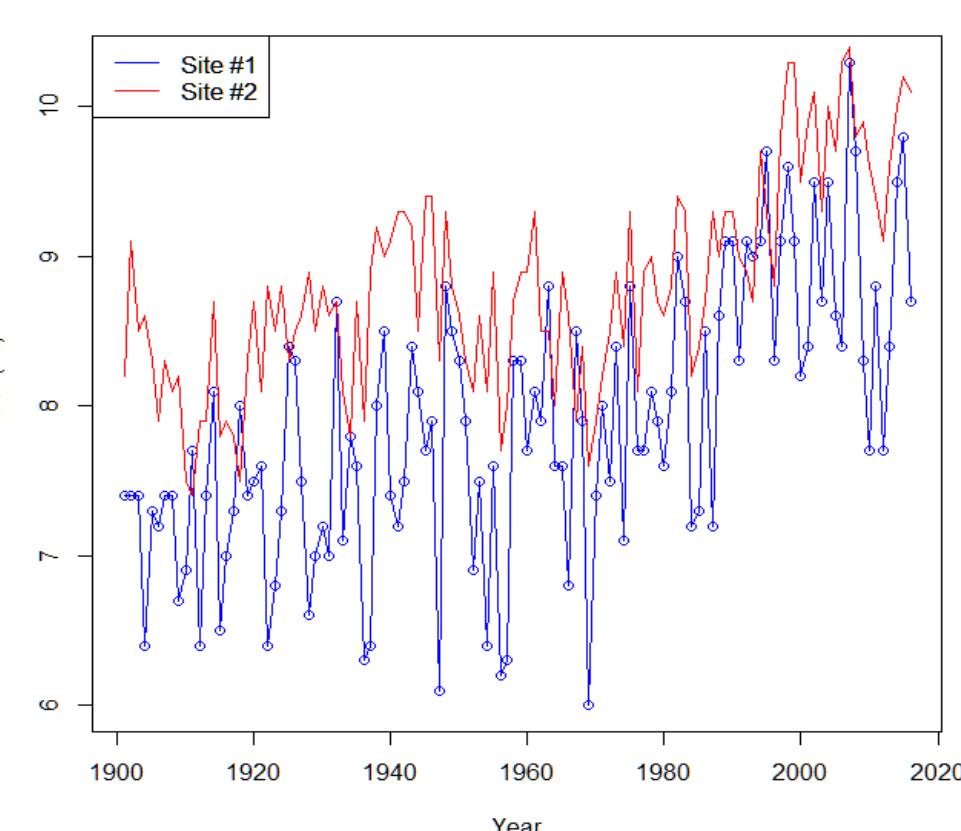
ClimateAP-desktop version

ClimateAP can generate climate data for any specific locations in Asia-Pacific region. It also allows users to produce climate data at any desirable spatial resolutions. It covers monthly climate data for historical (1901-2016) and future (2011-2100) years and periods.

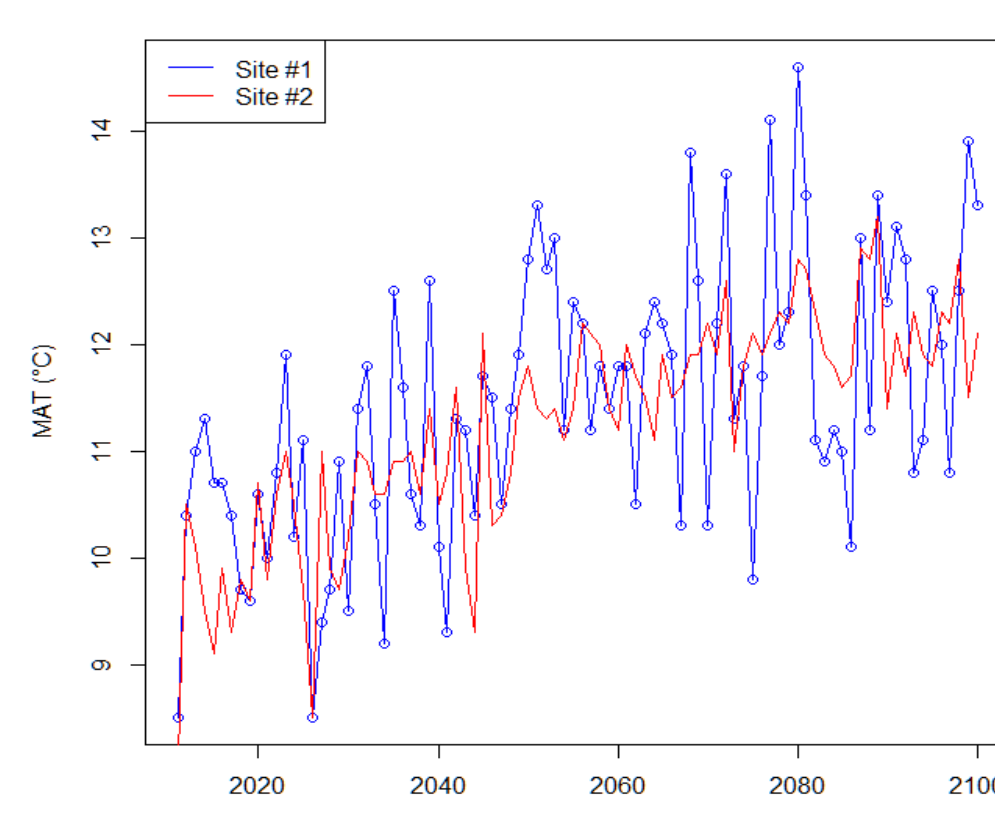


Historical and future time-series functions in ClimateAP enable users to obtain climate data time-series for multiple locations by a few clicks.

Climate time-series for a historical period



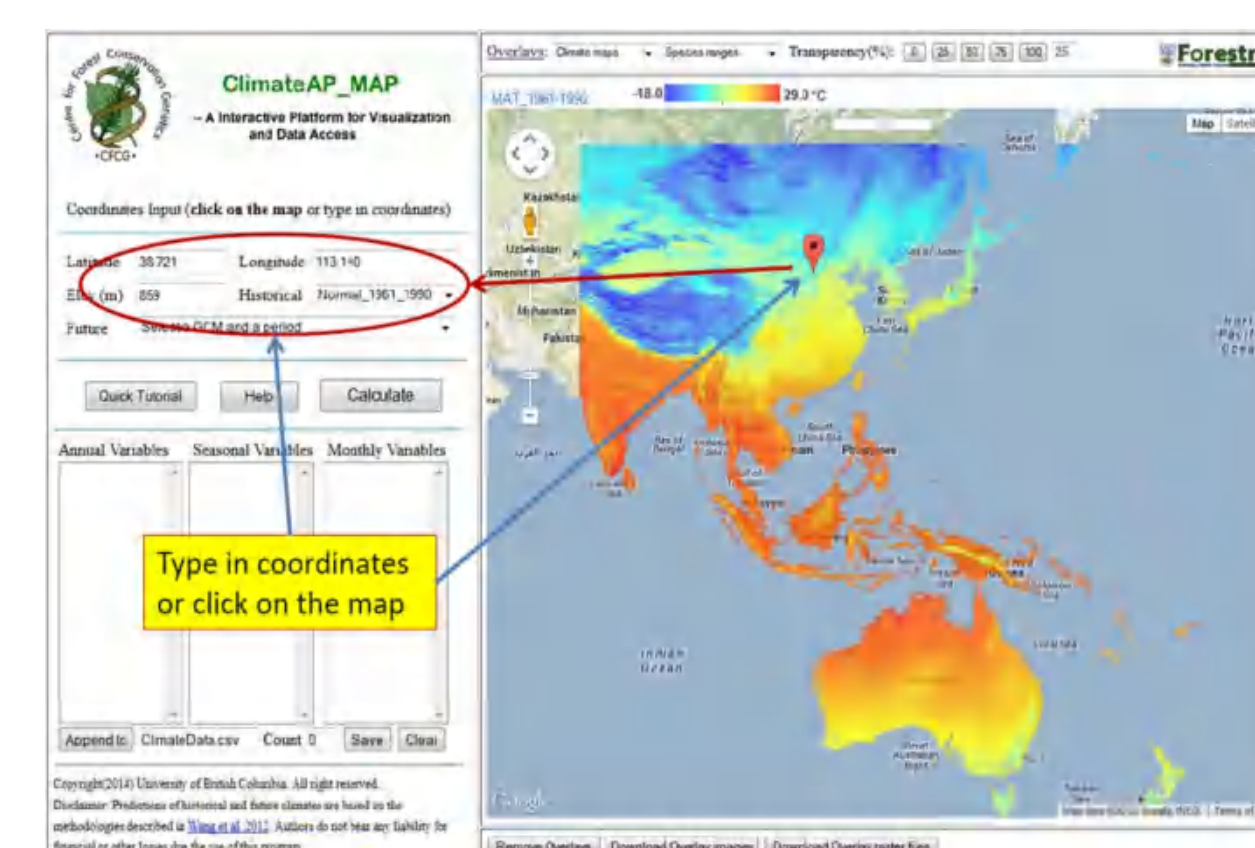
Climate time-series for a future period



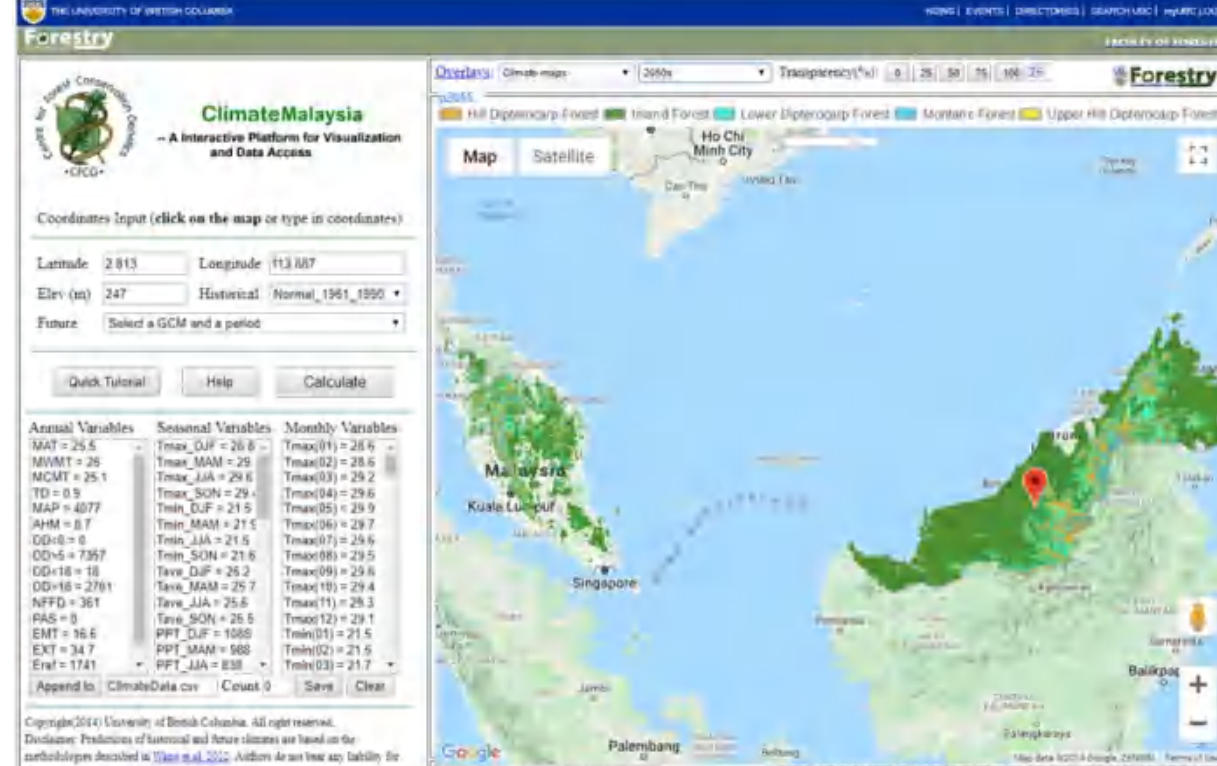
ClimateAP-Web version

With web-based ClimateAP embedded in Google Maps, users can access climate data and visualize climatic and species distribution maps locally or regionally by zooming in or out. (<http://Climateap.net>)

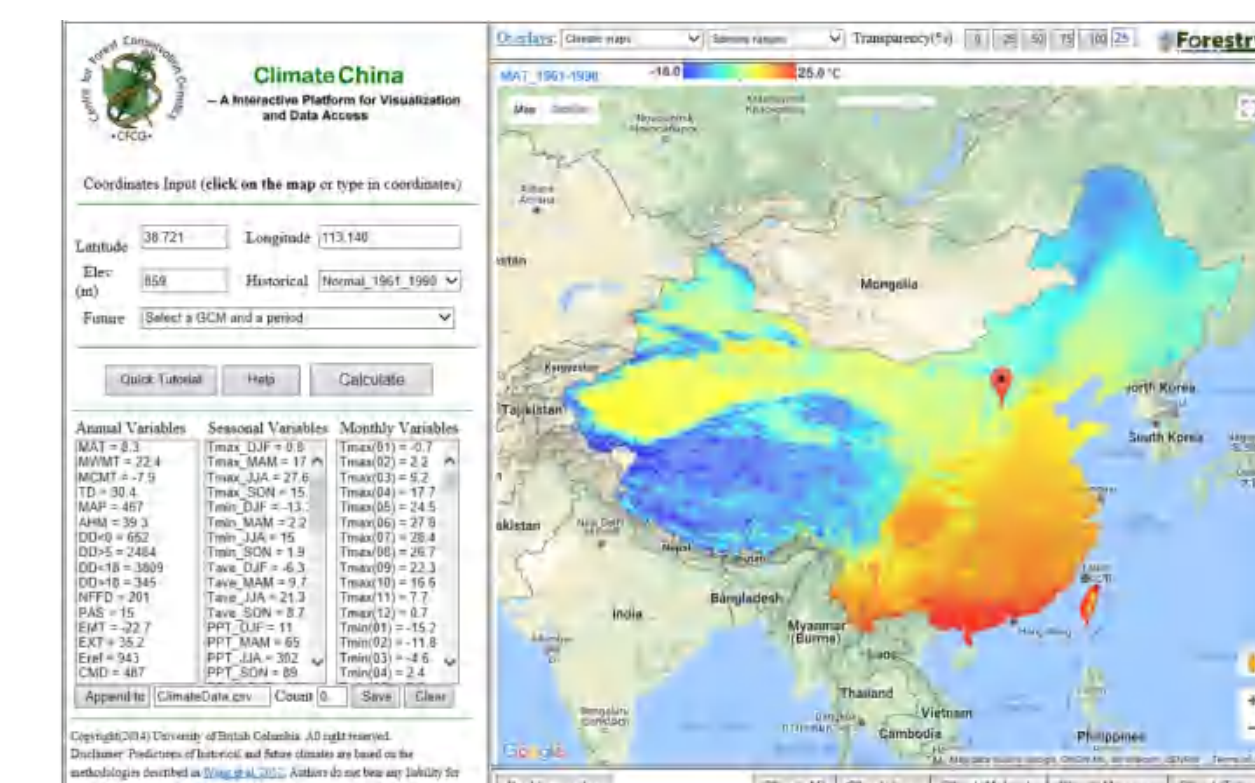
Interface of web-ClimateAP



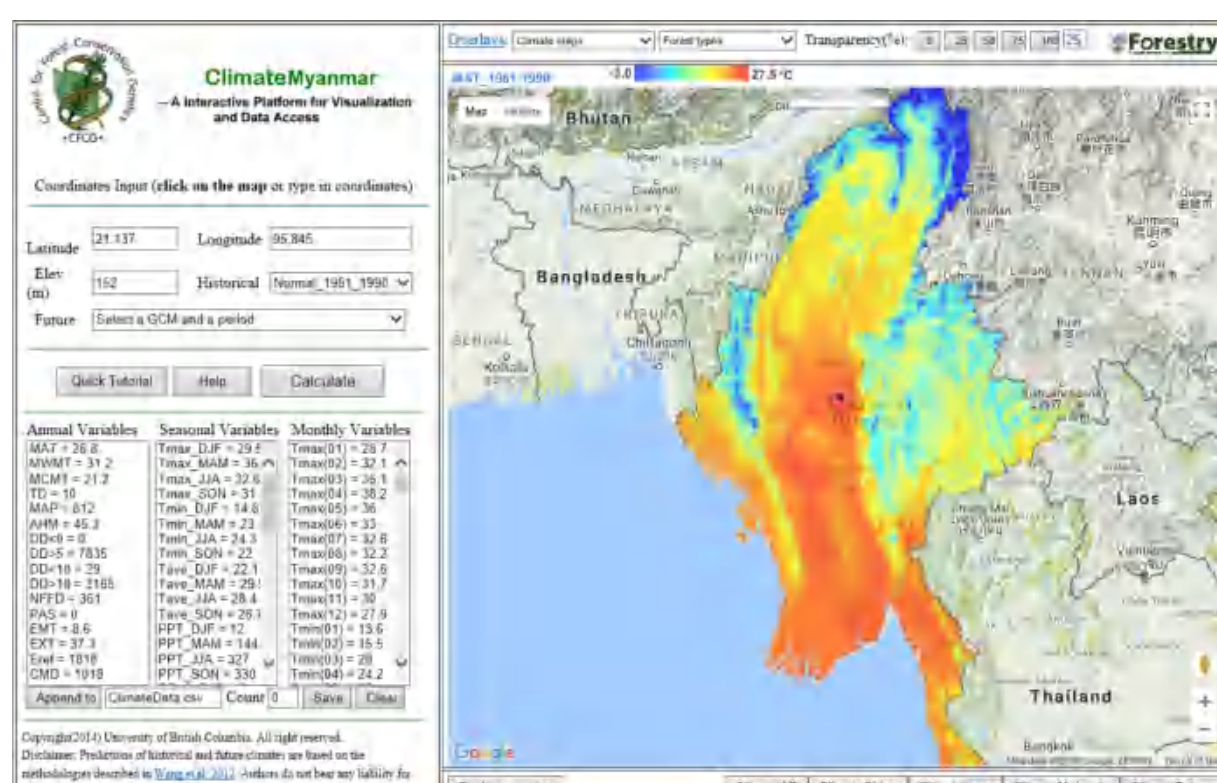
Climate niche overlays for forest ecotypes in Malaysia for 2050s' climates



Interface for ClimateChina



Interface for ClimateMyanmar



Climate niche models (CNM)

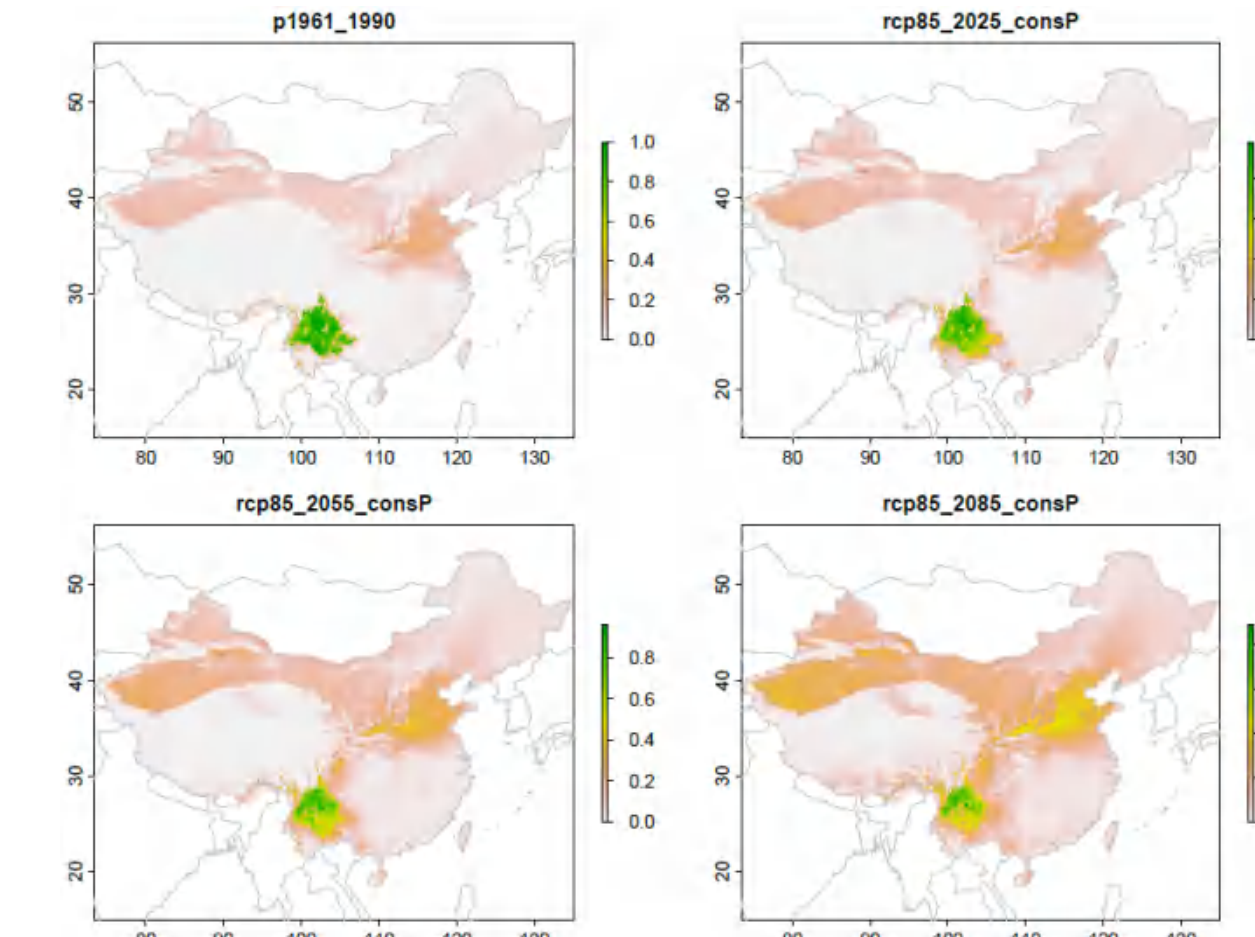
Climate niche models has been developed for 5 tree species in Phase I and 10 species and several forest ecotype in phase II.

Three unique features of our climate niche models:

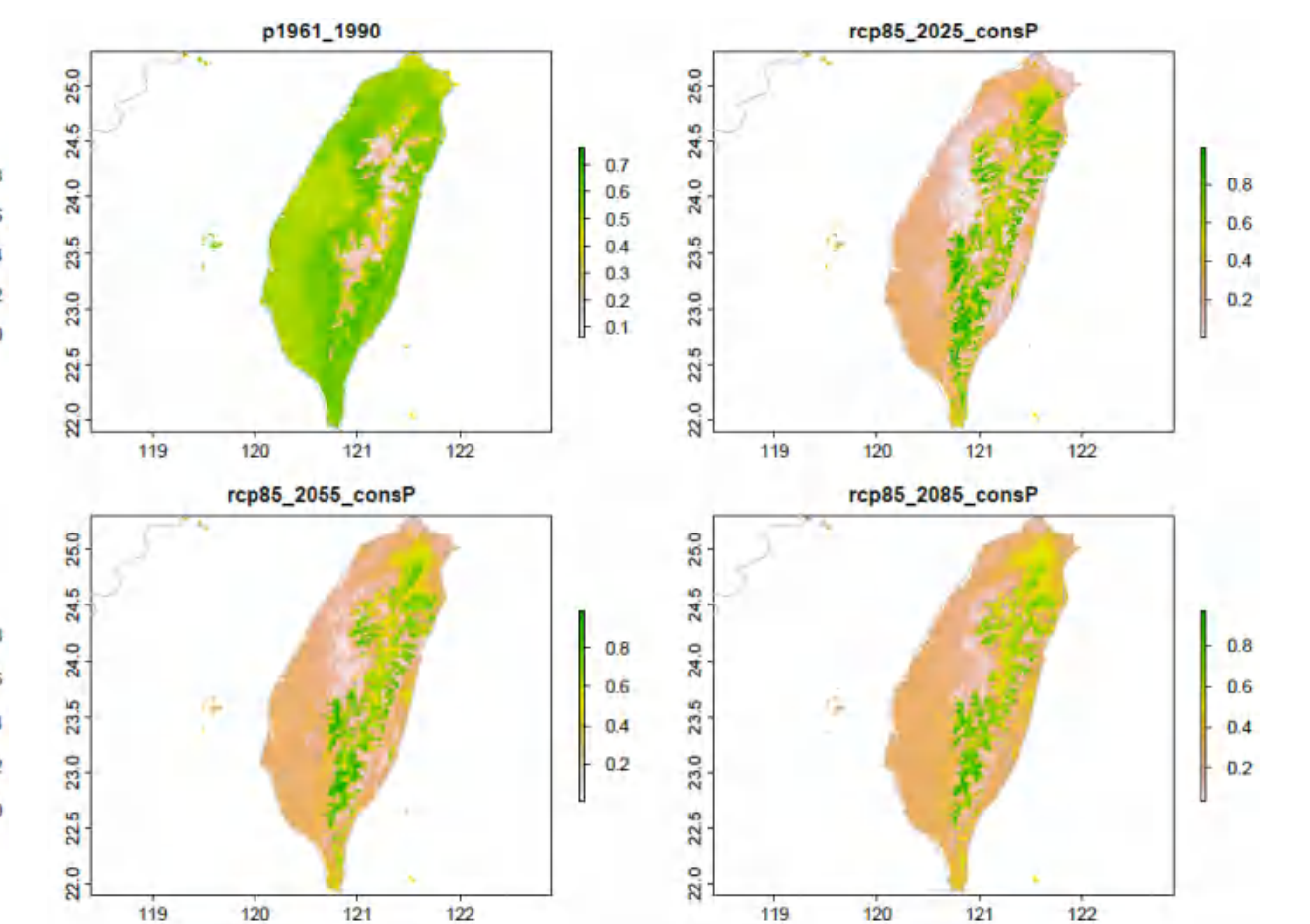
- Accurate climate data: Climate data from ClimateAP represents specific locations instead of grid average;
- State-of-art modeling: Random Forest and multiple forests;
- Consensus projection: projection are based on 10 climate change scenarios rather than one or two.

Climate niche models for species

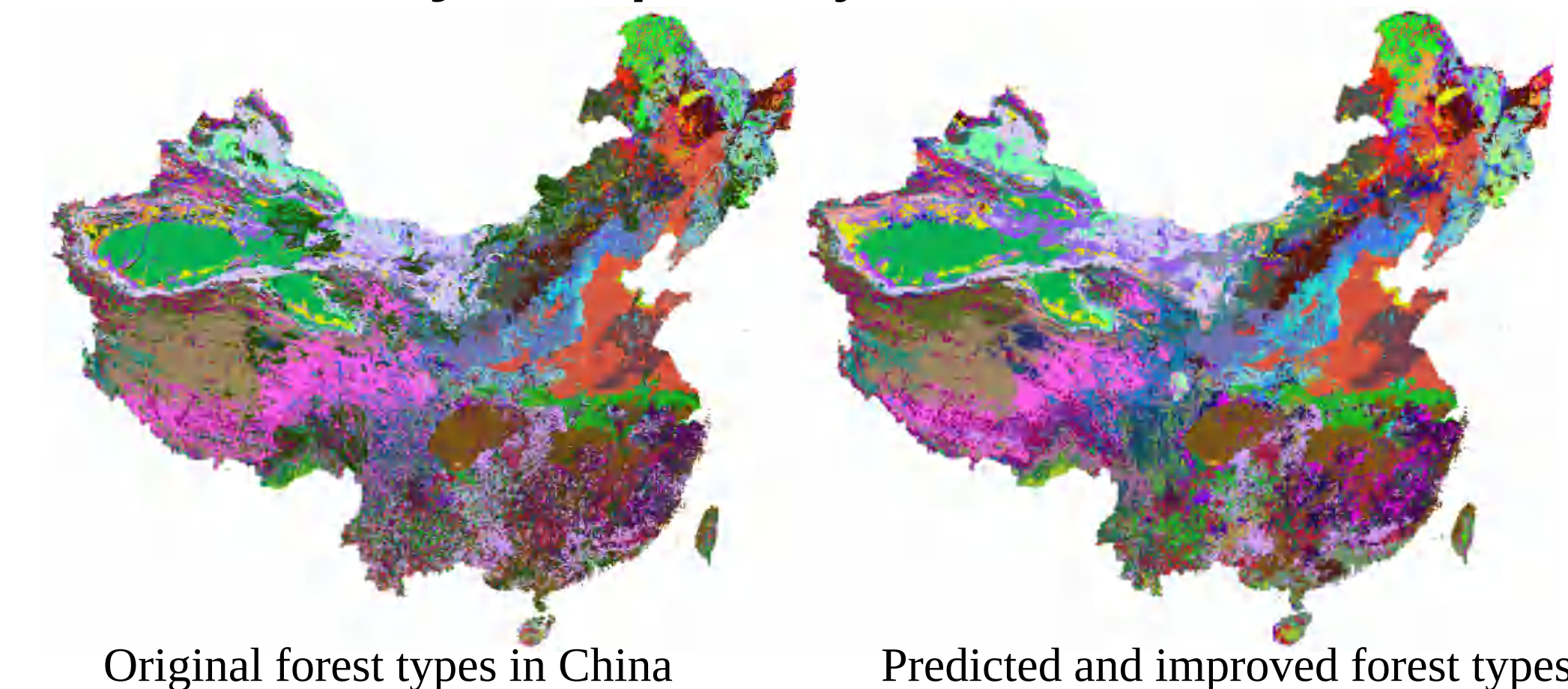
CNM for *Pinus yunnanensis* in China



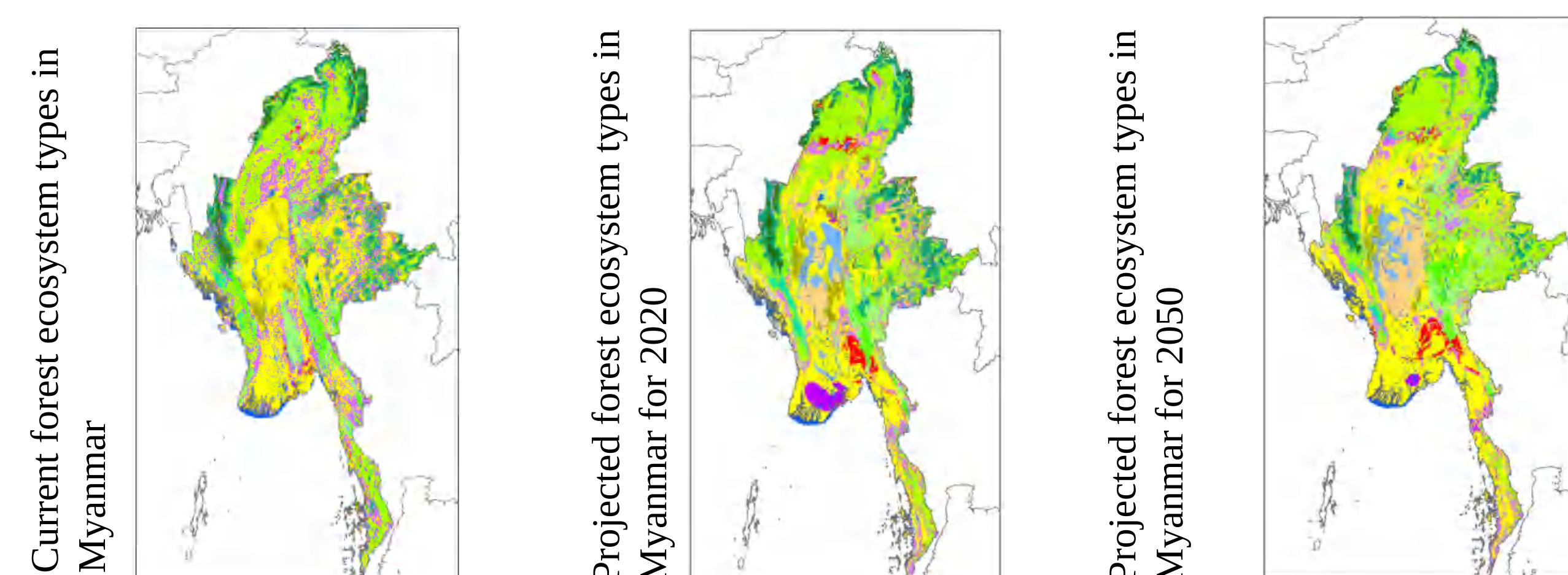
CNM for *Cyclobalanopsis longinx* Chinese Taipei



Consensus Projection for ecosystem



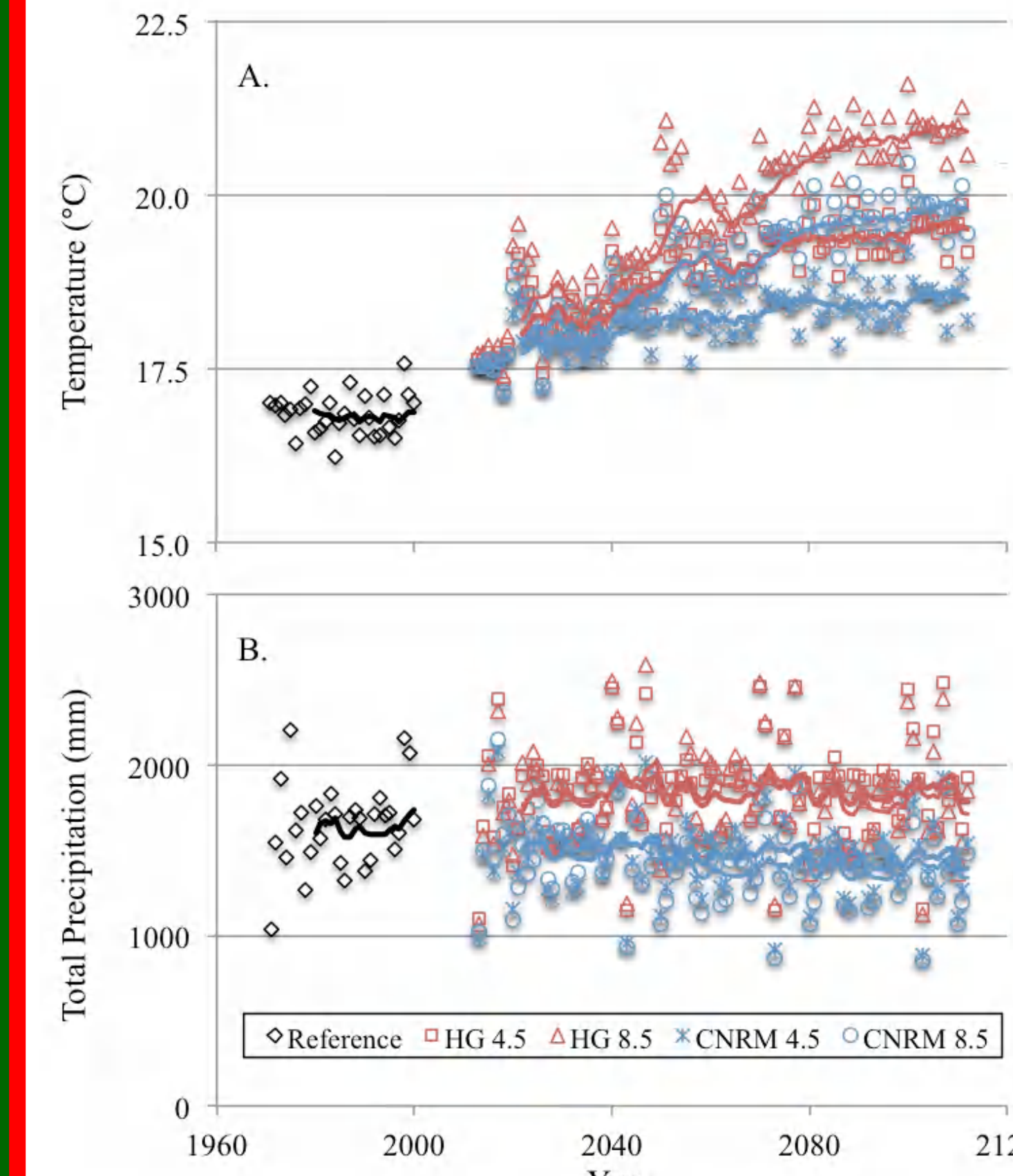
Climate niche models for ecosystems



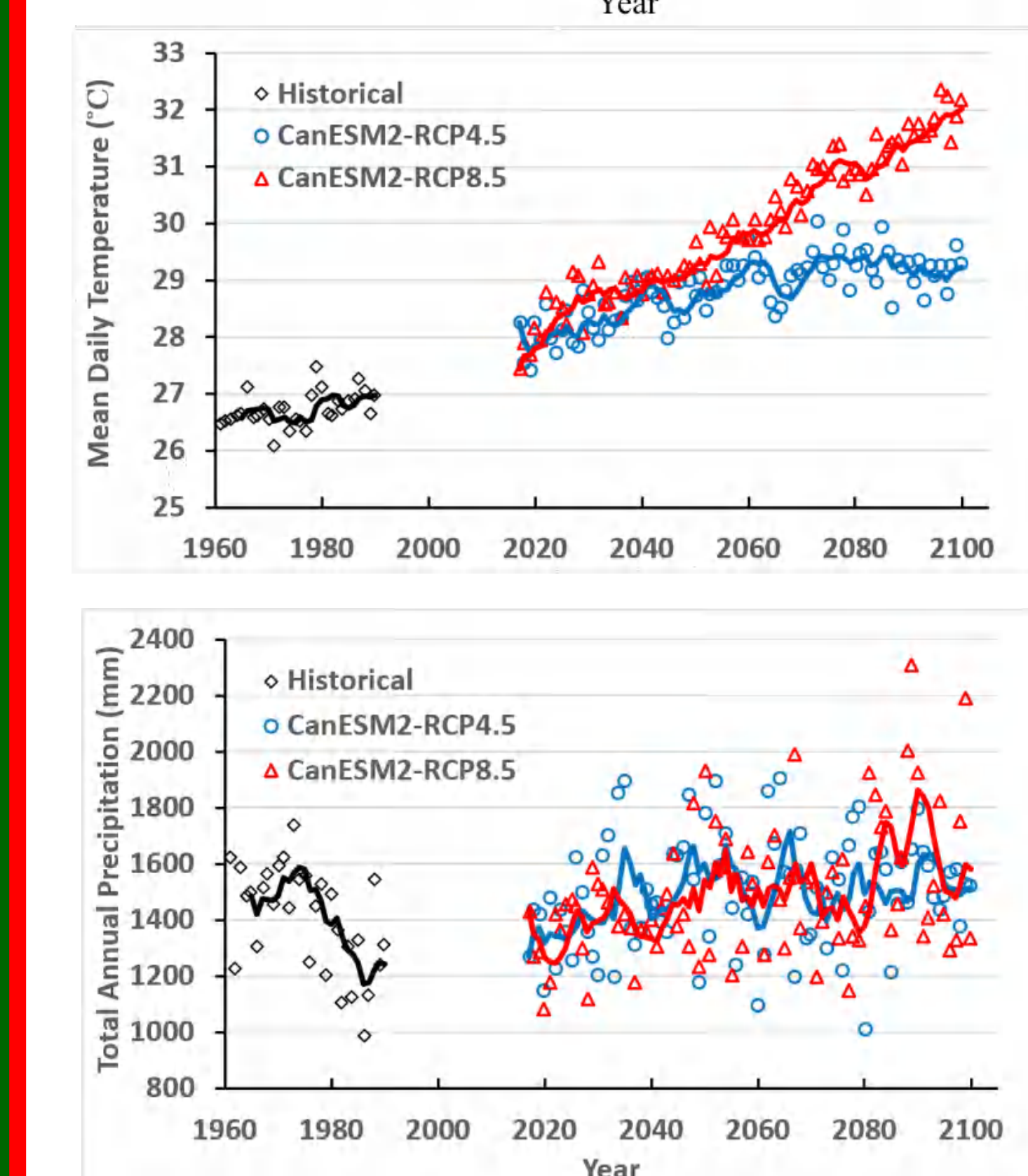
Process based model

FORECAST/FORECAST Climate model can be used for trade-off analysis to evaluate the impacts of alternative management/climate change scenarios on long-term key species/forest productivity, water balance, nutrient cycling and carbon storage.

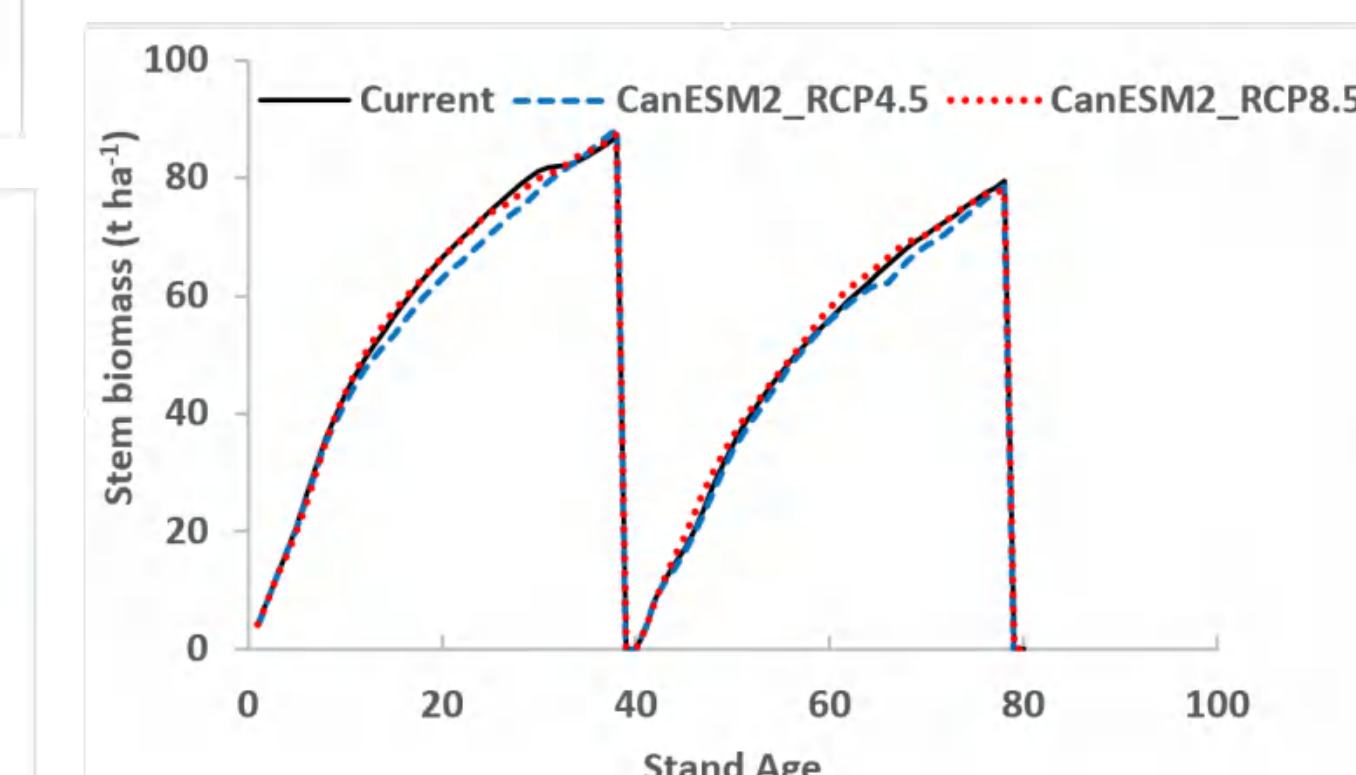
Climate Change Scenarios



A result of **FORECAST Climate model** for Chinese fir plantations in Fujian province predict modest increases in productivity (6.1 to 12.1%) over the next 30 to 60 years (2013-2110) due to a lengthening of the growing season

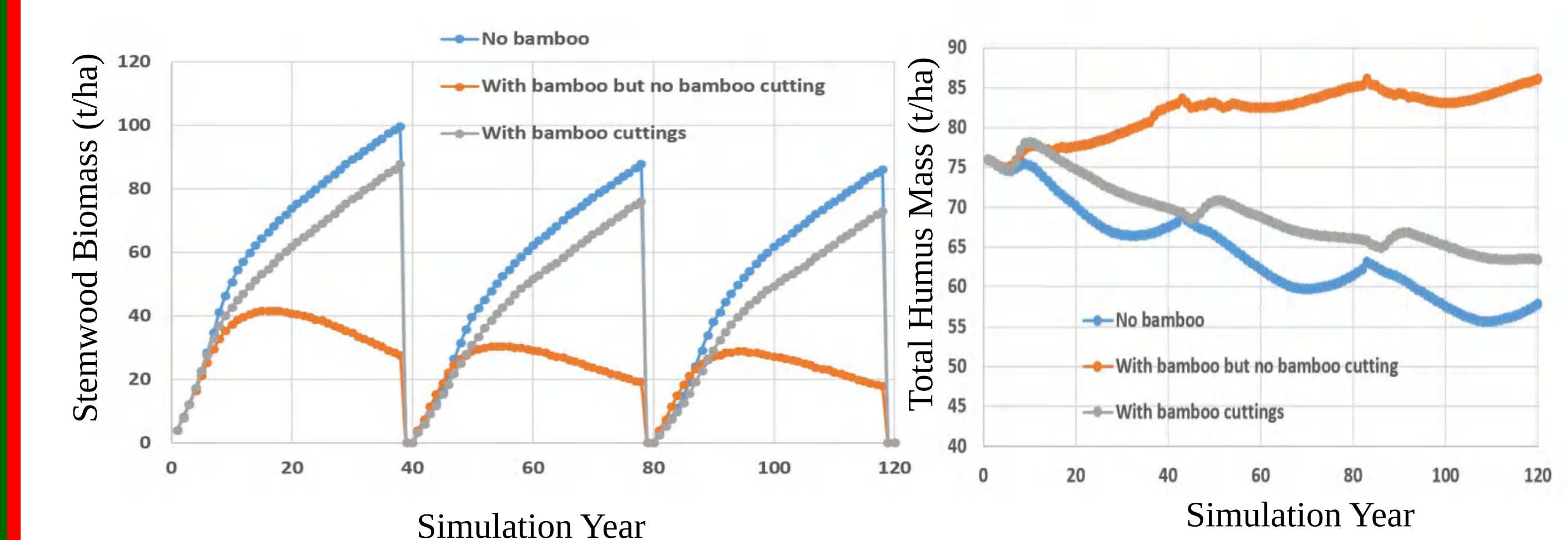


A result of **FORECAST Climate model** for Teak plantations in Myanmar predict a slightly lower stemwood biomass production in CanESM-RCP4.5 attributed to drought related mortality.



Management Scenario

A result of FORECAST model for Teak plantation productivity in Myanmar with and without Bamboo competition



Capacity building and outreach

Knowledge transfer and capacity building of partner economies is a key component of the project



HANDBOOK: TRAINING WORKSHOP ON MODELLING CLIMATE AND FOREST ECOSYSTEMS IN A CHANGING CLIMATE

Edited by Guangyu Wang, Tongli Wang, Brad Seely and Shari Wang

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