APFNet PROJECT

To Demonstrate the Development and Application of Standing-Tree Carbon Equations to Improve the Accuracy of Forest-Cover Carbon Stock Estimates in Thailand
[Project ID: 2015P6-THA]

TECHNICAL REPORT NO. 2

APPLICATION OF STANDING-TREE CARBON EQUATIONS: PREPARATION OF CARBON STOCK MAPS

Kasetsart University Faculty of Forestry, Thailand

AND

Asia-Pacific Network for Sustainable Forest Management and Rehabilitation

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Bangkok, Thailand

ABOUT THE PROJECT

Project title	To demonstrate the development and application of standing-tree carbon equations to improve the accuracy of forest-cover carbon stock estimates in Thailand [2015P6-THA]
Supervisory agency	Royal Forest Department, Bangkok, Thailand
Executing agency	Kasetsart University Faculty of Forestry, Bangkok, Thailand
Project Director: Dr. Khwanchai Duangsathaporn	
Target area: Ngao Demonstration Forest, Lampang Province, Thailand	
Project implementation duration: 1/2017 to 12/2018 (24 months)	

ACRONYMS

GOT	Government of Thailand
MONRE	Ministry of Environment and Natural Resources of Thailand
PD	Project Director
PSC	Project Steering Committee
RFD	Royal Forest Department of Thailand
SFM	Sustainable Forest Management

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PART I: INTRODUCTION

BACKGROUND AND RATIONALE

This project originates from the Kasetsart University Faculty of Forestry (KUFF), Bangkok, Thailand. The rationale for this project is that there is uncertainty in the accuracy of national estimates of Thailand's forest-cover carbon stocks, incomplete reporting of carbon stocks and limited knowledge of the methods of carbon stocks assessment among the stakeholders. This, in turn, affects the national planning and other policy decisions that rely on information on national carbon stocks.

The carbon stock estimates are inaccurate because the commonly used equations to estimate tree volume are biased (over- or under-estimate tree volume). The bias occurs because (1) the sample trees used to develop the equations was small (because of the need to minimize destructive sampling of trees and lack of instruments to accurately measure standing tree upper stem diameters) and, in some cases, not representative of the economy; 2) some of the equations were local volume equations, which used only DBH as the independent variable and did not include tree height; (3) the past equations were focused on areas to be logged (mainly big trees), yet, since the national logging ban, the interested has shifted to protected areas that include smaller trees; and (4) the species grouping was too broad (e.g., volume equations by tree family). The commonly used existing equations are the local tree volume equations developed by Pochai and Nanakorn (1992). These equations developed by the RFD based on upper stem diameter measurements of standing trees using a Spiegel Relaskop. However, these equations were developed for one local area in northern Thailand using a small sample of trees. Yet, they are commonly applied nationally. As well, the specific gravity coefficients used to convert volume to biomass were developed based on a small sample of trees. Finally, the generally assumed carbon/biomass fraction of 0.47 (IPCC 2006), for converting biomass to carbon, is too general. The IPCC indicates that "… higher tier methods may allow for variation with different species, different components of a tree or a stand (stem, roots and leaves) and age of the stand …" (IPCC 2003, page 3.25).

A new and novel approach has been developed at KUFF to estimate standing tree carbon content as a function of standing tree attributes (total height and DBH), using sample tree increment cores. Some research has been successfully done by Kasetsart University Faculty of Forestry (KUFF) on ways to directly estimate carbon content on standing trees using wood samples (increment cores) (Duangsathaporn et al. 2011). Other studies have used wood samples to determine carbon content (e.g., Kraenzel, et al. 2003; Wutzler, et al. 2006). Through this project, Thailand sought financial assistance and limited technical support from APFNet to demonstrate this new approach that could be used to develop new national standing-tree carbon equations. These equations could be used to estimate carbon stocks in Thailand's natural forests. This project aims to demonstrate this process in the Mae Huad sector, Ngao Demonstration Forest in Lampang province.

PART II: ACQUISITION AND CLASSIFICATION OF REMOTE SENSING DATA

2.1 Acquire and Classify Remote Sensing Data

2.1.1 Background remote sensing data, in particular, existing satellite data of the project area were (Figure 1 and 2, Table 1). The majority satellite data used for this study are from Landsat constellation. The Landsat-8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS), the newest satellite in Landsat series, provides nine spectral bands with a spatial resolution of 30 meters for band 1 to 7 and 9. New band 1 (ultra-blue) is useful for coastal and aerosol studies. New band 9 is useful for cirrus cloud detection. The resolution for Band 8 (panchromatic) is 15 meters. Thermal band 10 and 11 are useful in providing more accurate surface temperatures and are collected at 100 meters. The newest satellite data were acquired to update forest area. The project attempted to classify those forest areas into forest type and the others land use classes using satellite imageries and available aerial photographs. Although the Thaichote provide higher resolution and details a large amount of the data scene and budget required. In terms of the vast area of Ngao Demonstration Forest, Landsat-8 provides a satisfactory output, especially Band 8 Panchromatic (PAN) (0.50 - 0.68 µm) 15 m resolution. The other reason is that the Thaichote (Thai Resource Satellite) data is not available at consistent period of twelve months.

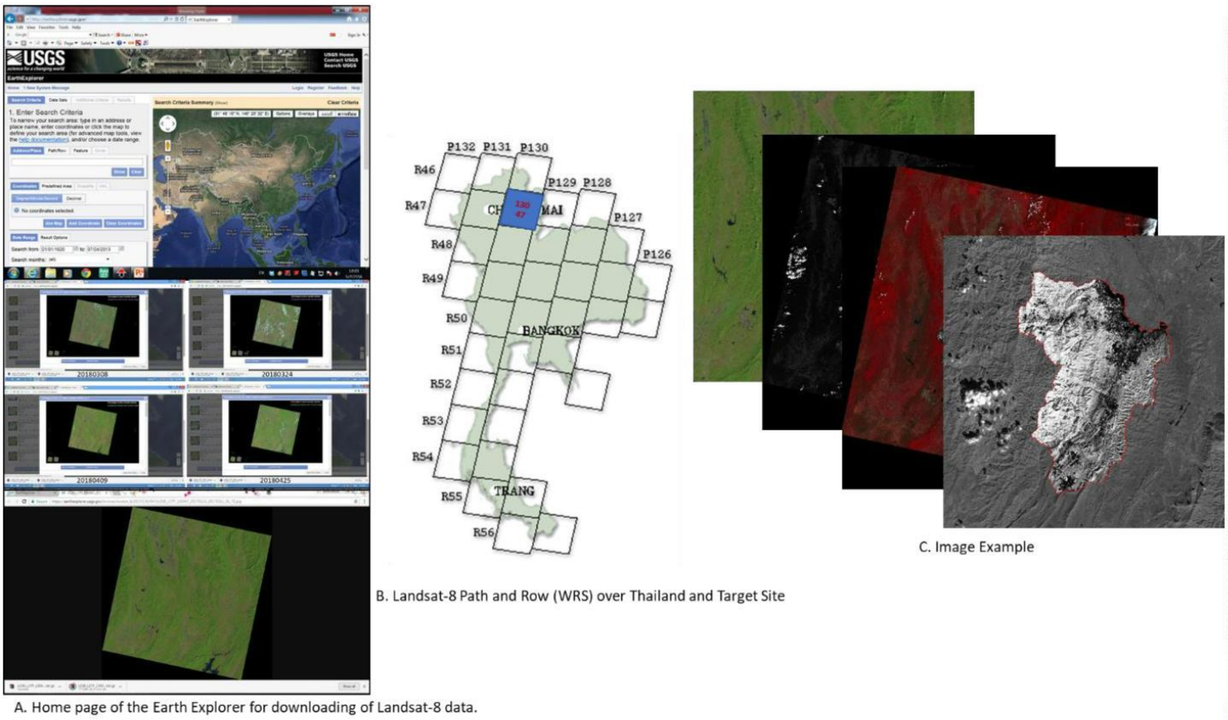

Figure 1 Home page of the Earth Explorer for downloading of Landsat-8 data

Table 1 Landsat-8 data of good quality acquired during 2015 and 2018

Landsat-8 Data												
Year/Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2015	27	28		01&17						26		13
2016	30	15	18	19								
2017	16	1&17	05	06&22						31		02
2018	19			09&25								
Acquired from : USGS-Earth Explorer-http://earthexplorer.usgs.gov/												
	Cold/Winter				Dry/Summer				Rainy			Cold/Winter

2.2 Generate the Vegetation Index (VI)

The vegetation index (VI) **was generated** by means of normalized vegetation index, which is a spectral transformation of two image bands (red and near infrared band) and designed to enhance the contribution of vegetation properties and allow reliable spatial and temporal inter-comparisons of terrestrial photosynthetic activity and canopy structural variations. The optical satellite data provides spectral reflectance data (Band) in the digital number format which can be used as parameter in the mathematical equation to calculate the VI. The application of the VI value to classify forest cover from satellite data is an effective method and widely used. The project attempted to apply the VI for carbon calculation and mapping. The combination of the VI value and field plot data will be integrated for carbon calculation for each forest stand.

Since the project collected long period of available Landsat-8 data (2015 till 2017), Normalized Deference Vegetation Index (NDVI), which is a spectral transformation of two image bands (red and near infrared band), sought the best combination for carbon mapping. This stage attempted to generate NDVI by utilizing Landsat-8 images that were acquired during the late of 2015, 2016 and 2017, and to select the best output for further application, i.e., linkage between NDVI and sample carbon plots on a systematic grid. The results also illustrate overall temporal changes via NDVI.

The NDVI indicate the strength of green vegetation. It quantifies the amount of vegetation by ratioing the result of difference between reflectance of near-infrared (which vegetation strongly reflects) and red band (which vegetation absorbs) divided by the sum of near-infrared and red band. The NDVI value always ranges from -1 to +1. But there isn't a distinct boundary for each type of land cover. The negative values mean highly likely reflect from water surface. On the other hand, if NDVI value is close to +1, it is high possibility that it is dense green leaves. But when NDVI is close to zero, or both band have close reflectance value, which isn't green leaves but will be an urbanized area or open land.

As shown below, NDVI uses the surface reflectance value of NIR and red band in the form of:

$$\text{NDVI} = \frac{\text{Near Infrared Band - Red Band}}{\text{Near Infrared Band + Red Band}}$$

To obtain NDVI raster value, analysis tool or raster calculator is needed. The NDVI calculation has been done by map algebra expression, by means of either inserting reflectance value of certain bands (NIR and Red) or can also be done by default mode.

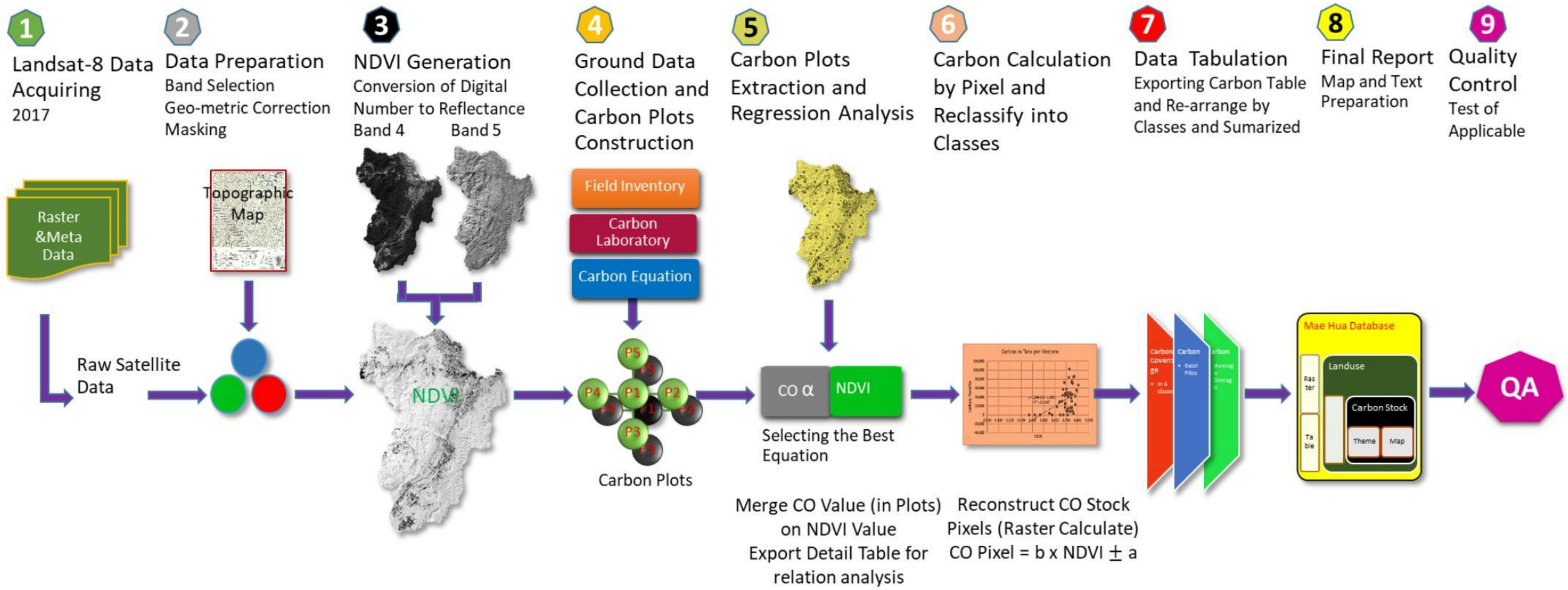

Figure 2 Flow Diagram Depicting Entire Process for Carbon Stock Map Generation and Classification for Mae Huad sector, Ngao Demonstration Forest, Lampang Province

2.3 Preliminary Satellite Data Preparing for NDVI Classification

The NDVI index explains the contrast of two bands characteristics which is recorded in the form of multispectral raster dataset. The chlorophyll pigment absorb the red wavelength (band) and release high reflectivity by plant structure; such as cell wall and fiber in the range of near infrared band. The steps for preparing the NDVI generation are as follows:

a) The methodology starts with preparing raw Landsat-8 data improvement, which are atmospheric and geometric correction. This first step reduces the scattering from surrounding environment (cloud, haze, smoke and etc.) and the last step ensures good matching with correct geographic coordinate system (WGS 1984 reference map source).

Meta Data of Landsat-8 File for RADIOMETRIC_RESCALING Coefficient of each band are:

REFLECTANCE_MULT_BAND_1 to BAND 8 = 2.0000E-05
REFLECTANCE_ADD_BAND_1 to BAND 8 = -0.100000

The formula for transforming digital number (DN) to top of atmosphere reflectance (TOA) is:

TOA = (Band Specific Reflectance Mult_Band x DN Values) + Reflectance_Add_Band

The reflectance measured at the satellite sensor on board must be corrected by the light angle from the sun, then the amount of reflectance is:

Adjust TOA = (TOA REFLECTANCE)/Sin (SUN_ELEVATION in Radians) or
Adjust TOA = (TOA REFLECTANCE)/Sin (Degrees x T)/180)

Radians = (Degrees x T)/180

When sun elevation in meta data file is expressed in degree and always varied due to season, for examples:

SUN_ELEVATION on January 16, 2017 = 42.57195840
SUN_ELEVATION on February 17, 2017 = 48.94642044
SUN_ELEVATION on March 05, 2017 = 53.61009660
SUN_ELEVATION on April 06, 2017 = 62.88127699
SUN_ELEVATION on October 31, 2017 = 51.64369730
SUN_ELEVATION on December 02, 2017 = 44.18415614

This process aims to improve scene data to be clearer since some atmospheric haze and scattering are reduce (Figure 3).

b) Utilized all those 2 band scenes (band 4 and 5) that had the effect of reducing atmospheric scattering to create the NDVI. Landsat-8 data acquired during 2015 to 2017 have been used. All twelve period of NDVIs have produced.

c) Mask or extract processed data by target boundary (Ngao-demonstration area). Only NIR band and Red band are used for the calculation. Then export atmospheric correction data and add back again to be able to make the calculation.

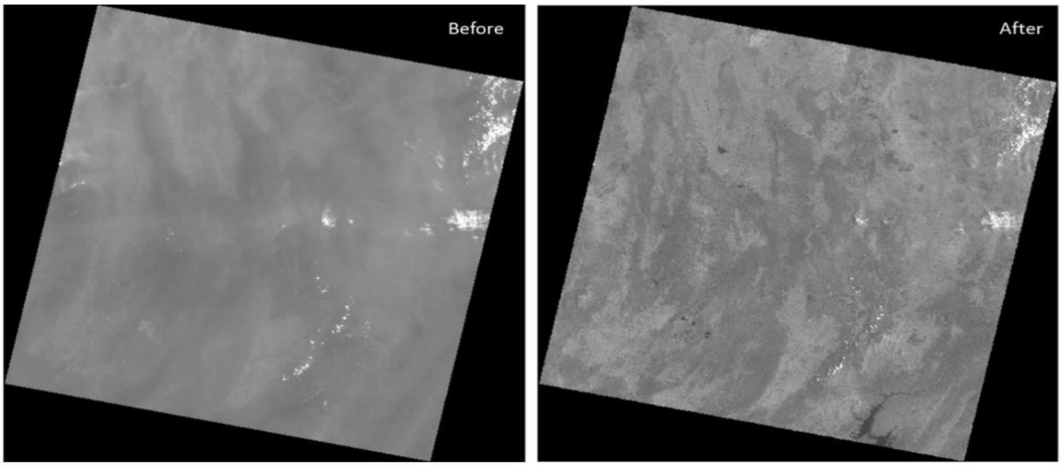

Figure 3 NDVI transformation result (raw data on the left and after transformation on the right)

For NDVI generation, the contrast of two bands characteristics was recorded in the form of multispectral raster dataset. The chlorophyll pigment absorbed the red wavelength (band) and released high reflectivity by plant structure; such as cell wall and fiber in the range of near infrared band.

The optical satellite data provided spectral reflectance data (Band) in the digital number format which could be used as parameter in the mathematical equation to calculate the Index. There were various vegetation index those had been studied and accepted to use for forest stand classification. The application of vegetation index for classification of forest cover from satellite data was an effective method and widely used. The project introduced this technique to interpolate carbon calculation and mapping. The combination of NDVI value and field plot data were integrated for carbon prediction model.

As shown below, the **Normalized Difference Vegetation Index (NDVI)** used the surface reflectance value of NIR and red band in the form of:

$$\text{NDVI} = \frac{\text{Near Infrared Band - Red Band}}{\text{Near Infrared Band + Red Band}} \quad \text{(Weier and Herring, 2008)}$$

This stage attempted to generate Normalized Difference Vegetation Index (NDVI) by utilizing Landsat-8 images that were acquired during the late of 2015, 2016 and 2017, and to select the best output for further application, i.e., linkage between NDVI and sample carbon plots on a systematic grid. To obtain NDVI raster map, some analysis tool or raster calculator was needed for map algebra calculation in each pixel. The NDVI calculation had been done by map algebra expression, by means of inserting DN value of certain bands (NIR and Red) in the formula. NDVI could also be done by default mode.

The NDVI classification were diverse when executed by different acquired date. NDVI generation revealed different temporal change during 2015, 2016 and 2017. It represented growing stage during the rainy to the late of winter (October to January), and the others (February to June) represent for dry or summer seasons (Figure 4).

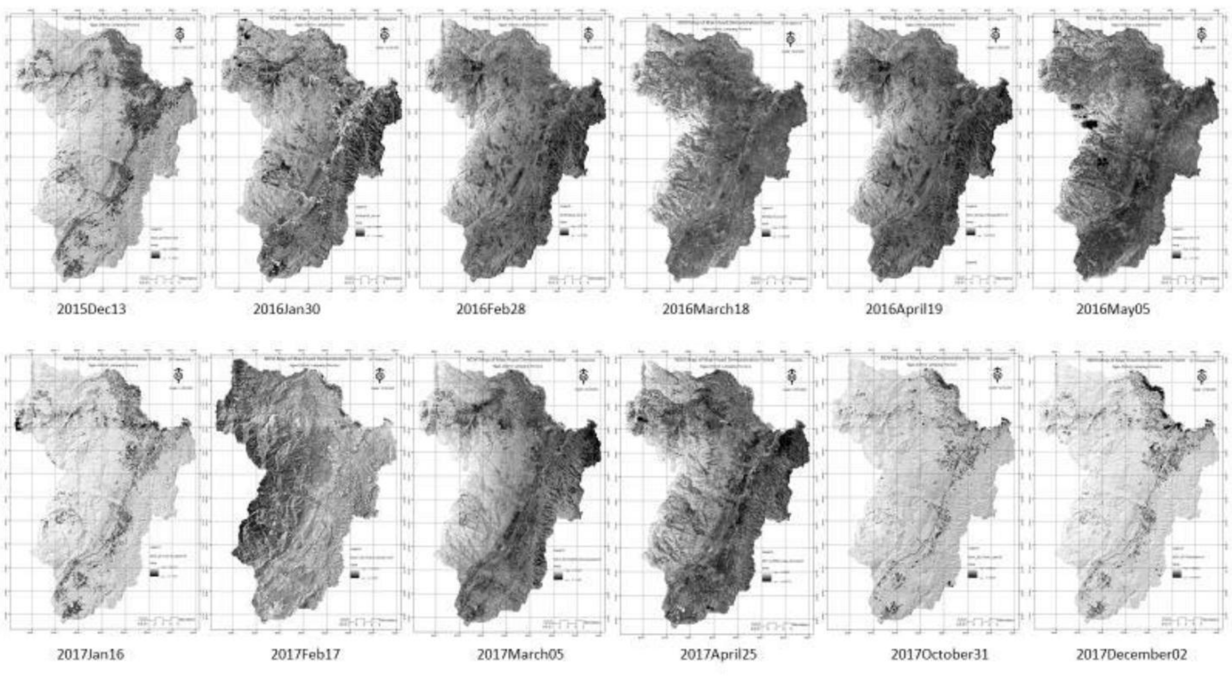

Figure 4 A set of NDVI maps, with 30 meters resolution, based on Landsat- 8 data during 2015 to 2017

In general, the NDVI values were ranged from -1 0 to +1. In this study, the best NDVI result was derived by using January 16, 2017, which NDVI values were ranged from the highest value of 0.849149 to the lowest value of -0.717048. The high negative values represented water or moist soil, while low negative value or close to zero represented exposed rock, sand and bare soil when they showed lower reflection in the NIR range than in the red range. In the other hand, the NDVI value normally shifted to positive when green vegetation appeared. Sparse coverage of plants, grass/shrub land, farm crops and vegetable garden showed in small positive value. Moderate NDVI value quantize from reflectance of dense plantation, dense or mature horticultural crops and wood that showed better reflection in the NIR range than in the red range. The bright on the NDVI map illustrated strong positive value due to produce very high reflection in NIR range than in the red range which was good in absorption, such as dense humid forest and thick or multiple canopy community. Deciduous forest showed lower positive value than those evergreen forest.

PART III: MODELLING THE RELATIONSHIP BETWEEN GROUND AND REMOTE SENSING DATA

The NDVI will be used as an independent parameter in a linear regression equation for predicting the carbon in each pixel for carbon mapping. The relation of NDVI value and carbon field plot data will be integrated for carbon calculation for each pixel.

The NDVI is a standard criterion for grouping the greenness of vegetation which is related to carbon storage to some degree. The NDVI also indicates the vegetation density, plant stress and plant growing stage. The leaf areas in the site are altered over time and NDVI. Flushed deciduous forest in rainy season will show higher NDVI value than in dry season when shedding their leaf during dry period of year. It reflects less pigment to indicate high NDVI value and reflect high absorption in red band. It is notable that the NDVI value in the growing period shift to more positive values than in the dry period. The NDVI value calculated using dry period data become more negative than in the growing stage.

3.1 Plots Used for Carbon Stock Mapping

The carbon content analyzed from all sample trees in a plot (as shown in the project Technical Report No.1) were converted to stand (per hectare) carbon values. A total of 54 plots (named carbon plots) (Table 2) were applied for carbon stock mapping. Adding plots with known coordinates was done via an Excel table through GIS software.

Table 2 Illustration of part of the table prepared for carbon linkage

Point_Number	Forest Type	X	Y	In_Tree	Species	BAF	Basal_area/ha	Tree/ha	Carbon_kg	Carbon_Tons
1	MDF	585,809	2,074,552	10	L. duperreana Pierre	3.06	33.69	407.86	66,448.65	66.45
2	MDF	589,101	2,074,942	13	P. macrocarpus Kur	1.56	21.88	256.65	8,638.54	8.64
3	MDF	592,000	2,075,000	9	Anogeisus acuminat	3.06	27.56	1,454.44	57,241.25	57.24
4	PD	595,000	2,075,000	-	Paddy	3.06	-	-	-	-
5	MDF	583,633	2,071,724	5	Dalbergia assamica	1.56	7.81	71.17	2,668.06	2.67
6	DDF	585,968	2,071,974	14	S. siamensis Miq.10	3.06	42.88	599.07	102,484.69	102.48
7	DDF	588,691	2,071,914	10	Shorea siamensis M	3.06	33.69	308.70	70,177.85	70.18
8	AFC	592,000	2,072,000	-	Maiz	3.06	-	-	-	-
9	MDF	594,999	2,072,037	10	Pterocarpus macroc	3.06	30.63	1,659.10	47,420.85	47.42
10	PD	597,834	2,072,026	-	Paddy	3.06	-	-	-	-
11	DEF	582,994	2,068,964	7	Eugenia megacarpa	1.56	10.94	106.32	3,162.46	3.16
12	MDF	586,007	2,069,108	8	Albizia ordoratissim	3.06	24.50	6,924.34	22,792.13	22.79
45	DDF	597,271	2,054,496	12	Tectona grandis L.f.	3.06	36.75	1,263.64	74,931.79	74.93
46	PT	589,000	2,051,000	6	Dalbergia cana Gra	3.06	18.38	550.00	8,811.21	8.81
47	MDF	591,977	2,050,935	6	Terminalia triptera	3.06	18.38	552.07	30,514.44	30.51
48	MDF	594,964	2,050,950	10	Albizzia odoratissim	3.06	30.63	280.33	57,412.93	57.41
49	MDF	596,705	2,050,582	9	S. siamensis Miq.7,	3.06	27.56	1,223.44	45,449.43	45.45
50	DDF	589,000	2,048,000	11	T. grandis L.f., Term	3.06	33.69	440.49	72,233.96	72.23
51	MDF	591,923	2,048,001	7	Anogeissus acumina	3.06	21.44	580.68	43,186.27	43.19
52	MDF	594,745	2,048,025	5	Maiz	3.06	15.31	76.06	37,770.55	37.77
53	AFC	589,000	2,045,000	-	0	3.06	-	-	-	-
54	DEF	591,700	2,045,567	11	T. grandis L.f., P. ma	1.56	17.19	28.07	15,759.18	15.76

3.2 Carbon Plot Extraction and Regression Analysis

The carbon plots become one carbon layer in the GIS database in the point format, when the carbon table with known coordinates are imported into the GIS system. The NDVI values are represented as raster values. In order to create new layer that contains carbon data in the pixel of the raster, those two layers (points shape file and NDVI raster file) are overlaid and merged together as per the areas defined by the project. The output attribute table is inserted in the new extract layer containing coordinate points of the carbon plots, NDVI value and carbon details.

3.3 Selection of the Best Period for NDVI

Since there are many landsat-8 data available for NDVI classification, the study attempted to find the best NDVI that is suitable for carbon plots matching. All carbon plots gathered in the field were overlaid by points (3x3 km. systematic grid lay out) on corresponding NDVI raster value. The NDVI of different date are paired to a set of carbon plots of the same location to see the fit between the carbon plots and NDVI Value. Figure 5 reveals different scatter plots between carbon plots and NDVI raster value. The best fit is derived from January 16, 2017 and produced highest coefficient of determination.

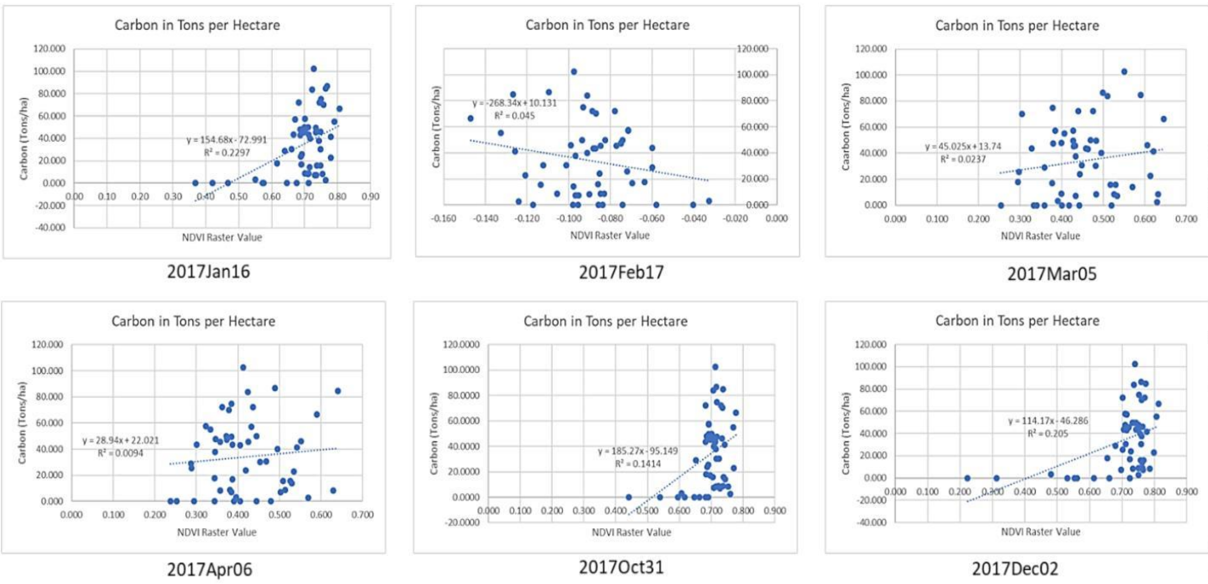

Figure 5 Scatter plots of six carbon regression equations of 2017 show the relationship between carbon and NDVI raster value.

PART IV: PREPARATION OF CARBON STOCK MAP

The regression equation was used for carbon calculation for the entire raster of the project area. The regression model that represented carbon amount that varied by NDVI raster value and was used to regenerate carbon in each pixel for entire site. A total of about 4,300,000,000 pixels of carbon are reclassified into 6 classes and illustrated as carbon stock map. The attribute table of the carbon layer was exported to dBase file for further editing.

4.1 Carbon Calculation by Pixel and Reclassify into Classes

The coordinate points of the carbon plots, NDVI value and carbon details store in the database system are then export into database file (.dbf) and then the dbf file is converted to normal excel file for ease of regression calculation. The regression analysis aimed to find the relationship between carbon (in tons per hectare) and NDVI raster value, when carbon is dependent variable and NDVI raster value is the independent variable.

All of six periods of the year 2017 are processed as the same way. Iterated integration for the relationship between carbon and NDVI raster value produce 6 regression equations. The best fit for linear equation is in January 16,2017 with the highest coefficient of determination (R^2) of 0.2297 (Figure 6).

The suitable relationship between carbon value and NDVI value in form of regression modelling is in the form of simple linear approach. This linear form explains good relation between those two variables, although it provides a coefficient value of about 0.2297 which was slightly lower than the value derived from the polynomial equation (as shown in appendix figure 2). The preliminary test to determine the differences in carbon stock between the carbon stock map and the ground plot estimates indicated the minimal differences when using the simple linear regression. Thus, linear function is used for carbon calculation pixel by pixel when NDVI value are altered by raster calculator tools. This step produced numerous carbon pixels which represent the amount of carbon storage in each NDVI raster (pixel) value. The regression model in the form of linear equation is:

$$C = 154.68\ NDVI - 72.991$$

when R^2 = 0.2297
= Coefficient of Determination
C = Carbon Storage in tons per hectare
NDVI = Normalized Difference Vegetation Index Raster Value

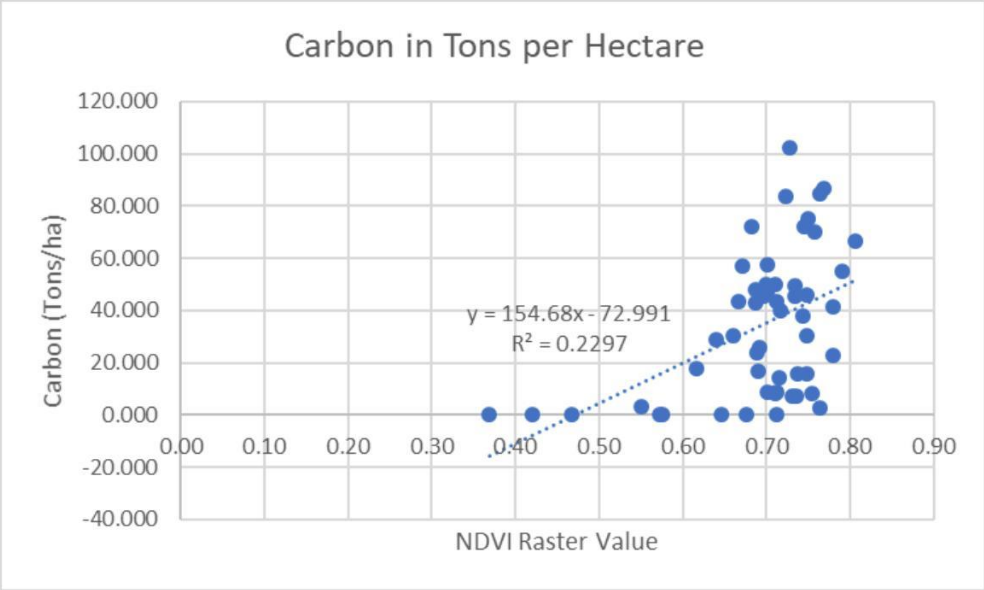

Figure 6 A linear regression model used for carbon simulation in the study area

4.2 Carbon Stock Map

All carbon raster pixels or grids are reclassified and reconstructed as the carbon coverage or stock map. The final output is reclassed carbon stock map which contains different carbon classes attach by the attribute table. The carbon classes separation is based on standard deviation of ± 1 SD and grouped into 6 carbon stock classes.

4.3 Area Calculation

This step is processed after NDVI reclassification when attribute table still not exist. Area calculation need reclassification of NDVI to build the attribute table which attach the number of pixel count in each class. Then add new field for area calculation (calculation of geometry). The area for each NDVI class was calculated by multiplying the number of pixel count by cell size 30x30 meters (x and y dimensions).

4.4 Result

The carbon stock map reveals 6 carbon classes and summary of carbon storage in each class and sum are illustrated in Table 4 and Figure 12. Amongst the NDVI reclassification, it depicts 2 outstanding classes which are NDVI class 5 and 4 covering the area of 190.0863 (41.536%) and 184.7862 (40.378%) square kilometers, while the rest of the classes 3,2,1 and 6 account for 46.7838 (10.223%), 21.1941 (4.631%), 14.4864 (3.165%) and 0.3006 (0.066%) square kilometers, respectively.

The amount of carbon ranked from largest to smallest are class 5, 4, 3, 2, 6 and 1, or 901,670.771419; 625,973.766835; 95,047.497910; 14,344.916091; 1,691.963458; and 0 tons of carbon, respectively.

In conclusion, the total carbon sink in the form of living standing trees (boles) in the Mae Huad sector, Ngao Demonstration Forest is estimated at 1,638,728.92 tons. The carbon coverage map with 6 carbon classes are show by Figure 8.

Table 3 Average carbon storage (tons) in 6 carbon classes from the 1st inventory

Carbon Class Range	Area (Sq.km)	Area (%)	Total Carbon (Tons)
Class 1 -183.906204 - -0.022538	14.4864	3.165	0
Class 2 -0.022538 - 13.536705	21.1941	4.631	14,344.916091
Class 3 13.536705 - 27.095947	46.7838	10.223	95,047.497910
Class 4 27.095947 - 40.655189	184.7862	40.378	625,973.766835
Class 5 40.655189 - 54.214431	190.0863	41.536	901,670.771419
Class 6 54.214431 - 58.357986	0.3006	0.066	1,691.963458
Total	457.6374	100.000	1,638,728.915713

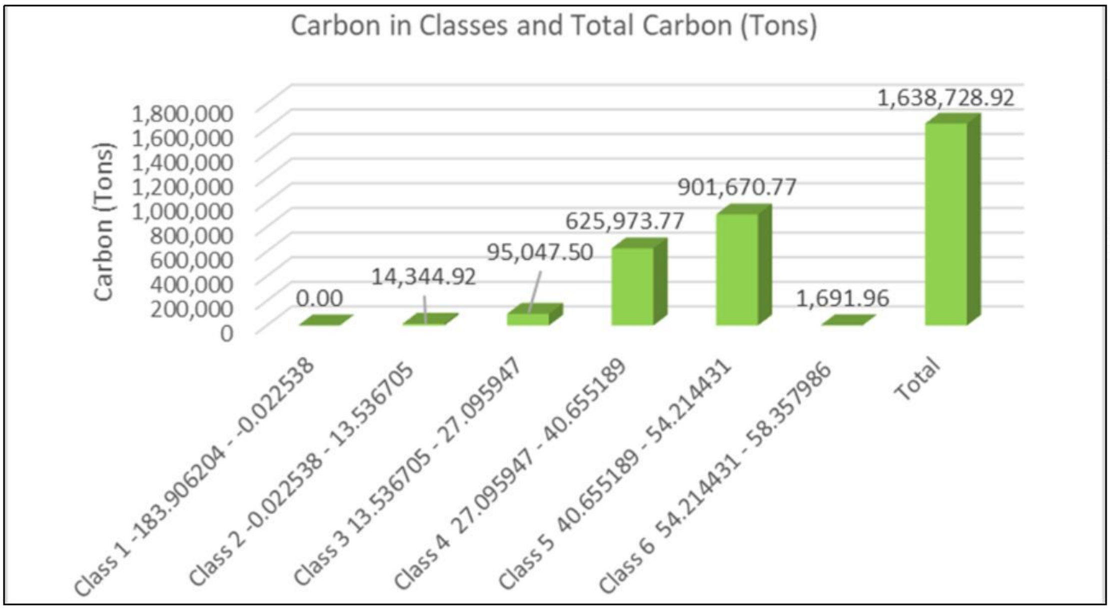

Figure 7 Average carbon storage (tons) in 6 carbon classes and the total carbon storage

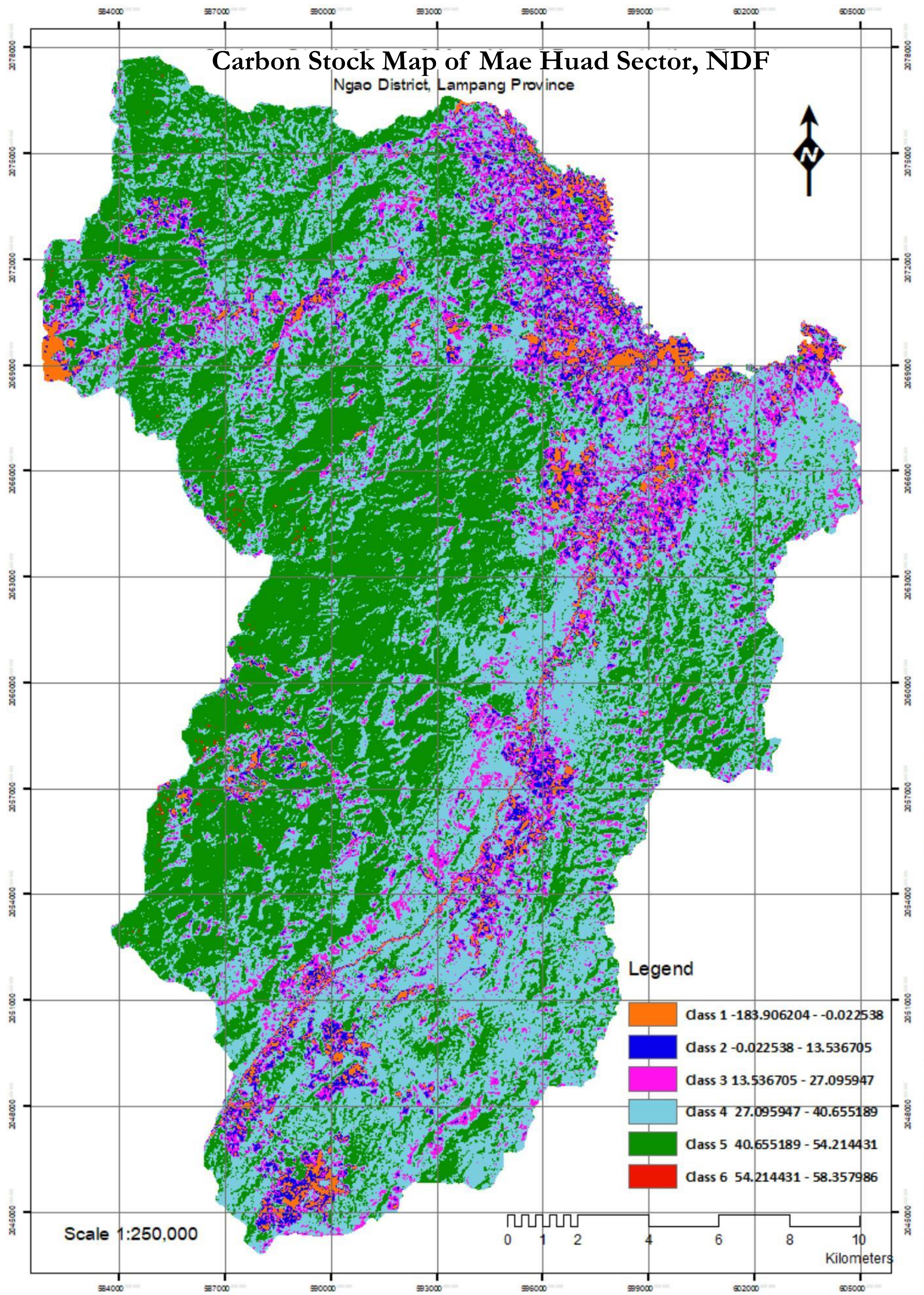

Figure 8 Carbon Stock Map of Mae Huad sector of Ngao Demonstration Forest, Ngao District, Lampang Province, generated from the 1st inventory.

PART V: DETERMINATION OF THE APPLICATION OF CARBON STOCK MAP

5.1 Testing Application of the Carbon Coverage Map

This step is aimed at carbon product comparison between carbon map generated by 1st inventory data and 2nd inventory data.

It also ensures the applicability of the carbon coverage map derived by integration of carbon plots and NDVI value. The second inventory for standing trees was conducted independently after the first inventory as follows.

1) New grid layout of 3x3 kilometers was used to locate new sampling points, a total of 45 sample points located in geographic system. Then the UTM coordinate points were exported into GPS for the field inventory.
2) The field inventory data collected were tree species, diameter at breast height and total height.
3) For each tree found in the variable sample plots, carbon content was calculated using the carbon equations formulated from the first inventory process.
4) The new output of carbon plots is tied with NDVI raster value (of 2017 January,16 Landsat-8 data)
5) Repeat the process of regression analysis; choosing the linear model for generating the new carbon pixels according to NDVI raster value.
6) Export the attribute table attached in the new carbon coverage map to summarize the carbon storage in classes (6 classes as well).

Comparison of carbon storage in the classes (6 classes) between the last and new carbon stock maps indicates different amounts among the classes. This occurs when different points of inventories are shifted to other locations, where the forest are not homogeneous.

The carbon storage gain from the 2nd carbon coverage estimation details are illustrated in Table 6 and Figure 15 & 16. Reclassification of carbon generation using 2nd inventory data reveals different classes value when compared to those in the first inventory. Then, this affects the carbon coverage area and carbon amount falling in each class. The grand total of carbon contained in the map is 1,714,496.879033 tons. However, the carbon grand total is quite close to the first inventory, with the first map estimated at 1,638,728.9157129 tons of carbon. The ratio of the two carbon totals is about 1.05.

Table 4 Average carbon storage (tons) in 6 carbon classes after 2nd inventory

Carbon Class Range	Area (Sq.km)	Area (%)	Total Carbon (Tons)
Class 1 -232.7130 - 17.189556	6.0363	1.319	5,188.065844
Class 2 17.189556 - 22.584798	5.4909	1.200	10,919.850293
Class 3 22.584798 - 27.980040	11.7315	2.563	29,660.070436
Class 4 27.980040 - 33.375282	26.1783	5.720	80,308.902605
Class 5 33.375282 - 38.770524	127.2411	27.803	458,995.592153
Class 6 38.770524 - 41.62280	280.9746	61.395	1,129,424.397702
Total	457.6527	100.000	1,714,496.879034

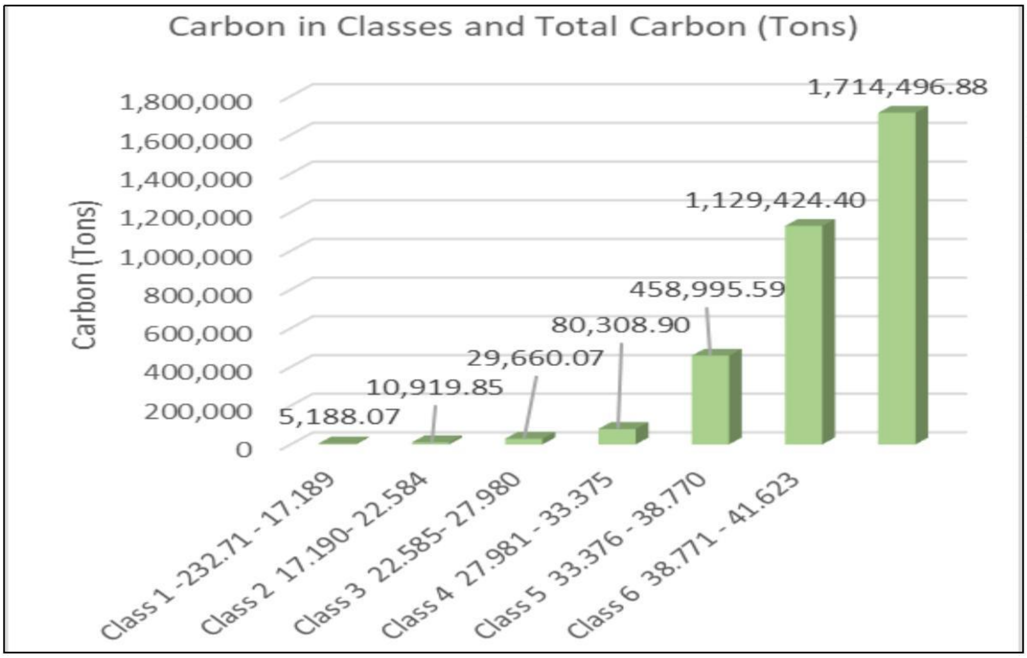

Figure 9 Average carbon storage (tons) in 6 carbon classes and the total after 2nd inventory

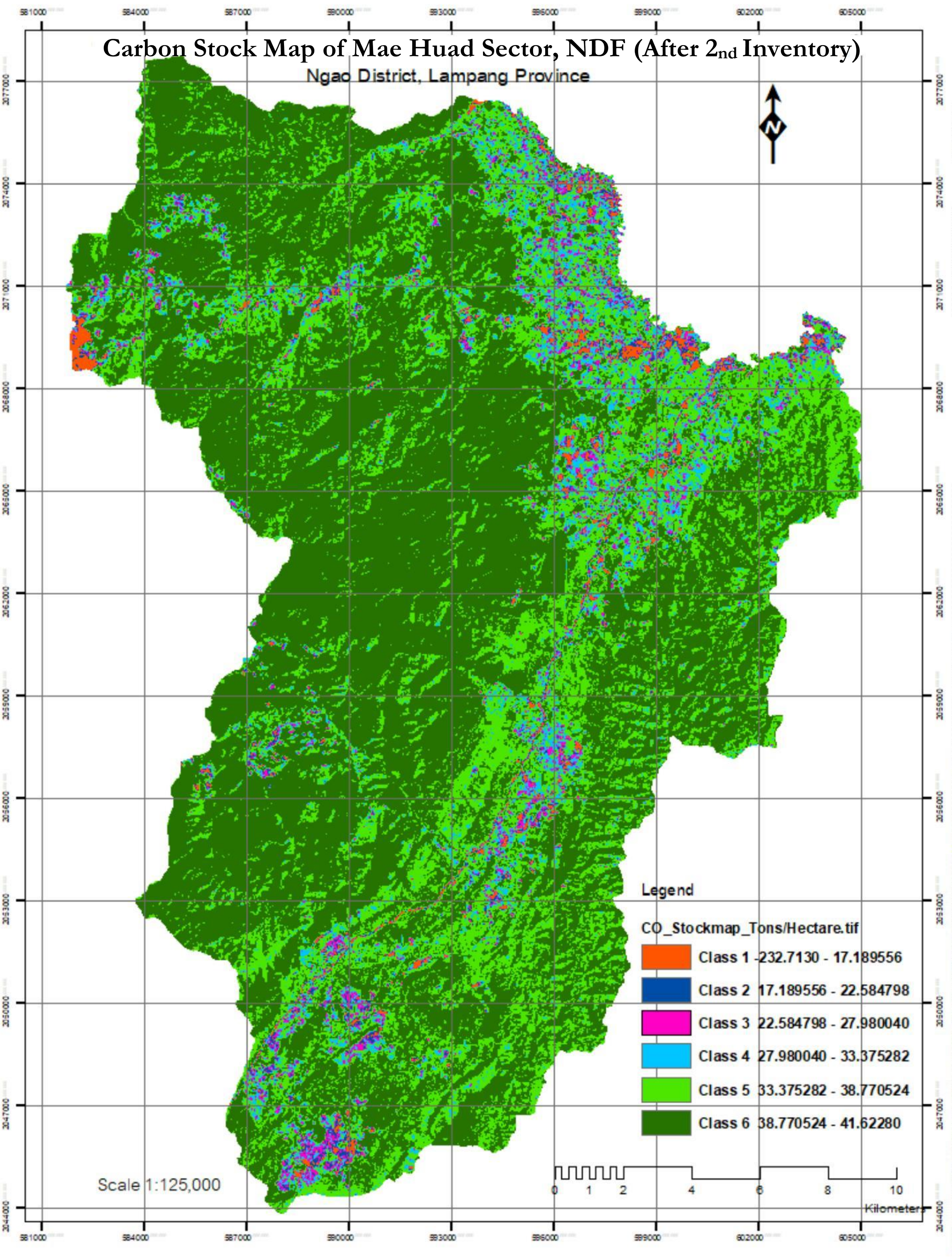

Figure 10 Carbon stock map of Mae Huad sector, Ngao Demonstration Forest, Lampang Province, generated from the 2nd inventory.

5.2 Determine the Differences in Carbon Stock between the Carbon Stock Map and the Ground Plot Estimates

The Data Analysts compared the new ground-based carbon estimate and those obtained from the carbon stock map at the same corresponding points. They conducted statistical tests to determine if the differences between the estimates are statistically significant, and the ratio between the mean ground estimates and the mean map carbon estimates.

The statistical analysis provided a satisfactory result, where the carbon mean extracted (read) from the carbon map was 34.339 tons/ha while the mean indicated by ground inventory was 36.976 tons/ha. The ratio between the mean map carbon estimates and mean ground estimates was equal 1.0768. Other descriptive statistics are depicted in Table 5.

Table 5 Descriptive statistics of carbon stock (tons/ha) between carbon map and independent ground-based estimate.

Map Carbon (tons/ha)		Independent Inventory Carbon (tons/ha)	
Mean	34.339	Mean	36.976
Standard Error	2.5584	Standard Error	2.9507
Minimum	-34.95	Minimum	0
Maximum	50.608	Maximum	72.928
Sample size (n)	45	Sample size (n)	45
Confidence Level (95.0%)	5.156	Confidence Level (95.0%)	5.9467

The new carbon sample plots are compared to the carbon displayed on the carbon stock map. The statistics applied for testing these differences are descriptive statistics, F-test, Student's t-test and the ratio between the mean ground estimates and the mean map carbon estimates. The variance between the two data sources is unequal, then statistical tests to determine any statistically significant differences by Student's t-test also assume to be unequal variance (Table 6).

Table 6 The t-test of the difference between carbon stock map and independent ground-based estimates

t-Test: Two-Sample Assuming Unequal Variances		
	Variable 1	**Variable 2**
Mean	36.98	34.34
Variance	391.787	294.535
Number of Observations	45	45
Hypothesized Mean Difference	0	
Df	88	
t Stat	0.675045325	
P(T<=t) one-tail	0.25072893	
t Critical one-tail	2.370493226	
P(T<=t) two-tail	0.50145786	
t Critical two-tail	2.634212309	

The t-value calculated is less than the t-value in the table at alpha=0.01, that is, it is considered that there are no statistically significant differences between the two estimates.

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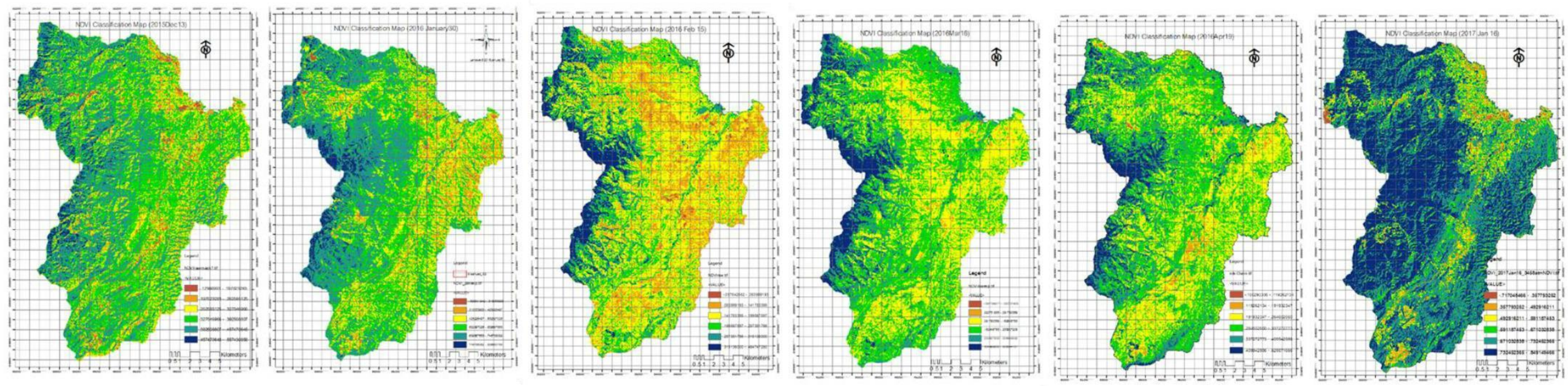
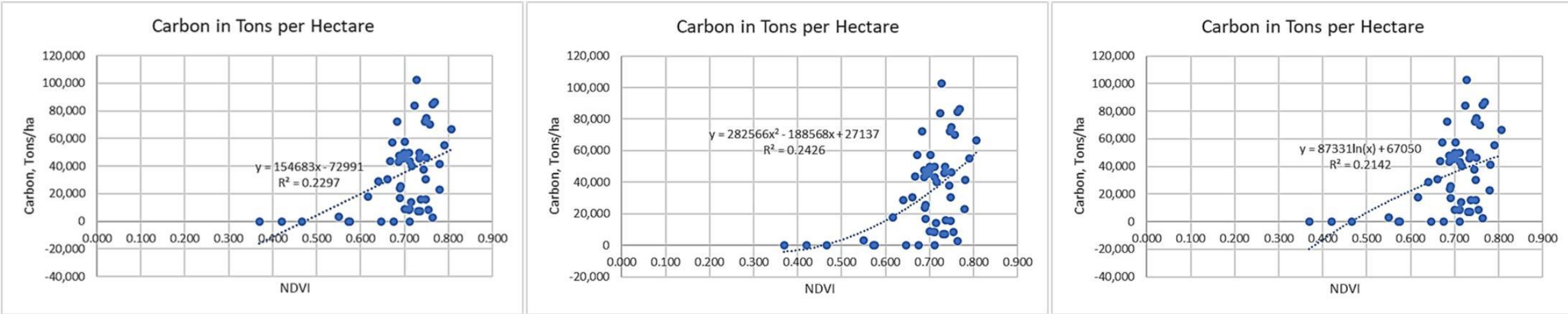
APPENDICES



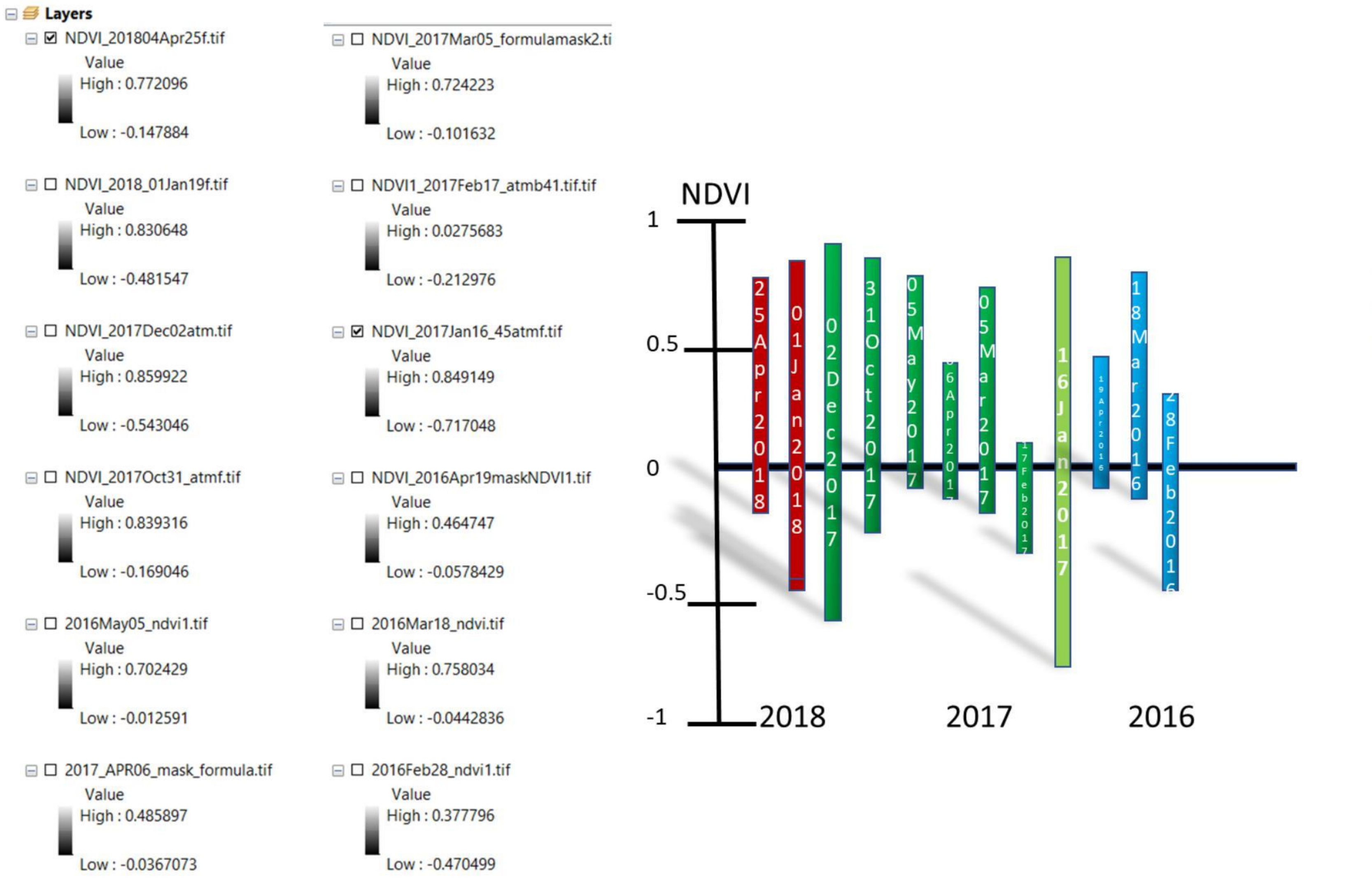
a) 13 December 2015 b) 30 January 2016 c) 15 February 2016 d) 18 March 2016 e) 19 April 2016 f) 16 January 2017

Appendix Figure 1 Annual seasonal change in NDVI of Ngao Demonstration Forest, Lampang Province derived from Landsat-8 LOI data which acquired during the late of 2015 to early 2017.



Simple Linear Equation | Polynomial Equation | Logarithmic Equation

Appendix Figure 2 Comparison for the best fit equation for predicting stand carbon stock in 2018.



Appendix Figure 3 Comparison of the NDVI ranges derived from Landsat-8 data.