

GEOINFORMATICS TECHNOLOGY INTEGRATION FOR OPTIMUM FOREST AND LAND COVER CLASSIFICATION AND ABOVE GROUND BIOMASS ESTIMATION

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Abstract

Image classification is a prerequisite for remote sensing applications, such as thematic mapping, environment monitoring, and forest management. The main objectives of the study were (1) to classify forest and land cover using the optimum classification and regression trees (CART) model and (2) to estimate the above ground biomass (AGB) of forest types and plantations with the optimum AGB estimation model. The research methodology consisted of 3 main components: (1) data collection and preparation, (2) the optimum CART model development for forest and land cover classification, and (3) the optimum AGB estimation model development. From the results, an optimum CART model was developed using 10 independent variables consisting of blue, red, near infra-red (NIR), shortwave infra-red (SWIR)-1, SWIR-2, simple ratio (SR), normalized difference water index (NDWI), wetness, elevation, and slope. The classified forest and land cover map provided strong agreement between the classified and the ground reference information with an overall accuracy of 91.18% and a kappa hat coefficient of 89.06%. Meanwhile, for the AGB estimation models, a simple linear model of dense dry evergreen forest (DDEF) with NIR provided a normalized root mean square error (NRMSE) of 0.2449 and coefficient of determination (R^2) of 0.94 while the exponential model of moderate dry evergreen forest (MDEF) with the forest canopy density (FCD) provided a NRMSE of 0.5097 and R^2 of 0.82. Likewise, the simple linear model of mixed deciduous forest (MDF) with a normalized difference vegetation index (NDVI) provided a NRMSE of 1.0835 and R^2 of 0.85, while the logarithm model of forest plantation (FPT) with the FCD provided a NRMSE of 0.8039 and (R^2) of 0.75. In conclusion, it can be concluded that geoinformatics technology, particularly remote sensing and GIS, can be efficiently used as tools to classify forest and land cover with a CART model and to estimate the AGB of forest type and plantation with simple linear and non-linear regression analysis.

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Introduction

Fundamentally, geoinformatics technology includes remote sensing, GIS, and GPS (Virtanta and Haggren, 2000; Meresa, 2015). The advent of geoinformatics has revolutionized natural resources assessment, monitoring, and development, besides considerably bringing down the time and cost (Kushwaha, 2008). Moreover, it is also applied to assess and monitor the biomass and carbon inventory of forests with remotely sensed data (Kushwaha, 2008; Poulain *et al.*, 2012).

Meanwhile, land use and land cover (LULC) data is a basic GIS dataset required by various users, e.g. land and resources managers, city planners, or decision-makers. Weih and Riggan (2010) stated that LULC data have proven to be valuable assets for resource managers interested in landscape characteristics and the changes that occur over time. Li *et al.* (2009) claimed that remote sensing image classification is generally required for various applications such as thematic mapping, forest management, and environment monitoring.

In recent years, research and applications utilizing the classification and regression trees (CART) method have increased and successfully been applied in image processing (Lawrence and Wright, 2001; Herold *et al.*, 2003). The CART was first introduced by Breiman and colleagues in 1984 (Gordon, 2013) and it uses historical data to construct decision trees depending on the available information about the dataset (Timofeev, 2004). Moreover, CART is a simple powerful analytic tool that helps determine the most important variables in a particular dataset, and it can help researchers craft a potent explanatory model (Morgan, 2014). The CART method had been applied to classify remote sensed imagery by many researchers (Lawrence *et al.*, 2001; Bittencourt and Clarke, 2003; Htun *et al.*, 2011; Gómez *et al.*, 2012; Qian *et al.*, 2015; Chaudhary *et al.*, 2016).

With regard to the global carbon cycle, forests play an important role in global carbon cycling, as they are large pools of carbon as

well as potential carbon sinks and sources to the atmosphere (Muukkonen and Heiskanen, 2007). The estimation of biomass is increasingly important in the context of using forests to mitigate global climate change through emerging mechanisms such as reducing emissions from deforestation and forest degradation (REDD) of the United Nations Framework Convention on Climate Change (UNFCCC, 2008). There is already growing interest in addressing biomass estimation and the potential for carbon sequestration (Walker *et al.*, 2008; Bombelli *et al.*, 2009; Epron *et al.*, 2009), as well as in implementation of the Kyoto Protocol of the Climate Change Convention through its clean development mechanism projects. Labrecque *et al.* (2006) stated that 2 main approaches for mapping forest biomass include radiometric modeling and linking a conversion table to a thematic classification of the image. They claimed that radiometric methods have been widely used, and entail regression analysis to link spectral values to measured or estimated biomass at corresponding locations.

This study aims to develop a new approach using geoinformatics technology for classifying forest and land cover and estimating the above ground biomass (AGB) of natural forest and plantation. The specific objectives of the study were (1) to classify forest and land cover using the optimum CART model, and (2) to estimate the AGB of forest type and plantation with the optimum AGB estimation model.

Materials and Methods

Study Area

Lam Phra Phloeng sub-watershed, which covers Khoa Phu Luang National Reserved Forest at Takhob sub-district of Pakthongchai district, Nakhon Ratchasima province, was selected as the study area (Figure 1). It consists of a natural forest area more than 50% of

which has varieties of land cover types. Additionally, it is also situated in the Pha Khoa Phu Luang Non-hunting area. The total study area is 135.99 sq.km.

Research Methodology

The research methodology consisted of 3 components: (1) data collection and preparation, (2) the optimum CART model development for forest and land cover classification, and (3) the optimum AGB estimation model development (Figure 2).

Component 1: Data collection and preparation

Basic remotely sensed data and the digital elevation model (DEM) were collected and prepared for analysis and modeling. Herein, the 16 bit integer values of Landsat 8 OLI and TIR data in 2015 were firstly downloaded from the USGS website (<https://earthexplorer.usgs.gov>) and converted to top of atmosphere (TOA) spectral reflectance (USGS, 2016) as:

$$\rho\lambda' = M_{\rho} * Q_{cal} + A_{\rho} \quad (1)$$

where, $\rho\lambda'$ is the TOA spectral reflectance without correction for the solar angle (unitless), M_{ρ} is the reflectance multiplicative scaling factor for the band from the metadata file, Q_{cal} is the quantized and calibrated standard product digital numbers (DNs), and A_{ρ} is the reflectance additive scaling factor for the band from the metadata file.

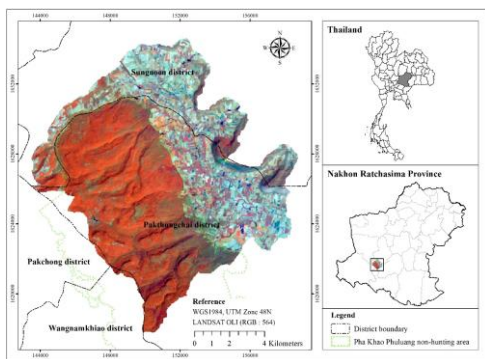


Figure 1. Location with Landsat 8 OLI data of the study area

Then, the derived $\rho\lambda'$ was corrected for the effect of the solar elevation angle (USGS, 2016) as:

$$\rho\lambda = \frac{\rho\lambda'}{\sin(\theta_{SE})} \quad (2)$$

where, $\rho\lambda$ is the TOA spectral reflectance and θ_{SE} is the local sun elevation angle (degree) from the metadata file.

After that, the corrected TOA spectral reflectance data were further used to calculate the vegetation indices species richness (SR, NDVI, NDWI, SAVI, TVI, RSR, and Kauth-Thomas Tasseled Cap Transformation (B, G, and W)) as biological factors on forest and land cover distribution (Table 1). Meanwhile, physical factors that dictate forest distribution (Kutintara, 1999) including elevation, slope, and aspect were extracted from the DEM of the Land Development Department. Figure 3 displays

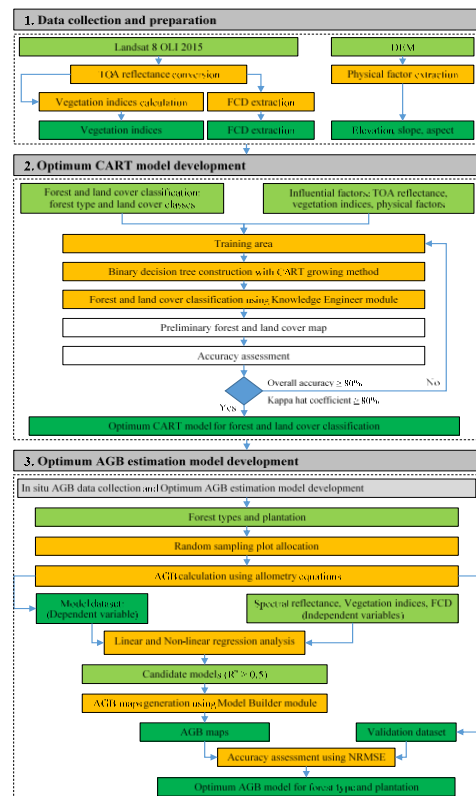


Figure 2. Research methodology component and its workflow

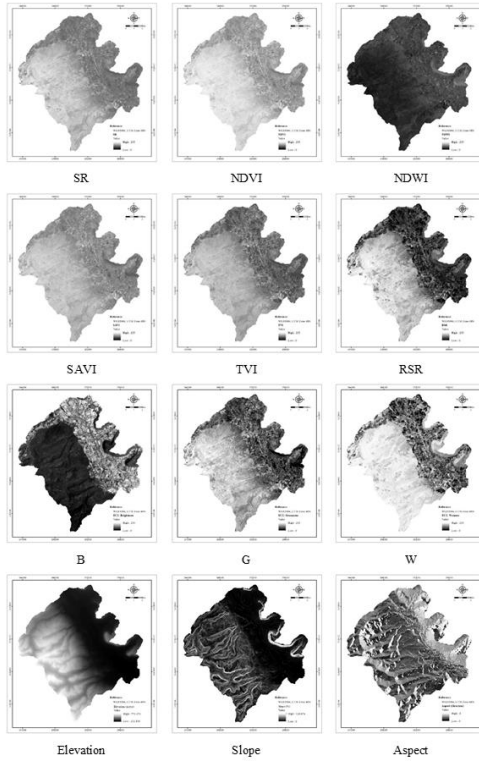


Figure 3. The derived bio-physical factors on forest and land cover distribution

the derived bio-physical factors on forest and land cover distribution.

In addition, forest canopy density (FCD) was prepared for an optimum AGB estimation model development using relevance equations (Rikimaru *et al.*, 2002) including advanced vegetation index (AVI), bare soil index (BI), shadow index (SI), thermal index (TI), vegetation density (VD), and scaled shadow index (SSI) as follows:

For the AVI calculation,

$$\text{if } \rho_{nir} - \rho_{red} < 0, \text{ then } AVI = 0 \quad (3)$$

$$\text{if } \rho_{nir} - \rho_{red} > 0, \text{ then } AVI = \sqrt[3]{(\rho_{nir} + 1) * (256 - \rho_{red}) * (\rho_{nir} - \rho_{red})} \quad (4)$$

$$BI = \frac{(\rho_{swir-1} + \rho_{red}) - (\rho_{nir} + \rho_{blue})}{(\rho_{swir-1} + \rho_{red}) + (\rho_{nir} + \rho_{blue})} * 100 + 100 \quad (5)$$

$$SI = \sqrt[3]{(256 + \rho_{blue}) * (256 - \rho_{green}) * (256 - \rho_{red})} \quad (6)$$

$$TI = \frac{K_2}{\ln\left(\frac{K_1 + 1}{L_\lambda}\right)} \quad (7)$$

where, ρ_{blue} is the blue reflectance value, ρ_{green} is the green reflectance value, ρ_{red} is the red reflectance value, ρ_{nir} is the NIR reflectance value, ρ_{swir-1} is the SWIR-1 reflectance value, λ is the TOA spectral radiance (watts/m² srad

Table 1. Equations of spectral indices

Spectral index	Equation	Reference	Note
Simple Ratio (SR)	$SR = \frac{\rho_{red}}{\rho_{nir}}$	Birth and McVey, 1968;	ρ_{red} is red
Normalized Differential Vegetation Index (NDVI)	$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}$	Colombo <i>et al.</i> , 2003	reflectance value,
Normalized Difference Water Index (NDWI)	$NDWI = \frac{\rho_{green} - \rho_{nir}}{\rho_{green} + \rho_{nir}}$	Rouse <i>et al.</i> , 1974;	ρ_{nir} is NIR
Soil Adjusted Vegetation Index (SAVI)	$SAVI = \frac{(\rho_{nir} - \rho_{red})}{\rho_{nir} + \rho_{red} + L} (1 + L)$	Deering <i>et al.</i> , 1975	reflectance value,
Triangular Vegetation Index (TVI)	$TVI = 0.5 (120(\rho_{nir} - \rho_{green})) - 200(\rho_{red} - \rho_{green})$	McFeeters, 1996; Gao, 1996	ρ_{green} is green reflectance value,
Reduced Simple Ratio (RSR)	$RSR = \frac{\rho_{nir}}{\rho_{red}} \left(1 - \frac{(\rho_{swir} - \rho_{swirmin})}{(\rho_{swirmax} - \rho_{swirmin})} \right)$	Huete, 1988; Huete and Liu, 1994	L is a canopy background adjustment factor (default is 0.5),
Kauth-Thomas Tasseled Cap Transformation	$B \text{ (Brightness)} = 0.2909\rho_{blue} + 0.2493\rho_{green} + 0.4806\rho_{red} + 0.5568\rho_{nir} + 0.4438\rho_{swir-1} + 0.1706\rho_{swir-2}$	Broge and Leblanc, 2000	ρ_{swir} is SWNIR reflectance value.
	$G \text{ (Greenness)} = 0.2728\rho_{blue} - 0.2174\rho_{green} - 0.5508\rho_{red} + 0.7221\rho_{nir} + 0.0733\rho_{swir-1} - 0.1648\rho_{swir-2}$	Chen <i>et al.</i> , 2002	
	$W \text{ (Wetness)} = 0.1446\rho_{blue} + 0.1761\rho_{green} + 0.3322\rho_{red} + 0.3396\rho_{nir} - 0.6210\rho_{swir-1} - 0.4186\rho_{swir-2}$	Crist and Kauth, 1986; Lunetta <i>et al.</i> , 2002	

μm), and K_1 and K_2 are band specific thermal conversions from the metadata file. For band 10 of Landsat 8 TIR, K_1 is 774.89 and K_2 is 1321.08. Herein, the DN data of thermal band 10 was converted to the TOA spectral radiance with the radiance scaling factors (USGS, 2016) as:

$$L_\lambda = M_L Q_{cal} + A_L \quad (8)$$

where, L_λ is the TOA spectral radiance ($\text{watts/m}^2 \text{srad } \mu\text{m}$), M_L is the band specific multiplicative rescaling factor from the metadata, A_L is the band specific additive rescaling factor from the metadata, and Q_{cal} is the quantized and calibrated standard product DNs.

After that, the derived vegetation index (VI) and BI data were stacked and transformed using principal component analysis (PCA) for extracting the VD with a value between 0 and 100. Meanwhile the derived SI data was linearly transformed for extracting SSI with a value between 0 and 100. Finally, the FCD was extracted using the following Equation:

$$FCD = \sqrt{VD * SSI + 1} - 1 \quad (9)$$

Figure 4 displays the derivative products for the FCD extraction.

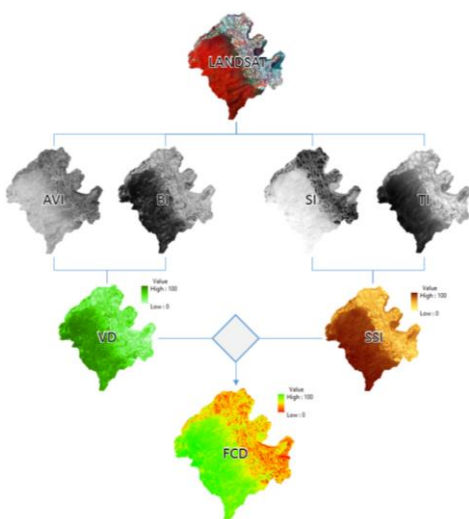


Figure 4. The derivative products for FCD extraction

Component 2: Optimum CART model development for forest and land cover classification

The selected influential factors on forest and land cover distribution as independent variables, which include the derived spectral reflectance data (blue, green, red, NIR, SWIR-1, and SWIR-2 bands) of Landsat 8 OLI, spectral indices (SR, NDVI, NDWI, SAVI, TVI, RSR, B, G, and W) and physical data (elevation, slope, and aspect), were firstly extracted for each forest and land cover type as dependent variables from the training areas (Figure 5) to construct a binary decision tree with the CART growing method under SPSS statistics software. Then, the derived decision tree was migrated to the

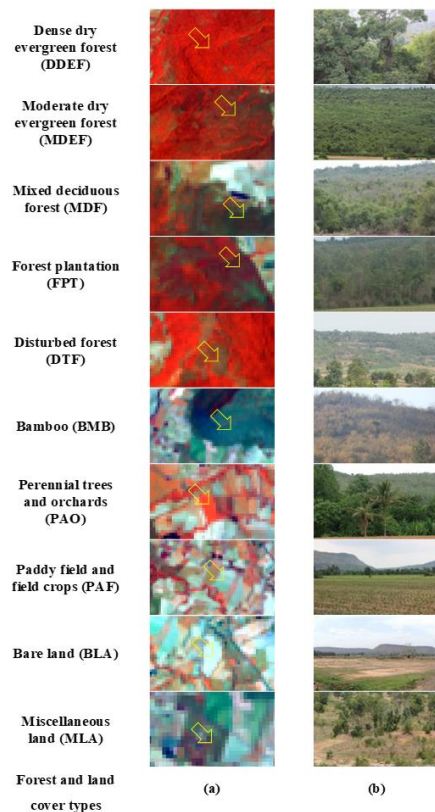


Figure 5. Training area of each forest and land cover for constructing decision tree structure: (a) Color composite image of Landsat 8 OLI (SWIR-1, NIR, Red: RGB), and (b) ground photographs

Knowledge Engineer module of ERDAS Imagine software for forest and land cover classification. In this study, the forest and land cover classification system consisted of (1) dense dry evergreen forest (DDEF), (2) moderate dry evergreen forest (MDEF), (3) mixed deciduous forest (MDF), (4) forest plantation (FPT), (5) disturbed forest (DTF), (6) bamboo (BMB), (7) perennial trees and orchards (PAO), (8) paddy field and field crops (PAF), (9) bare land (BLA), and (10) miscellaneous land (MLA) including scrub and grass. The classified forest and land cover map was further used to assess its accuracy using the overall accuracy and kappa hat coefficient to identify an optimum CART model. If both accuracy values were equal or greater than 80 percent, the derived decision tree was chosen as the optimum model for forest and land cover classification, or else the process was reiteration until achievement of the threshold values.

For accuracy assessment, the number of sample sizes were derived based on binomial distribution (Fitzpatrick-Lins, 1981) with an expected accuracy of 85% at the allowable error of 5%, and the stratified random sampling technique was selected for observing the points allocation. In this study, 204 sampling points were applied in field survey for accuracy assessment in 2016.

Component 3: Optimum AGB estimation model development

Two major tasks included in situ AGB data collection and optimum AGB estimation model development that were integrated under this component.

In Situ AGB Data Collection

A square plot with a size of 20×20 m, which was allocated using the random sampling technique, was used to measure trees data in each stratum of forest type and plantation. Herein, 8 plots were applied for each stratum. At the plot level, all trees with a size more than 4.5 cm were identified by scientific name and measured for the diameter at breast height (cm) and total height (m) for the AGB calculation. In addition, the plant profile which represents the horizontal and vertical

structure of the forest type and plantation was collected with a size of 10×50 m.

The AGB of each forest type and plantation was here calculated using the existing allometry equations as follows:

$$(1) \text{ Dry evergreen forest (Tsutsumi et al., 1983)} \\ \text{Stem } (W_s) = 0.0509(D^2H)^{0.919} \quad (10)$$

$$\text{Branch } (W_B) = 0.00893(D^2H)^{0.997} \quad (11)$$

$$\text{Leaf } (W_L) = 0.0140(D^2H)^{0.669} \quad (12)$$

$$(2) \text{ Mixed deciduous forest (Ogawa et al., 1965)} \\ \text{Stem } (W_s) = 0.0396(D^2H)^{0.9326} \quad (13)$$

$$\text{Branch } (W_B) = 0.003487(D^2H)^{1.027} \quad (14)$$

$$\text{Leaf } (W_L) = ((28.0/W_s) + W_B + 0.25) - 1 \quad (15)$$

$$(3) \text{ Eucalyptus camaldulensis Dehnh. plantation} \\ \text{(Viriyabuncha et al., 2005)}$$

$$\text{Stem } (W_s) = 0.0215(D^2H)^{0.9900} \quad (16)$$

$$\text{Branch } (W_B) = 0.0011(D^2H)^{1.1472} \quad (17)$$

$$\text{Leaf } (W_L) = 0.0197(D^2H)^{0.6867} \quad (18)$$

where, D is the diameter at breast height (cm) and H is the total height of the tree (m). Later on, the calculated AGB data of the sampling plot size were further converted to be a pixel size 30×30 m for the optimum AGB estimation model development.

After that, the in situ AGB data were randomly divided into 2 datasets: one set for modeling and another set for validating with a ratio of 75:25 percent. The modeling dataset was here used to develop the AGB estimation model while the validation dataset was used to assess the accuracy for identifying an optimum model for AGB estimation.

Optimum AGB Estimation Model Development

Simple linear and non-linear (logarithmic, power, S curve, and exponential model) regression analysis were here applied to identify the relationship between the AGB of natural forest and plantation as dependent variables and the spectral reflectance values of the blue, green, red, NIR, SWIR-1, and SWIR-2 bands, the

spectral indices (SR, NDVI, NDWI, SAVI, TVI, RSR, B, G, and W), and the FCD as independent variables using the SPSS statistics software. Then, all derived linear or non-linear equations that provided the coefficient of determination (R^2) value equal or greater than

0.5 as candidate models were used to generate AGB maps using the Model Builder module of ERDAS Imagine software. Then all derived AGB maps from the candidate linear and non-linear models were assessed for accuracy using the normalized root mean square error (NRMSE) (Equation 19) with validation dataset. The best candidate linear and non-linear equation of natural forest and plantation which provided the lowest NRMSE and/or highest R^2 was finally chosen as an optimum AGB estimation model for assessing the AGB in the study area.

$$NRMSE = \frac{RMSE}{\text{Maximum observed value} - \text{Minimum observed value}} \quad (19)$$

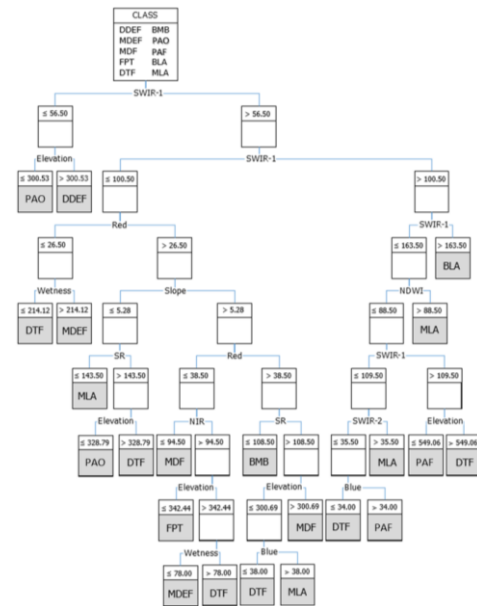
$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n [\text{Estimated value} - \text{Observed value}]^2} \quad (20)$$

where n is the number of observations (plots) and RMSE is the root mean square error.

Result and Discussion

Optimum CART Model for Forest and Land Cover Classification

An optimum CART model for forest and land cover classification applies 10 independent variables including blue, red, NIR, SWIR-1, SWIR-2, SR, NDWI, W, elevation, and slope to construct a decision tree



Note: DDEF: dense dry evergreen forest; MDEF: moderate dry evergreen forest; MDF: mixed deciduous forest; FPT: forest plantation; DTF: disturbed forest; BMB: bamboo; PAO: perennial trees and orchards; PAF: paddy field and field crops; BLA: bare land; and MLA: miscellaneous land.

Figure 6. Decision tree structure for forest and land cover classification

Table 2. Accuracy assessment of decision tree classification based on training areas

Independent variable observed	Independent variable classification										Percent Correct
	DDEF	MDEF	MDF	FPT	DTF	BMB	PAO	PAF	BLA	MLA	
DDEF	423	2	0	3	0	0	0	0	0	0	98.80
MDEF	3	360	0	0	2	0	0	0	0	0	98.60
MDF	0	5	168	1	1	0	0	0	0	2	94.90
FPT	0	2	1	116	0	0	5	0	0	1	92.80
DTF	0	4	2	2	82	0	0	0	0	1	90.10
BMB	0	0	0	0	0	54	0	0	0	0	100.00
PAO	0	3	0	1	0	0	91	4	0	0	91.90
PAF	0	0	0	0	0	0	3	561	0	3	98.90
BLA	0	0	0	0	0	0	0	7	201	0	96.60
MLA	0	0	0	0	0	0	1	15	2	132	88.00
Overall Percentage	18.80	16.60	7.60	5.40	3.80	2.40	4.40	25.90	9.00	6.10	96.60

Note: DDEF: dense dry evergreen forest; MDEF: moderate dry evergreen forest; MDF: mixed deciduous forest; FPT: forest plantation; DTF: disturbed forest; BMB: bamboo; PAO: perennial trees and orchards; PAF: paddy field and field crops; BLA: bare land; and MLA: miscellaneous land.

(Figure 6). The binary decision tree structure consists of 42 nodes that include 22 terminal nodes with labelled forest and land cover classes by a sequence of decisions rule and its condition. The constructed decision tree can provide an overall accuracy of model-based inference statistic at 96.60% (Table 2). In theory, the model-based inference statistic is not concerned with the accuracy of the thematic map but it regards estimating the error of model that applies to generate the thematic map, and it can provide a quantitative assessment of each classification decision to users (Stehman, 2000; Stehman, 2001).

At the same time, thematic accuracy assessment of classified forest and land cover by a field survey in 2016 revealed that the overall accuracy is 91.18% and the kappa hat coefficient is 89.06%. Herewith, producer's accuracy (PA), which represents omission error, varies between 77.78% for the MDF and 100.00% for the DTF and BMB. Likewise, user's accuracy (UA) which represents commission error, varies between 80.00% for the PAO and 100.00% for the FPT, DTF, and BMB (Table 3). Based on Fitzpatrick-Lins (1981), the kappa hat coefficient of more than 80% represents strong agreement or accuracy between the classified map and the reference map.

As a result, the derived accuracy assessment of the CART model in this study is

similar with the previous work of Lawrence and Wright (2001), who applied CART for LULC classification with an overall accuracy of 96% and a kappa hat coefficient of 92%. Likewise, Ghose *et al.* (2010) who applied CART for forest and land cover classification with an overall accuracy of 98% and a kappa hat coefficient of 97%.

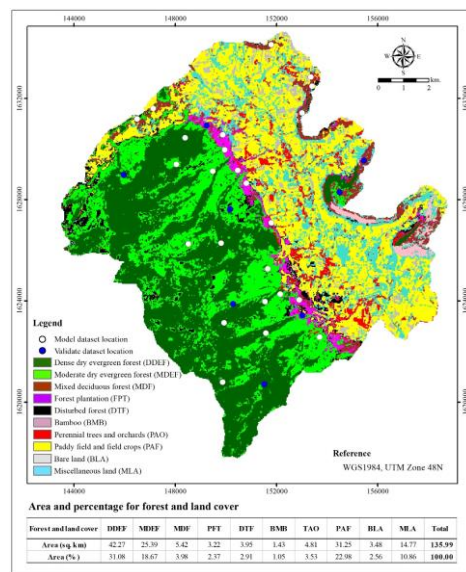


Figure 7. Distribution of forest and land cover classification

Table 3. Error matrix and accuracy assessment of forest and land cover classification map

Classified forest and land cover	Ground truth data										Total	UA (%)
	DDEF	MDEF	MDF	FPT	DTF	BMB	PAO	PAF	BLA	MLA		
DDEF	57	5	0	0	0	0	0	0	0	0	62	91.94
MDEF	0	37	1	0	0	0	1	0	0	0	39	94.87
MDF	0	0	7	1	0	0	0	0	0	0	8	87.50
FPT	0	0	0	5	0	0	0	0	0	0	5	100.00
DTF	0	0	0	0	6	0	0	0	0	0	6	100.00
BMB	0	0	0	0	0	3	0	0	0	0	3	100.00
PAO	0	0	0	0	0	0	6	1	0	0	7	80.00
PAF	0	0	0	0	0	0	1	42	1	3	47	86.36
BLA	0	0	0	0	0	0	0	1	4	0	5	85.71
MLA	0	0	1	0	0	0	0	2	0	19	22	89.36
Total	57	42	9	6	6	3	8	46	5	22	204	
PA (%)	100.00	88.10	77.78	83.33	100.00	100.00	75.00	91.30	80.00	86.36		
Overall accuracy (%)	91.18											
Kappa hat coefficient (%)	89.06											

Note: DDEF: dense dry evergreen forest; MDEF: moderate dry evergreen forest; MDF: mixed deciduous forest; FPT: forest plantation; DTF: disturbed forest; BMB: bamboo; PAO: perennial trees and orchards; PAF: paddy field and field crops; BLA: bare land; and MLA: miscellaneous land.

Distribution of the final forest and land cover classification is displayed in Figure 7. It revealed that the most dominant forest cover class is DDEF which is mostly situated in the non-hunting area, and covers an area of 42.27 sq.km or about 31% of the total area. Meanwhile the most dominant agricultural utilization is PAF which covers an area of 31.25 sq.km or about 23% of the total area.

In Situ AGB Data

The AGB data of each forest type and plantation as dependent variables of the linear and non-linear regression analysis for the optimum AGB estimation model development are summarized in Table 4. It was found that an average AGB of the DDEF and MDEF from the sampling plots (20×20 m) are 5230.92 and 4690.46 kg/plot, respectively while the MDF

and FPT are 3176.31 and 2740.78 kg/plot, respectively.

From the results, the average AGB data of the DDEF and MDEF in the study area are similar with the previous study of Terakunpisut *et al.* (2007) who found that the average AGB data of DEF at Thong Pha Phum National Park, Kanchanaburi province was about 5623 kg/plot. In contrast, they are rather low when they are compared with the previous study of Diloksumpun *et al.* (2005) who found that the average AGB data of DEF at Sakaerat Environmental Research Station, Nakhon Ratchasima province was about 12172 kg/plot. Meanwhile, Kantirach (2002) found that the AGB of DEF at Huai Tuptun- Huai Samran Wildlife Sanctuary, Surin province was about 10700 kg/plot and Nuanurai (2005) found that the AGB of DEF at Kaeng Krachan National

Table 4. In situ AGB data of natural forest and plantation

Plot No.	Natural forest and forest plantation	Above ground biomass (kg)	
		At sample plot (20×20 m)	At pixel size (30×30m)
1*	Dense dry evergreen forest	6016.29	13536.66
2	Dense dry evergreen forest	4956.92	11153.08
3	Dense dry evergreen forest	5555.26	12499.34
4	Dense dry evergreen forest	4498.52	10121.67
5	Dense dry evergreen forest	4455.58	10025.05
6	Dense dry evergreen forest	6066.11	13648.75
7	Dense dry evergreen forest	5280.60	11881.35
8*	Dense dry evergreen forest	5018.11	11290.74
1*	Moderate dry evergreen forest	4967.38	11176.61
2	Moderate dry evergreen forest	4717.76	10614.95
3	Moderate dry evergreen forest	4806.77	10815.24
4	Moderate dry evergreen forest	4556.24	10251.55
5	Moderate dry evergreen forest	4676.27	10521.60
6	Moderate dry evergreen forest	4546.43	10229.46
7	Moderate dry evergreen forest	5555.31	12499.44
8*	Moderate dry evergreen forest	3697.52	8319.42
1*	Mixed deciduous forest	3065.59	6897.58
2	Mixed deciduous forest	2993.98	6736.45
3	Mixed deciduous forest	2574.90	5793.51
4	Mixed deciduous forest	3560.20	8010.46
5	Mixed deciduous forest	2694.90	6063.51
6	Mixed deciduous forest	3883.78	8738.50
7	Mixed deciduous forest	3099.30	6973.43
8*	Mixed deciduous forest	3537.79	7960.03
1*	Forest plantation	2717.33	6114.00
2	Forest plantation	2359.32	5308.48
3	Forest plantation	2756.29	6201.66
4	Forest plantation	2107.30	4741.41
5	Forest plantation	2683.17	6037.14
6	Forest plantation	3429.04	7715.34
7	Forest plantation	2827.63	6362.17
8*	Forest plantation*	3046.15	6853.84

Note: * Sample plots that are applied for model validation using NRMSE.

Park, Petchaburi province was about 8308 kg/plot. Likewise, the calculated average AGB data of the MDF in this study is similar to the previous study of Terakunpisut (2007) who found the average AGB data of MDF was about 3851 kg/plot. In contrast, it is higher than the previous study of Nuanurai (2005) who found the average AGB data of MDF was about 2741 kg/plot. On the contrary, it is rather low when it is compared with the previous study of Kantirach (2002) who found the average AGB of MDF was about 7486 kg/plot. Likewise, the calculated average AGB data of a *Eucalyptus camaldulensis* plantation in the study is lower than the previous study of Trephattanasuwan *et al.* (2010) who found that the AGB of a *Eucalyptus* plantation at Pu Parn Royal Development Study Centre, Sakon Nakhon province was about 3289 kg/plot.

These findings suggest that the AGB of natural forest and plantation varies from place to place due to a variety of bio-physical factors on natural forest and plantation. In addition, the category of forest conservation areas (national park, wildlife sanctuary, and national reserved forest) and their functions also play an important role on the quality and quantity of natural forest and plantation.

The plant profile of natural forest and plantation (DDEF, MDEF, MDF, and FPT) is displayed in Figure 8. From the results, the dominant species of DDEF are *Hopea odorata* Roxb., *Dipterocarpus tuberculatus* Roxb., and *Walsura trichostemon* Miq., while *Hopea odorata* Roxb., *Walsura trichostemon* Miq., and *Atalantia monophylla* (DC.) Correa are the dominant species of MDEF. For the MDF, the dominant species are *Indora siamensis* Teijsm.

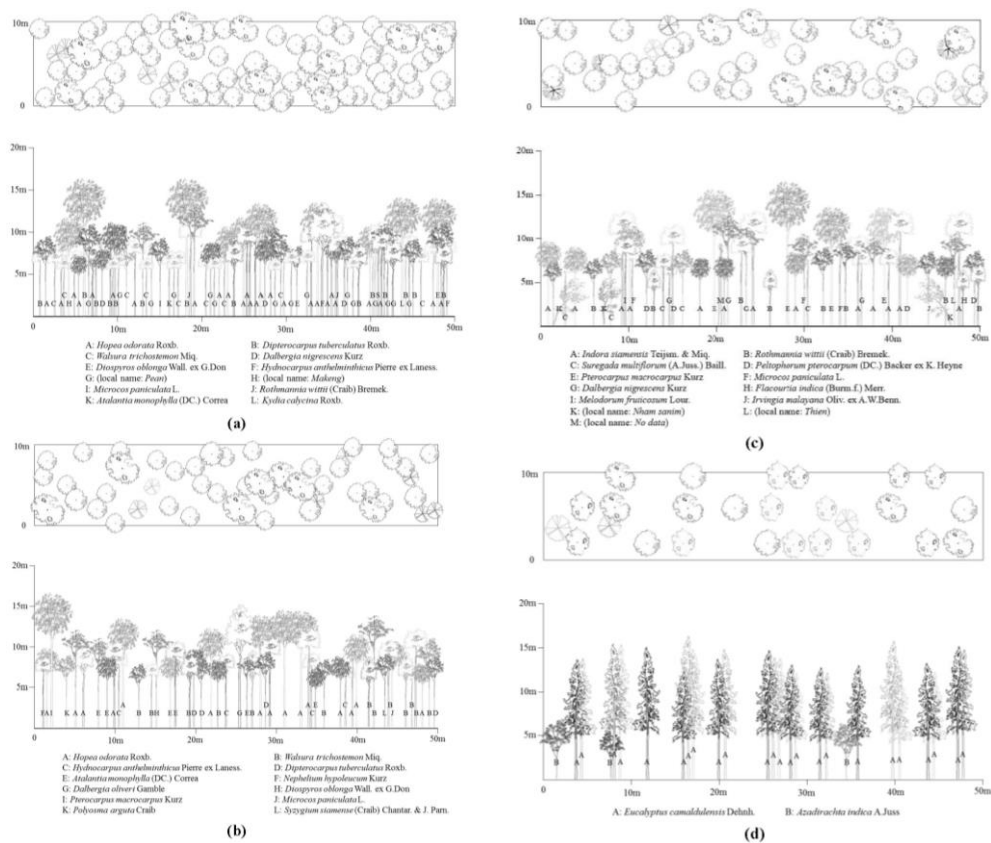


Figure 8. Plant profile: (a) Dense dry evergreen forest, (b) Moderate dry evergreen forest, (c) Mixed deciduous forest, and (d) Forest plantation

& Miq., *Rothmannia wittii* (Craib) Bremek., and *Suregada multiflorum* (A. Jus.) Baill. Meanwhile, the main specie in the FPT is *Eucalyptus camaldulensis* Dehnh.

Simple Linear Regression Analysis for AGB Estimation Model Development

Simple linear regression analysis of forest type and plantation that provides R^2 equal or greater than 0.5 and a NRMSE value of accuracy assessment is presented in Table 5. It was found that most of the vegetation indices including SR, NDVI, SAVI, and G except RSR and FCD are highly correlated with the AGB of DDEF ($R^2 \geq 0.80$). The NRMSE values from the AGB map accuracy assessment of DDEF vary between 0.2449 and 0.6320. In contrast, most vegetation indices are moderately correlated with the AGB of MDEF but the FCD is highly correlated with the AGB of MDEF (R^2 of 0.806). NRMSE values from the AGB map accuracy assessment of MDEF vary between 0.5689 and 0.6127.

Meanwhile, SR, NDVI, and SAVI show high correlations with the AGB of MDF ($R^2 \geq 0.8$) while FCD shows a moderate correlation with the AGB of MDF ($R^2 = 0.643$). NRMSE values from the AGB map accuracy assessment of MDF vary between 0.5400 and 1.4654. Conversely, SR and NDVI show moderate

correlations with the AGB of FPT and FCD is highly correlated with the AGB of FPT. NRMSE values from the AGB map accuracy assessment of FPT vary between 0.8143 and 1.5408.

According to the results, the derived equation from NIR is chosen as the best candidate equation of DDEF to compare with the best candidate equation of non-linear regression analysis for identifying an optimum AGB estimation model of DDEF, because it provides the highest correlation with its AGB with R^2 of 0.941 and it provides the highest accuracy for AGB estimation with NRMSE of 0.2449.

Meanwhile, the derived equation from FCD is here chosen as the best candidate equation of MDEF to compare with the best candidate equation of non-linear regression analysis for identifying an optimum AGB estimation model of MDEF, because it shows the highest correlation with its AGB with R^2 of 0.806 and it provides moderate accuracy for the AGB estimation with NRMSE of 0.5963. Even though the derived NIR equation provides the highest accuracy for the AGB estimation with NRMSE of 0.5689, it shows moderate correlation with the AGB with R^2 of 0.605. The efficiency of the NIR equation is rather low when it is compared with the FCD

Table 5. List of simple linear equations for AGB estimation model development

No.	Equation	R^2	NRMSE	Remark
1	$AGB_{DDEF} = -7285.594 + 727.455 * NIR$	0.941	0.2449	Dense dry evergreen forest (DDEF)
2	$AGB_{DDEF} = -3731.979 + 5330.144 * SR$	0.831	0.4814	
3	$AGB_{DDEF} = -8719.484 + 42150.430 * NDVI$	0.835	0.4905	
4	$AGB_{DDEF} = -2624.756 + 47769.664 * SAVI$	0.898	0.3620	
5	$AGB_{DDEF} = -3499.325 + 6392.893 * RSR$	0.675	0.6141	
6	$AGB_{DDEF} = 5118.237 + 92836.092 * G$	0.908	0.3597	
7	$AGB_{DDEF} = -9139.415 + 259.649 * FCD$	0.520	0.6320	
1	$AGB_{MDEF} = -212.200 + 414.426 * NIR$	0.605	0.5689	Moderate dry evergreen forest (MDEF)
2	$AGB_{MDEF} = 83.381 + 3900.239 * SR$	0.690	0.6059	
3	$AGB_{MDEF} = -1928.566 + 27381.400 * NDVI$	0.667	0.5968	
4	$AGB_{MDEF} = 2197.222 + 29369.411 * SAVI$	0.644	0.5827	
5	$AGB_{MDEF} = -180.864 + 5275.485 * RSR$	0.747	0.6127	
6	$AGB_{MDEF} = 6925.715 + 56742.597 * G$	0.653	0.5702	
7	$AGB_{MDEF} = -8050.142 + 252.482 * FCD$	0.806	0.5963	
1	$AGB_{MDF} = -43496.199 + 23518.382 * SR$	0.850	1.1067	Mixed deciduous forest (MDF)
2	$AGB_{MDF} = -36619.832 + 119814.747 * NDVI$	0.852	1.0853	
3	$AGB_{MDF} = -21910.688 + 126385.447 * SAVI$	0.822	1.4654	
4	$AGB_{MDF} = -1005.176 + 217778.896 * G$	0.708	1.3078	
5	$AGB_{MDF} = -26247.727 + 570.048 * FCD$	0.643	0.5400	
1	$AGB_{FPT} = -22528.979 + 12980.710 * SR$	0.541	1.5408	Forest plantation (FPT)
2	$AGB_{FPT} = -18560.810 + 65658.250 * NDVI$	0.528	1.4218	
3	$AGB_{FPT} = -25057.352 + 508.430 * FCD$	0.750	0.8143	

equation and the accuracy of both equations is not much different.

In the meantime, the derived equation from NDVI is chosen as the best candidate equation of MDF to compare with the best candidate equation of non-linear regression analysis for identifying an optimum AGB estimation model of MDF, because it shows the highest correlation with its AGB with R^2 of 0.852 and it provides moderate accuracy for the AGB estimation with NRMSE of 1.0853. Although the FCD equation provides the highest accuracy for AGB estimation with NRMSE of 0.5400, it shows moderate correlation with its AGB with R^2 of 0.643. The efficiency of the FCD equation is lower than the NDVI equation.

For the meantime, the derived equation from FCD is chosen as the best candidate equation of FPT to compare with the best candidate equation of non-linear regression analysis for identifying an optimum AGB estimation model of FPT, because it provides the highest correlation with its AGB with R^2 of

0.941 and it delivers the highest accuracy for AGB estimation with NRMSE of 0.8143.

Simple Non-linear Regression Analysis for AGB Estimation Model Development

The derived equations of simple non-linear regression analysis of forest type and plantation are separately summarized as shown in Tables 6 to 9. It was found that the influence degree of independent variables on the AGB in each forest type and plantation is similar to simple linear regression analysis. However, the derived R^2 values of 4 different models of simple non-linear equation of each independent variable are slightly different.

From the results, the derived NIR equation from the logarithmic model is chosen as the best candidate equation of DDEF to compare with the best candidate equation of linear regression analysis for identifying an optimum AGB estimation model of DDEF, because it provides the highest correlation with its AGB with R^2 of 0.942 and NRMSE of 0.2549. Even though the exponential model of

Table 6. List of simple non-linear equations of DDEF for AGB estimation model development

Independent	Model	Equation	R^2	NRMSE
NIR	Logarithm.	$AGB_{DDEF} = -50643.25 + (19125.773 * \ln(NIR))$	0.942	0.2549
	Power	$AGB_{DDEF} = 56.949 * NIR^{1.632}$	0.928	0.2444
	S curve	$AGB_{DDEF} = e^{11.008 - (42.788 / NIR)}$	0.930	0.2495
	Exponential	$AGB_{DDEF} = 2305.441 * e^{(0.062 * NIR)}$	0.925	0.2331
SR	Logarithm.	$AGB_{DDEF} = -5060.736 + (15812.487 * \ln(SR))$	0.835	0.4860
	Power	$AGB_{DDEF} = 2828.878 * SR^{1.333}$	0.804	0.4796
	S curve	$AGB_{DDEF} = e^{10.731 - (3.942 / SR)}$	0.807	0.4846
	Exponential.	$AGB_{DDEF} = 3167.535 * e^{(0.449 * SR)}$	0.799	0.4761
NDVI	Logarithm.	$AGB_{DDEF} = 26779.023 + (20754.887 * \ln(NDVI))$	0.837	0.4946
	Power	$AGB_{DDEF} = 41513.418 * NDVI^{1.752}$	0.807	0.4875
	S curve	$AGB_{DDEF} = e^{11.145 - (0.861 / NDVI)}$	0.809	0.4923
	Exponential.	$AGB_{DDEF} = 2076.372 * e^{(3.556 * NDVI)}$	0.805	0.4839
SAVI	Logarithm	$AGB_{DDEF} = 29341.204 + (14601.072 * \ln(SAVI))$	0.902	0.3770
	Power	$AGB_{DDEF} = 51940.093 * SAVI^{1.239}$	0.879	0.3580
	S curve	$AGB_{DDEF} = e^{10.627 - (0.377 / SAVI)}$	0.884	0.3718
	Exponential.	$AGB_{DDEF} = 3453.1 * e^{(4.048 * SAVI)}$	0.873	0.3425
RSR	Logarithm	$AGB_{DDEF} = -1513.061 + (15300.788 * \ln(RSR))$	0.669	0.6094
	Power	$AGB_{DDEF} = 3817.127 * RSR^{1.29}$	0.644	0.6165
	S curve	$AGB_{DDEF} = e^{10.663 - (3.08 / RSR)}$	0.638	0.6117
	Exponential	$AGB_{DDEF} = 3228.816 * e^{(0.539 * RSR)}$	0.649	0.6215
G	Logarithm	$AGB_{DDEF} = 29646.177 + (6735.47 * \ln(G))$	0.913	0.3909
	Power	$AGB_{DDEF} = 53521.117 * G^{0.573}$	0.894	0.3733
	S curve	$AGB_{DDEF} = e^{9.953 - (0.041 / G)}$	0.895	0.386
	Exponential	$AGB_{DDEF} = 6651.205 * e^{(7.877 * G)}$	0.885	0.3400
FCD	Logarithm	$AGB_{DDEF} = -79038.281 + (20696.168 * \ln(FCD))$	0.509	0.6282
	Power	$AGB_{DDEF} = 6.100 * FCD^{1.723}$	0.477	0.6341
	S curve	$AGB_{DDEF} = e^{11.071 - (137.033 / FCD)}$	0.466	0.6319
	Exponential	$AGB_{DDEF} = 2049.670 * e^{(0.022 * FCD)}$	0.488	0.6307

NIR provides NRMSE of 0.2331, this model provides R^2 of 0.925 less than the logarithmic model of NIR (Table 6).

Meanwhile, the derived FCD equation from the logarithmic model is chosen as the best candidate equation of MDEF to compare with the best candidate equation of linear regression analysis for identifying an optimum AGB estimation model of MDEF, because it offers the highest correlation with the AGB with R^2 of 0.816 and it provides the highest accuracy with NRMSE of 0.5097 (Table 7).

For the meantime, the derived NDVI equation from the exponential model is chosen as the best candidate equation of MDF to compare with the best candidate equation of linear regression analysis for identifying an optimum AGB estimation model of MDF, because it provides the highest correlation with the AGB with R^2 of 0.850 and it delivers the accuracy with NRMSE of 1.0940. Even though the logarithmic model of FCD provides NRMSE of 0.5369, it shows moderate correlation with

its AGB with R^2 of 0.637 less than the exponential model of NDVI. (Table 8).

In the meantime, the derived FCD equation from the logarithmic model is chosen as the best candidate equation of FPT to compare with the best candidate equation of linear regression analysis for identifying an optimum AGB estimation model of FPT, because it shows the highest correlation with the AGB with R^2 of 0.748 and it provides the highest accuracy with NRMSE of 0.8039 (Table 9).

Optimum AGB Estimation Model of Forest Type and Plantation

By comparison of the NRMSE and R^2 values of the best candidate equations from simple linear and non-linear regression analysis, an optimum AGB estimation model of forest type and plantation is presented in Table 10.

From the results, the simple linear model of DDEF shows a very high correlation between

Table 7. List of simple non-linear equations of MDEF for AGB estimation model development

Independent	Model	Equation	R^2	NRMSE
NIR	Logarithm	$AGB_{MDEF} = -25003.658 + (10921.229 * \ln(NIR))$	0.587	0.5717
	Power	$AGB_{MDEF} = 455.615 * NIR^{0.965}$	0.593	0.5678
	S curve	$AGB_{MDEF} = e^{10.242 - (25.366 / NIR)}$	0.575	0.5682
	Exponential	$AGB_{MDEF} = 4073.227 * e^{(0.037 * NIR)}$	0.612	0.5975
SR	Logarithm	$AGB_{MDEF} = 45.16 + (10659.331 * \ln(SR))$	0.668	0.5961
	Power	$AGB_{MDEF} = 4168.82 * SR^{0.941}$	0.674	0.5957
	S curve	$AGB_{MDEF} = e^{10.222 - (2.564 / SR)}$	0.651	0.5891
	Exponential	$AGB_{MDEF} = 4184.192 * e^{(0.344 * SR)}$	0.696	0.6049
NDVI	Logarithm	$AGB_{MDEF} = 20503.893 + (12647.516 * \ln(NDVI))$	0.649	0.5908
	Power	$AGB_{MDEF} = 25389.019 * NDVI^{1.117}$	0.655	0.5899
	S curve	$AGB_{MDEF} = e^{10.395 - (0.515 / NDVI)}$	0.636	0.5819
	Exponential	$AGB_{MDEF} = 3501.834 * e^{(2.418 * NDVI)}$	0.674	0.5970
SAVI	Logarithm	$AGB_{MDEF} = 21267.764 + (8507.009 * \ln(SAVI))$	0.617	0.5810
	Power	$AGB_{MDEF} = 27163.847 * SAVI^{0.751}$	0.623	0.5791
	S curve	$AGB_{MDEF} = e^{10.029 - (0.217 / SAVI)}$	0.597	0.5737
	Exponential	$AGB_{MDEF} = 5040.652 * e^{(2.594 * SAVI)}$	0.650	0.5799
RSR	Logarithm	$AGB_{MDEF} = 2666.063 + (11122.578 * \ln(RSR))$	0.730	0.5957
	Power	$AGB_{MDEF} = 5274.603 * RSR^{0.977}$	0.728	0.6032
	S curve	$AGB_{MDEF} = e^{10.275 - (2.052 / RSR)}$	0.710	0.5885
	Exponential	$AGB_{MDEF} = 4108.939 * e^{(0.463 * RSR)}$	0.746	0.6201
G	Logarithm	$AGB_{MDEF} = 20875.976 + (3735.68 * \ln(G))$	0.591	0.5698
	Power	$AGB_{MDEF} = 26216.868 * G^{0.33}$	0.595	0.5628
	S curve	$AGB_{MDEF} = e^{9.604 - (0.021 / G)}$	0.533	0.5790
	Exponential	$AGB_{MDEF} = 7656.345 * e^{(5.004 * G)}$	0.658	0.5671
FCD	Logarithm	$AGB_{MDEF} = -70320.148 + (18811.536 * \ln(FCD))$	0.791	0.5828
	Power	$AGB_{MDEF} = 8.226 * FCD^{1.664}$	0.801	0.5862
	S curve	$AGB_{MDEF} = e^{10.946 - (123.811 / FCD)}$	0.786	0.5820
	Exponential	$AGB_{MDEF} = 2034.169 * e^{(0.022 * FCD)}$	0.816	0.5097

the NIR and the AGB with R^2 of 0.94 while the simple linear model of MDF also displays very high correlation between the NDVI and AGB with R^2 of 0.85. Meanwhile, the exponential model of MDEF and the logarithm model of FPT shows high correlations between FCD and the AGB with R^2 values of 0.82 and 0.75, respectively. The most derived R^2 values of the AGB estimation models of natural forest and plantation with different vegetation indices and FCD in the current study show higher

values than the previous studies. For example, Domrongsutsiri (2001), who applied various vegetation indices to estimate the AGB of DDF and MDF by using regression analysis at Phu Kradung National Park, Loei province, found that the simple linear model of both forest types with SR provided R^2 values of 0.5211 and 0.4568, respectively. Likewise, Kantirach (2002) found that the power model of DEF with TNDVI (Transformed Normalized Difference Vegetation Index) provided R^2 of

Table 8. List of simple non-linear equations of MDF for AGB estimation model development

Independent	Model	Equation	R^2	NRMSE
SR	Logarithm	$AGB_{MDF} = -31572.484 + (50491.705 * \ln(SR))$	0.847	1.1041
	Power	$AGB_{MDF} = 32.217 * SR^{7.03}$	0.843	1.1137
	S curve	$AGB_{MDF} = e^{15.876 - (15.095 / SR)}$	0.840	1.1107
	Exponential	$AGB_{MDF} = 6.147 * e^{(3.273 * SR)}$	0.845	1.1136
NDVI	Logarithm	$AGB_{MDF} = 51039.581 + (43574.378 * \ln(NDVI))$	0.848	1.0816
	Power	$AGB_{MDF} = 3221176.492 * NDVI^{6.077}$	0.846	1.0908
	S curve	$AGB_{MDF} = e^{14.917 - (2.21 / NDVI)}$	0.843	1.0855
	Exponential	$AGB_{MDF} = 15.857 * e^{(16.7 * NDVI)}$	0.850	1.0940
SAVI	Logarithm	$AGB_{MDF} = 49361.233 + (28706.494 * \ln(SAVI))$	0.814	1.4697
	Power	$AGB_{MDF} = 2611443.3 * SAVI^{4.02}$	0.819	1.4124
	S curve	$AGB_{MDF} = e^{12.838 - (0.913 / SAVI)}$	0.812	1.4193
	Exponential	$AGB_{MDF} = 121.298 * e^{(17.683 * SAVI)}$	0.826	1.4100
G	Logarithm	$AGB_{MDF} = 32100.965 + (7583.528 * \ln(G))$	0.678	1.2811
	Power	$AGB_{MDF} = 240251.942 * G^{1.071}$	0.695	1.2611
	S curve	$AGB_{MDF} = e^{9.862 - (0.037 / G)}$	0.667	1.2497
	Exponential	$AGB_{MDF} = 2242.658 * e^{(30.681 * G)}$	0.722	1.2929
FCD	Logarithm	$AGB_{MDF} = -128472.404 + (33320.677 * \ln(FCD))$	0.637	0.5369
	Power	$AGB_{MDF} = 7.328E-05 * FCD^{4.517}$	0.601	0.5652
	S curve	$AGB_{MDF} = e^{13.369 - (263.793 / FCD)}$	0.594	0.5621
	Exponential	$AGB_{MDF} = 76.305 * e^{(0.077 * FCD)}$	0.607	0.6317

Table 9. List of simple non-linear equations of FPT for AGB estimation model development

Independent	Model	Equation	R^2	NRMSE
SR	Logarithm	$AGB_{FPT} = -16537.502 + (28630.672 * \ln(SR))$	0.533	1.4622
NDVI	Logarithm	$AGB_{FPT} = 30216.601 + (24618.409 * \ln(NDVI))$	0.519	1.3384
FCD	Logarithm	$AGB_{FPT} = -122691.980 + (31297.094 * \ln(FCD))$	0.748	0.8039
	Power	$AGB_{FPT} = 6.132E-06 * FCD^{5.032}$	0.721	0.8429
	S curve	$AGB_{FPT} = e^{13.763 - (309.791 / FCD)}$	0.720	0.8195
	Exponential	$AGB_{FPT} = 40.369 * e^{(0.082 * FCD)}$	0.722	1.0294

Table 10. An optimum model for AGB estimation of forest type and plantation

Natural forest/ Plantation	Equation	NRMSE	R^2	Model
DDEF	$AGB_{DDEF} = -7285.594 + (727.455 * NIR)$	0.2449	0.94	Linear model
MDEF	$AGB_{MDEF} = 2034.169 * e^{(0.022 * FCD)}$	0.5097	0.82	Exponential model
MDF	$AGB_{MDF} = -36619.832 + (119814.747 * NDVI)$	1.0853	0.85	Linear model
FPT	$AGB_{FPT} = -122691.980 + (31297.094 * \ln(FCD))$	0.8039	0.75	Logarithm model

Note: DDEF: dense dry evergreen forest; MDEF: moderate dry evergreen forest; MDF: mixed deciduous forest; FPT: forest plantation.

0.82 and the S-curve model of MDF with NIR provided R^2 of 0.66. Similarly, Nuanurai (2002) revealed that a simple linear model of DEF with NIR provided R^2 of 0.7346 and a simple linear model of MDF with GVI (Global Vegetation Index) provided R^2 of 0.7051. Likewise, Chailangka (2010), who applied various indices to estimate the AGB of a Eucalyptus plantation in Nakhon Ratchasima province, found that a simple linear model of FPT with greenness provided R^2 of 0.718. Also, Sricharienchot (2014), who applied various indices to estimate the AGB of MDF at Huai Lan sub-watershed, Ngao district, Lampang province, found that a simple linear model of MDF with red provided R^2 of 0.463.

In addition, the distribution of the AGB estimation based on an optimum AGB estimation model of each forest type and plantation is displayed in Figure 9. It was found that the total AGB of natural forest and plantation in

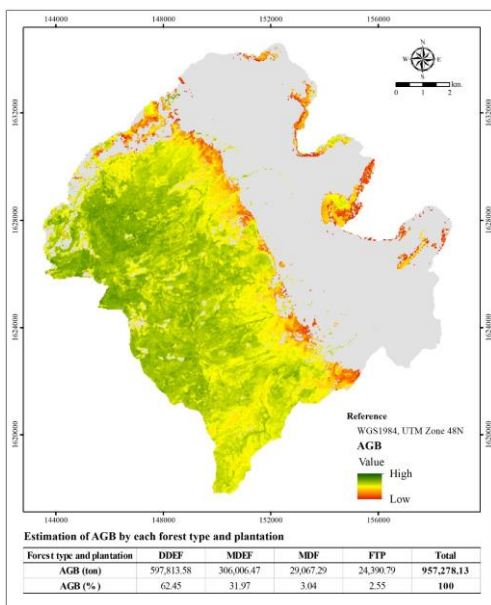
the study is about 957278 tons. In fact, DDEF, which is the dominant forest cover class in the study area, can provide the highest AGB with about 62.45% of the total AGB in the area.

Conclusions

An optimum CART model for forest and land cover classification, which applied blue, red, NIR, SWIR-1, SWIR-2, SR, NDWI, W, elevation, and slope information was here successfully developed in the current study and it could provide overall accuracy and a kappa hat coefficient of 91.18% and 89.06%, respectively. The most dominant forest cover class in the study area was DDEF and covered an area of 42.27 sq.km or 31% of the total area.

Meanwhile, an optimum AGB estimation model for forest type and plantation was also successfully implemented using linear and non-linear regression analysis based on in situ AGB data and the influential factors including spectral reflectance value of Landsat data, vegetation indices, and FCD. For the AGB estimation models, a simple linear model of DDEF with NIR provided NRMSE of 0.2449 and R^2 of 0.94 while the exponential model of MDEF with FCD provided NRMSE of 0.5097 and R^2 of 0.82. Likewise, the simple linear model of MDF with NDVI provided NRMSE of 1.0835 and R^2 of 0.85 while the logarithm model of FPT with FCD provided NRMSE of 0.8039 and R^2 of 0.75. According to the derived AGB estimation model of each forest type and plantation, the total AGB of natural forest and plantation in 2015 was about 957278 tons in the study area.

In conclusion, it can be stated that geoinformatics technology, particularly remote sensing and GIS, can be efficiently used as



Note: DDEF: dense dry evergreen forest; MDEF: moderate dry evergreen forest; MDF: mixed deciduous forest; FPT: forest plantation.

Figure 9. Distribution of above ground biomass (AGB) in the study area

tools to classify forest and land cover with a CART model and to estimate the AGB of forest type and plantation with simple linear and non-linear regression analysis. The developed research methodology may have the potential to be implemented in the other areas that have similar biological and physical characteristics.

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