



USING LANDSAT SATELLITE IMAGE AND GIS TO ESTIMATE AND MONITOR THE AMOUNT OF ABSORBED CO₂ IN DIPTEROCARP FOREST, DAK LAK PROVINCE

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Abstract. Dipterocarp forest is a typical ecosystem in Central Highlands of Viet Nam and Dak Lak province. Dipterocarp forest plays significant role about biodiversity values, CO₂ absorption and concentration. However, there is a lack of awareness of biological potentials in the local people after years of logging. It is necessary to collect data about forest biomass and carbon stored on maps by space and time in order to estimate and monitor CO₂ absorbed in the large area. Hence, using GIS to develop relationships between biomass factor and carbon stock with digital values for monitoring carbon sequestration is important and meaningful in dipterocarp forest ecosystem; this method can generate the necessary database and information in terms of CO₂ emission. The research results can create a basis for the dissemination and promotion of payment for environmental services according to REDD+ program.

Unsupervised classification into 3-4-5 class and overlap forming combinations were close relationships with TAGTB derived from square plots (30 × 30 m) and achieved confidence level 86.8 % which were applied to estimate biomass and forest carbon through Landsat image. In this study, remote sensing and management of data in ArcGIS software through allometric equations model showed Dipterocarp forest in Ea Soup and Ea Hleo districts (Dak Lak province) with the total area of 125,404.8 hectares and biomass tanks (above and below ground) of forest trees reaching at 8,156,667.6 tons. Total carbon stored was 4,093,501.1 tons. Total CO₂ absorbed was 15,023,149.1 tons.

Keywords: dipterocarp forest ecosystem, biomass, carbon stored, CO₂ absorbed, GIS.

Classification numbers: 3.5.1; 3.5.3.

1. INTRODUCTION

Dipterocarp forest is an unique ecosystem that grows in Southeast Asian such as Myanmar, Thailand, Cambodia, Laos, and Malaysia. In Vietnam, dipterocarp forest is a typical ecosystem

in Central Highlands, particularly in Dak Lak province. It brings not only biodiversity values into land use, but also satisfies the requirements of environmental sustainability including CO₂ absorption and sequestration in the system, reduction of greenhouse effects, and a contribution to climate change mitigation. However, there is a general lack of research in environment and ecological values of dipterocarp forest that has not been concerned fully. The total forest carbon stock at any time is determined by two factors: the total forest area, and the carbon per hectare of forest (carbon density). This means changes can be measured by two factors: area and carbon density [1]. In order to build database for participating in UN-REDD programme, Chackapong Chaiwong et al. [2] estimated carbon storage above ground and below ground at different soils in dipterocarp forest in Huai Hong Khrai, Chiang Mai province, Thailand. The paper showed that there were several conventional methods to predict biomass and carbon through remote sensing. Therefore, managers could recognize the change of data on land surface and frequency of information which has analyzed data over remote sensing system. The practice of satellite images has increasingly been applied worldwide to calculate the volume of vegetation biomass by Landsat, SPOT, NOAA images. In India, assessment of forest cover with Landsat MSS created a map of forest cover with biennial in period 1981-1983. Moreover, using data from remote sensing satellites Silvia H Petrova et al. [3] and Dong et al. [4] estimated carbon storage with data from 167 provinces and states in six countries (Canada, Finland, Norway, Russia and the USA for a single time period and Sweden for two periods) based on NDVI index. In Cambodia, using Landsat 5 and 7 images could analyze deforestation rate and forest cover by land use maps from 1990 to 2004 [5]. Basuki [6] used Landsat 7 ETM⁺ to estimate biomass above ground based on the reflection of plants and soil in dipterocarp forest in Southeast Asia.

Application of remote sensing requires integration of extensive remote sensing data with ground-truth measurements or data to characterize areas associated with multiple features. This is generally achieved most cost effectively using a GIS [7]. GIS can be used to detect locations of changes when using data from two different periods [8]. Recent developments in remote sensing technology have advanced its application in estimating carbon stocks while participating REDD⁺ in Vietnam. New technologies, integrating satellite imagery, analytical photogrammetry and geoinformation systems (GIS) offer new possibilities, especially for general interpretation and mapping and will be a challenge for future research and application [9]. A recent study about remote sensing lacks the relationships between biomass, forest carbon with image value for dipterocarp forest in Vietnam. Bao Huy et al. [10] used SPOT image to establish the relationship between biomass and forest carbon with image value for evergreen broadleaf forest in Central Highlands. However, characteristics of dipterocarp forest are different with evergreen broadleaf forest. Overall, the study presents a generalizable methodology of assessing CO₂ absorbed for dipterocarp forest by Landsat Thematic Mapper in Dak Lak province based on fundamental methods of the evergreen broadleaf forest.

2. MATERIALS AND METHODS

2.1. Research materials

The study used information from Landsat 8 in 2015 (Table 1).

Basic maps including terrain, river, administrative map in Ea Soup and Ea H'Leo districts with scale 1/25000; and the software ENVI 4.7, ArcGIS 10.2 and Statgraphics Centurion Plus were used. 18 sample plots of Forest Resources and Environment Management Department

(FREM) at Tay Nguyen University were inherited to check on supervised classification method. 43 sample plots with three types of sample stacked.

Table 1. The information of Landsat 8.

Channel	Wavelength	Solution
Band 1 - Coastal aerosol	0.433 - 0.453	30
Band 2 - Blue	0.450 - 0.515	30
Band 3 - Green	0.525 - 0.600	30
Band 4 - Red	0.630 - 0.680	30
Band 5 - Near Infrared (NIR)	0.845 - 0.885	30
Band 6 - SWIR 1	1.560 - 1.660	30
Band 7 - SWIR 2	2.100 - 2.300	30
Band 8 - Panchromatic	0.500 - 0.680	15
Band 9 - Cirrus	1.360 - 1.390	30
Band 10 - Thermal Infrared (TIR) 1	10.3 - 11.3	100
Band 11 - Thermal Infrared (TIR) 2	11.5 - 12.5	100

2.2. Research methodology

2.2.1. Sampling design

3 types of sample plots have been conducted at one central point including:

Type 1: Square plots: The plot area of 900 m² with size of 30 × 30 m, divided into 9 secondary cells with 10 × 10 m. Data collection: species, height (m), diameter at breast height (D_{1.3} cm) with D_{1.3} ≥ 6 cm.

Type 2: Stratification circle plots: A total area of 1000 m², a radius of 17.84 m. It divided into sub-plots with different radius to measure diameter:

Plots with radius between 0 - 17.84 m (Area 1000 m²). Identifying the trees have D_{1.3} (cm) ≥ 42 cm with species name, height (m) and D_{1.3} (cm) parameters.

Plots with radius between 0 - 12.62 m (Area 500 m²). Identifying the trees have 42 cm > D_{1.3} (cm) ≥ 22 cm, with species name, height (m) and D_{1.3} (cm) parameters.

Plots with radius between 0 - 5.64 m (Area 100 m²). Identifying the trees have 22 cm > D_{1.3} (cm) ≥ 6 cm, with species name, height (m) and, D_{1.3} (cm) parameters .

Plots with radius between 0- 1 m (Area 3.14 m²). Identifying the trees have D_{1.3} (cm) < 6 cm with species name, height (m) and, D_{1.3} (cm) parameters.

Type 3: Prodan plots: Using tap measure to determine 6 trees was D_{1.3} ≥ 6 cm which was nearest plots center. Tree farthest center was 6th trees. Identify indicators of plants, including the name of species, D_{1.3} (cm), H (m).

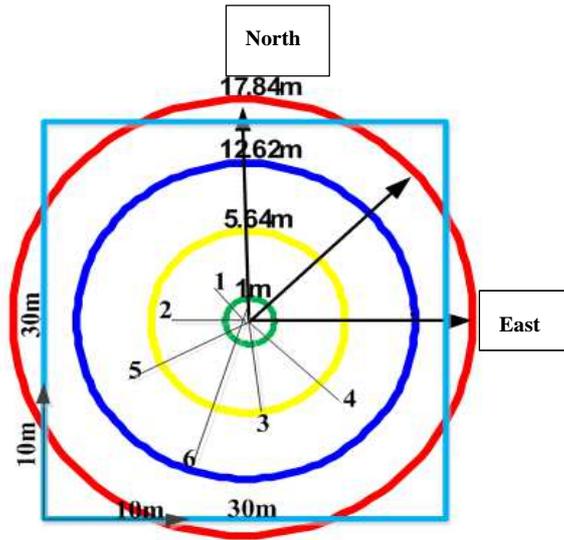


Figure 1. The shape of 3 types different sample having been conducted at a point.

2.2.2. Data analysis

Estimation of biomass, forest carbon for 3 plots type through D1.3 (cm), H (m):

- Calculation density (number of trees/ha) and volume (m³/ha) according to formula in forest inventory.
- Using two allometric equations established in dipterocarp forest to estimate above-ground biomass (AGB), carbon above-ground biomass (C_AGB) of each individual tree by Bui Hien Duc [11].
- Based on the indicators such as density (N), decentralization number of trees toward diameter to determine total above-ground tree biomass (TAGTB, ton/ha) and total above-ground tree carbon (TAGTC, ton/ha) for each plots type:

+ Square plots 30 × 30 m:

$$TAGTB(\text{ton/ha}) = \frac{10^4}{900} \times \sum AGB(\text{kg / tree}) \times 10^{-3}$$

$$TAGTC(\text{ton/ha}) = \frac{10^4}{900} \times \sum C(AGB)(\text{kg / tree}) \times 10^{-3}$$

+ Stratification circle plots:

$$TAGTB(\text{ton / ha}) = \sum AGB(\text{kg}) \times N \times 10^{-3}$$

$$TAGTC(\text{ton / ha}) = \sum C(AGB)(\text{kg}) \times N \times 10^{-3}$$

In which, density (N) for each diameter level calculated according to the formula:

$$N / \text{ha} = \frac{10^4}{100.\text{no}} \sum N(6 < D < 22\text{cm})$$

$$N / \text{ha} = \frac{10^4}{500.\text{no}} \sum N(22 < D < 42\text{cm})$$

$$N / ha = \frac{10^4}{1000.no} \sum N(D > 42cm) \quad (\text{no is number of plots})$$

+ Prodan plots:

$$TAGTB(\text{ton} / ha) = \frac{10^4}{\pi \times r^2} \times \sum AGB(kg) \times 10^{-3}$$

$$TAGTC(\text{ton} / ha) = \frac{10^4}{\pi \times r^2} \times \sum C(AGB)(kg) \times 10^{-3}$$

2.2.3. Application of satellite images to estimate biomass and forest carbon

a) Unsupervised image classification technique and building biomass relationship with inventories factors and image values for 3 plots type

In unsupervised classification, the first group pixels into “clusters” based on their properties. In order to create “clusters”, analysts use image clustering algorithms such as K-means and ISODATA. Humans naturally aggregate spatial information into groups. In this study, using ISODATA was created classes about biomass and forest carbon. Then it established the relationship between biomass, carbon with layers of image value. Comprises following steps:

Step 1: Automatical image classification: Applying ISODATA method. This method was flexible and natural without permanent number of classes. After picking a clustering algorithm, you identify the number of groups you want to generate. In which, the relationship detected different layers with biomass, carbon stocks in sample plots. It was good reason to set up system of unsupervised classification based relation with biomass, forest carbon. This study experimented to merge clusters into 3 clusters: split from 2-4 clusters to create 3 classes; Split from 3-5 clusters to create 4 classes; Split from 4-6 clusters to create 5 classes.

Step 2: Setting models: The relationship between the total biomass, forest carbon on ground for three sample plots types with class code (id_class) classified on image: Building the model of TAGTB, TAGTC = f (Class_id) based combinations between 3 classes, 4 classes, 5 classes. Establishing the biomass, carbon (yi) model with inventory factor value, the image value (xi) in the form yi = f (xi); where yi and xi have changed variables and combinations of variables to seek function and variables appropriately.

Step 3: The models were selected according to statistical indicators: Basing on the method demonstrated by Bao Huy [10], the models should ensure statistical indicators such as: R²% adj max, AIC, CF, Cp, S1% and S2% min.

- **Mallow’Cp**

Mallows' Cp allows the researchers to choose the best multiple regression models. In which, Mallows' Cp is smallest and closest the number of predictors in model plus the constant (p). A small Mallows' Cp value indicates that model has small variance in estimating true regression coefficients and predicting future responses.

$$Cp = \frac{SSE_p}{s^2} - N + 2P$$

where: SSE_p is Sum of Square Error for model with P regressors; S² is residual mean square after regression on complete set of K regressors and can be estimated by mean square error MSE; N is sample size.

- **Akaike Information Criterion**

AIC estimates the quality of each model, related to other models. Optimal model when an algebraic value of AIC is smallest: $AIC = n \cdot \ln(RSS/n) + 2K$

where: n is sample size; RSS is Residual Sums of Squares; K is the number of estimable parameters (freedom degrees).

- **Correction factor (CF)**

CF using for model variable change y form log, used to evaluate reliability of model. The best regression model is a model with CF value close to 1: $CF = \exp(RSE^2/2)$

where RSE: Residual standard error.

- **Average volatility S1% and relative error S2%**

S1% to assess false level and average volatility of value estimated by model and compared with actual observations. S1% of model is smaller than real value illustration closely relationship. S2% is relative error of estimated value by model compared with reality.

$$S1\% = \frac{100}{n} \sum_{i=1}^n \frac{|Y_{ilt} - Y_i|}{Y_i}$$

$$S2\% = \frac{100}{n} \sum_{i=1}^n \frac{Y_{ilt} - Y_i}{Y_i}$$

where: Y_{ilt} is forecast value by model; Y_i is real value of biomass and carbon; n is sample size.

Considering statistical criteria, compare biomass relational model with investigating factors, class system to choose best model corresponding with a complex class system. In which, number of class system needs to divide with relationship closest with biomass and forest carbon on ground following suitable plots type for dipterocarp forest.

b) Supervised classification technique and division forest following biomass levels

In ENVI there are three different classification algorithms that can be chosen from in the supervised classification procedure. This research used Maximum Likelihood: Assumes that the statistics for each class in each band are normally distributed and calculated the probability that a given pixel belongs to a specific class. Each pixel is assigned to the class that has the highest probability (that is the maximum likelihood). This is the default. This method is based on data of sample plots observation on field to classify image into similar classes about biomass and forest. Then uses independent accreditation plots to assess reliability of classification. Comprises following steps:

Step 1: Biomass decentralization from data of 3 plots type.

Step 2: Isolated image following biomass level of 3 plots type. Using Maximum Likelihood on ENVI software.

Step 3: Evaluate confidence level of isolated result: using 18 sample plots of FREM (size 50×50 m).

2.3. Application GIS in management and supervision of biomass, forest carbon

Relying on satellite images were interpreted and classified according to each level of biomass, carbon and establish a database of biomass, carbon for an area. Comprises following steps:

Step 1: Converting image into vector with attributes TAGTB (ton/ha) has done interpretation in ArcGIS

Step 2: Using allometric equations model in forest stand to calculate indirect biomass value, carbon in other pool and total forest stand.

Step 3: Editing map of forest carbon and export to databases.

Step 4: Monitoring and updating area change, carbon stocks in ArcGIS through update function of fields by allometric equations. CO₂ absorption or emission from deforestation over time was calculated according to Difference stock method (IPCC, 2006):

$$\Delta C_B = \frac{C_{t_2} - C_{t_1}}{t_2 - t_1}$$

where: ΔC_B = annual biomass, carbon stock, CO₂ change in pool; C_{t^*} = Biomass, carbon, CO₂ in pool at time t_1 or t_2 ; t = time measure.

Biomass, carbon, and CO₂ in later time were quickly updated through unsupervised classification method and relationship with TAGTB. Then just updating TAGTB field, all databases would automatically recalculate according to allometric equations and showed biomass value, carbon, CO₂ at a period later. From which, we could calculate the amount of CO₂ absorption or emission in forest management.

3. RESULTS AND DISCUSSION

3.1. Biomass and carbon of forest stand

According to Bui Hien Duc (2014) [11], allometric equations used for AGB and CAGB for 3 sample plots types includes:

$$\mathbf{Ln(AGB_kg) = -3.25897 + 0.183087*Ln(H_m) + 2.5682*Ln(DBH_cm)}$$

with R^2 .adj = 95.92; P value < 0.001; AIC = -387.99; CF = 1.05; Cp = 1.00; S₁% = 25.8.

$$\mathbf{Ln(C_AGB_kg) = -4.35124 + 2.56549*Ln(DBH_cm) + 0.366245*Ln(H_m)}$$

with R^2 .adj = 96.51; P value < 0.001; AIC = -195.31; CF = 1.05; Cp = 1.00; S₁% = 26.3.

3.2. Supervised classification technique and building biomass, forest carbon relationship with various layers

This study experimented to classify image into 3, 4, 5 layers. Select the number of pixels in a layer at least 6 pixels (pixel size 30 × 30 m) with an area of 5.400 m².

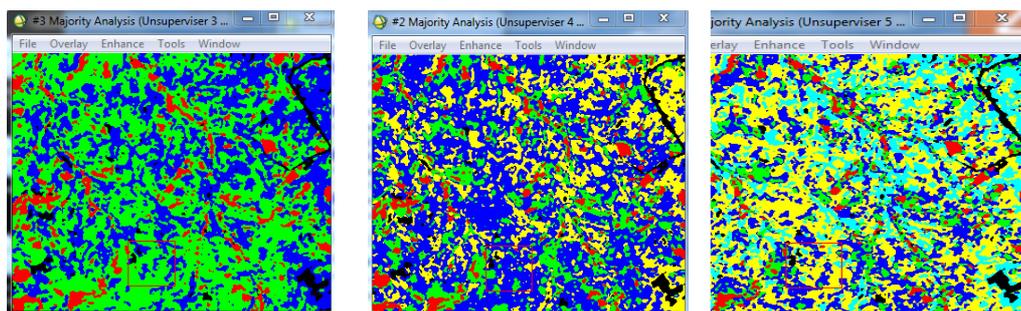


Figure 2. Supervised classification technique into 3, 4, 5 class (from the left to right).

Conversion data raster type of image classified unsupervised into vector with class. Then overlay coordinates of sample plots were calculated TAGTB for 3 sample types stick with 3 layers classified following 3, 4, 5 class. Creating a database the relationship between biomass and forest carbon with system class which was classified as different combinations from 3, 4, 5 class in ArcGIS with 3 sample types: square plots, stratification circle plots, and Prodan plots. Overlay with 3 classification system be exported to a database file to build relational equation TAGTB (ton/ha) = f (Class_3_id, Class_4_id, Class_5_id). Within each combination of classification level to find the relationship between forest biomass with class_id for each plot types. Classification results unsupervised into different class would create an unclassified class. Hence, a number of plots in unclassified class did not use in this modeling. Results of 34 plots overlayed on image classified into 3 classes, 4 classes; and 32 plots overlayed on image classified into 3-4-5 classes or 3-5 classes. For each relation models TAGTB with combination class, select models with best statistical criteria: R^2_{adj} maximum, $P < 0.05$, $S_1\%$ and $S_2\%$ minimum, AIC minimum and CF minimum. Finally, evaluate difference between TAGTB through image with actual value of sample plots by $P(T \leq t_{one-tail}) > 0.05$ standard, meaning no difference in levels $P > 95\%$.

Table 2. Building TAGTB (ton/ha) relationship with various layers for 3 plots types.

Equations	Statistical indicators								
	R ² % Adj	P-Value	N	Cp	CF	AIC	S ₁ %	S ₂ %	P(T<=t) one-tail
$\text{Ln}(\text{TAGTB_CY}) / \text{Class_4_Id} = 3.96753 + 0.709204 * \text{Ln}(\text{Class_3_Id})^2 - 2.84193 * \text{Ln}(\text{Class_4_Id})$	92.49	0.00	34	1.00	1.06	-68.80	61.14	21.11	0.360
$\text{Ln}(\text{TAGTB_SQ}) / \text{Class_4_Id} = 3.94929 + 0.101204 * \text{SQRT}(\text{Class_3_Id}^3 * \text{Class_5_Id}) - 3.02242 * \text{Ln}(\text{Class_4_Id})$	94.07	0.00	32	3.00	1.05	-71.03	48.17	13.20	0.970
$\text{Ln}(\text{TAGTB_PR}) / \text{Class_5_Id} = 3.18606 - 1.60526 * \text{Ln}(\text{Class_3_Id}) + 1.56692 * \text{Ln}(\text{Class_3_Id} / \text{Class_5_Id})$	72.27	0.00	32	1.00	1.16	-33.96	86.71	43.51	0.282

In which: The relationship model including TAGTB_CY with combinations classified into 3 and 4 classes; TAGTB_SQ with combinations classified into 3, 4 and 5 classes; TAGTB_PR with combinations classified into 3 and 5 classes). From a result above showed that: Prodan plots was largest errors (43.5 %) because of the number of trees observed at least, data collected from plots also estimates incorrect by image were large fluctuations, confidence level not high; Square

plots was smallest errors (13.2 %) but it was difficult to set up in complicated terrain; Therefore, stratification circle plots were of higher errors than square plots (21.1%) but it has advantaged in complicated terrain. Overall, assessment results showed that dipterocarp forest should apply unsupervised classification method and building biomass relationship for square plots with overlapping data from 3-4-5 classes. The relationships between biomass ground above and image index were closely relative with error 13.20% and 86.80% of confidence level. Therefore, the model selected was:

$$\text{Ln}(\text{TAGTB_SQ})/\text{Class_4_Id} = 3.94929 + 0.101204 * \text{Sqrt}(\text{Class_3_Id}^3 * \text{Class_5_Id}) - 3.02242 * \text{Ln}(\text{Class_4_Id})$$

R² adj = 94.07 %; P < 0.000; n = 32; Cp = 3.00; CF = 1.05 AIC = -71.03; S₁% = 48.17 %; S₂% = 13.20 %; P(T<=t) one tail = 0.970 > 0.05.

3.3. Supervised classification technique and division biomass levels

3.3.1. Division biomass levels of TAGTB for 3 sample plots types

Using 18 sample plots of FREM to test plots independent of supervised classification. From 43 sample plots identified TAGTB for each plots type: square plots, stratification circle plots, and Prodan plots. With biomass, value calculates volatility on confidence level P = 99 % and division into 3 level for 3 sample plots types: Level 1: Low biomass located on the left of estimate for 99 %. Level 2: Average biomass located on estimate 99 %. Level 3: High biomass located on the right of estimate for 99 %. In which, biomass level for square plots achieved minimum with 19.46 ton/ha and maximum with 200.07 ton/ha while the figures for stratification circle plots achieved minimum with 13.80 ton/ha and maximum with 167.53 ton/ha. By contrast, Prodan plots were significantly fluctuated in terms of different categories of biomass level minimum with 3.17 ton/ha and maximum with 264.56 ton/ha.

Table 3. Decentralization TAGTB followed 3 plots types.

Biomass levels	TAGTB_SQ (ton/ha)		TAGTB_CY (ton/ha)		TAGTB_PR (ton/ha)	
	Min	Max	Min	Max	Min	Max
1	19.5	56.1	13.8	52.3	3.2	41.9
2	56.1	87.8	52.3	81.4	41.9	86.8
3	87.8	200.1	81.4	167.5	86.8	264.6

3.3.2. Supervised classification technique followed 3 biomass levels for 3 plots types

Using image file to cut forest area was classified into 3 biomass levels for 3 plots types on Envi. Each plots overlay coordinates file classified on an image by ArcGIS and convert into ROI file. Option Convert each record of an EVF layer to a new ROI and select field in order to decentralization. Open ROI file just created to gross ROI with the same level divided. Supervised classification into biomass level based on ROI created for 3 plots types. Using classification function of Envi.

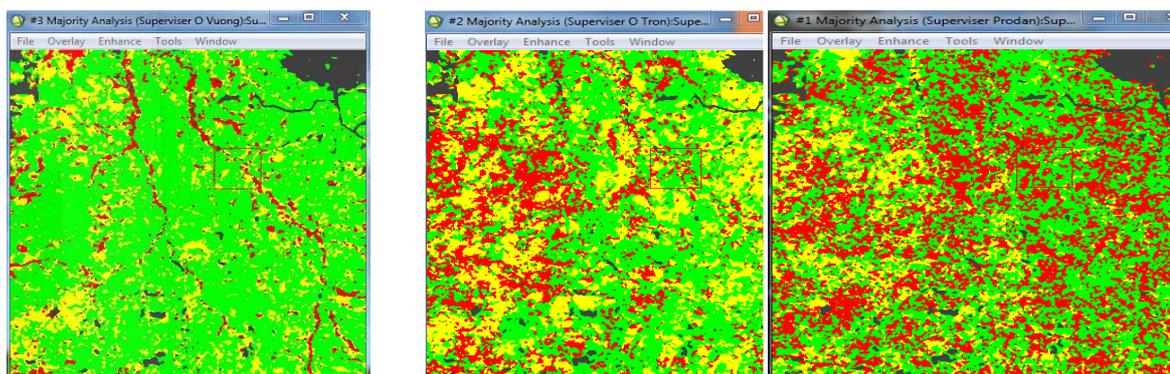


Figure 3. Supervised classification into 3 biomass level of square plots, stratification circle plots and Prodan plots (from the left to right).

3.3.3. Evaluation of confidential level of image classification followed biomass level for plots types

The results of classification should be checked before establishment a map. Using 18 sample plots to measure independent model which was not involved in processing of image classification and calculation TAGTB to test classification results. Evaluation results based on statistical criteria with overall accuracy, producer's accuracy, and user accuracy.

Table 4. Evaluation the accuracy of supervised classification based on biomass level of 3 sample plots types.

Image classification into three biomass levels follow 3 sample plots types	Overall Accuracy	Kappa Coefficient
Square plots	41.66 %	0.1250
Stratification circle plots	50.00 %	0.2088
Prodan plots	25.00 %	-0.2135

The results presented that overall accuracy of supervised classification method following three biomass levels for 3 sample plots types were different. Stratification circle plots type was highest at 50 %, square plots reached 41.66 % and Prodan plots was lowest with 25.00 % of overall accuracy. Variation in biomass between biomass levels of each plots types affected by classification results. It illustrated that at the same of investigation site there was a difference about volume and forest biomass. In which, Prodan was always higher square plots and stratification circle plots.

3.4. Comparion of two methods for image classification

The method of unsupervised classification and combination 3-4-5 classes with TAGTB_SQ data from square sample plots reached the highest confidence level in model: TAGTB_SQ = f(Class_Id from combination 3-4-5 classes) with confidence level 86.8 %. Method of supervised classification with biomass level for stratification circle plots achieved the highest confidence level with 50.0 %.

Therefore, unsupervised classification method and biomass relationship between square plots with overlapping data of image from 3-4-5 classes considered the most effective and easiest. Satellite image classification, estimation of biomass and carbon for dipterocarp forest should use this method as well as setting up square sample plots would bring best result with higher of estimating confidence. Because stratification circle plots was suitable for complex forest terrain, steep slopes. In addition, natural forest was complex structure and distribution uneven diameter sizes. By contrast, Prodan method was of larger error as it depends on diameter and spacing of 6 trees nearest on plots center. Therefore, Prodan plots should apply for plantations forest and natural forests with standard structure.

3.5. Application GIS in management, supervision of biomass and forest carbon

Combination of image analysis (supervised classification and unsupervised classification) and method of setting 3 types sample plots illustrated that unsupervised method was closed relationship with biomass ground above from square sample plots. Using this method to divide forest biomass into 3-4-5 classes and calculating biomass average value of each combination was determined through relational model. Using 18 sample plots and allometric equations of AGB and C(AGB) to calculate biomass and carbon above ground and below ground throughout DBH and H. The values estimated including TAGTB, TAGTC, TGBTB and TBTGC (ton/ha). dipterocarp forest was known annual burning forest so the amount of herb, litter and dead wood was small proportion. Simultaneously, carbon volume was always stable in soil, it should not put into system management and monitoring by GIS. Therefore, the models selected were:

Table 5. The models estimated biomass, forest carbon above ground and below ground.

Models	Equations	Statistical Indicators						
		R ² % (Adj)	P value	N	Cp	CF	AIC	S ₁ %
TGBTB = f(TAGTB)	$\text{Ln}(\text{TGBTB}_{\text{t_ha}}) = (-0.927495 + 1.21604 * \text{sqrt}(\text{Ln}(\text{TAGTB}_{\text{t_ha}})))^2$	95.20	0.00	18	0.0	1.00	-122.0	6.54
TAGTC = f(TAGTB)	$\text{TAGTC}_{\text{t_ha}} = (-0.261063 + 0.759504 * \text{sqrt}(\text{TAGTB}_{\text{t_ha}}))^2$	99.84	0.00	18	0.0	1.00	-100.1	1.51
TBTGC = f(TAGTB)	$\text{TBTGC}_{\text{t_ha}} = \text{sqrt}(-2.54323 + 0.160415 * \text{TGBTB}_{\text{t_ha}}^2)$	99.32	0.00	18	0.0	1.00	33.4	6.49

Using above mentioned models to calculate TGBTB ton/ha, TAGTC ton/ha and TBTGC ton/ha according to TAGTB were identified through satellite image by unsupervised method with combination 3-4-5 classes. TTB, TTC for stand forest on above ground and below ground determined on image for each level by a formula:

$$\text{TTB (ton/ha)} = \text{TAGTB} + \text{TGBTB}; \text{ TTC (ton/ha)} = \text{TAGTC} + \text{TBTGC}.$$

Total biomass, TTC level and TTB level were divided into the area of each class with combinations classified on image:

TTB level (ton) = TTB (ton/ha)* Area of each level; TTC level (ton) = TTC (ton/ha)* Area of each level.

Amount of CO₂ absorbed at each time of each level: TCO₂ level (ton) = TTC level (ton)*3.67.

Using input databases of Landsat image and basic information of 3-4-5 classes were decentralized biomass, calculated TAGTB and area of each level on ArcGIS. Moreover, applying allometric equations to calculate the value of biomass, carbon for new fields by the way open fields about biomass and carbon data on ArcGIS with various fields including TBGTC, TAGTC, TBGTC, TTB, TTC, TTB level, TTC level, TCO₂ level.

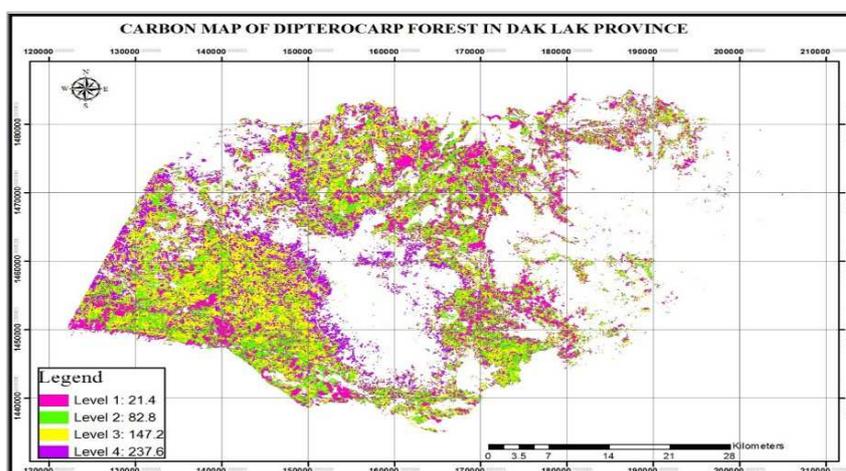


Figure 4. A map of carbon decentralization in dipterocarp forest.

Following the data of biomass and carbon in ArcGIS could be transferred to Excel database to calculate for a reporting on Table 6.

Table 6. Total biomass, carbon and CO₂ absorb in dipterocarp forest area.

TAGTB levels	Area (ha)	TAG TB (t/ha)	TBG TB (t/ha)	TAG TC (t/ha)	TBG TC (t/ha)	TTB (t/ha)	TTC (t/ha)	TTB level (ton)	TTC level (ton)	TCO ₂ level (ton)
1	103,223.3	37.3	6.8	19.2	2.2	44.1	21.4	4,552,147.5	2,208,978.6	8,106,951.5
2	21,528.2	135.8	22.7	73.8	9.0	158.5	82.8	3,412,219.7	1,782,535.0	6,541,903.5
3	588.9	238.4	39.5	131.5	15.7	277.9	147.2	163,655.3	86,686.1	318,138.0
4	64.4	381.4	63.4	212.3	25.3	444.8	237.6	28,645.1	15,301.4	56,156.1
Total	125,404.8							8,156,667.6	4,093,501.1	15,023,149.1

As a result, total area was 125,404.8 hectares, total biomass above and below underground of trees were 8,156,667.6 tons. Total carbon stored was 4,093,501.1 tons and 15,023,149.1 tons CO₂ absorbed. Hence, based on different time of image interpretation, we could estimate total biomass and forest carbon for dipterocarp forest at detail time through the relationship between value of image interpretation, biomass and forest carbon.

4. CONCLUSION

Unsupervised classification method into 3-4-5 classes and overlap forming combinations were close relationships with TAGTB from square plots (30 × 30 m). Using this method and model below was achieved confidence level 86.8 % when estimating biomass and forest carbon through Landsat image. Model to estimate TAGTB through Landsat image was:

$$\text{Ln}(\text{TAGTB_SQ})/\text{Class_4_Id} = 3.94929 + 0.101204 * \text{Sqrt} (\text{Class_3_Id}^3 * \text{Class_5_Id}) - 3.02242 * \text{Ln}(\text{Class_4_Id}).$$

The result of two image classification methods combined with 3 plots types showed that applying unsupervised classification method and overlapping according to combination 3-4-5 classes to establish relations with biomass from square plots obtained the highest confidence level. With confidence level 86.8 % was acceptable for estimating, monitoring forest carbon and CO₂ fluctuation when participation REDD+.

Remote sensing in combination with GIS will be increasingly used in recent years to indicate the role of dipterocarp as a contributing factor in global climate change adaptation and mitigation processes and orients the promotion for environmental services including the reduction of carbon emission. The research on satellite image interpretation and management in ArcGIS software through allometric equations model demonstrated dipterocarp forest in Ea Soup and Ea Hleo district (Dak Lak province) has a total area of 125,404.8 hectares, total biomass (above and below ground) of forest trees of 8,156,667.6 tons. Total carbon was stored 4,093,501.1 tons. Total CO₂ was absorbed 15,023,149.1 tons.

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ABBREVIATIONS

AGB	Above ground biomass (kg/tree);
C(AGB)	Carbon in ABG (kg/tree);
CY	Cycle plots;
SQ	Square plots;
Pr	Prodan plots;
TAGTB	Total above ground tree biomass (ton/ha);
TAGTC	Total above ground tree carbon (ton/ha);
TTB	Total tree biomass (ton/ha);
TTC	Total tree carbon (ton/ha);
TCO ₂	Total Carbon dioxit;
TBGTC	Total below ground tree carbon (ton/ha);
TBGTB	Total below ground tree biomass (ton/ha);
REDD	Reducing emissions from deforestation and forest degradation.