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GEOGRAPHICALLY WEIGHTED REGRESSION MODELLING FOR ABOVE-GROUND BIOMASS ASSESSMENT FROM SATELLITE IMAGERY IN TAD SUNG WATERFALL PARK FOREST, THAILAND

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Abstract

The estimate of carbon sequestration in terms of above-ground biomass (AGB) within the tree from the high-resolution image. The objective of this paper to assessment of AGB in Tad Sung Waterfall park forest in Kalasin province, Thailand. The allometric equations used to calculate the AGB from field measurement of 62 samples plot, by each plot has a dimension of 40m × 40 m. The normalized difference vegetation index (NDVI), soil-adjusted vegetation index (SAVI), and Fractional vegetation cover (FVC) from the satellite imagery was use to assessment of AGB using the geographically weighted regression (GWR) model. The results The results found that the total number of 4682 trees in the 62 sample plots and the calculated the AGB of the tree in the sample plot using the allometric equation was 79.6 Ton per hectare. The results of spatial analysis of AGB base on GWR found that the R^2 value of the global regression and GWR model were 0.366 and 0.856, respectively and the optimal bandwidth estimation for GWR in this study was 48.78. The adjusted R^2 values of the GWR model achieved a significant improvement in the global regression from 0.108 to 0.59.

***Keywords**: Spatial Regression Model; Vegetation Indices; Biomass; Above-ground Biomass (AGB); Remote Sensing*

Introduction

Greenhouse gases (GHGs) are equally mixed that trap heat or longwave radiation in the atmosphere, making no difference to climate emissions. The Clean Development Mechanism (CDM) of the Kyoto Protocol (UNFCCC, 1997) introduces the importance of trading carbon from the forests for reducing global warming in the carbon dioxide emissions for determining the cost for countries with commitments by funding forestry activities. Although the forest owner has been benefited from the carbon trade in forests, managing forests is difficult for forest owners unless organizations or governments support compensation for forest environmental services [1]. However, investing in forestry projects is quite risky for long-term projects to manage in the countries. Because the income from the carbon trade is very low in the carbon markets, which the most of carbon income is provide by government not the companies [2]. Thailand submitted its Intended Nationally Determined Contributions (INDC) to the UNFCCC that identified Thailand's INDC goals and action plans to achieve the INDC goals. Thailand proposed to reduce GHGs emissions by 20% following the INDC targets [3].

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In recent decades, several scientists have been working on reducing the GHGs in terms of forest ecosystem or agriculture for capturing carbon dioxide (CO2) from the atmosphere and transforming it into biomass through photosynthesis. The process for reducing carbon dioxide in the atmosphere by using the methods of capturing and storing carbon dioxide from the ecosystem this method is called carbon sequestration. Reducing GHGs in the agriculture sector is an approach for the international community is focused on as a cost-effective approach. This is compared to reducing GHGs emissions in other activity sectors such as the energy, transportation, and forestry sectors, and also to solve climate change in the long term. Intergovernmental Panel on Climate Change (IPCC) [4] was a definition for carbon pools used in forest ecosystems including dead organic matter, soil organic matter, above-ground biomass (AGB), and below-ground biomass (BGB). AGB includes all biomass of the ecosystem or vegetation such as above the soil, live or dead, including stem, stump, branches, both woody and herbaceous, bark, seeds, and foliage [4]. AGB represents the carbon pools in the carbon stock and the importance of changes in carbon pools are an indicator of changes or effects of interventions, benefits associated with both carbon reduction and other matters [5].

In recent years, the application of remote sensing to estimate carbon sequestration such as [6-11] are used Landsat satellite image to estimate spatial biomass in large areas by using the spectral reflection of the vegetation. The normalization difference vegetation index (NDVI) and ratio vegetation index (RVI) is used wildly to calculate the biomass density [11-13]. The summaries of techniques for estimating biomass using NDVI and RVI indices of Landsat data include k-nearest neighbors (KNN), neural network (NNs), and statistical regression [4, 5, 8, 13]. The summaries of techniques found that used Landsat data for data analysis in large areas focused on the estimated biomass in the forest area mostly. The general techniques were used for estimating the AGB from the remote sensing imagery based on the parametric and nonparametric algorithms [5, 14]. The common statistical regression is the expression relationships between the dependent variable (AGB) and the independent variable (derived from remote sensing data) is clearly and easy to calculate [14]. The suitability of the remote sensing variables is the key for the strong relationships with biomass to determine the AGB [15,16].

The model of local spatial analysis focuses on the exception of the general trends represented by more traditional global spatial analysis models [17]. This paper focused on the spatial regression model to estimate AGB according to the parameters derived from the remote sensing imagery. The parameters are based on vegetation indices from the remote sensing imagery provided for the independent variable. The near infrared band and red band of Sentinel-2 imagery were used to calculate the NDVI and soil-adjusted vegetation index (SAVI). The fractional vegetation cover (FVC) was calculated from the NDVI value. The spatial analysis based on local spatial analysis in this paper uses the geographically weighted regression (GWR) technique for an estimate of the AGB with the vegetation indices.

Experimental part

Materials

Study area

The study was implementation in Phu Pha Wua Forest Park, Kalasin province, Thailand shown in figure 1. The study area (16.534385 N, 104.189437 E) covers approximately 7.84sq.km.

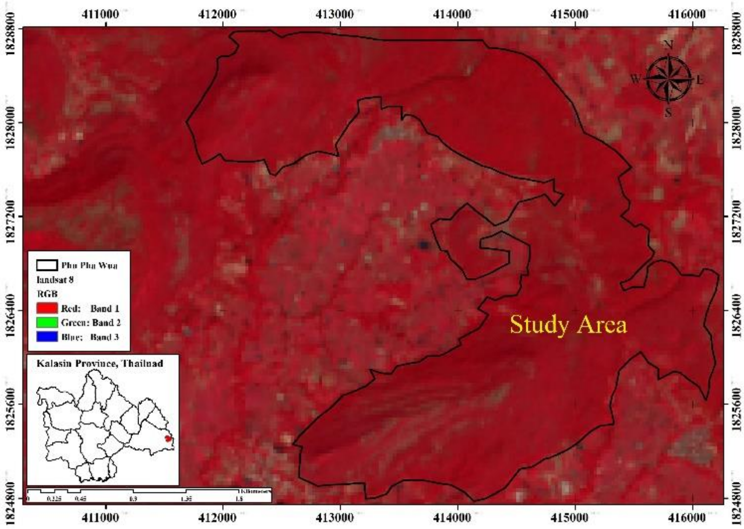

Fig. 1. The study area, Phu Pha Wua Forest Park, Kalasin province, Thailand

Methods

Vegetation indices

The NDVI, SAVI, and FVC was used to improve the ability to separate healthy vegetation from other land cover types. The normalized values of NDVI, SAVI, and FVC provide values between −1 to 1. The advantage of the vegetation indics can be show the healthy of the forest on the remote sensing imagery. The values of these vagattaion indics in this paper was higher values show the good healthy or show that the high vegetation and low or positive values show the bad healthy or show that the non vegetation. The NDVI is a normalized ratio of NIR (near infrared) and Red (red band) defined as [18]:

$$NDVI=(NIR-Red)/(NIR+Red) \quad (1)$$

SAVI

The SAVI was developed for improve influence of soil brightness in the NDVI defined as [Huete 1988]. The structured of the SAVI similar to the NDVI which includes a correctio factor of the near infrared band following:

$$SAVI=[(NIR-Red)/(NIR+Red+L)](1+L) \quad (2)$$

The soil brightness correction (L) factor in this paper was used 0.5;

FVC

The FVC show that the ratio of percentage of vegetation in the area and is an important of the parameter describing in the ecology system.

$$FVC= (NDVI- NDVI_s)/(NDVI_v - NDVI_s) \quad (3)$$

where: $NDVI_v$ correspond to representative values of $NDVI_{max}$ and $NDVI_s$ correspond to representative values of $NDVI_{min}$.

Field survey to determine the carbon content in the plot areas

The study site is located in Phu Pha Wua Forest Park, Kalasin province, Thailand which containing various forest types. The sampling plot was the enumeration of randomly sample plots using the stratified random method was used to be a group study case. The number of permanent sampling plots in the tree is a total of 62 plots, by each plot has a dimension of 40×40m., and all of the trees in the plot are measuring the higher of the trees at 1.20 meters. The data collection of the tree includeing names of tree, number of trees, sizes, length of leaves and heights of trees [19].

Above-ground biomass (AGB) from field survey

The analysis of above ground biomass in this paper was used the allometric equation developed by Klinhom *et.al* [20] with suitable for local plants in Thailand. The method was used to estimate the above ground biomas following [21]:

$W_s = 0.396(D^2\ H)^{0.933}$

$W_b = 0.349(D^2\ H)^{1.030}$

$W_l = [28/(W_s+W_b+0.025)]^{-1}$

$W_t = W_s+W_b+W_1$

where: W_t is the above ground total biomass; W_s is the stem biomass; W_b is the branches biomass; W_l is the leaves biomass; D is the tree diameter at breast height; H is the height of tree.

Spatial analysis of AGB based on statistical regression model

The basic of spatial analysis is the technique for predict or estimate the values of a geographic variable that have known at the location to predict or estimate the unkhown values. Moreover, the spatial techniques is an important in term of modeling and decision making for determine the unkhonw value at the local and global scales, respectively [22, 23]. The statistical regression model is one of the paramedic algorithms which produce good results for an estimate of the AGB with the valiables from the remote sensing imagery. In general, the parametric algorithms to predict new data that requires the parameters of the model. The common type of statistical regression model used to archive that aim estimate in which relationship from one or more independence variable and a single dependent variable [24]. Geographically weighted regression (GWR) is the techniques for exploring spatial data with relationships between the variables for the local techniuqe [25]. GWR is a non-stationary technique is applied for local or spatially varying parameters with the weighted of regression analysis, therefore the different of the regression parameters in each value or location [26]. The GWR form is regularly expressed [27]:

$$y_i = \beta_0(\mu_i, v_i) + \sum_{k+1}^{p} \beta_k\,(\mu_i, v_i) x_{ik} + \varepsilon_i \quad (4)$$

where: y_i is the AGB values (μ_i,v_i); $\beta_0\ (\mu_i,v_i)$ is the intercept; $\beta_k\ (\mu_i,v_i)$ is the coefficient of k^{th} for vegetation indices (μ_i,v_i); x_{ik} is the k^{th} for vegetation indices with position *i;* ε_i is the random error of position *i.*

The independent variable the x_{ik} were the NDVI, SAVI, and FVC indices of satellite imagery were selected to represent the value of each plot for analysis of spatial analysis of AGB using the GWR model. The GWR 4.0 software package was used in this paper was developed by the department of Geography, Ritsumeikan University, Kyoto, Japan which allows for modeling spatially varying relationships among variables to identify the weights of regression and optimize bandwidth of the parameters for the model [28].

Evaluation of spatial analysis of AGB models

The models were evaluated using the mean absolute error (MAE) [29, 30], root mean square error (RMSE) [31, 32], and determination coefficient (R2) [33]. The equations follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_{is} - y_{it})^2}{N}} \quad (5)$$

$$MAE = \frac{\sum_{i=1}^{N} |y_{is} - y_{it}|}{N} \quad (6)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_{is} - y_{it})^2}{\sum_{i=1}^{N} (y_{is} - \bar{y}_{is})^2} \quad (7)$$

where: y_{is} is the simulated AGB value of the i value; y_{it} is the observed AGB value of the i-plot value; $\bar{y}_{is}$ is the average of simulated AGB value; N is the number of the simulated samples.

Results

The results of Above-ground biomass (AGB) from field survey

The results of the data collected from the field surveyed sample plot with 62 plots found that the total number of 3,363 trees. The calculated of an allometric equation for assessment of AGB from the parameter were the AGB total, stem biomass, branches biomass, leaves biomass, tree diameter at breast height, and tree height. The results of AGB from field survey of the tree where stem biomass was 21,369 Ton per Rai, branches biomass was 7,069 Ton per Rai, and leaves biomass was 0.11 Ton per Rai. the AGB of the tree in the sample plot using the allometric equation was 215 Ton per Rai.

The results of spatial analysis of AGB using GWR

The results of vegetation indexes from satellite images.

To investigate relationship between NDVI, SAVI, and FVC indexes for assessment of AGB. The significant result of NDVI was between -0.027 to 0.544. The high of NDVI values show that high density of tree that mean the high biomass values. The high of NDVI values was distribution of the study area that shown in figure 2.

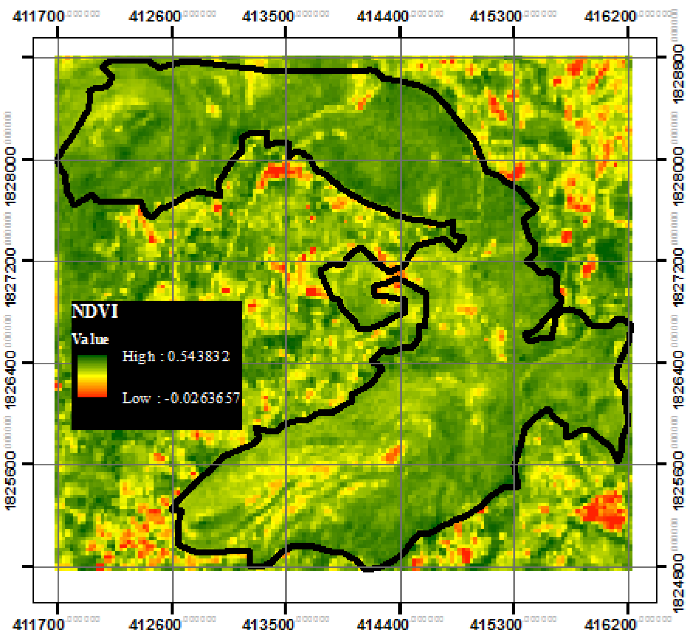

Fig. 2. NDVI mapping from satellite imagery

The significant result of SAVI was between -0.039 to 0.815 The high of SAVAI values show that high density of tree that mean the high biomass values. The lower the value (yellow and red color) the lower the biomass that shown in figure 3. The significant result of FVC was between -0.000 to 0.707 The high of FVC values show that high density of tree that mean the high biomass values. The lower the value (yellow and red color) the lower the biomass that shown in figure 4.

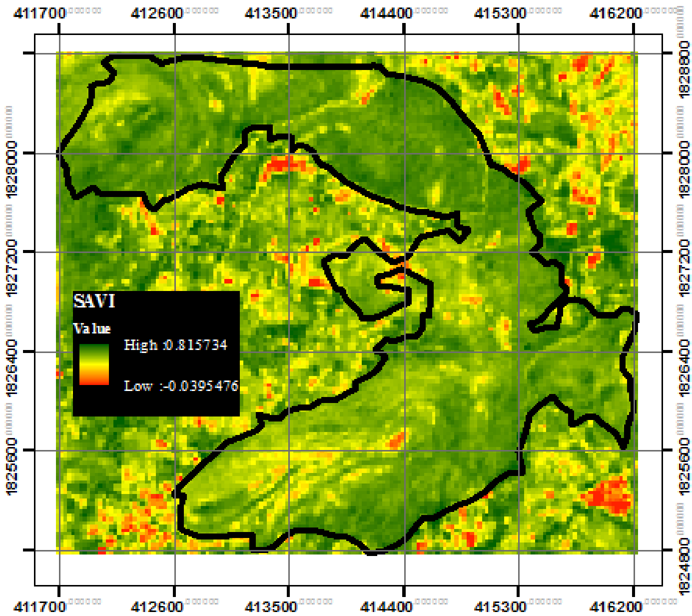

Fig. 3. SAVI mapping from satellite imagery

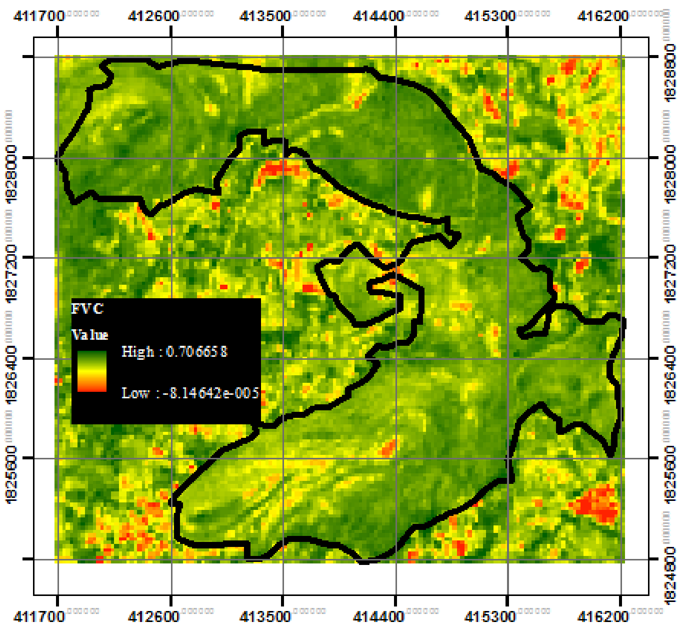

Fig. 4. FVC mapping from satellite imagery.

The spatial analysis of AGB using GWR model and remote sensing data

The results of the NDVI and RVI were selected for the assessment of AGB using the GWR model. Table 1 shows summarize the comparison of the regression analysis between the global and local (GWR) regression from the field surveyed with the vegetation indices.

Table 1. Summarized the results of the global regression and GWR model

Variable	Global regression			GWR	
	Estimate	**SE**	**T value**	**Mean**	**STD**
Intercept	223.33	11.68	19.10	230.60	24.22
NDVI	-42.72	85.25	-0.50	-27.63	57.41
SAVI	-38.01	117.60	-0.32	-29.01	111.65
FVC	116.70	92.93	1.25	88.57	111.74
R^2		0.36		0.85	
Adjusted R^2		0.10		0.59	
Residual sum		490198.59		319516.48	
bandwidth		-		48.78	

*Significant at the 0.01 level

The R^2 value of the global and GWR regression were 0.366 and 0.856, respectively and the optimal bandwidth for the simple of GWR in this study was 48.78. The adjusted R^2 values of the GWR model achieved a significant improvement in the global regression from 0.108 to 0.59 and the residual sum of squares (RSS) by the GWR was very small than the global regression. The value of RSS of GWR and global regression was 319516.48 and 490198.59, respectively.

The ANOVA statistics in Table 2 shows comparison of GWR model shown that the significant improvement over with the global regression at the 0.01 level of significance can be show in the F value. The simulated residuals of the GWR model were 319516.48 is less than that of the global regression model was 490198.59.

Table 2. Comparison of ANOVA Table between GWR and global regression models.

Source	SS	DF	MS	F
Global Residuals	490198.59	58.00		
GWR Improvement	170682.11	9.83	17349.75	
GWR Residuals	319516.48	48.16	6634.16	2.61

The GWR model applied to estimate the spatial mapping of carbon sequestration in the orchard or perennial tree area. The results of spatial mapping of AGB of some plot area of shown in figure 5 and the results of estimated the AGB in the tree area was 1,055,540.80 tCO_2e.

The evaluated of spatial analysis of AGB model using the MAE, RMSE and R^2 values was 0.139, 0.280, and 0.891, respectively.

Discussions

The results of spatial analysis of AGB using GWR model and remote sensing data. The R^2 and adjust R^2 values of the GWR model higher than the global regression and the RSS value show the performance of GWR model to improve the residual sum of global regression with 170682.11. In addition, the evaluated of the MAE and RMSE values show the results of GWR model with the vegetation indices to estimate the AGB suggested that the produces less error. The AGB volume was high as well as the NDVI value was high, the RVI value was high, and FVC value was high. Consequently, the GWR model has better performance than the global regression model [34] for the estimated the spatial analysis of AGB in the tree.

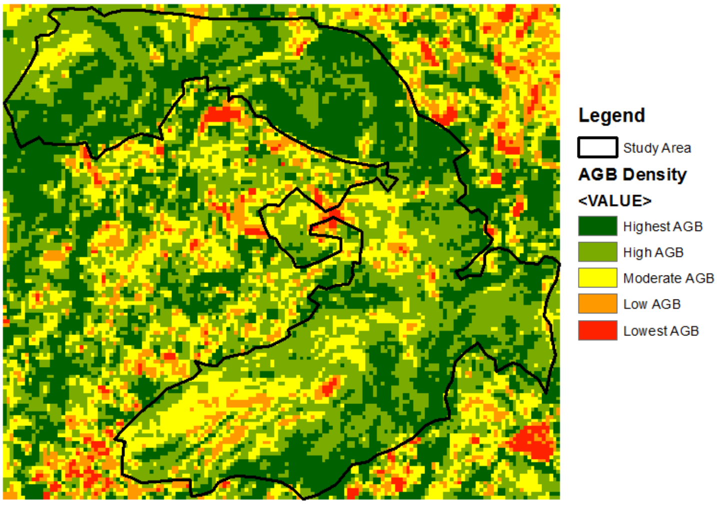

Fig 5. The spatial analysis of estimate the AGB in the study area

Conclusions

The estimated AGB from the field survey sample plot to data collected for field measurement to estimate the AGB of the orchard or perennial using the allometric equation. The 62 sample plot from field surveyed show that the total number of 3,363 trees. The spatial analysis of AGB using GWR model with the AGB volume from field survey and the NDVI, RVI, and FVC indices. The results show that a significant correlation between the NDVI, RVI, and FVC with the GWR model by the R2 value. The spatial map of AGB volume form the GWR model depended on the value of NDVI, RVI, and FVC value. However, the independent variable should have studied more variable such as the physical factor or the vegetation indices (SR, SAVI, and etc.) for applied to the GWR model. Moreover, the methods for estimated the AGB volume should be studied more technique such as machine learning technique or data mining technique or etc.

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