Estimating Aboveground Biomass of Rubber Tree Using Remote Sensing in Phuket Province, Thailand

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***Abstract*—Rubber tree is an important economics crop in Thailand as well as the Association of South East Asian Nation (ASEAN) region. In addition, it also help to absorb the carbon dioxide stored in the form of biomass. Biomass of plants is one of the essential variables in explaining the climate system and carbon cycle. The objective of this study was to estimation the above ground biomass of the rubber tree using high spatial resolution spaceborne multispectral sensor (i.e., WorldView-2). The 8 spectral bands from WorldView-2 imagery were used as input variables of Stepwise Multiple Linear Regression and Artificial Neural Networks for estimate the biomass of the rubber tree at Paklok sub-district, Thalang district, Phuket Province. The results showed that Artificial Neural Networks provide the most accurate (Root Mean Square Error (RMSE) = 11.97) when compared with stepwise multiple linear regression (RMSE = 13.07). We hope that the methodology presented in this study can be used as a guideline for study in other area and for rubber tree plantation management or predictions the rubber yield in the future.**

***Index Terms*—rubber tree, biomass, remote sensing, stepwise multiple linear regression, neural networks**

I. Introduction

Rubber tree (*Hevea brasiliensis Muell*.) is an important economics crop in Thailand as well as the ASEAN region. It is the source of natural rubber, wood products, and rubber products such as rubber smoked sheet, block rubber, concentrated latex, tires, rubber gloves, medical products, etc. Approximately 97% of global natural rubber supply comes from Southeast Asia [1], [2]. Thailand is the world leading producer and exporter of Para rubber. In addition to main economics crop, the rubber tree also helps to absorb the carbon dioxide stored in the form of biomass [3]-[6]. Biomass of plants is one of the crucial variables to explaining the yield, carbon accumulation and forest production processes [7], climate system, power exchange with the atmosphere [8], carbon cycle and the hydrological model [9]-[10]. Therefore, fast and accurate biomass mapping of rubber tree are importance. To the acquisition of rubber plantation parameters by conventional method such as field survey methods in over large areas is time-consuming, expensive, and labour-intensive [11]-[13]. Fortunately, such difficulties have been improved by earth observation remote sensing technique. The remote sensing technology is powerful tool for this purpose because this method do not destroy the sample [14]-[16] and suitable for the vast areas. Furthermore, it also reduce cost and time of field survey [17]-[20]. It is obvious that remote sensing instruments are now operationally used for mapping and monitoring rubber tree at the broad level [2], [11], [12], [21]-[31]. The previous studies [31] reported that the normalized difference vegetation index (NDVI) derived from SMMS satellite image can be used for classified the rubber stand age and rubber mapping with good accuracy. Likewise, [32] found that soil-adjusted vegetation index (SAVI) derived from SPOT-5 was strong related to leaf area index (LAI) of rubber tree at Namom district, Songkhla province. Several studies of others vegetation type found that vegetation index such as NDVI has high correlation with Biomass and LAI [33]-[36]. However, can be unstable due to the saturation problem, especially in high leaf area cover, dense forest structure and high biomass regions [37]-[43]. For tackle the saturation problem the multiple linear regression techniques were used for estimated the biophysical variables instead of the vegetation indices that used only two spectral bands [44]-[51]. However, this method frequently faced with multicollinearity problem [52]-[54]. Several studies found that Artificial Neural Networks (ANNs) can be improved the biomass and LAI estimation of boreal forests, forests (*Shorea robusta Gaertn, Acacia catechu* (L.f.) Willd., *Dahlbergia sissoo* Roxb., *Trewia nudiflora* Linn., mixed forests and grasslands) when compared with multiple linear regression [15], [55]-[57]. However there is still no conclusion which method is the suitable method to estimate the biomass of rubber tree.

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Consequently, this study aim to use the multispectral spectral bands of high spatial resolution satellite image (i.e., WorldView-2) for estimate the biomass of rubber tree at Paklok sub district, Thalang district, Phuket province, Thailand. The multispectral bands of WorldView-2 will use as the input variable for multiple linear regression and artificial neural network to models the biomass of rubber tree.

II. Methodology

A. Study Sites

The study site is at a part of the Paklok sub district, Thalang district, Phuket province, in the south of Thailand. It is located between 98° 23’ 50.4306” E to 8° 4’ 47.6754”N (Fig. 1). The average elevation in the region is 21 meters above mean sea level. The climate of the study area is tropical with a mean annual temperature of 27.60 ℃ and a mean annual rainfall of 2240 mm. The dry period occurs during April to November, and the rest of the year is dominated by the monsoons (rainy season). It is the favorable climate for rubber tree. The rubber tree is a main crop in this area: Approximately 3095 ha were planted with rubber trees.

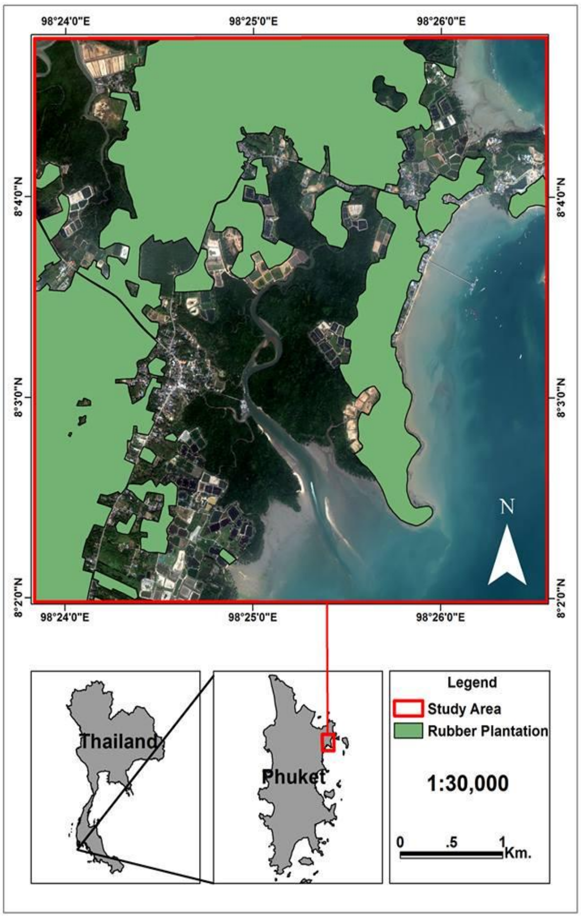

Figure. 1. The worldview-2 image of the study area overlaid with rubber tree land cover.

B. Image Pre-Processing

The WorldView-2 image was acquired on December 27, 2013, within the rubber tapping season (between March and December). The image has 8 bands with 1.84 meter spatial resolution (see the characteristics of the satellite in Table I). The image was then applied radio metric correction to normalize satellite images for factors such as sensor degradation, Earth–Sun distance variation, incidence angle, view angle, and time of data gathering. The process involved converting Digital Number (DN) into radiance and, consequently, radiance into reflectance using calibration coefficients provided by the metadata files.

TABLE I. The Characteristic of WorldView-2 Satellite Imagery

WorldView-2 Satellite Sensor Characteristics	
Sensor Resolution	Panchromatic 0.46 m
	Multispectral 1.84 m
Sensor Bands	Panchromatic: 450 – 800 nm
Sensor Bands (8 Multispectral)	B1: Coastal: 400 – 450 nm
	B2: Blue: 450 – 510 nm
	B3: Green: 510 – 580 nm
	B4: Yellow: 585 – 625 nm
	B5: Red: 630 -690 nm
	B6: Red Edge: 705 – 745 nm
	B7: Near-IR1: 770 – 895 nm
	B8: Near-IR2: 860 – 1040 nm
Swath Width	16.4 km at Nadir

C. Sample Biomass Data Collection

The field data collection was conducted between December, 2013 (during rubber tapping season). A random sampling method was used for locating the sampling plots with Line Transect method. The three class of rubber tree stand age mapping (our ongoing research on rubber tree stand age with overall accuracy is 96.61%) was used to sampling the samples plots. The 90 sampling plots was distributed throughout the stand age interval of rubber tree mapping with 30 plots of each class. The 10x 10 square meter was use as sampling plots size and 10 meter interval of plots in line transect was used. For each tree in the 90 plots, the diameter at breast height (DBH) and rubber tree heights were measured. The height of each rubber tree was measured using a clinometer, and tree diameters were measured using a tapes. The Differential Global Positioning System (DGPS) technique with UTM system was used to record the centre coordinates of each plots. The mapping control point of Department of Lands, Thailand was used as control point of DGPS correction.

D. Calculation of above Ground Biomass

The DBH and rubber tree height were used for calculate the above ground biomass of each rubber tree by allometric equation from [58] study as in (1). The ratio between total above ground biomass of every rubber tree in the sample plots and area in square meter of the plots was used to represent the above ground biomass of each plots.

$$\text{Above Ground Biomass} = 0.0046(DBH^2H)^{1.2046} \text{ (kg)} \quad (1)$$

where DBH is diameter at breast height (DBH) (i.e., 130 cm. above ground).

H is rubber tree heights (m.).

E. Biomass Model Development

The 90 samples were randomly divided in 70:30 percent to create training and evaluating data for biomass model developments. The stepwise multiple linear regression and artificial neural network models were created that related plot above ground biomass data to the multispectral reflectance from the remote sensing data.

1) Stepwise Multiple Linear Regression (SMLR): Stepwise Multiple Linear Regression method was used to find the best variables to estimate. It starts with no predictors (i.e., spectral bands) in the regression equation and at each step it adds the most statistically significant spectral bands (highest F-value or lowest p-value) and procedure computes the removal statistic for each spectral bands and removes it (lowest F-value or highest p- value). In this study, use F probability value of 0.05 and 0.10 as stepping method criteria for independent variables entry and removal, respectively. The selected spectral bands were used to creating linear regression model [11], [47], [59]-[60]. The output of the Stepwise Multiple Linear Regression as in (2).

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3+\ldots..+ b_nX_n \qquad (2)$$

where Y is the dependent variable to be predicted (i.e., Biomass)

X_1, X_2, X_3,….., X_n is the Independent variable (i.e., 8 spectral bands of worldview-2)

b_1, b_2, b_3,….., b_n is Coefficient of Regression

The 8 multispectral band (see Table I) were used to input variables of the Stepwise Multiple Linear Regression model.

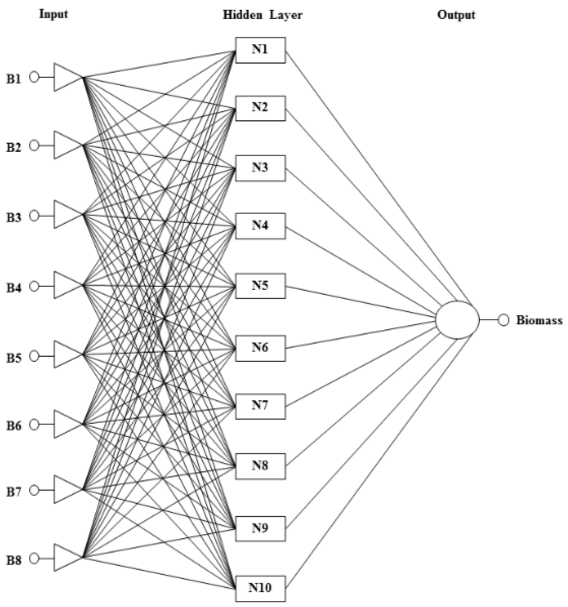

Figure. 2. Multi-layered perceptron

2) Artificial Neural Networks (ANNs): For this study, the neural networks structure were simulated in the Neural Network module of MATLAB [61]. The back-propagation multilayer perceptron (MLP) is a widely used in remote sensing was used in this study [15], [62]-[64]. The network structure, and learning algorithms were tested to determine optimal algorithm characteristics. The combinations of Worldview-2 with 8 spectral bands were used as input data of neural networks. The structure of the hidden layers was examined to determine the optimal number of hidden layers and number of nodes per layer required. Furthermore, the early stopping by adjusting the training mean square error (MSE) goal and automated regularization utilizing the Bayesian Regularization (BR) learning algorithm were used for generalization and reduce overfitting problem. As a result, the network structure was constructed with 8 node of input layer, 10 node of hidden layer and one node of output layer as Fig. 2.

3) Performance evaluation and comparison: The coefficient of determination (R^2) and root mean square error (RMSE) were used to performance evaluation in both stepwise multiple linear regression and artificial neural network. The equations employed for root mean square error (RMSE) calculated as in (3). The plotting between measured biomass and estimated biomass as well as the statistics of both techniques were compared. The model which have lower RMSE value indicated that the model better than other model.

$$RMSE = \sqrt{\frac{1}{n}\sum(\hat{y}_i - y_i)^2} \qquad (3)$$

where n is the number of the observations

$\hat{y}_i$ is the estimate biomass

y_i is the measured biomass

III. RESULTS AND DISCUSSION

The 8 spectral bands were used as input variables of SMLR and ANNs. Table II contains a summary of the biomass retrieval results. The R^2 and RMSE of both models were compared (see Table II). Moreover, the best combination of spectral bands (i.e., Red band, Red Edge and Near-IR2 band) for SMLR and coefficients were reported. For the selected wavelengths (bands), the red and Near-infrared band is the strong chlorophyll absorption band and used for in numerous vegetation indices formulas. Similarly, Red Edge band is strong chlorophyl absorption and leaf internal scattering [65], [66]. Furthermore, [67] found that the narrow-bands vegetation indices that used 2 spectral bands in red-edge region can be overcome the saturation problem in biomass estimation.

TABLE II. THE PERFORMANCE OF THE BIOMASS ESTIMATION METHOD

Method	R^2	RMSE
SMLR Biomass=798.50*B5 +504.26*B6-510.29*B8 - 18.25	0.33	13.07
ANN	0.66	11.97

where B5 is Red band, B6 is Red Edge band and B8 is Near-IR2 band (see Table I)

Comparisons of estimated versus measured biomass using the SMLR and ANNs methods are plotted as Fig. 3 and 4. Linear regressions of estimated versus measured

Biomass from ANNs method considerably better than results from SMLR. The results indicated that ANNs can be significantly improved the biomass estimation performance when compared with SMLR, The R^2 increased from 0.33 to 0.66. Likewise, the RMSE was improved from 13.07 to 11.97. This result agrees with the previous work of [55], [57] who reported that the artificial neural network model provided a more accurate biomass estimation than multiple linear regression. This study used 23 years old rubber tree allometric equation [58]. Whereas, the study area of this study have rubber stand age from 6 to 25 year old. This issue should be take into account in future study.

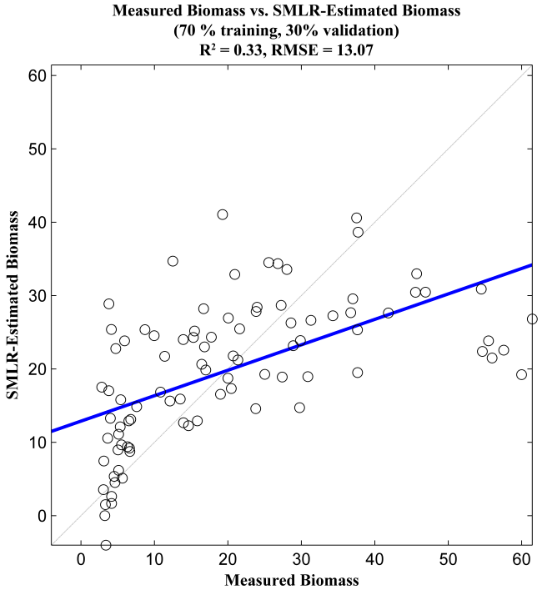

Figure. 3. Estimated biomass versus measured biomass using the SMLR method.

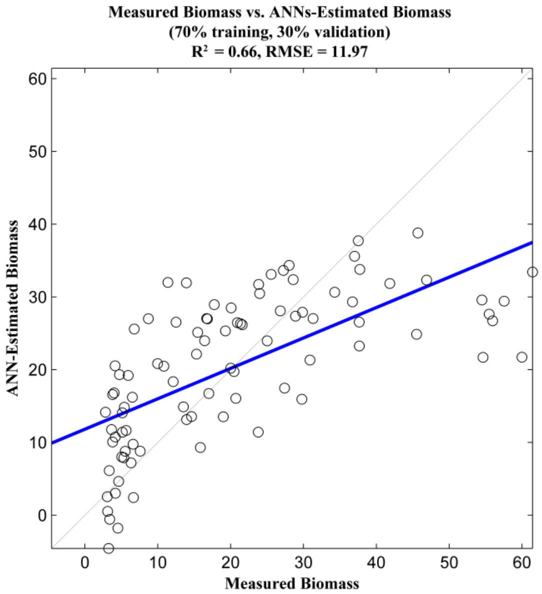

Figure. 4. Estimated biomass versus measured biomass using the ANNs method

IV. Conclusion

This study investigated the estimation of above ground biomass of rubber tree using remote sensing at Paklok sub district, Thalang district, Phuket province, Thailand. The stepwise multiple linear regression (SMLR) and artificial neural networks (ANNs) were used as biomass model development. The selected bands from SMLR related to chlorophyl absorption and leaf internal scattering wavelength. The ANNs method can be improved the biomass estimation performance by R^2 from 0.33 to 0.66 and RMSE 13.07 to 11.97, respectively. It was indicated that ANNs method more suitable to use biomass estimation model. We hope that the methodology presented in this study can be used as a guideline for study in other area and for rubber tree management or predictions the rubber yield in the future.

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