Above-ground biomass estimation of *Eucalyptus* plantation using remotely sensed data and field measurements

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Abstract. Biomass has had an essential role in the energy sector of the world due to applications in bioenergy. Stand level biomass is frequently calculated from allometric models with field measurements, which is usually time-consuming and costly. They are limited because of the consideration of spatial pattern analysis of above-ground biomass (AGB) across the landscape. Therefore, the development of reliability and low-cost methods is necessary for AGB estimations in landscape level. This study aims to develop a model for estimating AGB for *Eucalyptus* plantation located in the Sahacogen Green Co., Ltd., in Lampang province, Thailand using remotely sensed data. The AGB value was coupled which calculated from field measurement (tree height, H and diameter at breast height, DBH) using the allometric equation with various vegetation indices. The 55 sample plots and 5 vegetation indices derived from Thailand Earth Observation System (THEOS) were used to develop a model for estimating AGB of *Eucalyptus* plantation. After discussing the results of the investigation, the Transformed Normalized Difference Vegetation Index (TNDVI) showed a robust correlation with AGB compared to other indices ($r = 0.833$). Based on stepwise linear regression between AGB and 5 vegetation indices demonstrated TNDVI was only selected while the other indices were eliminated because their relationship was not significant. The developed model $R^2$ was 0.693, adjusted $R^2$ was 0.684 and SEE was 12.41 Mg ha⁻¹. The relationship between observed AGB and predicted AGB from the THEOS model of *Eucalyptus* plantation with $R^2$ of 0.742 and RMSE of 9.63 Mg ha⁻¹ indicated that remotely sensed data from THEOS can be useful for AGB estimation with high accuracy.

Keywords: Above-ground biomass, Remotely sensed data, *Eucalyptus* Plantation

1. Introduction

Interest in fast-growing tree plantations to produce energy has been increasing interest worldwide in recent years [1] since they provide energy generation that can be sustained for a long term. The goal of last Alternative Energy Development Plan (AEDP) of Thailand is to increase the use of renewable energy in Thailand’s economy from 12 to 30% of total final energy consumption in 2036. In particular, biomass will be used more than twice from the present [2]. Increasing demand of biomass energy in Thailand, particularly fuelwood, has brought about a rapid expansion of fast-growing tree plantations such as *Eucalyptus*. Biomass estimation in forest plantation is necessary to use of their forest plantations for the management decision. Stand level biomass is frequently calculated from
allometric models with field measurements which is usually time-consuming and expensive. They are limited when considering large plantation area analysis level [3]. Thus, it is necessary to develop reliable and low-cost methods that can be used in case of the large plantation area level.

In recent years, vegetation indices from remotely sensed data have been developed and applied to biomass estimation [3]. The spectral bands data and vegetation indices have been shown to correlate with AGB estimation [4]. The most popular and widely used methods for estimating AGB with remotely sensed data are multiple regression [5, 6] and linear or nonlinear regression models [7]. The vegetation index is a transformation of spectral bands usually calculated from near-infrared (NIR) and red reflectance [8]. Normalized Difference Vegetation Index (NDVI) is the proportion of vegetation covering the surface calculated from the difference of reflection of NIR and red reflectance. However, it has limitations due to sensitivity to several disturbing factors such as atmospheric, cloud and soil [9]. Tucker C.J., 1979 [10] demonstrated a TNDVI that developing from NDVI and the TNDVI indicates a slightly better correlation with AGB [9-11]. Soil adjusted vegetation index (SAVI) was proposed to reduce the effect from soil reflectance in low vegetation cover area [9]. Furthermore, SAVI was found to apply for developing a model of the dynamic soil-vegetation systems [12]. Due to negative effect of high degree of exposed soil surface on NDVI, Qi et al., 1994 proposed the Modified Soil Adjusted Vegetation Index 2 (MSAVI2) to solve this problem [13].

Eucalyptus is a fast-growing tree with high potential in the renewable energy system in Thailand. The allometric equation was usually calculated for biomass estimation and frequently found in previous research. However, allometric equation was time-consuming and costly since the study area was large. THEOS is the natural resources survey satellite of Thailand. However, utilization of THEOS for Eucalyptus biomass estimation has not been discussed in previous literature. Therefore, this study aims to model the relationship between vegetation indices resulting from THEOS satellite data and ground estimated AGB of Eucalyptus plantation by assessing the accuracy and validating a predictive model of the AGB estimates with field observations.

2. Materials and Methods

2.1. Study location

The study location includes of almost 115 ha of managed pure stand species of Eucalyptus (E. camaldulensis) with a 2 m × 3 m spacing located in Sahacogen Green Co., Ltd., Kokha district, Lampang province, Northern Thailand (18°06′–18°09′N, 98°18′–99°21′E) as shown in Figure 1.

![Figure 1](image.png)  
*Figure 1.* The study location used for AGB model development and validation.
The plantation age ranges between 1 and 10 years. The study area is characterized by tropical climate; the soils are mixture of sandy and sandy clay loam. The altitude is 268 m a.s.l., the mean annual temperature and mean annual rainfall are 26.2 °C and 1231 mm with around 3 rainy months, respectively.

2.2. Ground biomass data investigation

Ground biomass data measurements were conducted in June to July 2019. A total of 55 plots with a dimension of 10 m × 12 m were investigated, divided into 35 plots for model fitting and the other 20 plots for validation. Samples were selected according to tree age and tree size using a stratified random sampling. Sampling areas with various AGB in a plantation will be sampled from this method. In each sample plot, diameter at breast height (DBH) and tree height (H) were measured by using measuring tape and measuring pole, respectively. The geographical location of each sample plot was also recorded with a global positioning system (GPS). AGB of each tree was calculated using the allometric equation developed specifically for Eucalyptus (Developed from 72 destructively sampled with $R^2$ of 0.987 and SEE of 1.11 Mg ha$^{-1}$) as shown in Equation (1).

$$\text{AGB} = 0.045(\text{DBH})^{1.692}(\text{H})^{0.045}$$ (1)

2.3. Remotely sensed data and vegetation index calculation

A THEOS multispectral image (15 m resolution) acquired on February 2, 2019 was employed in this study. The image was orthorectified using Geo-Imaging Accelerator (GXL) satellite processing system before calculation of vegetation indices. Reflectance included four individual bands ($B_1 = \text{blue}, B_2 = \text{green}, B_3 = \text{red} \text{ and } B_4 = \text{near-infrared}$) used to calculate vegetation indices for this investigation as shown in Table 1.

**Table 1.** Vegetation indices equations calculated with reflectance of THEOS data.

| Vegetation indices                                      | Equations                                                                 | References |
|---------------------------------------------------------|---------------------------------------------------------------------------|------------|
| Transformed Normalized Difference Vegetation Index (TNDVI) | $\text{TNDVI} = \sqrt{\frac{B_4 - B_1}{B_4 + B_1}} + L \text{ with } L = 0.5$ | [10]       |
| Soil Adjusted Vegetation Index (SAVI)                    | $\text{SAVI} = \frac{(1 + L)(B_4 - B_1)}{B_4 + B_1 + L} \text{ with } L = 0.5$ | [12]       |
| Modified Soil Adjusted Vegetation Index 2 (MSAVI2)      | $\text{MSAVI2} = \frac{2(B_4 + 1) - \sqrt{(2B_4 + 1)^2 - 8(B_4 - B_3)}}{2}$ | [13]       |
| Simple Ratio (SR)                                       | $\text{SR} = \frac{B_4}{B_1}$                                            | [14]       |
| Normalized Difference Vegetation Index (NDVI)            | $\text{NDVI} = \frac{B_4 - B_1}{B_4 + B_1}$                             | [14]       |

2.4. Modeling relationship and validation

AGB and vegetation indices were plotted and analyzed using Linear regression. Vegetation indices models evaluation was performed using Pearson correlation coefficient ($r$) and R-squared ($R^2$). Higher $r$ and $R^2$ of vegetation indices were presented to corresponded with AGB estimation. Moreover, Stepwise linear regression was applied into models between AGB (dependent variable) and vegetation indices (independent variables) by using SPSS. $R^2$ and standard error of estimate (SEE) were used to
evaluate the model accuracy. Validation of the modeling was evaluated from 20 observed AGB plotted against predicted AGB.

3. Result and Discussion

3.1. Field data of Eucalyptus plantation

DBH and H of the 821 trees were recorded from 55 sample plots having a good relationship with AGB (Figures 2 and 3). The analysis of Spearman correlation with 95% confidence level shows robust positive correlations between AGB with DBH (Rho = 0.966) and AGB with H (Rho = 0.970). The AGB per hectare covers a relatively various range (Figure 4), with 14.5% of the sample trees indicating values below 20 Mg ha\(^{-1}\); 54.5% between 20 Mg ha\(^{-1}\) and 40 Mg ha\(^{-1}\); 18.2% between 40 Mg ha\(^{-1}\) and 60 Mg ha\(^{-1}\) and 12.7% above 60 Mg ha\(^{-1}\), with a minimum of 4.8 Mg ha\(^{-1}\) and maximum of 97.35 Mg ha\(^{-1}\). The mean and standard deviation are 31.85 Mg ha\(^{-1}\) and 20.75 Mg ha\(^{-1}\), respectively.

![Figure 2](image1.png) **Figure 2.** The relationship between DBH and AGB measured at 55 plots.

![Figure 3](image2.png) **Figure 3.** The relationship between H and AGB measured at 55 plots.

![Figure 4](image3.png) **Figure 4.** Histogram showing the range of field AGB within 55 sample plots.

3.2. Models for estimating above-ground biomass

The performance of five vegetation indices derived from THEOS satellite data and AGB resulting from linear regression are shown in Table 2. The correlation value demonstrates from 0.709 to 0.833, \(R^2\) varied between 0.498 to 0.693 and SEE distributed from 12.41 to 15.88 Mg ha\(^{-1}\). As can be seen, all vegetation indices was significantly shown as good correlation with AGB. The best independent variable was TNDVI which conformed to AGB \((r = 0.833, R^2 = 0.693)\) followed by MSAVI2, NDVI, SAVI and SR, respectively. The AGB increased with increasing TNDVI due to NIR reflectance...
NIR reflectance increased with increasing leaf thickness and amount of the tree canopy [15].

NDVI is almost popular index and widely used to estimate green biomass because of an acute sensitivity to low leaf area index (LAI) and variation in evergreen biomass easily detected with NDVI [16]. However, reflecting background soil usually has negative effects to NDVI on the accuracy of AGB estimation [15]. This study found that the accuracy of AGB estimation forasmuch can be improved by adding soil adjustment factor (L = 0.5) to NDVI, and taking the square root to get TNDVI resulting in high acute sensitivity to topography than other indices [17].

Table 2. Performance of the five vegetation indices and AGB resulting from linear regression.

| Vegetation indices | r   | $R^2$ | SEE  |
|--------------------|-----|-------|------|
| NDVI               | 0.710 | 0.504 | 15.78 |
| TNDVI              | 0.833 | 0.693 | 12.41 |
| SR                 | 0.706 | 0.498 | 15.88 |
| SAVI               | 0.709 | 0.503 | 15.80 |
| MSAVI2             | 0.713 | 0.508 | 15.72 |

Figure 5. Relationship between TNDVI and AGB of Eucalyptus plantation.

The result of Stepwise linear regression analysis in the investigation between Eucalyptus AGB and five vegetation indices (NDVI, TNDVI, SR, SAVI and MSAVI2) from THEOS data was provided in Table 3. Among five vegetation indices, only TNDVI was selected in stepwise method, in the criteria of $p_{\text{enter}} \leq 0.500$ and $p_{\text{remove}} \geq 0.100$. Predictor variables NDVI, SR, SAVI and MSAVI2 were eliminated because their relationship was not significant. The final model, $R^2 = 0.693$, Adjusted $R^2 = 0.684$ and its SEE = 12.41 Mg ha$^{-1}$. The final model explained about 69.3% of the variations in AGB, and the final model for Eucalyptus AGB estimation in this investigation is presented as Equation (2).

\[
\text{AGB} = 412.253 \text{TNDVI} - 262.857
\] (2)

Field measurement data of 20 sample plots were used to validate the predictive model by using simple linear regression. The result of this study has shown a robust correlation between predicted AGB and observed AGB with $R^2$ of 0.742 (Figure 6). Root mean square error (RMSE) of the predicted AGB and observed AGB values was 9.63 Mg ha$^{-1}$. 
Table 3. Performance of stepwise linear regression model.

| Variables entered | Excluded variables | $r$  | $R^2$  | Adjusted $R^2$ | SEE | Sig. | Tolerance | VIF |
|------------------|-------------------|-----|-------|---------------|-----|------|-----------|-----|
| TNDVI            |                   | 0.833 | 0.693 | 0.684 | 12.41 | .000 | 1.000 | 1.000 |
| NDVI             |                   | .115 | 0.148 |       | 6.762 | .14 | 6.762 |
| SR               |                   | .153 | 0.163 |       | 6.133 | .14 | 6.133 |
| SAVI             |                   | .108 | 0.147 |       | 6.783 | .14 | 6.783 |
| MSAVI2           |                   | .103 | 0.141 |       | 7.115 | .14 | 7.115 |

Criteria of probability of $p_{enter} \leq 0.500$ and $p_{remove} \geq 0.100$.

Figure 6. Relationship between observed AGB and predicted AGB from the remote sensing-based model of *Eucalyptus* plantation.

4. Conclusions

THEOS multispectral data can be utilized to estimate AGB for *Eucalyptus* plantation. Vegetation indices resulting from THEOS satellite data showed that TNDVI established from red and near-infrared bands, constant 0.5 with taking the square root, had a robust correlation with AGB since comparison with other vegetation indices. The AGB estimation model resulting from stepwise linear regression analysis was strong ($R^2 = 0.693$). The relationship between observed AGB and predicted AGB from the THEOS model of *Eucalyptus* plantation with $R^2$ of 0.742 indicated that remotely sensed data could be utilized to predict *Eucalyptus* AGB with high accuracy.

Due to a strong correlation of AGB with the remotely sensed data from THEOS, the finding in this investigation would be beneficial use as sources for above-ground biomass estimation especially *Eucalyptus* over the large area. Furthermore, this information will be provide accurate biomass energy data in landscape level for crop management to make decision on renewable energy systems. In addition, the remotely sensed data from THEOS can also be applied to other evergreen plant species which are very useful in the efficient management of biomass in the future.

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