Indonesian Journal of Electrical Engineering and Computer Science
Vol. 4, No. 3, December 2016, pp. 586 ~ 593
DOI: 10.11591/ijeecs.v4.i3.pp586-593

Model for Estimating Above Ground Biomass of Reclamation Forest using Unmanned Aerial Vehicles

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Abstract

Among various stand parameters, the density of biomass volume is oftenly used as an indicator on evaluating the forest growth succes. The forest reclamation, which is intended to restore the land cover by revegetation process, the evaluation of biomass content has been a critical issue. Forest reclamation is expected to restore the land function to a proper state that might give better environment as well as productivity. In this study the authors develop a method for estimating above ground biomass (AGB), particularly in the ex open-pit coal mining area of PT. Bukit Asam Tbk using remotely-sended data taken from unmanned aerial vehicle (UAV) and developed using the least squares method. The main objective of this study is to develop a mathematical model of biomass estimation using UAV imagery having 10-cm spatial resolution. The study found that the best model of biomass estimation is: AGB(ton/ha)=0.2377Ci$^{1.3688}$ with the correlation coefficient of 0.844, mean deviation of 2.29, aggregate deviation of -0.023, bias of 0.98, and Root Mean Square Error (RMSE) of 1.784 and mean deviation (MD) < 10% while Ci. This research concluded that UAV imagery could be used to estimate above ground biomass accurately.

Keywords: *model, reclamation forest, unmanned aerial vehicles (UAV), above ground biomass.*

1. Introduction

Indonesia is a second largest country, after Brazil, that has been suffering from high deforestation and forest degradation. About 684 thousand hectares have been lost in the period of 2010-2015 or equal to deforestation rate of 0.7% [1]. Through cooperation agreement mechanisms between countries under the International Conference, Indonesia declared its commitment to reduce greenhouse gas emissions (GHG) by 29% from business as usual and 41% with international support in 2030 [2].

Mining activities, mainly the open-pit mining system has lead to deforestation and forest degradation, particurlarly for the mining activities that are located within the forest cover. Deforestation and forest degradation in mining activities may reduce forest capability in absorp carbon dioxide from the air [3-4]. Indirectly, deforestation may cause a decrease in the amount of biomass, as well as declining productivity of forests, soil and and forest land [5-7].

In Indonesia, forest reclamation in ex-mining areas is a must, as outlined in the act No. 4 of 2009 Article 96; PP.78 Year 2010 Article 2 Paragraph 1. Referring to the guidelines for forest reclamation of P.4/Menhut-II/2011, the mining company is obligided to report, monitor and evaluate the reclamation success. However, the assessment of reclamation success mainly done based on terrestrial observation which is time consuming, costly and less accessible. Therefore, it is necessary to conduct a study which can provide a rapid, precise, accurate and less-time consuming method to assess the reclamation success [8].

One of the indicators in assessing the success of ex-coal mining reclamation was biomass [9]. The studies related to the above ground biomass and its relationship with forest structure, forest ecosystem types and spatial distribution had been documented in several articles [8-11]. Remote sensing-based biomass estimation model developed by combining the field and image data had been another issues and examined by several researches [12-15]. Recent studies related to the development of above ground biomass estimation model, standing stock and teak site quality using unmanned aerial vehicle (UAV) have been successfully examined with high accuracy [15-16].

Received Juni 3, 2016; Revised September 26, 2016; Accepted October 11, 2016

The UAV or commonly known as “drone” is an unmanned aircraft remotely controlled by ground pilot. This is also known as a complex system of UAS (unmanned aerial systems) [17]. Remote sensing drone applications in the field of forestry research have been emerged due to the advantages of UAV which can be operated timely, can be operated anywhere and periodically feasible, low-flying to produce very high resolution image, low-cost image acquisition and aircraft maintenance, various applications, as well as relatively safe because it does not require a human pilot [18-19]. Another advantage is to ensure the adequacy of the sample and the accuracy of the data [20]. High-resolution image obtained from the UAV can be used as a decision making input for forest stand management [21]. Biomass estimation in the reclaimation area by using UAV has never been conducted. Therefore, this research aims to build an estimation model of forest biomass in ex-coal mining area by using the very high resolution UAV image. The study is expected to provide the actual information of above ground biomass on the ex-coal mining reclamation area. The main objective of this study is to develop a biomass estimation model using unmanned aerial vehicle (UAV) imagery having 10-cm spatial resolution.

2. Research Method

2.1. Date and Study Site

The study was performed in the ex-coal mining reclamation area of PT. Bukit Asam, located within 103.40°–103.48° E and 3.41°–3.46° S. Administratively, the study area is located in subdistrict of Muara Enim Regency Tanjung Enim in South Sumatra Province, Indonesia. To perform the analysis, the data collection was done from the beginning of 2015, particularly to collect data related to revegetation having ages between 1 to 20 years after plantation (Figure 1).

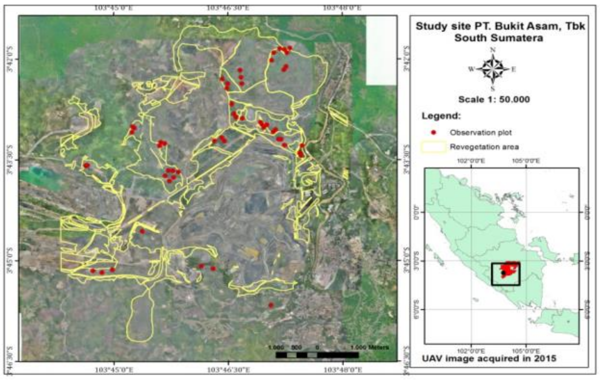

Figure 1. Study Site

2.2. Image Data

The used image data were acquired using UAV platform with the following characteristics (Table 1):

Table 1. UAV Characteristics

Specification	Type/ dimension
Name	*Sensefly Ebee*
Type	Fixed wing
Wingspan	96cm
Take-off weight	± 0.7 Kg
Cruise speed	36 – 57 Km/hour
Camera resolution	16Mpix
Radio link range	± 3 Km
Maximum flight duration	± 50 menit (45 minutes)
Maximum height	± 500 m (400 m)
Coverage	1.5 – 10 Km² (Scene: 5 cm)
Band	RGB
File format	TIFF

2.3. Sampling Design

The plot was selected on the basis of stratified sampling technique, where the age clases were considered as strata. The canopy coverage were divided into three classes, namely sparse class with percentage of canopy coverage between 10% and 40%; medium class with percentage of canopy coverage between 40% and 7 and dense class having percentage of canopy coverage more than 70% [22]. Futhermore, field data inventory was outlined systematically encompassing all reclamation area within the study area. Sample plot size was developed on the basis of the stand age, namely 0.02 hectares size for young age stand (between 1 and 4 years old), 0.04 hectares plot size for middle age stand (between 5 and 8 years old) and 0.1 hectares plot size for mature age stand (more than 8 years old). Data measurement on the UAV images was done manually by visual measure. All visual analyses were done after orthocorrection, and object delineation was done using “on the screen digitization method”.

The field data measured is the following: diameters breast height (D), tree height, free bole height, canopy cover (Cf), number of trees (Nf), canopy diameter (DTf), litter and tree condition. On the UAV image, the measured stand variable were percentage canopy coverage (Ci), the number of trees (Ni) and canopy diameter (DTI). The percentage of canopy coverage is calculated on the basis of the ratio between the extent canopy coverage within each plot and the extent of plot. Technically, canopy cover measurement can be found in [23-25]. Number of trees (Ni) was counted with a simple counting device [24-25]. The formula for canopy diameter referred [23]:

$$DTi = \frac{DT_{NS} + DT_{EW}}{2}$$

Remark:
DTi : canopy diameter
DT_{NS} : canopy diameter (north to south)
DT_{EW} : canopy diameter (east to west)

2.3. Biomass Estimation

Actual biomass in field was calculated by using the allometric formula [26] described in Table 2. For other species that do not have an allometric formula, biomass was calculated using the axisting allometric equations [27]. Furthermore, estimation of actual field biomass might be estimated by using the variable measured on the remotely sensed data. Biomass was estimated using above ground biomass allometric equations that has been developed by previous studies. The biomass allometric equations have been developed with the assumption that tree dimension (tree diameter) have high correlation with biomass. Calculation of undergrowth and litter biomass was done by calculating the ratio between dry weight and wet weight [28].

Table 2. Allometric Equation of Species in Field

Local name	Latin name	Allometric	Sources
Akasia daun kecil	*Acacia auriculiformis*	$W= 0.027\ D^{2,891}$	BALITBANG 2012
Akasia daun lebar	*Acacia mangium*	$W= 0.070\ D^{2,58}$	BALITBANG 2012
Puspa	*Schima wallichii*	$W= 0.459\ D^{1,364}$	BALITBANG 2012
Sengon	*Paraserianthes falcataria*	$W= 0.148\ D^{2,299}$	BALITBANG 2012
Jenis lain	-	$W= 0.11BjD^{2.62}$	Kettering *et al.* 2001

Bj= Wood density, D= Diameter at breast hight

2.4. Normality and Correlation Test

Normality was tested to determine whether the data are normally distributed, with P-value <0.05. The Normality tested was evaluated using Kolmogorov-Smirnov formula available on Minitab 16. The correlation was tested with Pearson approach to see relationship stand variables on the image (Ci, DTi and Ni) with ground stand variables (Cf, DTF and Nf). Strong relationship would be shown by correlation values large than 0.75.

2.5. Biomass Model

The biomass estiomation models were developed by using measured variables on the UAV image namely Ci, DTi and Ni. To the develop the model, 40 sample plots were used. The models selection was performed using statistical analysis that includes the evaluation of determination coefficient (r^2), root mean square error (RMSE) and P-value. The models having r^2 more than 0.51, RMSE close to zero and P-value large than 0.05 would be selected. The independent variable (X) was able to explain the variability of its dependent variables (Y). Mathematical models examinated in this study are as follows:

1. Linear : $Y = b_0 + b_1X$
2. Power : $Y = b_0X^{b1}$
3. Exponential : $Y = e^{b0 + b1X}$
4. Polynomial : $Y = b_0X^2 + b_1X_1 + b_2$
5. Logarithmic : $Y = b_0 + ln(X)$, $y = b_0 + log(X)$

Remarks:

Y = Above ground biomass (ton/ha)

X = Measured variables from the UAV image (Ci,DTi dan Ni)

2.6. Model Test

The developed biomass models were then descendingly sorted according to their coefficient of determination (r^2) value. Furthermore, satatistical tests were conducted to assess model acceptability. The model examination was performed using the least square approach as performed in earlier researches [14]. To meet the least square assumption, the performed statistical analysis covers F-test, t-test, normality and heteroscedasticity test. Biomass models that met the assumptions of least squares were the models that have normal distribution (Kolmogorof Smirnov test), non-autocorrelation (Durbin Watson test) and homogeneity of variance (using Glejser test for heteroscedasticity assessment).

2.7. Model Validation

Model validation was done by comparing the biomass calculated by selected model (expected value) with the estimated biomass using allometric equations (actual value). Several researcher [8], [14], [16] and [29] stated that model validation can be performed using the Chi-Square, aggregate deviation (SA), mean deviation (SR), bias (e) and RMSE to compare between the generated best model. The best model is selected based on the criteria of $t_{value} < t_{table}$ at 5% significance level or significance value > 0.05. A good estimation model possessed SA value between -1 to +1, SR less than 10%, e and RMSE close to zero.

3. Results and Analysis

3.1. Normality and Correlation Test

Prior to any other analysis, the data normality was performed. On the basis of the normality test, the distribution of biomass data, field and image were normaly distributed as indicated by the P-value of less than <0.05. The correlation analysis also recognized that there are close correlation between the variables measured in field and images (Table 3). The relationship between variables in field and variables in the image also described in Figure 2.

Table 3. Correlation between Field Variable dan Image Variable

Model	Coeefficient of correlation (r)
Ci dan Cf	0.871
DTi dan DTf	0.379
Ni dan Nf	0.672

The study found that canopy coverage measured in the field and UAV images has a very close correlation value (r) of about 0.871. A relatively low correlation value was found between the canopy diameter measured in the field and on the images. This is might be due to the relief displacement as well as due to tilt displacement and image motion (blurred image).

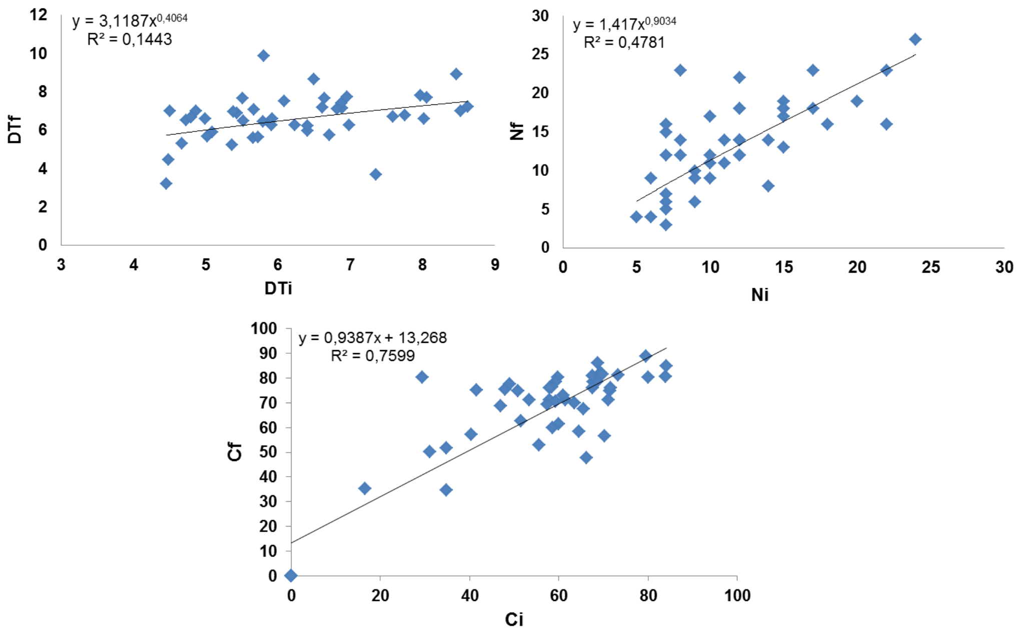

Figure 2. Scatterplot Expressing the Relationship between Field Variable and Image Variable

One of main problems in the processing of UAV image data is an image motion, which may cause a blurring image. The image motion can be reduced if the flight height is increased. On the blurred image, the measurement of crown diameter might be less accurate. In this study, the correlation between field crown diameter and image-based crown diameter was relatively low. Strong wind, turbulence and miss-navigation are other factors that may affect the quality of images [30]. In this study only the canopy coverage was examined as independent variable.

3.2. Biomass Model

Canopy coverage is one of the measurable stand variables on UAV image. For estimating the biomass content, this study found that the canopy coverage measured in the UAV image closely related to the canopy coverage measured in the field. (Figure 2). Several previous studies expressed that canopy coverage on each stand was able to be measured consistently in the UAV image, UAS and non-metric aerial photographs [31-33]. In this study, the biomass estimation models developed using canopy coverage is summarized in Table 4.

Table 4. Biomass Estimation Models using the Canopy Cover

Model code	Equation	r^2
M1	$y = 0.237X^{1.368}$	0.712
M2	$y = 1.580X - 28.86$	0.607
M3	$y = 16.52e^{0.022x}$	0.695
M4	$y = 286.225 - 7.72x + 0.067X^2$	0.642
M5	$y = 17.37e^{0,022x}$	0.566
M6	$y = 30.307\log10(X) - 341.553$	0.453

X = crown cover, *y* = AGB

3.3. Model Assessment

The analysis performed in this study obtained six biomass estimation models. Since the models use only single a independent variable as the predictor, then autocorrelation analysis did not performed. F-test and t-test results shown that six models have Sig.F < α dan P-value < α at significance level α=0,05. This analysis means that the variability of biomass could be explained by variability of canopy coverage for all selected models. All five models meet least square assumption, in particular normal data and homoscedasticity. The result could be seen in Table 5.

Table 5. Statistical Analysis for Regression Models

Model	*Sig.F*	*P.value*	Normality	Heteroscedasticity
M1	0.00	0.00	Normal	Homoscedastic
M2	0.00	0.00	Normal	Homoscedastic
M3	0.00	0.00	Normal	Homoscedastic
M4	0.00	0.00	Normal	Homoscedastic
M5	0.00	0.00	Normal	Homoscedastic
M6*	0.00	0.00	Not normal	Homoscedastic

*: Model was not meet the validity criteria

3.5. Model Validation

Model validation was performed for all selected models to assess the model validity. Basically, this process was performed by comparing the value of the estimated biomass and the actual biomass in the field (Table 6). Since several measures were applied, then the best model was selected by using scoring method. Table 7 shows that M1 was the best model with the lowest score. M1 model have met the statistical criteria, having bias (e) and RMSE close to 0, SA value are in the interval -1 to 1 and SR <10%. Validation results shown that canopy cover could be used to estimate above ground biomass. This study is inline with the previous study on estimating tree biomass and carbon stock [35].

Table 6. Statistical Criteria on Model Validation

Model	r^2	S	*Chi-Square*	SR	SA	*E*	RMSE
M1	0.712	19.425	72.767	2.290	-0.023	0.984	1.784
M2	0.607	20.479	71.928	0.482	0.000	2.780	1.824
M3	0.695	20.596	68.839	2.293	-0.022	1.175	1.897
M4	0.642	18.970	102.738	3.296	0.038	14.133	6.025
M5	0.566	20.801	66.236	0.274	0.003	3.784	1.985

Table 7. Rank Value of Validation Model

Model	r^2	S	*Chi-Square*	SR	SA	*E*	RMSE	Total score	Rank
M1	1	2	4	4	4	1	1	17	1
M2	4	3	3	2	1	3	2	18	2
M3	2	4	2	3	3	2	3	19	3
M4	3	1	5	5	5	5	5	29	5
M5	5	5	1	1	2	4	4	22	4

4. Conclusion

From the foregoing finding and discussion, the study found that the canopy cover (Ci) measured on the UAV image could be used as an independent variable for estimating the aboveground biomass in ex-coal mining reclamation area, especially in forest reclamation area at PTBA. The best model for estimating the aboveground biomass is $AGB = 0.237\ Ci^{1.368}$ with correlation of coefficient of 0.712.

Acknowledgment

The authors would like to extend sincerely appreciation to the Directors of PT. Bukit Asam, Tbk for permissions and support during data collection performed by author. High appreciation is also extended to the anonymous reviewer for such excellent inputs, comments and correction during improvement of the manuscript.

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