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Biomass estimation model for peat swamp forest ecosystem using light detection and ranging

Muhamad Rizal[1], M. Buce Saleh[2], Lilik Budi Prasetyo[3]
[1, 2]Departement of Forest Management, Faculty of Forestry, IPB University, Indonesia
[3]Departement of Conservation of Forest Resources and Ecotourism, Faculty of Forestry, IPB University, Indonesia

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ABSTRACT

Peat swamp forest plays a very important role in absorbing and storing large amounts of terrestrial carbon, both above ground and in the soil. There has been a lot of research on the estimation of the amount of biomass above the ground, but a little on peat swamp ecosystems using light detection and ranging (LiDAR) technology, especially in Indonesia. The purpose of this study is to build a biomass estimation model based on LiDAR data. This technology can obtain information about the structure and characteristics of any vegetation in detail and in real time. Data was obtained from the East Kotawaringin Regency, Central Kalimantan. Biomass field was generated from the available allometry, and Point cloud of LiDAR was extracted into canopy cover (CC), and data on tree height, using the FRCI and local maxima (LM) method, respectively. The CC and tree height data were then used as independent variables in building the regression model. The best-fitted model was obtained after the scoring and ranking of several regression forms such as linear, quadratic, power, exponential and logarithmic. This research concluded that the quadratic regression model, with R^2 of 72.16% and root mean square error (RMSE) of 0.0003% is the best-fitted estimation model (BK). Finally, the biomass value from the models was 244.510 tons/ha.

Corresponding Author:

M. Buce Saleh
Faculty of Forestry
IPB University
Lingkar Akademik St., IPB Campus Dramaga, Bogor, Jawa Barat 16680, Indonesia
Email: buce.saleh@gmail.com

1. INTRODUCTION

Peat swamp forests have unique characteristics but are prone to degradation [1-3]. From 2004 to 2011, about 5.8 million ha of this forest was degraded [4, 5], therefore, proper management is needed to solve this problem as soon as possible. The right decision on the management of this forest requires detailed, accurate and up-to-date information. Furthermore, data on forest composition, structure (vertical and horizontal) and other biophysical data are important components in the decision-making process [6]. Remote sensing has advantages in conditions where the forest is inaccessible, and covers a wider area, especially in terms of forest mapping, monitoring, and modelling [7, 8]. UNFCCC (United Nations Framework Convention on Climate Change) recommends and measures the amount of carbon loss by combining field measurement and remote sensing. This is done in order to produce more accurate data [9]. LiDAR (light detection and ranging) which high accuracy is one of the most recent remote sensing technologies [10, 11]. It functions by sending laser pulses from its sensor, which is mounted on a flying platform, to a target on the surface of the earth, and this pulse reflecting back to it. The returning light is then analyzed to measure the distance between the sensor and the object, and generate a 3D point cloud, through the position data, and orientation of the sensor [12]. This remote sensing technology can record various pulsed signal from several surface layers, such as primary signals which are pulsed by the top surface layer of vegetation, and the secondary signal and so on, which are pulsed from other surface layers such as bush and shrub. Lastly, the final signal is the pulse from the surface [13]. LiDAR generally produces 3D point cloud data such as digital surface model (DSM) which represents the elevation of vegetation canopy, digital terrain model (DTM) which represents ground elevation, and canopy height model (CHM), obtained by subtracting DTM from DSM which representing the height of vegetation.

The technology is able of obtain data on canopy surface, and vegetation parameters such as height, tree density, canopy dimension, basal area, and profile of vertical canopy, which are required for the modeling an environment [14]. Popescu *et al.* [15] discovered the strong relationship between the field measurement data (canopy cover) and point density using this technology. Moreover, the estimation accuracy of above ground biomass increases simultaneously with the increase in point density [16]. As stated earlier on, LiDAR point cloud data, which has high resolution is capable of estimating the above ground biomass (AGB), by implementing allometric relationships of height point density and carbon stock data from the field sample [17]. Furthermore, Wan-Mohd-Jaafar *et al.* [18] developed the relationship between height and width data on canopy and it was validated with the field data. Therefore, it can predict the above ground biomass in tropical forests. This relationship could also be used to assess carbon stock [19, 20]. This research was conducted to study LiDAR technology, which can provide complete, fast, and accurate data, and when combined with field data can be used for planning, managing, and monitoring peatland ecosystems. In addition, it also aims to estimate the above ground biomass (AGB) model using LiDAR data.

2. RESEARCH METHOD

2.1. Location and time

Field measurement was conducted in the restoration area of the peatland ecosystem in PT. Rimba Makmur Utama, which is administratively located in East Waringin Regency of Central Kalimantan as shown in Figure 1 and has a IUPHHK-RE area of 217.755 ha. Data was collected between July-August 2018. And were analyzed in the Spatial Analysis and Modeling Laboratory, Department of Conservation of Forest Resources and Ecotourism, Faculty of Forestry, IPB University.

2.2. Tools and materials

The tools used were digital, and DSLR camera, fisheye lens, tripod, global positioning system (GPS), machete, phiband, hypsometer, compass, measuring tape, and ropes. While the software for managing and analysing the data were ArcGIS 10.3, Rstudio, HemiView 2.1, and Microsoft excel. Lastly, other materials utilized includes plot plan and coordinates of plot reference on GPS and tally sheet.

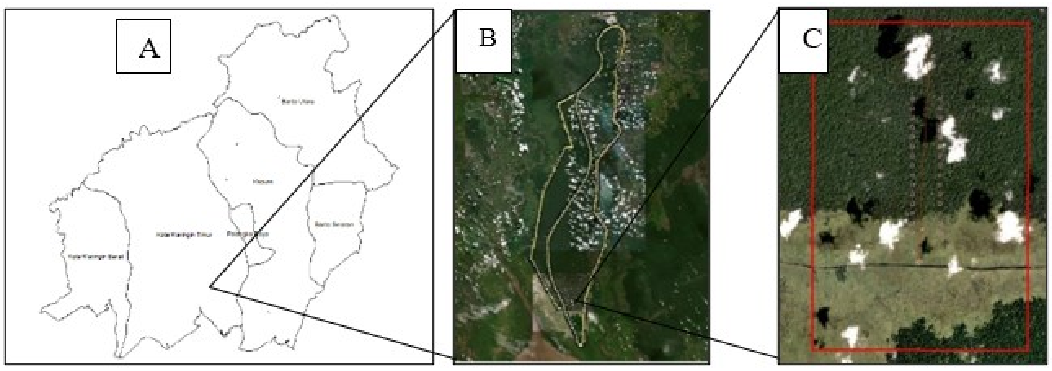


Figure 1. Research location; (a) in Central Kalimantan Province, (b) East Kotawaringin Regency, and (c) IUPHHK-RE PT. Rimba Makmur Utama

2.3. Data collection

LiDAR Point clouds data and vegetation data were the basic data used in this study. The data used for formulating biomass estimation model. Each of these data was obtained from direct acquisitions although by processed data. The types of data and research flow can be seen in Table 1 and Figure 2.

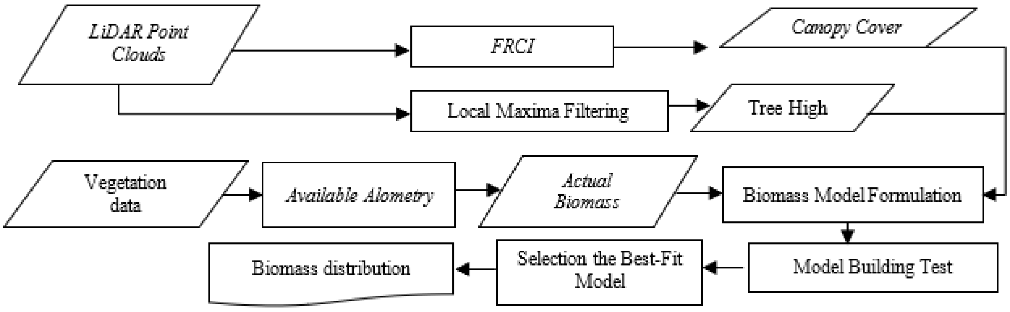


Figure 2. Research flow

Table 1. Types of data in the research

No	Type of Data	Year	Method
1	Tree Diameter and Height	2018	Direct measurement
2	Point Cloud (LiDAR)	2018	Direct measurement
3	Tree canopy photo	2018	Hemispherical photograph

2.4. Field data measurement

Determination of field survey to obtain vegetation and LiDAR data was performed by placing a plot of 40x40 (m) within the LiDAR flight range, which is 2x1 (km) or 200 ha, using the systematic sampling method as shown in Figure 2. The Vegetation data collected were the diameter at breast height (dbh) of the trees with diameter ⩾10 cm, total height of tree, tree species (common name and Latin name), plot coordinates, and anything related to growth sites around the measurement plots. To facilitate the measurement, the main plot (40x40) was divided into quadrant of 20x20 (m). Canopy density measurement was carried out at each central point of the quadrant, and central point of the main plot, therefore, the total observation point in each plot was 5 points. The measurements were carried out using hemispherical camera and densitometer. LiDAR data was obtained from the third party (PT. Ocron Global) with acquisition parameters as shown in Table 2. The type of LiDAR sensor was the Yellow Scan Mapper, mounted on DJI Matrice 600 drone.

Table 2. LiDAR Acquisition Parameters

Parameter	Specification
Drone	DJI Matrice 600
Speed	6-10 m/s
Flight altitude	70-100 m above sea level
Laser speed	2 s
Horizontal accuracy	20-30 cm using GCP and more than 1 without GCP
Vertical accuracy	10-15 cm
LiDAR point density	12-18 points/m^2
Spatial resolution	5-15 cm/pixel depends on flight altitude
Flight sidelap	60%
Flight overlap	80%
Scanning range	0.1-30 m
Data acquisition rate	43,200 points/sec

2.5. Data analysis

2.5.1. Actual biomass

Above ground biomass data can be measured directly from destruction sampling by cutting the trees. Unfortunatelly this method was costly and complicated, another way that we conducted was using allometric model. By using this allometric equation, we just measured tree diameter in the field. Data analysis of the above ground biomass (AGB) estimation, especially for the tree, was performed using the allometries equation developed by Jaya *et al*. [2] of $AGB = 0.107\ D^{2.486}$. D represented tree diameter of breast height (DBH).

2.5.2. LiDAR data processing

2.5.2.1. Designing of digital terrain model (DTM)

Terrestrial model or DTM is the representation of a terrain obtained from the point features of LiDAR data of ground class. This data which was used for designing the ground model was edited to clear up the terrain point cloud, which was directly intersected with waters, and corrected proportionally. DTM making process was performed on the point cloud class of ground feature, to obtain a 2D raster. This creation was carried out using the interpolation method, with a 0.5 resolution RStudio software. DTM was used for the normalization of the data on actual height, in order to estimate the canopy cover and tree height.

2.5.2.2. LiDAR canopy cover (CC) estimation

Canopy cover estimation in percentage was performed using LiDAR data, in the form of digital terrain model (DTM), which had been normalized and filtered. The method used was the first return canopy index (FRCI). According to Ma *et al*. [21], FRCI could generate higher canopy cover data due to LiDAR penetration in forest areas. Furthermore, its calculation compares the first with the single returns as referred in [21, 22].

$$FRCI = \frac{\sum \text{First Canopy} + \sum \text{Single Canopy}}{\sum \text{First Total} + \sum \text{Single Total}} \quad (1)$$

Description: FRCI = first return canopy index (%), First canopy=first return intersecting the canopy, Single canopy = single return intersecting the canopy, First total=total number of first return, Single total = total number of single return.

2.5.2.3. LiDAR tree height estimation

The normalized and filtered point cloud was used to determine the top of each tree, which represents their position and height. The algorithm used was local maxima (LM) filtering in squares on Rstudio. As implemented by Popescu *et al.* [15], it shows that LM method with square windows is better than with circle ones. This research used 3x3 cm windows of 40x40 m according to the plot size of field data collection. The mean of the identification results of each tree height were estimated to represent the height value for each plot [23].

2.5.3. Regression model formulation

The formulated models were LiDAR height and biomass estimation models. The CC (canopy cover) and Tree High that were extracted by the point cloud LiDAR data were used as independet variable in formulation model. Here are several regression models to formulate:

- Linear regression:

$$\mathrm{Y = a + bX} \quad (2)$$

- Logarithmic regression:

$$\mathrm{Y = a + b \ln X} \quad (3)$$

- Quadratic regression:

$$\mathrm{Y = a + bX^2} \quad (4)$$

- Exponential regression:

$$\mathrm{Y = a + exp^{bX}} \quad (5)$$

- Power regression:

$$\mathrm{Y = a\, X^b} \quad (6)$$

2.5.4. Classic assumption test

The classic assumption test was performed at the test level of 5% or $\alpha = 0.05$. It was the normality test, and aimed to determine the distribution of data. Furthermore, it was carried out by the Kolmogorov-Smirnov test. The next test conducted was the heteroscedasticity test, which was intended to check the uniformity of the rest of the model, using the Gletser statistical test.

2.5.5. Correlation and accuracy test

The statistical test used was the correlation test, and it aimed to find out the relationship between variables in the biomass estimation. The relationship between the biomass and LiDAR data was analyzed used the correlation approach of Pearson's product moment (r). Correlation test was performed to find out the difference between the value obtained from field biomass and the best biomass from LiDAR, Leaf Area Index (LAI) and canopy cover of LiDAR (FRCI), and actual tree height and LiDAR tree height. When the correlation value is approaching 1/-1 it means that the value of estimation model has a close relationship with the actual value of the field data. On the contrary, if the correlation value approaching 0, it means that the value of the estimation model has a distant relationship from the actual value. Accuracy test was performed to ascertain the accuracy of the estimation as compared to the actual data. This test could be performed by looking at the RMSE (root mean square error), aggregate deviation (SA) and s (deviation standart) value [24]. According to Spurr [25], a good equation has aggregate deviation (SA) value ranges from -1 to +1. The smaller the standard deviation is, the more accurate the expected value [26].

2.5.6. Selection of the best-fit model

For a model to be feasible as a regression model for the estimation of biomass, it needs to have a high coefficient of determination value. In addition, aggregate deviation value is also considered a criteria for selecting the best model. When a model has an Aggregate deviation value of -1 to 1 it means that that it is feasible to be used as the best estimation model [2]. Selection of the best biomass estimation model was conducted by ranking the comparative values (S, SA, RMSE), where the best rank was given to the greatest score. The score was identified using the (7):

$$\text{Score} = \left(\left(\frac{\text{ev}-\text{min}}{\text{max}-\text{min}}\right) \text{x}\ (5-1)\right) + 1 \qquad (7)$$

where, Ev: Estimation value, min: minimum value, and max: maximum value.

3. RESULTS AND ANALYSIS

3.1. Field inventory

The measurement of vegetation characteristics which includes, height, diameter, tree species and number of tree was performed manually using simple measuring tools. It was discovered that the average height, and diameter (DBH) of the trees was 27 m and 57 cm respectively. In addition, the number of tree at research location was 2632, and consisted of 68 types, and 36 Family. However, one of them could not be identified and so was labelled as unknown. The data was varied based on the height and tree data at each plot.

3.2. Actual biomass

Biomass considered in this research was limited to the tree with diamater at breast height (DBH) greater than the 10 cm, and with plot area of 40x40 m. The highest biomass content using allometry by Jaya *et al.* [2] (BK) was 37.079 tons/plot and the lowest was 0.033 tons/plot as shown in Figure 3. The average biomass stock was 20.97 tons/plot at BK calculation. The results of the calculation using two allometries showed that both were not significantly different as shown in Figure 4. Therefore, in order to determine the biomass estimation model, the two results, and each biomass estimation models were used in Table 3.

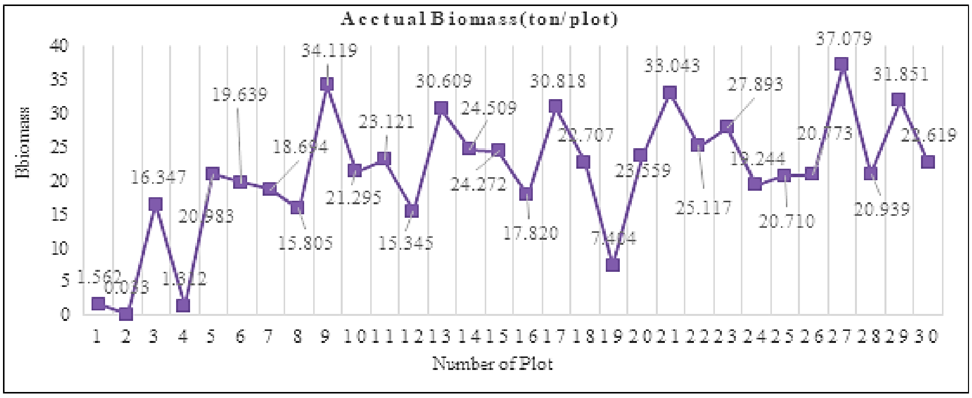
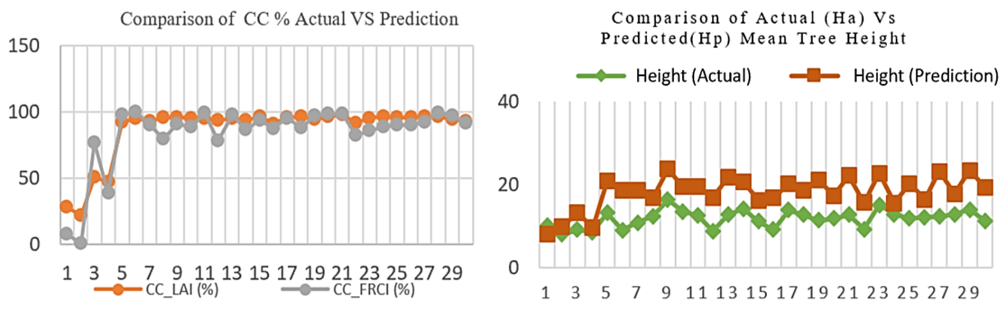


Figure 3. Result calculation field biomass

3.3. Estimation of canopy cover and height from LiDAR

Canopy cover represented by FRCI value [21] resulted in the highest value at plot 6 with 99.82% and the lowest at plot 2 of 0.42% as shown in Figure 4. The plot with low density value was in the open forest, with vegetation composition dominated by shrubs, ferns and weeds, which could reach 2 m height. Therefore, the canopy cover was relatively low.

The comparison chart between actual and predicted canopy cover (Figure 4) showed almost similar changing pattern. In addition, similar distribution pattern showed a close relationship between the actual and the estimated value, with correlation value of 0.93 (LAI:FRCI). The high estimation value of LiDAR based on mean local maxima (LM) resulted in the range of mean tree height being 7.92-23.76 m, with the average at 18.12 m. In addition, the tallest tree was at plot 9 while the lowest at plot 1 as shown in Figure 4. Data on height would be used as independent variable in designing the biomass estimation model. The comparison between the actual and predicted mean tree height in each plot (Figure 4) showed that the predicted height was greater, but both chart pattern were almost the same, and slightly intersected in plot 1, 2 and 4, which were the low plots. It indicated that tree height estimation from LiDAR was better in the area with low canopy cover. However, the predicted tree height had a close relationship with that of the actual tree, with correlation (r) value of 0.724 as shown in Table 4, and based on accuracy test, it showed a good RMSE= 0.986 and SA=0.352, since its value was within the recommended range of - 1 to 1 [25].



Description: CC LAI=CC actual, CC p =CC prediction

Figure 4. CC and tree high prediction value and their comparison with actual value per plot

3.4. Biomass estimation model

The biomass estimation model was design based on the analysis of the relationship between the dependent variable (Y), which id the biomass, the independent variable (X), CC (X1) and tree height (X2) from LiDAR data. Furthermore, it was designed using 30 biomass field data, canopy cover (CC) from LiDAR and tree height from LiDAR. Selection of its equation was based on scatter diagram pattern.

Table 3. Estimation model biomass calculation results

Model	BK Regression Equation
M1	$Y = -3.370 + 27.970*X_1$
M2	$Y = - 18.480 + 2.122*X_2$
M3	$Y = -18.470 + 0.030\ X_1 + 2.121*X_2$
M4	$Y = 22.045 + 5.387*LN(X_1)$
M5	$Y = -69.506 + 31.214*LN(X_2)$
M6	$Y = -73.062 – 0.424*LN(X_1) + 32.397*LN(X_2)$
M7	$Y = 0.123 + 26.307*X_1^2$
M8	$Y = -2.164 + 0.064*X_2^2$
M9	$Y = -3.498 + 5.395*X_1^2 + 0.056*X_2^2$
M10	$Y = 26.058*\ X_1^{1.808}$
M11	$Y = 0.035*X_2^{\ 2.168}$
M12	$Y = -12.145*X_1^{-0.031} + X_2^{1.197}$
M13	$Y = 2.70735*exp^{\ (2.286*X1)}$
M14	$Y = 2.175*exp^{(0.118*X2)}$
M15	$Y = 1.508*exp^{\ (0.712*X1+0.104*X2)}$

Note: Y=BK, X_1=CC, X_2=Height of LiDAR

3.5. Model building test

3.5.1. Classic assumption test

A good model is one that meets classical assumptions with the expectation that it can provide accuracy and consistency in making estimations. The classic assumption tests used in this research were normality and heteroscedasticity test. Normality test was conducted to spot the normal distribution of the remainder of the model using Kolmogorov-Smirnov test, and the results (Table 4) showed that the models with the Y2 variable (BK) all met the normality assumption. The next test was the heteroscedasticity test. It aims to spot the uniformity of the rest of the model using glacier statistical test. The results of the significance test of variables were within the range of 0.087-0.995, therefore, it can be said that all models were homogeneous because when the significance value of the independent variable is greater than 0.05, it means there is no heteroscedasticity or H0 rejection [27, 28]. The results of normality and heteroscedasticity tests provided information about the next model to be tested.

Table 4. Results of normality test

BK VS CCp;A_Hp				
	Normality Test		Heteroscedasticity Test	
Model	P-Value	Description	P-Value	Description
M1	>0.150	Normal	0.990	Constant
M2	>0.150	Normal	0.639	Constant
M3	0.064	Normal	0.554	Constant
M4	>0.150	Normal	0.195	Constant
M5	>0.088	Normal	0.383	Constant
M6	>0.078	Normal	0.460	Constant
M7	<0.06	Normal	0.087	Constant
M8	>0.150	Normal	0.479	Constant
M9	>0.075	Normal	0.594	Constant
M10	>0.150	Normal	0.096	Constant
M11	>0.150	Normal	0.582	Constant
M12	>0.150	Normal	0.520	Constant
M13	>0.151	Normal	0.429	Constant
M14	>0.152	Normal	0.176	Constant
M15	>0.150	Normal	0.995	Constant

3.5.2. Correlation test

The relationship between the dependent (Y) and independent variable (X) can be identified through correlation test. Moreover, to discover the relationship among the structuring variables in designing the model, a correlation test was performed on the actual and predicted values, which were the canopy cover value from CCa, the predicted canopy cover value from FRCI/CCp, actual mean tree height (A_Ha), and Mean tree height from LiDAR (A_Hp). CCa and FRCI represented the actual and predicted canopy cover (Table 5), and data on the later was collected from the previous studies. The correlation test aimed at proving that the field and predicted variable (LiDAR variable) were closely related.

The results of the correlation analysis, which are shown in Table 5 show that the correlation between the actual and prediction variables were positive. Furthermore, the closeness relationship test was conducted between the parameter of the field and prediction, and the results showed that a strong relationship existed between them, such as between the actual and predicted height of 0.724, and between CCp and CCa of 0.934. This means that the parameters of tree height and canopy cover from LiDAR, as the predictive variables could represent the actual vegetation parameters. Therefore, the variable from LiDAR could be used as independent variable in the biomass estimation model. The results of the analysis in Table 5 showed that the correlation between the dependent (Y) and the independent variable (X) had a positive correlation, with range value of 0.671-0.824. Furthermore, the positive correlation coefficient values were greater than 0.5 on each variables, and this indicated a close relationship between the biomass variable to the CC variable and the height variable from LiDAR data. The positive correlation value explained that an increase in biomass value would be followed by an increase in the CC and tree height value from LiDAR and vice versa.

Table 5. Results of correlation test between variables

Variable	CCa	A_Ha	CCp	A_Hp
A_Ha	0.554			
CCp	0.934	0.499		
A_Hp	0.805	0.724	0.801	
BK	0.735	0.671	0.745	0.824

Note: CCp=predicted canopy cover (%/plot), CCa= actual canopy cover from LAI (%/plot), A_Hp=predicted mean height from LiDAR (m/plot), A_Ha=actual mean height from field measurement (m/plot), BK= Biomass of equation calculation result (ton/plot),

3.5.3. Accuracy test

Accuracy test was performed to find out how accurate the estimated values were, compared to the actual ones. In addition, the accuracy test used was RMSE. Model validation test aimed at determining the reliability of the resulted estimation by looking at the SA. Validation and accuracy tests were carried out by census, using all data (30 observation plots) (Table 6). The results of accuracy and validity tests (Table 6) showed acceptable value (CCp vs CCa2 RMSE = 0.005 and SA = -0.042), or in other word, FRCI variable could explain the actual variable. Accuracy tests were then performed on the biomass estimation model by comparing the difference between the estimated and the actual value of each independent variable.

The table shows that the estimated accuracy [28] of the range of RMSE values obtained from equation (BK) is 0.0001-1.5915 (%) (Table 7). Besides RMSE, the accuracy test value also used were Standard Deviation (S), and their value ranged from 5.25-7.27. According to Draper and Smith [26] the smaller the S value is the better model.

SA value represented the validity value of the model. In addition, the smaller it is, the more valid the model is because the difference between the estimated and actual value would be smaller as well. The results of the analysis showed that value of SA ranged from –0.0125037 – 0.0090767 (Table 7). Furthermore, this was within the range of values required by Spurr [25], which is -1 to 1. Lastly, S, RMSE and those values would be used as the criteria to determine the best biomass estimator model.

Table 6. Results of accuracy tests of tree height and canopy cover

Variable	RMSE	SA
CCp VS Cca	0.005	-0.042
A_Hp Vs A_Ha	0.986	0.352

Note: CCp=predicted canopy density, CCa= actual canopy cover from LAI, A_Hp=predicted mean height from LiDAR, A_Ha=actual mean height (field measurement)

Table 7. Results of accuracy tests BK

Model	Code	BK Equation	S	SA	RMSE (%)
Linear	M1	$Y = -2.500+28.120*X1$	5.27	-0.0000914	0.0085
	M2	$Y = -13.260+1.889*X2$	5.31	-0.0002748	0.0191
	M3	$Y = -12.840+9.02\ X1+1.45*X2$	5.25	0.0005719	0.0715
Logarithmic	M4	$Y = 23.108+5.56*LN(X1)$	5.33	-0.0000014	0.0004
	M5	$Y = -60.890+28.55*LN(X_{\backslash})$	5.57	-0.0000064	0.0007
	M6	$Y = -53.455+0.887*LN(X_1)+26.081*LN(X2)$	6.27	-0.0000066	0.0005
Quadratic	M7	$Y = 1.407+25.924*X1^2$	6.29	-0.0125037	0.0002
	M8	$Y = 1.709+0.056*X^2$	6.21	-0.0000004	0.0001
	M9	$Y = -1.109+11.395*X1^2+0.039*X2^2$	5.41	-0.0000005	0.0003
Power	M10	$Y = 26.4616*X1^{1.47094}$	5.50	0.0023165	0.3520
	M11	$Y = 0.161876*X2^{1.67175}$	7.27	0.0056497	1.1523
	M12	$Y = -5.686*X1^{-0.164} + X2^{1.138}$	7.27	0.0000301	0.0622
Exponential	M13	$Y = 3.612*exp^{2.021 * X1}$	5.72	0.0090767	1.5915
	M14	$Y = 3.607*exp^{0.094*X2}$	5.29	0.0077671	1.1587
	M15	$Y = 2.326*exp^{(1.017* X1 + 0.069*X2)}$	6.42	0.0072017	1.2023

3.5.4. Selection of the best biomass estimation model

The models used in obtaining the biomass estimation equation are linear, logarithmic, power, quadratic and exponential models (see Table 7). Furthermore, the best regression equation model was obtained by scoring the standard deviation (s), aggregate deviation (SA) and root mean square error (RMSE). The highest score was ranked first, or in other words, it is the best biomass estimator model (Table 8). The scoring results showed that M9 which is a quadratic regression model was the best model in the BK equation, as it had a score of 14.973. Furthermore, it had a RMSE of 0.0003%, S of 5.41 and validation value (SA) of 0.0000005 (Table 7). This validation results could be categorized as good since it approached the score '0', and in other words the estimation model could increasingly describe the actual state. The M9 regression equation model was $Y = -1.109+11.395*X_1^2+0.039*X_2^2$ (see Table 7), with R^2 of 72.16%, and it can be interpreted that the variable Y (Biomass) could be explained by FRCI and LiDAR tree height of 72.16%.

3.6. Biomass distribution

The biomass distribution of the results of each calculation can be seen in Figure 5. Biomass at the research location ranged majorly from 27-55 (ton), with an average value of 39.871 tons. However, in some locations there were biomass stocks which had minus and zero values. This was due to the low FRCI variable (0). BK estimation model showed that the biomass value at the research location (logged-over secondary peat swamp forest) with an area of 200 ha was 244.314 tons/ha. This result was almost similar to that obtained in Novita's research (276.95 tons/ha) [29], which was conducted in the logged-over peat swamp forests in Merang, South Sumatra, but higher than that mentioned in Rochmayanto [30] research, of 166.93 tons/ha, in a secondary peat forests, and Kroshendera *et al.* [31] of 159.9 tons/ha in a logged-over secondary forests. In addition, the biomass in the mixed peat forests, in Central Kalimantan was 311 tons/ha [32]. Some variations in the results of these calculations were due to differences the calculation method, and the condition of research areas.

Tabel 8. The chosen model of BK best biomass equation

Model	R^2	S	SA	RMSE	Score	Ranking
M9	72.16%	4.974	5.000	4.999	14.973	1
M5	69.36%	4.893	5.000	4.998	14.892	2
M3	69.90%	5.000	4.996	4.821	14.817	3
M2	67.85%	4.845	4.999	4.952	14.796	4
M8	67.19%	4.371	5.000	5.000	14.371	5
M1	55.55%	2.984	5.000	4.979	12.962	6
M7	55.35%	2.955	5.000	5.000	12.955	7
M10	66.09%	3.097	4.981	4.116	12.193	8
M14	63.27%	4.684	4.937	2.088	11.709	9
M11	56.38%	4.523	4.937	2.104	11.565	10
M4	40.26%	1.000	5.000	4.999	10.999	11
M6	69.73%	1.000	5.000	4.999	10.999	12
M15	68.28%	4.080	4.935	1.978	10.993	13
M12	69.50%	4.931	1.000	4.844	10.775	14
M13	53.92%	2.683	4.914	1.000	8.597	15

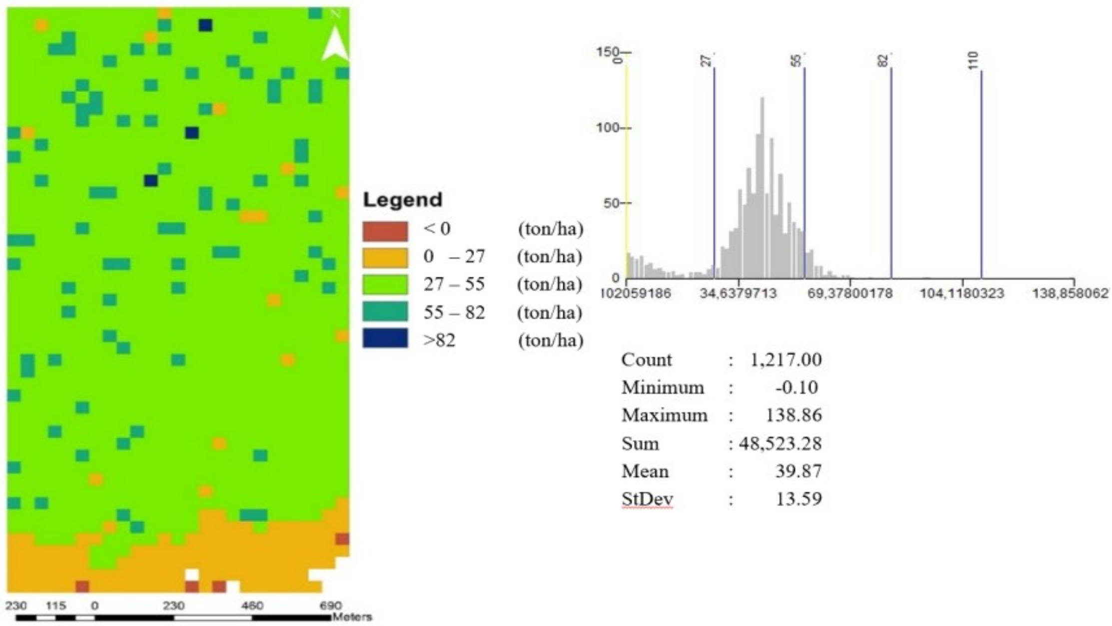


Figure 5. Biomass distribution of BK equation

4. CONCLUSION

CC and tree height from LiDAR could be used as variables to estimate the amount of biomass, since there was accuracy (RMSE = 0.005, SA = -0.042) between the actual and predicted CC, and mean tree height (RMSE = 0,986, SA = 0,352). The biomass estimation model used the quadratic model, with equation $Y1=-3.498+5.395*X_1^2+0.0564*X_2^2$. In addition, the SA value was 0.0000005 (BK), and the resulting R^2 was 72.16% (BK). The models produced a biomass value of 244.510 tons/ha (BK). This study only used 30 samples because of limited resources. Therefore, in future studies, more samples should be used in order to obtain more accurate estimator models. Lastly, advanced analysis which integrates LiDAR and satellite imagery is needed to obtain the area (PT. RMU area) of the biomass.

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BIOGRAPHIES OF AUTHORS

Muhamad Rizal has completed his Master's degree in 2020 from Forest Management Science Department, Faculty of Forestry, IPB University. His research Interest in GIS and Remote sensing using LiDAR data to support forest planning activity. He got his bachelor degree of forestry in 2015 from Forest Management, Faculty of Forestry and Enviromental Science, Halu Oleo University.

Dr. M. Buce Saleh is a permanent associate professor at the Forest Management Department, Faculty of Forestry, IPB University. Has expertise in Mathematics and Geoscience, Forest Planning, Remote sensing, and GIS. He got his PhD in 2002 from Niigata University, Master's degree in 1988 from Bandung Institute of Technology, bachelor's of forestry in 1981 from Forest Management Department, Faculty of Forestry, IPB University.

Prof. Lilik Budi Prasetyo is a permanent professor of Landscape Ecology at Dept. of Conservation of Forest Resouces and Ecotourism, Faculty of Forestry, IPB University. has conducted several research and projects activities related to the application of remote sensing and GIS for Land use and land cover changes, and Spatial modelling. He got his PhD in 1996 from Institute of Agriculture and Forestry University of Tsukuba, Master's degree in 1993 from Environmental Sciences, University of Tsukuba, bachelor's degree in 1986 from Faculty of Agriculture, IPB University.