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Article

Development of allometric equation for the prediction of young Makila (*Litsea angulata* BI) biomass for handling climate change

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Abstract: Every plant is significantly important in tackling climate change, including Makila (*Litsea angulata* BI) an endemic wood species found in the forest of Moluccas Provinces. Therefore, this research aimed to examine the role of the Makila plant in tackling climate change by measuring biomass content using constructing an allometric equation. The method used was a destructive sampling, where 40 units of Makila plant at the sampling level were felled, and sorted according to root, stem, branch, rating, and leaf segments. Each segment was weighed both at wet and after drying, followed by a classical assumption test in data processing, and the formulation of an allometric equation. The regression model was examined for normality and suitability in predicting independent variables, ensuring there were no issues with multicollinearity, heteroscedasticity, and autocorrelation. The results yielded a multiple linear regression, namely: $Y = -1131.146 + 684.799X_1 + 4.276X_2$, where Y is biomass, X_1 is the diameter, and X_2 is the tree height. Based on the results of the t-test: variable X_1 partially affected Y while variable X_2 partially had no effect on Y. The F-test indicated that variables X_1 and X_2 jointly affected Y with R Square: 0.919 or 91.9% and the rest was influenced by other unexplored factors. To simplify biomass prediction and field measurement, a regression equation that used only 1 independent variable, namely tree diameter, was used for the experiment. Allometric equation only used 1 variable, $Y = -1{,}084{,}626 + 675{,}090X_1$, where X_1 = tree diameter, Y = Total biomass with $R = 0.957$, and $R^2 = 0.915$. Considering the potential for time, cost, and energy savings, as well as ease of measurement in the field, the biomass of young Makila trees was simply predicted by measuring the tree diameter and avoiding the height. This method used the strong relationship between biomass, plant diameter, and height to facilitate the estimation of biomass content accurately by entering the results of field measurements.

Keywords: allometric equation; classic assumption test; biomass; sapling; climate change

1. Introduction

Makila (Litsea angulata BI) is an endemic wood species primarily found in the forest of Moluccas Provinces. The wood is highly valued for its natural durability and is extensively used mainly for residential house constructions, doors, furniture, and window products [1]. The Makila plant is locally known as 'kalangkala' in South Kalimantan, Central Indonesia, and is a species of the genus Litsea, belonging to the Lauraceae family. Most of these plants thrive in the wild in forest areas and are usually cultivated to extract their sturdy wood as building materials [2]. Other species such as Litsea boerlagei K. are spread in the Maluku region (Eastern Indonesia) and their synonym names include Litsea ambigua (Blume) Boerl. and Malapoenna ambigua (Blume) Kuntze [3]. The genus Litsea is dominant in tropical and subtropical areas of India, China, Taiwan, and Japan. This plant has been widely explored due to its medicinal properties and is used traditionally to treat various gastrointestinal diseases, including diarrhea, stomach ache, indigestion, and gastroenteritis, as well as diabetes, colds, edema, asthma, arthritis, and traumatic injuries. Furthermore, Litsea is renowned for its essential oils, which have shown effectiveness against several bacteria, provide acute toxicity, possess antioxidant, antiparasitic, cytotoxic, genetic properties, and prevent several types of cancer [4]. Currently, research has been carried out on the chemical composition, antioxidant, toxicity, and antimicrobial activity of L. angulata BI leaf essential oil in vitro. The results showed that the essential oil from L. angulata BI leaves was non-toxic, with the potential as an antimicrobial agent against oral pathogens [5]. Apart from the leaves, the bark of Litsea glutinosa, (Lour.) C.B.Rob, a member of the Lauraceae family, is commonly found in the western region of Indonesia and can be used as a traditional medicine to treat rheumatism, diarrhea, and dysentery [6]. In India, this tree serves as a binding agent in the incense industry in tablet formulations and as a plaster for broken limbs [7]. The wood is used locally and also traded as a source of 'medang' [8).

Makila trees are often found in the Maluku Forest and are also components of traditional agroforestry areas or 'dusung'. This is because the hamlet area is usually filled with agricultural and forestry crops, thereby serving as a carbon store and playing an indirect role in controlling climate change. This is consistent with international efforts to carry out climate change mitigation by reducing emissions from forest land or Reducing Deforestation and Degradation Emissions (REDD+). The determination of tree allometric equation is also an important tool for measuring forest resources. These equations are a statistical model primarily used to express the relationship between various components of a tree in relative size. Consequently, foresters' transit from simple tree measurements such as stem diameter to characteristics including carbon stock and tree biomass, which are more difficult, expensive, and damaging to measure. This method considers the use and development of countries, biomes, climate, and species to minimize errors in propagation, increase accuracy, and reduce the bias resulting from the general model. Regarding the categorization of allometric equations in the database, it is carried out on biomass, volume, carbon stock, and tree height. The biomass equation represents half of the total equation listed, followed by the volume. Meanwhile, the height diameter equation is included as part of the assessment information, which is often used as a reference when calculating tree volume and biomass [9].

The morphological conditions of Litsea spp trees including trunk, branching, and crown, particularly the relationship between trunk diameter and total tree height, trunk diameter and crown width, and total tree height and crown width, in East Kalimantan (Central Indonesia) Educational Forest have been investigated [10]. Based on the results, the regression coefficient values between diameter and height, as well as diameter and crown width showed moderate correlation values. This has led to extensive research on the Litsea genus concerning medicinal uses, construction, and morphological characteristics. There is no significant gap in understanding its relationship with biomass content, specifically through destructive sampling for handling climate change. Forest biomass is calculated using a standard general allometric equation and can be implemented in large forest areas. Therefore, this research was carried out to establish an allometric equation to relate the diameter, height, and biomass of L. angulata BI, serving as a local model to support REDD+.

Generally, the aboveground biomass predictors are easy to determine, as only stem diameters are required to be measured mainly in dense forests.

2. Materials and methods

This research was carried out in 2 stages, which included the collection of data in the field and the laboratory testing of samples. The material used consisted of 40 young Makila vegetation (L. angulata BI) planted in polybags beside the greenhouse of the Faculty of Agriculture, Pattimura University, Ambon, as shown in **Figure 1**. The ages of young Makila plants were 1, 2, and 3 years, while the planting medium was red and yellow podzolic soil. This type of soil is characterized by low productivity due to intensive leaching and further weathering, resulting in poor soil physical and chemical properties [11]. Therefore, to enhance soil fertility and nutrient content, the media was enriched with NPK fertilizer in a 3:1 ratio.

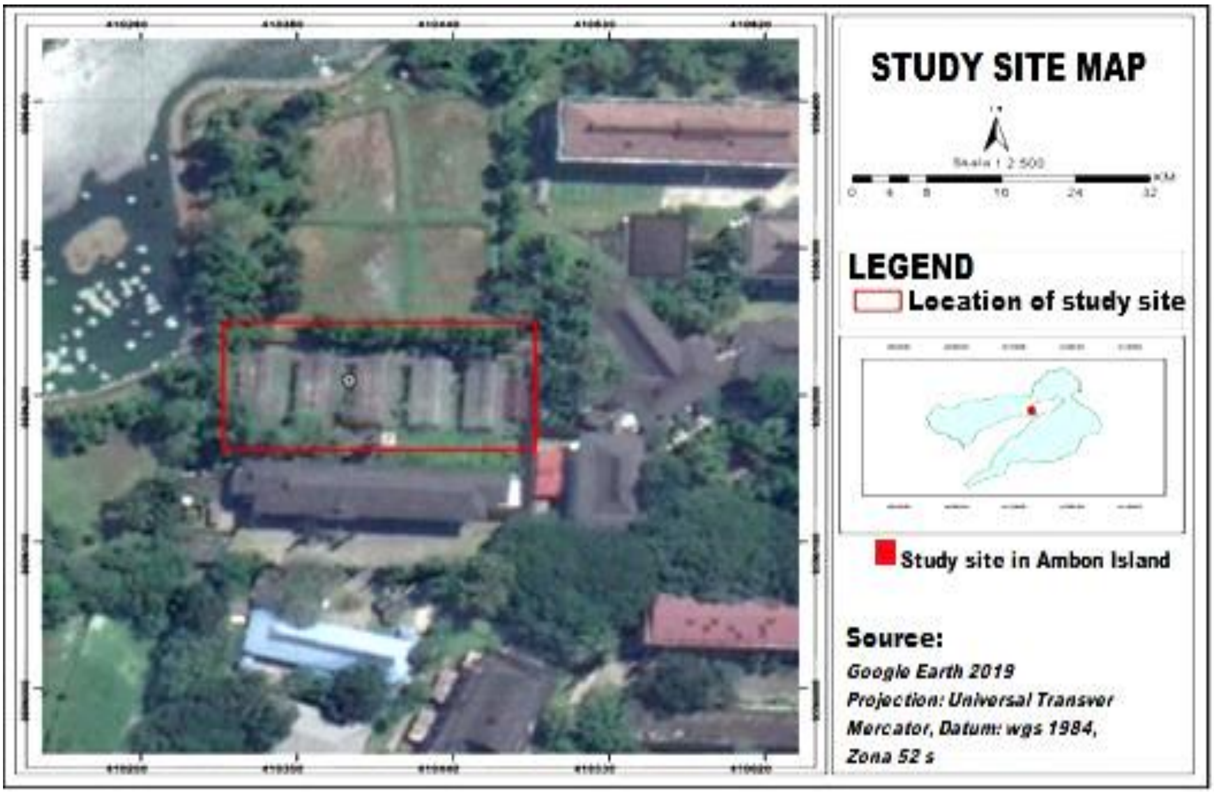

Figure 1. Research location map.

Maintenance of the Makila plant was carried out regularly every month to ensure the cleanliness of the planting location and remove lianas, grass, and other disruptive vegetation. Although there was no specific action for watering plants, it was only carried out incidentally, when extreme drought occurred due to a long drought. Plant diameter ranged from 1.5 cm to. 5.0 cm and the height varied from 0.65 m to 3.6 m. Samples of young Makila plants are presented in **Figure 2**.

Figure 2. Young plants of Makila (L. angulata BI).

The equipment used for collecting data in the field were hand saws, meters, scales, sieves, newsprints, machetes, tarpaulins, plastic bags, and stationery. Meanwhile, ovens and analytical scales were used for laboratory testing of samples. The diameter of each sample was measured from aboveground level to a height of 5 cm and numbered 1 to 40. After coding, the plant samples were cut down and all young trees were divided into segments for stems, branches, twigs, leaves, and roots. The root segments were collected carefully to facilitate each separation from the soil in the polybag. The part of the root that still contained soil was cleaned with a machete and brush until it was clean of soil and other debris. Subsequently, each segment was weighed for its wet (in g) and dry weight, allowing the determination of biomass content (in g) for each segment.

Data processing was carried out using the Multiple Linear Regression Equation method. The dependent variable (Y) was biomass and the 2 independent variables were diameter (X_1) and height (X_2) with the general formula:

$$\hat{y} = b_0 + b_1 \times x_1 + \ldots + b_n \times x_n + \epsilon$$

Multiple linear regression makes all the same assumptions as simple linear regression, following the points stated below:

1) Homogeneity of Variance (Homoscedasticity): The magnitude of the error that occurs in the prediction does not change significantly at various values of the independent variable.

2) Independence of observations: In data collection, observations are obtained through statistically valid sampling methods, without hidden relationships between variables. Some of the independent variables also correlate with each other, necessitating the importance of checking before developing a regression model. When two independent variables are excessively highly correlated (r^2 > ~0.6), only one should be used in the regression model.

3) Normality: The data collected is normally distributed.

4) Linearity: The line of best fit through the data points is a straight line, without a curve or grouping factor [12].

Regression analysis constitutes a significant part of supervised machine learning, consisting of the prediction of a continuous independent target from a set of other predictor variables. The difference between binary classification and regression is in the target range. This is because, in binary classification, the target only consists of two values, usually encoded as 0 and 1), while in regression the target has multiple values [13]. Regression analysis plays a significant role in various scientific fields, as it seeks to establish a functional relationship from data to explain or predict a natural phenomenon based on other observable factors. Most regression analyses depend on the least squares method to estimate the parameters in the model. However, this method is usually formed with several assumptions, such as linearity, absence of autocorrelation, no multicollinearity, homoscedasticity, and normally distributed errors [14]. The use of multiple linear regression allows for the exploration of relationships between the dependent variable and two or more independent variables [15]. To facilitate this process, a correlation analysis is used to measure the level of relationship between two variables. Furthermore, correlation analysis explains how the regression line describes the variation of the dependent values and the strength of the relationship between the two variables [16].

2.1. Data analysis

Data analysis was carried out examining the availability of missing datasets through frequency analysis. This was followed by an assessment of multivariate normality, linearity, freedom from extreme values, and multilinear relationships with the assumption of multiple regression analysis. Multivariate normality analysis was carried out after the univariate normality assumption was completed for each quantitative variable, by examining the skewness coefficient and the histogram chart. Subsequently, a scatter diagram matrix was prepared for the assumption of multivariate linearity. Simple correlation test, variance increase factors (VIF), tolerance values, and Condition Index (CI) were carried out to determine the potential for double ties within the data. When the data analyzed met the requirements for the various assumption set, linear regression analysis was carried out [17]. The data collected from various analyses were processed using Microsoft Excel and the SPSS software package (ver.21).

3. Results and discussion

3.1. Classic assumption test

The data collected from the 40 young Makila samples researched were processed, leading to the results of Descriptive Statistical Analysis, as presented in **Table 1**.

Table 1. Results of statistical descriptive analysis.

		Tree Diameter (cm) (X_1)	Tree Height (m) (X_2)	Bole (g)	Twig (g)	Leaf (g)	W above ground (g)	W below ground (g)	Total Biomass (g) (Y)
N	Valid	40	40	40	40	37	40	40	40
	Missing	0	0	0	0	3	0	0	0
Mean		3.060	3.932	344.30	160.82	281.30	765.32	215.82	981.15
Std. Error of Mean		0.1493	1.571	37.693	19.724	38.266	84.179	23.468	105.400
Median		3.00	2.50	255.00	165.50	192.00	613.50	204.50	792.50
Std. Deviation		0.944	9.935	238.393	124.745	232.760	532.396	148.422	666.607
Variance		0.892	98.706	56,831.241	15,561.379	54,177.437	283,445.610	22,028.969	444,365.464
Range		3.60	2.95	903	474	866	1,997	546	2,392
Minimum		1.40	0.65	23	4	47	82	10	105
Maximum		5.00	3.60	926	478	913	2079	556	2497
Sum		122.40	92.93	13,772	6433	10,408	30,613	8633	39,246

a. Multiple modes exist. The smallest value is shown.

Based on the results of the Classical Assumption Test, the following results were obtained:

(1) Residual normality test:

This normality test was used to determine whether the residual value was normally distributed. Residual values that were normally distributed indicated a good regression model. The detection was carried out by observing the pattern of data distribution at the diagonal source on the standard P-P Normal Plot regression graph, which was the basis for decision-making. When the data spread out and followed a diagonal line, the regression model was declared normal and suitable for predicting the independent variable and vice versa. The results of the normality test were presented in the normal P-P Plot Chart Regression output, as shown in **Figure 3.**

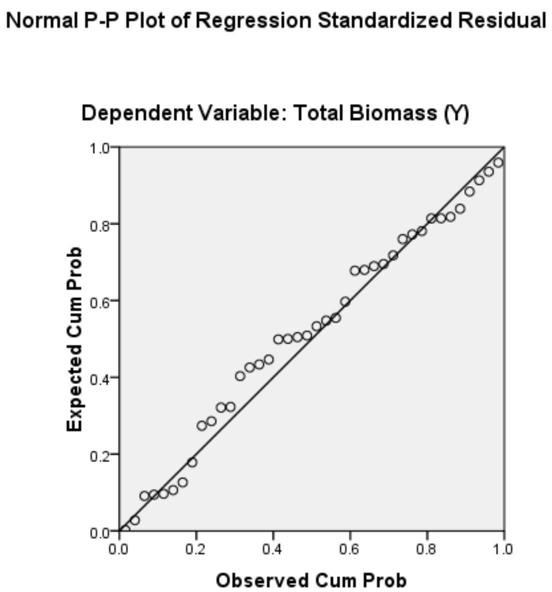

Figure 3. Normal P-P Plot of regression standardized.

Normal P-P Plot of regression standardized residuals indicated that the dots spread around the line and followed the diagonal line, confirming the normality of the regression model. This situation rendered the model suitable for predicting the independent variable and vice versa. To enhance the suitability of this assessment, the process can also be accompanied by another normality test, such as the One-Sample Kolmogorov Smirnov test method. The results of the residual normality test (NPar Test) are presented in **Table 2**. The residual is the difference between the observed and predicted values in the regression model, which is calculated as Remaining = Observed value—Predicted value. When these observed values are plotted and overlay the fitted regression line, the residual for each observation becomes the vertical distance between the observation and the regression line. Moreover, the standardized residual is used to identify outliers in a regression model. In practice, standardized residuals with absolute values greater than 3 are often considered to be outliers. This does not mean that the observation will be removed from the model but further investigation is required to verify whether these outliers are caused by data entry errors or unusual events [18].

Table 2. Residual normality test results.

One-Sample Kolmogorov-Smirnov Test					
		Tree Diameter (cm) (X_1)	**Tree Height (m) (X_2)**	**Total Biomass (g) (Y)**	**Unstandardized Residual**
N		40	40	40	40
Normal Parameters[a]	Mean	3.0600	3.9320	981.15	0.0000000
	Std. Deviation	0.94457	9.93508	666.607	1.89803389×10^2
Most Extreme Differences	Absolute	0.101	0.468	0.134	0.101
	Positive	0.065	0.468	0.134	0.055
	Negative	−0.101	−0.384	−0.113	−0.101
Kolmogorov-Smirnov Z		0.639	2.962	0.847	0.637
Asymp. Sig. (2-tailed)		0.809	0.000	0.470	0.813

a. Test distribution is Normal.

Based on **Table 2**, the significance value (Asym.sig 2 tailed) for the data residual is 0.813 > 0.05, indicating normally distributed. This condition further confirms that the regression model is suitable for predicting independent variables and vice versa.

(2) Multicollinearity test:

Multicollinearity is a situation where there is a perfect or close linear relationship between independent variables in a regression model. This situation arises due to a perfect linear function for some or all of the independent variables. Consequently, the effects of independent and dependent variables are difficult to observe. Symptoms of multicollinearity can be obtained by observing VIF and Tolerance values. When the VIF value < 10 and Tolerance > 0.1, it is stated that there is no multicollinearity. The results of the multicollinearity test are presented in **Table 3**.

Table 3. Multicollinearity test results.

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	−1131.146	111.322		−10.161	0.000		
	Tree Diameter (cm) (X_1)	684.799	33.832	0.970	20.241	0.000	0.953	1.049
	Tree Height (m) (X_2)	4.276	3.217	0.064	1.329	0.192	0.953	1.049

a. Dependent Variable: Total Biomass (Y).

The results presented in **Table 3** showed that there was no multicollinearity problem, as indicated by the VIF value for the two independent variables (tree diameter and tree height each 1.049) < 10 and the Tolerance value (tree diameter and tree height each 0.953) > 0.100.

(3) Heteroscedasticity test:

Heteroscedasticity is a situation where there are differences in residual values for all observations in a regression model. This test method is carried out using the Glejser Test, by regressing the independent variable on the absolute residual value. The residual is the difference between the observed and predicted values of the variable Y, and is absolute, indicating that all values are positive. When the significance value between the independent variables and absolute residuals is > 0.05, there is no heteroscedasticity problem. The results of this regression, specifically the Glejser Heteroscedasticity Test, are presented in **Table 4**.

Table 4. Heteroscedasticity test results.

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	67.273	67.897		0.991	0.328
	Tree Diameter (cm) (X_1)	27.463	20.635	0.215	1.331	0.191
	Tree Height (m) (X_2)	−1.667	1.962	−0.137	−0.850	0.401

a. Dependent Variable: ABS_RES.

The results of the heteroscedasticity test in **Table 4** show that the two independent variables (tree diameter and tree height) have a significance value of more than 0.05. This indicated that there was no problem heteroscedasticity in this regression model.

(4) Autocorrelation test:

Autocorrelation is a condition where there is a correlation between residuals in period t with the previous period (t−1) in a regression model. A good regression model should not have any autocorrelation problem. The results of the autocorrelation test obtained are presented in **Table 5**.

Table 5. Autocorrelation test results.

Model Summary[b]					
Model	*R*	R^2	Adjusted R^2	Std. Error of the Estimate	Durbin-Watson
1	0.959[a]	0.919	0.915	194.866	1.956

a. Predictors: (Constant), Tree Height (X_2), Tree Diameter (X_1).
b. Dependent Variable: Total Biomass (Y).

The results of the autocorrelation test presented in **Table 5** show that the Durbin Watson (DW) value = 1.956, ranging from 1.65–2.35. This condition indicated that there is no autocorrelation problem.

3.2. Results of multiple linear regression analysis

Multiple linear regression analysis was used to determine the effect of independent variables on the dependent variable, both partially with the *t*-test and collectively through the *F*-test. The multiple linear regression analysis was used to formulate the regression equation and discover the increasing or decreasing value of the variable Y for the change in X. The results obtained after the data were processed with Microsoft Excel and SPSS were presented in **Table 6**.

Table 6. Processing results of multiple linear regression analysis.

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	*t*	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
	(Constant)	−1131.146	111.322		−10.161	0.000		
1	Tree Diameter (cm) (X_1)	684.799	33.832	0.970	20.241	0.000	0.953	1.049
	Tree Height (m) (X_2)	4.276	3.217	0.064	1.329	0.192	0.953	1.049

a. Dependent Variable: Total above and below ground Biomass (g) (Y).

Based on **Table 6**, the regression equation is obtained, namely: $Y = -1131.146 + 684.799X_1 + 4.276X_2$

- Constant −1131.146, indicating that when X_1 and X_2 are 0, the magnitude of Y is negative −1131.146.
- The variable regression coefficient X_1 = 684.799, indicating that every time X_1 increases by 1 unit, it will increase Y = 684,799 units, assuming the values of the other independent variables remain constant.
- The variable regression coefficient X_2 = 4.276, indicating that with every increase in X_2 by 1 unit, it will increase Y = 4.276 units, assuming the other independent variables have a fixed value.

(1) *t*-test:

t-test in multiple regression was used to determine whether the independent variable regression model had a partially significant effect on the dependent variable. The results of the *t*-test presented in **Table 6** showed that Variable X_1 partially influenced Y, with a significance value of < 0.05 (0.000 < 0.05). This effect was positive due to the coefficient, indicating that an increase in X_1 led to a rise in Y. Meanwhile, variable X_2 partially did not affect Y because the significance value was >

0.05 (0.192 > 0.05). For more details, the Histogram and Scatterplot are presented in **Figures 4** and **5**.

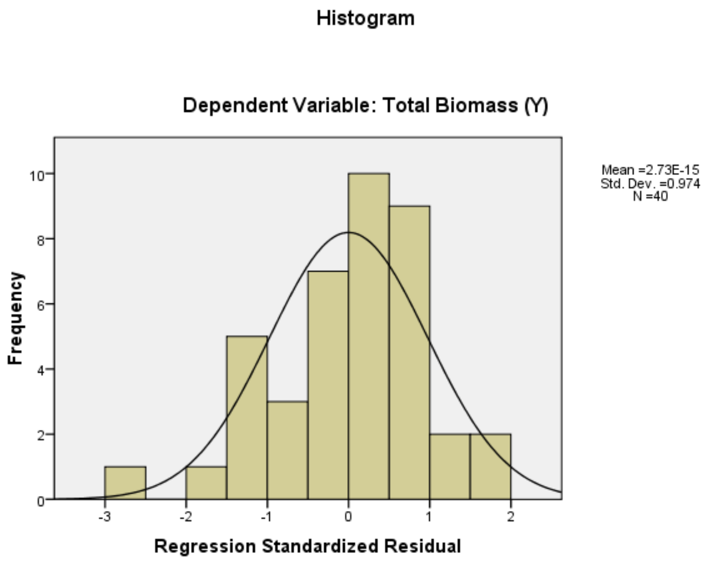

Figure 4. Histogram.

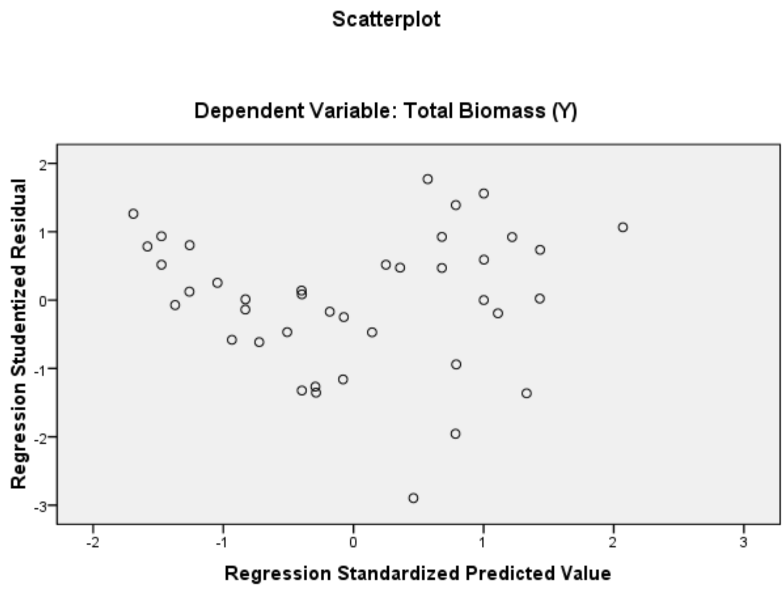

Figure 5. Scatterplot.

Table 7. *F* test results with analysis of variance.

ANOVA[b]						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
	Regression	1.593E7	2	7,962,632.686	209.694	0.000[a]
1	Residual	1,404,987.728	37	37,972.641		
	Total	1.733E7	39			

a. Predictors: (Constant), Tree Height (m) (X_2), Tree Diameter (cm) (X_1).
b. Dependent Variable: Total Biomass (g) (Y).

(2) *F* test: The results of the *F* test with analysis of variance are presented in **Table 7**.

In **Table 7,** a significance value < 0.05 (0.000 < 0.05) was obtained, indicating that variables X_1 and X_2 collectively affected *Y*. The results of the regression and determination analysis (R^2) are presented in **Table 8**

Table 8. Results of regression analysis and determination (R^2).

Model Summary[b]					
Model	***R***	***R* Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Durbin-Watson**
1	0.959[a]	0.919	0.915	194.866	1.956

a. Predictors: (Constant), Tree Height (X_2), Tree Diameter (X_1).

Table 8 showed that the regression coefficient value R was 0.959 or close to 1, indicating a very strong relationship between tree diameter (X_1), tree height (X_2), and total biomass (*Y*).

An R^2 of 0.919 was obtained, indicating that the variables X_1 and R^2 had been used over several decades to test the goodness of fit of regression models. However, it was under criticism over the last three to four decades due to diverse limitations and appropriateness for applicability to nonlinear models. This research reviewed some of the significant investigations, regarding the strengths and weaknesses of R^2, and cautioned the application of these statistics in the predictive methodology. According to [19], R^2 has been used for decades to test the suitability of regression models, making it a useful statistic in predictive modeling in the future. Most users remained emotionally attached to these statistics for a long time due to their ability to evaluate the performance of their model. However, there were negative comments, emphasizing the need for caution when applying R^2. This indicated that the strengths and weaknesses must be assessed first before implementing R^2.

The notation for correlation and regression coefficients needs to be established. This is because using *r* or *R*, but not r^2 or R^2, is appropriate to avoid confusion with other coefficients that have different meanings. As explained in **Table 6**, the equation model for estimating above and below-ground biomass of young Makila trees *(L.angulata* BI) was presented as follows $Y = -1131.146 + 684.799X_1 + 4.276X_2$, with an R^2 of 0.919. This supported previous research for young rain trees (*Albizia saman* (Jacq.) Merr) $Y = -10{,}310.50 + 1{,}820.89X_1 + 10.89X_2$, with R^2 was 0.859 [20]. Similarly, for young Canarium trees (*Canarium indicum* L.), the equation was $Y = -700{,}200 + 209.149X_1 + 3.922X_2$ with R^2 0.386 [21]. Based on the t-test in multiple regression in **Table 6,** Variable X_1 (tree diameter) partially influenced Y (total biomass) but Variable X_2 (tree height) partially did not influence *Y* (total biomass). In this situation, considering a regression equation that uses only 1 independent variable, namely tree diameter is important to facilitate easy measurements in the field, and save time, costs, as well as energy. This is because measuring tree height in the field experiences many difficulties, particularly in a dense forest. Based on the results of simple linear regression analysis, the equation obtained was $Y = -1{,}084{,}626 + 675{,}090\ X_1$, where X_1 = tree diameter and *Y* = total biomass, as presented in **Table 9.** Furthermore, there was also a very close relationship between tree diameter and total biomass with R = 0.957 and R^2= 0.915, as illustrated in **Table 10**. The data distribution and the regression line equation are presented in **Table 9**.

Table 9. Processing results of simple linear regression analysis.

Coefficients[a]								
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	***t***	**Sig.**	**Collinearity Statistics**	
		B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	−1,084.626	106.739		−10.161	0.000		
	Tree Diameter (cm) (X_1)	675.090	33.366	0.957	20.233	0.000	1.000	1.000

a. Dependent Variable: Total Biomass (g) (*Y*).

Table 10. Processing results of simple linear regression analysis.

Model Summary[b]					
Model	***R***	R^2	**Adjusted R^2**	**Std. Error of the Estimate**	**Durbin-Watson**
1	0.957[a]	0.915	0.913	196.823	1.980

a. Predictors: (Constant), Tree Diameter (cm) (X_1).
b. Dependent Variable: Total Biomass (g) (*Y*).

4. Conclusion

In conclusion, this research obtained an allometric equation for young Makila tree (*L.angulata* BI) of $Y = -1131.146 + 684.799X_1 + 4.276X_2$, where Y indicated biomass, X_1 represented diameter, and X_2 was the plant height with R^2 0.919. Before this allometric equation was established, a classical assumption test was carried out in data processing. Based on the results of the t-test: variable X_1 partially affected Y, while variable X_2 partially did not affect Y. The F-test analysis showed that variables X_1 and the rest were influenced by other unexplored factors. In this situation, a regression equation that used only 1 independent variable, namely tree diameter was used to save time, costs, as well as energy, and facilitate easy measurements in the field. This was because measuring tree height in the field experienced many difficulties, particularly in a dense forest. Allometric equation only used 1 variable, $Y = -1{,}084{,}626 + 675{,}090X_1$, where X_1 = tree diameter, Y = total biomass, R = 0.957, and R^2 = 0.915. Considering the potential for time, costs, and energy, as well as ease of measurement in the field, it would be better to predict the biomass of young Makila trees by measuring the tree diameter and avoiding height.

Conflict of interest: The author declares no conflict of interest.

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