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Aboveground Carbon Stock Estimation Model Using Sentinel-2A Imagery in Mbeliling Lanscape in Nusa Tenggara Timur, Indonesia

Serlina Hestiani Oktian[1]*, Wahyu Catur Adinugroho[2], Nengsih Anen[1], and Luluk Setyaningsih[1]

[1]Faculty of Forestry, Nusa Bangsa University, Indonesia
[2]Forest Research, Development and Innovation Agency, Ministry of Environment and Forestry, Indonesia

ORCID
Serlina Hestiani Oktian https://orcid.org/0000-0002-2424-8217

Abstract.
To determine emission levels, information on carbon stocks and changes in each carbon pool is required. Aboveground biomass, particularly on dry land, is one carbon pool that contributes significantly to carbon storage. The goal of this study was to develop a model for estimating aboveground carbon stocks in the Mbeliling landscape, in Nusa Tenggara Timur, using a vegetation index that was correlated with field carbon stocks. The best model was then used to create a map of the distribution of carbon stocks as the final result. Simple linear regression analysis and multiple linear regression analysis were used in the study. Google Earth Engine was used to process the images on a cloud system. When comparing the RGI index for measuring field carbon stocks to other indexes, the correlation test revealed a perfect correlation. The linear regression model for aboveground biomass = 14.046 + 272.496 RGI (R-sq = 0.86) was found to be the best model for aboveground biomass. In the multiple linear regression model, there were signs of multicollinearity. With an overall accuracy of 68% and a cappa accuracy of 54.23%, the best model was able to be used to create a carbon stock map in Mbeliling landscape.

Keywords: *Carbon stock estimation model, Above Ground Biomass, Sentinel 2A*

Corresponding Author: Serlina Hestiani Oktian; email: serlinaoktian@gmail.com

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1. Introduction

Climate change impacts the earth's biosphere, living things, and poses a threat to a global crisis [1]. Many countries and Indonesia have ratified an agreement to address the impacts of climate change (UNFCCC). Vegetation, necromass, and soil in forests play an essential role in mitigating climate change by absorbing and storing carbon [2]. This carbon stock is stored in 5 carbon storage sources, Aboveground Biomass, Belowground Biomass, Litter, Deadwood, and Soil [3].

Countries are expected to carry out forest carbon estimates to calculate the success of implementing climate change mitigation policies related to REDD+ [4]. Information on the amount of stored carbon can be known by estimating the potential of forest biomass reserves [5]. Remote sensing can be a more efficient solution in terms of natural resource inventory [6]. Remote sensing data have been used to produce biomass maps with varying degrees of accuracy [7]. Likewise, monitoring carbon stocks requires a remote sensing approach combined with current field measurement data of carbon stocks [8]. Sentinel-2A imagery used in this study is relatively new to remote sensing. Sentinel-2A imagery is a satellite image that can be accessed for free and has a high spatial resolution of 10x10 m^2/pixel compared to other free satellite images that are often used, such as Landsat imagery which has a spatial resolution of 30x30 m^2/pixel [9].

There is very little information regarding carbon stocks in a landscape in eastern Indonesia [10]; [11] and research related to creating a model for estimating carbon stocks in Nusa Tenggara Timur, especially the Mbeliling Landscape, has never been carried out. This research was conducted by making a carbon stock estimator model based on the correlation of the vegetation index with the carbon stock from field measurements in Mbeliling Landscape.

2. Materials and Method

2.1. Studi Site

The study was carried in Mbeliling Landscape, Nusa Tenggara Timur, Indonesia (119°47'60"-120°07'48" E dan 08°32'06"-08°52'12" S) with an area of ± 93,126 ha. Bentang Alam Mbeliling has two types of forest: semi-evergreen tropical forest on volcanic rocks located between 400-1,100 m above sea level and wet deciduous tropical forest on volcanic rocks below 400 m above sea level. The topography is mostly very steep with a dominant slope of 41-60%, The altitude of Bentang Alam Mbeliling 60% is at an altitude between 0-499 masl, the remaining 35% at an altitude of 500-1,000 masl and 5% above 1,000 masl. The study site has a dry climate with an average monthly rainfall of 58.1 mm [12]. The research location in Mbeliling Landscape in detail can be seen on the plot distribution map based on land cover in Figure 1

2.2. Data Collection

The carbon stock in this study is the result of the Mbeliling Landscape Carbon Stock Measurement Report, measured by the Indonesian Bird Foundation on 75 sample plots

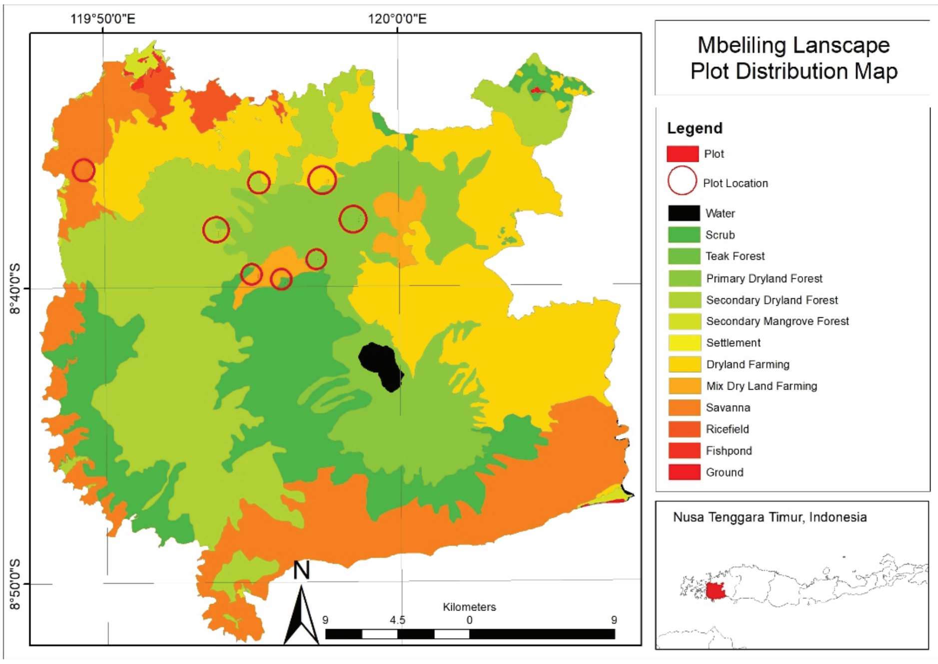

Figure 1: Studi Site.

of 8 land cover, shrubs, teak forest, primary dryland forest, secondary dryland forest, secondary mangrove forest, dryland agriculture, mixed dryland agriculture, and savanna (Table 1).

Table 1: Number of Field Measurement Plots by Land Cover.

No	Land Cover	Category	Number of Plots
1	Shrubs	Non Forest	12
2	Teak Forest	Forest	2
3	Primary Dryland Forest	Forest	13
4	Secondary Dryland Forest	Forest	23
5	Secondary Mangrove Forest	Forest	3
6	Dryland Agriculture	Non Forest	10
7	Mixed Dryland Agriculture	Non Forest	7
8	Savanna	Non Forest	5
Amount			75

The vegetation index used in this study is TVI, ARVI, RGI, DVI, IAVI, NDREI, and GEDI (Table 2). Based on a review of previous studies, there are three vegetation indexes with high accuracy and can explain carbon pool with high correlation, TVI [13], ARVI [14], RGI [15]. These three indexes still have weaknesses in explaining the reflectance of objects, the sensitivity of the ground background, and the effects of atmospheric aerosols. So that other vegetation indexes are used to describe the weakness of the previous vegetation index, namely DVI, IAVI [16], and NDREI [17]. Vegetation index analysis was carried out using the Google Earth Engine platform. Google Earth Engine is a remote-sensing data analysis management platform with many advantages, cloud-based data management, world-scale data sets, can be accessed for free, provides ready-to-analyze data, and is a solution for computer-based data analysis [18].

Table 2: Vegetation Index.

Vegetation Index		Logarithm
TVI	*Transformed Vegetation Index*	$\left(\frac{NIR-RED}{NIR+RED}+C\right)^{\frac{1}{2}}$
ARVI	*Atmospheric Resistant Vegetation Index*	$\frac{NIR-RB}{NIR+RB}$
RGI	*Red-Green Index*	$\frac{GREEN-RED}{GREEN+RED}$
DVI	*Difference Vegetation Index*	*NIR – RED*
IAVI	*Atmospherically Resistant Vegetation Index*	$\frac{NIR-[RED-\gamma(BLUE-RED)]}{NIR+[RED-\gamma(BLUE-RED)]}$
NDREI	*Normalized Difference Red Edge*	$\frac{NIR-RE}{NIR+RE}$
GEDI	*Global Ecosystem Dynamic Investigation* (Potapov, P)	

2.3. Model Construction

Correlation Analysis. Pearson correlation analysis was used to see the correlation between the carbon stock from the field measurements and the vegetation index.

H_0: r = 0, no correlation between the two variables

H_1: r ≠ 0, there is a correlation between the two variables

The hypothesis's decision rules can be seen through the p-value results from the correlation test using IBM SPSS Statistics Base 22.0 software. If p-value ≥ α/2, then accept H0. If the p-value ≥ α/2, then reject H0. Where is the probability of making an error of 5% or the confidence level of 95%.

Model Construction. The model development was carried out on 50 sample plots with simple linear regression and multiple linear regression selected based on the scatter diagram pattern between Aboveground Biomass and Vegetation Index. Simple linear regression and multiple linear regression are the best regression equations used by several previous researchers [7]. The form of the equation can be seen in Table 3.

TABLE 3: Regression Equation Model.

Model	Function
Linear Regression	AGB = a + bX
Multiple Lineear Regression	AGB = a + bX1 + cX2……+nXn

Classical Assumption Test. The classical assumption test is used to find out whether there are classical problems in the built model. The classical assumption test used is the Normality Test of the data using the Kolomogorov Smirnov Test at the 5% level, the Heteroscedasticity Test with the Glejser Test at the 5% level, and the Multicollinearity Test with the size of the VIF value, not more than 10.

Best Model Selection. The best carbon stock estimating equation model is obtained by testing the carbon stock estimating regression equations using several criteria. The criteria used have a significant value of the Coefficient of Determination (R^2) and Adjusted Coefficient of Determination (R^2 – adj). The greater the value of R^2, the greater the total diversity value that can be explained by the regression equation [19]. Analysis of variance and significance tests were conducted to determine whether there was a natural regression relationship between the independent and dependent variables. The analysis was carried out through the F-test significance test. The hypothesis used is :

H0 = βi = 0; Variable Y is not affected by variable X

H1 = βi ≠ 0; Variable Y is affected by variable X

The decision-making rule used is to accept H0 if the value of Fhit < Ftab and reject H0 if Fhit > Ftab with a confidence level of 95% (α = 0.05)

Model Validation. Model validation was carried out on 25 plots outside of those used for model development. Model validation aims to determine the deviation of the carbon stock estimator value from the selected model. This validation stage is carried out to determine the best regression model from all built-in regression models. The validation test of the built model was carried out using the Chi-Square, Aggregate Deviation (SA), Average Deviation (SR), Bias (e), and RMSE (Root Mean Square Error) (Table 4).

TABLE 4: Model Validation.

Model Validation	Function
Chi-Square	$\chi 2hitung = \sum_{i=1}^{n} \frac{(m-a)^2}{m}$
Aggregate Deviation	$SA = \left(\frac{\sum m - \sum a}{\sum m}\right)$
Average Deviation	$SR = \frac{\sum \frac{m-a}{m}}{n} \; x \; 100\%$
Bias	$e = \frac{\sum_{i=1}^{n} m-a}{n}$
Root Mean Square Error	$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (m-a)^2}{n}}$

2.4. Potential and Distribution of Carbon Stock

The final result of this research is a map of the potential and distribution of carbon stocks. The map of the potential and distribution of carbon stocks was carried out using selected models from all the models built. Potential and distribution maps are made by adding a model algorithm to the vegetation index chosen as the best model using Google Earth Engine. The distribution map is made based on a predetermined class [20].

The accuracy test was conducted to determine the level of representation and accuracy of the mapping of potential and distribution of carbon stocks. The mapping accuracy test is carried out by calculating the Overall Accuracy and Kappa Accuracy, assisted by a contingency matrix [21].

$$OA = \frac{\sum_i^r X_{ii}}{N} * 100\%$$

$$K = \frac{N\ \sum_{i=1}^r X_{ii} - \ \sum_{i=1}^r X_{i+}\ X_{+i}}{N^2 + \sum\ X_{i+}\ X_{+i}} * 100\%$$

3. Result and Discussion

The results of the Pearson correlation analysis that tested the relationship between the vegetation index and Aboveground Biomass are shown in Table 5.

Table 5: Results of the Pearson Correlation Analysis.

Carbon Pool	Vegetation Index						
	ARVI	DVI	GEDI	IAVI	NDREI	RGI	TVI
AGB	0.87**	0.84**	0.81**	0.86**	0.82**	0.91**	0.84**

All variables have a significant value with a 95% confidence level (α = 0.05) based on the correlation test results. The hypothesis decides to reject H0, which means a correlation between the variables being tested.

The equations used in this study are linear and multiple linear forms. The regression equation model was chosen based on the scatter diagram pattern between the vegetation index and the carbon pool Aboveground Biomass. The scatter diagram between the vegetation index and Aboveground Biomass can be seen in Figure 2.

The model built based on the regression analysis carried out can be seen in Table 6.

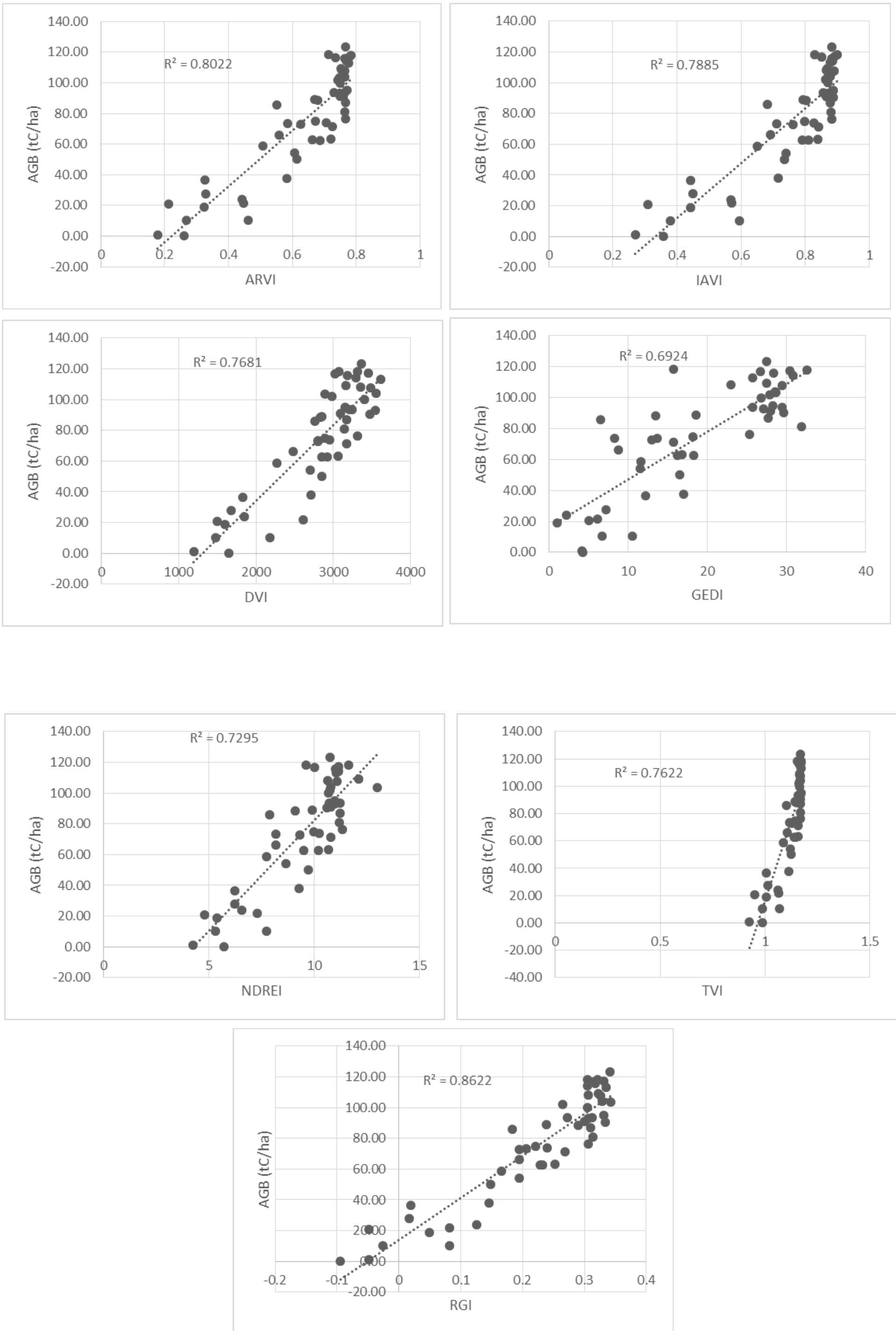

Figure 2: Scatter Plot.

The coefficient of determination of the built model ranges from 69.2% - 88.6%. This value shows an excellent value because it has a coefficient of determination of more than 50%. The highest coefficient of determination in the M8 model is 88.6%. This coefficient of determination explains the ability of the regression model to explain the

Table 6: Regression Model.

Code	Model	IV	Regression Equation	R^2 (%)	R^2-adj (%)	F-hit	F-tab
M1	Linear	ARVI	AGB = -40.368 + 181.989 ARVI	80.2	79.8	194.62	4.04
M2		DVI	AGB = -65.351 + 0.05 DVI	76.8	76.3	158.97	4.04
M3		GEDI	AGB = 16.271 + 3.08 GEDI	69.2	68.6	108.03	4.04
M4		IAVI	AGB = -59.276 + 178.221 IAVI	78.8	78.4	178.94	4.04
M5		NDREI	AGB = -61.487 + 14.388 NDREI	72.9	72.4	129.44	4.04
M6		RGI	AGB = 14.046 + 272.496 RGI	86.2	85.9	300.27	4.04
M7		TVI	AGB = -453.544 + 470.450 TVI	76.2	75.7	153.83	4.04
M8	Multiple Linear		AGB = -189.646 + 193.832 ARVI + 0.009 DVI + 0.89 GEDI + (-381.623) IAVI + (-4.513) NDREI + 347.402 RGI + 312.373 TVI	88.6	86.9	47.26	4.04

dependent variable. The significant value of the coefficient of determination describes the ability of the vegetation index variable to explain carbon stocks.

The Adjusted Coefficient of Determination (R^2 – adj) is a correlation coefficient value whose values of variables have been corrected whose advantages can compare the reliability of the models that have been built. R^2 - adj can be used as the basis for model selection because the test adds confidence in the acceptance of the model. The greater the coefficient of determination of a model, the better the model built will be. The most significant corrected coefficient of determination in this study was found in the M8 model, 86.9%, because of the increasing number of estimators used.

The results of the model selection analysis show that all models have an F-count value that is greater than the F-table at a 5% significance level, so that the decision taken is to reject H0, meaning that the model has a significant effect where the variable bound to the carbon pool Aboveground Biomass can be explained by vegetation index image variable. All models were then tested for the Classical Assumption Test, and the results can be seen in Table 7.

Kolmogorov Smirnov test results show that all models in the Aboveground Biomass carbon pool have a significance value of > 0.05. The decision taken is that all models have residual values that are usually distributed and pass the Kolmogorov Smirnov test. Heteroscedasticity test with the Glejser test results in a significance value <0.05 found in the M3 model with the GEDI variable. So that the basis for the decision taken for the

Table 7: Result of Classical Assumption Test.

Code	Kolmogorov Smirnov Test (Sig)	Glejser Test		Multikolinearitas Test (VIF Value)
		Variable	Sig.	
M1	0.2	ARVI	0.895	-
M2	0.2	DVI	0.675	
M3	0.2	GEDI	0.027	
M4	0.2	IAVI	0.972	
M5	0.2	NDREI	0.473	
M6	0.2	RGI	0.783	
M7	0.2	TVI	0.706	
M8	0.2	ARVI	0.858	636.686
		DVI	0.904	15.615
		GEDI	0.422	8.894
		IAVI	0.636	1172.21
		NDREI	0.218	26.451
		RGI	0.458	34.258
		TVI	0.901	453.799

M3 model occurs heteroscedasticity symptoms, and the model is excluded from the model selection analysis. The results of the multicollinearity test on the multiple linear regression model showed that there were symptoms of multicollinearity in the ARVI, DVI, IAVI, NDREI, RGI, and TVI indexes with VIF test results > 10. The index-free from multicollinearity symptoms in the model was only the GEDI index with a VIF value of 8.894 so that the basis for the decision taken is that the M8 model is excluded from the model selection analysis. Based on the classical assumption test, the models that passed the model selection analysis were the M1, M2, M4, M5, M6, and M7 models. Models that pass the classical assumption test are then tested for model validation, and the results of the validation test can be seen in Table 8.

χ^2 (Chi-Square) is the main criterion in model validation. The calculation of χ^2 is carried out to determine the difference between the estimated carbon stock and the actual carbon stock. From the analyses carried out, the calculated value of χ^2(Chi-Square), which is smaller than χ^2-table, is only found in the M1, M2, and M6 models. The meaning is to accept H0, where the estimated value of carbon stock based on the model does not differ from the carbon stock value from field measurements, where the smallest $\chi^2$is found in the M6 model with an RGI variable, which is 4.9.

SA and SR are criteria used to show the level of accuracy of the model equation. A good model is a model that has an SA value that is close to zero and an SR value

Table 8: Result of Validation Test.

Code	Model	Validation Test					
		χ^2tab	χ^2	SA	SR	e	RMSE
M1	AGB = -40.368 + 181.989 ARVI	66.34	60.66	0.06	23.13	-4.77	19.70
M2	AGB = -65.351 + 0.05 DVI	66.34	59.29	0.05	27.85	-3.99	21.60
M4	AGB = -59.276 + 178.221 IAVI	66.34	68.73	0.06	21.58	-4.93	20.14
M5	AGB = -61.487 + 14.388 NDREI	66.34	268.22	0.07	-15.58	-5.54	22.11
M6	AGB = 14.046 + 272.496 RGI	66.34	4.90	0.00	17.24	0.19	15.52
M7	AGB = -453.544 + 470.450 TVI	66.34	85.12	0.07	21.42	-5.45	21.20

of no more than 10%. The analysis results of SA values all meet these requirements, where the smallest SA value is in the M6 model, which is 0.00. The results of the SR value analysis show that all values do not meet the requirements or the value exceeds 10%. However, it can be seen smallest value for SR value is also found in the M6 model, which is 17.24%

The smallest the RMSE value of the model, the more accurate the model is in detecting carbon stocks. Based on the validation tests (Table 8), the smallest RMSE value in all models is found in the M6 model, 15.52. This value explains that the M6 model has a higher level of accuracy compared to other models.

Bias is a systematic error that may occur due to errors in measurement, sample selection, and parameter estimation techniques where the values can be negative and positive. A good model is a model that has a bias value close to zero. The validation test results in Table 8 show that the M6 model shows the smallest bias value, 0.19.

Overall, the validation of the carbon stock estimator model on the M6 model (AGB = 14.046 + 272.496 RGI) has a good reliability level on all validation criteria. So the M6 model is the best model that can be used to estimate the AGB carbon pool in Mbeliling Landscape, Nusa Tenggara Timur. The RGI Vegetation Index with the exponential model B = 2.7135 $e^{10.554(RGI)}$with the resulting R^2 value of 79% using Spot Imagery is the best model for estimating biomass in Kubu Raya, West Kalimantan [22].

A map of the distribution of carbon stocks in the AGB carbon pool, Mbeliling Landscape-Nusa Tenggara Timur, was made based on the best model tested, and a potential map based on the struges rule was made for 21 classes. However, based on existing data distribution, the distribution map of carbon stocks was only made for six classes. This potential map was created by adding the logarithm of the selected model based on the RGI variable (AGB = 14.046 + 272.496 RGI) using Google Earth Engine. The map of potential carbon stocks in the AGB can be seen in Figure 3.

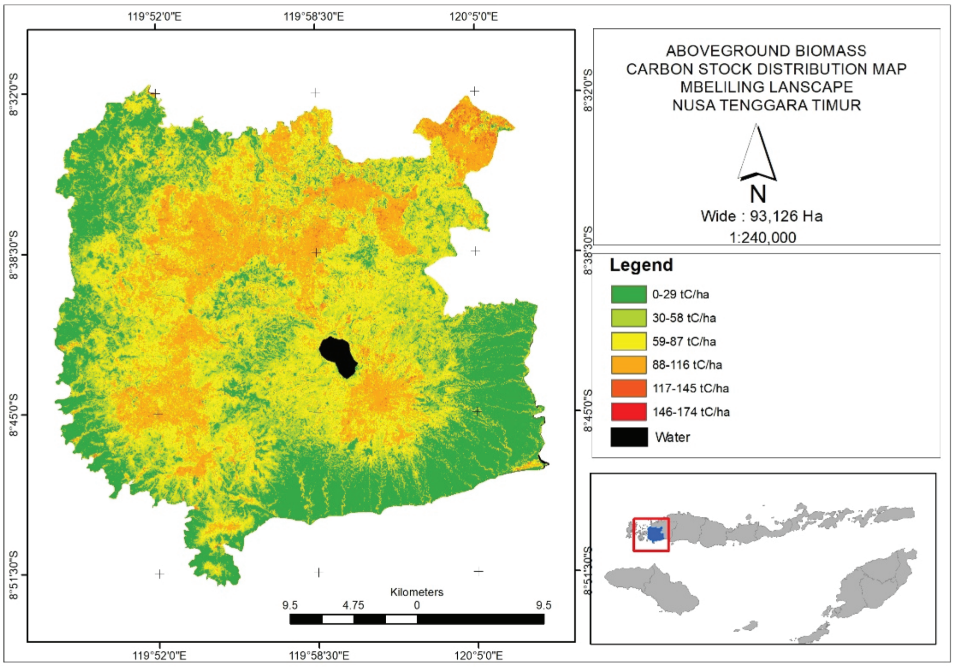

Figure 3: Aboveground Biomass Carbon Stock Distribution Map.

The accuracy test was conducted to determine the level of representation and accuracy of the mapping of potential and distribution of carbon stocks. The overall and Kappa accuracy were calculated to determine the map classification accuracy in Bentang Alam Mbeliling. The results showed that the Overall accuracy was 68%, and the Kappa accuracy was 54.23%.

Based on the carbon stock distribution map in the Aboveground Biomass carbon pool, the potential carbon stock in the Mbeliling Landscape area is 5,200,841.45 tC. The potential that dominates the Aboveground Biomass carbon pool in class 3 with carbon potential between 59-87 tC/ha spread over an area of 27,941.95 ha or 30.19% of the total Mbeliling Landscape area. The potential carbon stock of this Aboveground Biomass is equivalent to carbon dioxide emissions in the atmosphere of 19.01 MtCO_2-e. The potential values for the distribution and extent of each class can be seen in Table 9.

4. Conclusion

Based on the analysis, the best AGB estimator model shows that the M6 model with RGI variable is the best model to estimate Aboveground Biomass in Bentang Alam

Table 9: Potential Carbon Stocks and their Extent.

Class	Carbon Potential (tC/ha)	Area (ha)	Area (%)
1	0-29	26,777.21	28.93
2	30-58	16,042.99	17.33
3	59-87	27,941.95	30.19
4	88-116	21,182.27	22.89
5	117-145	609.66	0.66
6	146-174	2.02	0.002
Total		92,556	100

Note: Water bodies not include

Mbeliling. The ability of a model to explain AGB is 86%, which is described based on the coefficient of determination. Based on the selected model, which is applied to remote sensing parameters, the AGB potential in the Mbeliling Landscape is 5,200,841.45 tC. The potential that dominates the AGB carbon storage source is in class 3, with carbon potential between 59-87 tC/ha spread over an area of 27,941.95 ha or 30.19% of the total Mbeliling Landscape area. The potential carbon stock of this Aboveground Biomass is equivalent to carbon dioxide emissions in the atmosphere of 19.01 MtCO_2-e.

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