International Journal Of Health, Engineering And Technology (IJHET) *E-ISSN 2829 - 8683*
Volume 5, Number 2, July 2026, *Page. 2178 - 2188*
Email : editorijhess@gmail.com

Mapping Of Aboveground Biomass Estimation Based On Vegetation Index In Banjarbaru City

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Abstract

Climate change increases the importance of aboveground biomass information as an indicator of carbon stocks and a basis for urban vegetation management. This study aims to determine the best model for estimating aboveground biomass using Sentinel-2 imagery-based vegetation indices and to map biomass distribution in Banjarbaru City. The study uses a quantitative approach with remote sensing-based spatial analysis. The study population is all woody vegetation in Banjarbaru City, while the sample consists of 45 plots determined using stratified random sampling. The research instruments include Diameter at Breast Height (DHT), tree height, Global Positioning System (GPS), and Sentinel-2B Level-2A imagery. Data analysis was carried out through biomass calculations using allometric equations, Pearson correlation analysis, linear, exponential, polynomial, and power regressions, regression assumption testing, model validation using SA, SR, RMSE, bias, and chi-square, and spatial mapping. The results showed that the Linear SAVI model was the best model with the equation B = -287.341 + 517.644 SAVI and an R^2 value of 0.905. In conclusion, the Linear SAVI model is able to provide accurate and representative biomass estimates, while the application of masking improves the quality of biomass mapping, thereby supporting carbon inventory and green open space planning.

Keywords: ***Aboveground Biomass, Geographic Information System, Sentinel-2, Soil Adjusted Vegetation Index, Vegetation Index***

INTRODUCTION

Climate change triggered by increased greenhouse gas emissions is a global environmental challenge that requires sustainable mitigation efforts. Vegetation plays a crucial role in absorbing carbon dioxide (CO_2) through photosynthesis and storing it in the form of biomass. Therefore, aboveground biomass (AGB) is widely used as an indicator in estimating carbon stocks.(Rosianty et al., 2020;Santoso et al., 2021)Information on biomass distribution is important because it can illustrate a region's capacity to support climate change mitigation and serve as a basis for managing vegetation resources.

Advances in remote sensing technology have enabled biomass estimation to be performed more efficiently than field measurement methods, which are limited to sample points. Sentinel-2 imagery is widely used because of its high spatial resolution, good temporal coverage, and the provision of spectral channels that are sensitive to vegetation characteristics.(Phiri et al., 2020; Wai et al., 2022). Various vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), and Soil Adjusted Vegetation Index (SAVI), have been shown to have a close relationship with biomass so that they can be used to build regression-based biomass estimation models.(Bindu et al., 2020; Patty et al., 2022; Pietersz et al., 2024)However, the performance of each vegetation index may differ in areas with heterogeneous land cover characteristics, particularly urban areas that are influenced by variations in vegetation density and soil background.(Netsianda & Mhangara, 2025).

Banjarbaru City is one of the cities experiencing rapid regional development along with increasing development and population growth, thus potentially reducing the area of vegetation and carbon absorption capacity.(Muhaimin & Ramali, 2021; Badan Pusat Statistik, 2025). Previous research in Banjarbaru City showed that NDVI has a strong relationship with vegetation carbon stocks, but was still limited to the use of one vegetation index.(Nirwana et al., 2024)Therefore, this study compares the performance of NDVI, GNDVI, and SAVI in estimating aboveground biomass based on Sentinel-2 imagery. The results of this study are expected to produce the best regression model and spatial information on biomass distribution that supports green open space management and climate change mitigation efforts in Banjarbaru City.

RESEARCH METHODS

This study uses a quantitative approach combined with remote sensing-based spatial analysis to estimate aboveground biomass in Banjarbaru City, South Kalimantan. This approach integrates field measurement data with Sentinel-2B satellite imagery to produce a biomass estimation model that is then used to map biomass distribution spatially. All stages of the study include field data collection, satellite image processing, regression model development, model validation, and biomass mapping.

The data used consisted of primary and secondary data. Primary data were obtained through an inventory of woody vegetation in observation plots determined using the stratified random sampling method. This technique was chosen so that each vegetation density class could be represented proportionally, thus depicting biomass variations in the study area. In each plot, measurements of stem diameter at breast height (DHT), tree height, and coordinates were recorded using the Global Positioning System (GPS). Meanwhile, secondary data in the form of Sentinel-2B Level-2A imagery was obtained from the Copernicus Data Space Ecosystem with recording times adjusted to the implementation of the field survey to minimize differences in vegetation conditions due to seasonal changes.

Aboveground biomass was calculated using a non-destructive sampling method with an allometric equation developed byChave et al. (2014)This equation was chosen because it has been widely used to estimate tropical vegetation biomass without having to cut down trees, making it suitable for application in the research area.

$$Y = 0{,}0673 \times (\rho D^2 H)^{0.976}$$

Where AGB is the aboveground biomass (kg), ρ is the specific gravity of wood (g cm^{-3}), D is the stem diameter at breast height (cm), and H is the tree height (m).

The image processing stage begins with atmospheric correction to reduce the influence of atmospheric conditions on image reflectance values. Cropping is then performed according to the administrative boundaries of Banjarbaru City so that the analysis is only focused on the research area. The images are then compiled into a composite form and used to calculate three vegetation indices, namely the Normalized Difference Vegetation Index (NDVI), the Green Normalized Difference Vegetation Index (GNDVI), and the Soil Adjusted Vegetation Index (SAVI). These three indices were chosen because they have different characteristics in representing vegetation conditions, thus allowing for an evaluation of the most appropriate index for estimating aboveground biomass.

The equation used to calculate each vegetation index is as follows.

Normalized Difference Vegetation Index(NDVI)

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

Green Normalized Difference Vegetation Index(GNDVI)

$$GNDVI = \frac{(NIR - Green)}{(NIR + Green)}$$

Soil Adjusted Vegetation Index(SAVI)

$$SAVI = \frac{(NIR - Red)}{(NIR + Red)}\,(1 + L)$$

Where NIR is the reflectance of the Near Infrared channel, Red is the reflectance of the red channel, Green is the reflectance of the green channel, while L is the soil correction factor which in this study has a value of 0.5.

To ensure biomass estimation is performed only on woody vegetation, the image is first classified using a supervised classification method with the Maximum Likelihood algorithm. The classification results are used as a mask to separate vegetation pixels from non-vegetation objects, ensuring that the modeling process is not affected by the presence of water bodies, open land, or built-up areas, which could bias the estimation results.

Biomass values from field measurements were then correlated with NDVI, GNDVI, and SAVI values using Pearson correlation analysis to determine the strength of the relationship between variables. Next, four regression models were developed: linear, exponential, polynomial, and power. Each model was evaluated based on the coefficient of determination (R^2) and the significance of the ANOVA test to determine the model's ability to explain biomass variation. Prior to validation, the model was first tested against regression assumptions, including residual normality using the Shapiro-Wilk test, heteroscedasticity using the Glejser test, and autocorrelation using the Durbin-Watson statistic. Only models that met all of these assumptions proceeded to the validation stage.

Validation was performed by comparing the model-estimated biomass to the actual biomass at the observation point. Model performance was assessed not only by the coefficient of determination but also by the level of accuracy and the likelihood of prediction errors. Therefore, five validation parameters were used: Aggregate Deviation, Mean Deviation, Root Mean Square Error (RMSE), bias (e), and chi-square (χ^2). Using multiple parameters simultaneously provides a more comprehensive evaluation because each parameter describes a different aspect of model accuracy.

Aggregate Deviation is used to determine the tendency of the model to produce estimates that are higher or lower than the actual biomass, while the Average Deviation indicates the magnitude of the average relative deviation between the estimated results and the results of field measurements. The accuracy of the model is then evaluated using RMSE, while bias is used to identify the direction of the prediction deviation. The chi-square test is conducted to determine the level of agreement between the estimated biomass and the actual biomass. The equation for each validation parameter is used referring to the general formula used inFirmansyah et al. (2022)as follows:

Aggregate Deviation (AGD)

$$SA = \left(\frac{\sum_{i=1}^{n} \hat{y} - \sum_{i=1}^{n} y}{\sum_{i=1}^{n} \hat{y}} \right)$$

Mean Deviation (SR)

$$SR = \left(\frac{\left| \sum_{i=1}^{n} \frac{\hat{y} - y}{\hat{y}} \right|}{n} \right) x\ 100\%$$

Root Mean Square Error(RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(\frac{\hat{y} - y}{y} \right)^2}{n}}\ x\ 100\%$$

Bias (e)

$$e = \sum_{i=1}^{n} \left\{ \frac{\frac{\hat{y} - y}{y}}{n} \right\} x\ 100\%$$

Chi – square test

$$X^2 hitung = \sum_{i=1}^{n} \frac{(\hat{y} - y)^2}{y}$$

Information :
y : Actual biomass value
ŷ : Estimated biomass value
n : Amount of data

Models that met all validation criteria were then compared using a scoring method based on statistical parameters and validation results. The model with the best score was selected as the aboveground biomass estimation model and then applied to Sentinel-2B imagery to generate a biomass distribution map in Banjarbaru City. The resulting map was then analyzed to identify biomass distribution patterns and evaluate the effect of masking on the estimation results.

RESULTS AND DISCUSSION

An aboveground biomass inventory was conducted in 45 observation plots spread across various land cover conditions in Banjarbaru City. Measurements were made non-destructively by measuring stem diameter at breast height (DBH), tree height, and identifying vegetation types in each plot. The field data were then calculated using allometric equations.Chave et al. (2014)to obtain actual biomass values which are then used as reference data in the development of a biomass estimation model based on Sentinel-2 imagery. This approach was chosen because it is able to depict biomass conditions representatively without causing damage to vegetation, while also serving as a basis for linking vegetation spectral characteristics with biomass measured in the field.

Parameter	Mark
Number of Plots	45
Minimum Biomass (ton/ha)	23.15
Maximum Biomass (ton/ha)	199.71
Average Biomass (ton/ha)	129.54
Standard Deviation (ton/ha)	41.84

Based on measurements from 45 plots, biomass in Banjarbaru City ranged from 23.15 to 199.71 tons/ha, with an average of 129.54 tons/ha and a standard deviation of 41.84 tons/ha. This high variation indicates that vegetation conditions are not homogeneous but are influenced by differences in vegetation type, tree size, canopy density, and land use. Plots with large-diameter trees and dense canopies had higher biomass than areas dominated by young vegetation or built-up land. The relatively high average biomass value indicates that urban vegetation, including green open spaces and urban forests, still plays an important role in biomass storage, carbon sequestration, and maintaining ecological balance. These results align with research by Nirwana et al. (2024) which showed that areas with dense vegetation cover have a greater carbon storage capacity. Furthermore, the wide variation in biomass provides a good basis for developing biomass estimation models because it is able to represent various vegetation conditions, thereby improving the model's predictive ability across the entire study area.

Field biomass data was then linked to three vegetation indices—NDVI, GNDVI, and SAVI—to determine each index's ability to represent biomass variation. These three indices were chosen because they all utilize the near infrared channel as the primary indicator of vegetation condition, but they have different characteristics in responding to soil influences and canopy density. Therefore, analyzing the relationship between field biomass and the three vegetation indices is a crucial step in determining the most appropriate biomass estimation model for application in Banjarbaru City.

	NDVI	GNDVI	SAVI	Biomass
NDVI	-	0.955	1,000	0.951
GNDVI	0.955	-	0.955	0.933
SAVI	1,000	0.955	-	0.951
Biomssa	0.951	0.933	0.951	-

The analysis results show that all three vegetation indices have a very strong positive relationship with aboveground biomass. NDVI and SAVI have the highest correlation coefficients, each at 0.951, while GNDVI is 0.933. These results indicate that increasing biomass in the field is followed by increasing vegetation index values in Sentinel-2 imagery. Although NDVI and SAVI have similar correlation values, SAVI is better able to reduce the influence of ground reflectance through a soil correction factor, making it more stable for estimating biomass in areas with diverse land uses such as Banjarbaru City. Conversely, NDVI is more sensitive to variations in soil background, especially in areas with moderate to low vegetation cover.

The very strong correlation between field biomass and the three vegetation indices indicates that Sentinel-2 spectral data adequately represents the variation in vegetation conditions in Banjarbaru City. However, a high correlation coefficient does not necessarily indicate that an index is the best predictor for estimating biomass. Correlation only describes the closeness of the relationship between variables, while the model's ability to predict biomass is also influenced by the form of the regression equation, the characteristics of the data distribution, and the model's suitability to statistical assumptions. Therefore, each vegetation index was further developed into several forms of regression equations to obtain the most representative estimation model.

Type	Code	Equality	s	R^2	R^2adj	F count	Ftable	Sig. F
Linear	M1	*B = -287,370 + 776,450 NDVI*	8,536	0.905	0.902	277.22	4.18	0,000
	M2	*B = -297.549 + 901.813 GNDVI*	9,954	0.871	0.867	196.15	4.18	0,000
	M3	*B = -287,341 + 517,644 SAVI*	8,536	0.905	0.902	277.21	4.18	0,000
Exponential	M4	*B = 5.888 e^(5.720 NDVI)*	8,106	0.909	0.905	288.34	4.18	0,000
	M5	*B = 5.365 e^(6.681 GNDVI)*	9,196	0.884	0.880	221.42	4.18	0,000
	M6	*B = 5.888 e^(3.814 SAVI)*	8,106	0.909	0.905	288.31	4.18	0,000
Polynomial	M7	$B = 194,716 - 994,573\ NDVI + 1620,240\ NDVI^2$	8,144	0.917	0.911	154.17	3.34	0,000
	M8	$B = 383.571 - 1949.232\ GNDVI + 2972.261\ GNDVI^2$	9,338	0.891	0.883	113.92	3.34	0,000
	M9	$B = 194,607 - 662,803\ SAVI + 720,026\ SAVI^2$	8,145	0.917	0.911	154.16	3.34	0,000
Power	M10	*B = 882,510 NDVI^3,107*	8,024	0.908	0.905	287.00	4.18	0,000
	M11	*B = 1378.061 GNDVI^3.180*	9,276	0.881	0.877	214.39	4.18	0,000
	M12	*B = 250,067 SAVI^3,107*	8,037	0.908	0.905	286.97	4.18	0,000

The development of biomass estimation models using linear, exponential, polynomial, and power regression showed that all models exhibited a positive relationship between vegetation indices and biomass, with coefficients of determination (R^2) ranging from strong to very strong. For NDVI, the linear model produced an R^2 of 0.905, indicating that 90.5% of the variation in biomass can be explained by changes in NDVI values. However, NDVI has limitations in areas with high biomass due to the saturation effect, resulting in decreased sensitivity in dense vegetation. GNDVI also demonstrated a very strong relationship, but its performance was slightly lower because it was more sensitive to chlorophyll content than to the physical characteristics of vegetation that influence biomass. Meanwhile, SAVI provided the most consistent and accurate performance due to the soil adjustment factor that reduces the influence of soil reflectance, making it more suitable for application in areas with heterogeneous land use such as Banjarbaru City. The ANOVA test results showed that all models that met the criteria had a significance value of less than 0.05, thus the developed regression model was declared significant and suitable for use in estimating aboveground biomass.

However, a model with a high R^2 value may not be immediately usable for mapping. In regression analysis, meeting statistical assumptions is a crucial step because it impacts model reliability. Therefore, all resulting models were then tested using residual normality, heteroscedasticity, and autocorrelation tests to ensure that the regression equations met the basic assumptions of regression analysis.

Code	Model	Shapiro-Wilk Normality (Sig.)	Not e:	Heterosceda sticity (Sig.)	Note:	*Durbin-Watson*	Note:
M1	Linear NDVI	0.124	N	0.526	TH	1.82	TA
M2	Linear GNDVI	0.641	N	0.167	TH	1,948	TA
M3	Linear SAVI	0.124	N	0.526	TH	1.82	TA
M4	Exponential NDVI	0.003	TN	0.703	TH	1,674	TA
M5	Exponential GNDVI	0.567	N	0.318	TH	2,029	TA
M6	Exponential SAVI	0.003	TN	0.703	TH	1,674	TA
M7	NDVI Polynomial	0.024	TN	0.571	TH	1,817	TA
M8	GNDVI Polynomial	0.458	N	0.679	TH	2,047	TA
M9	SAVI polynomial	0.024	TN	0.571	TH	1,817	TA
M10	Power NDVI	0.002	TN	0.44	TH	1,674	TA
M11	Power GNDVI	0.366	N	0.956	TH	2	TA
M12	Power SAVI	0.002	TN	0.44	TH	1,674	TA

Information:
Normality: Shapiro-Wilk p-value > 0.05 = data is normally distributed.
Heteroscedasticity: significance value > 0.05 = not heteroscedasticity.
Autocorrelation: Durbin-Watson values approaching 2 indicate no autocorrelation.

The test results showed that not all models met the regression assumptions. Some models failed the residual normality test, while others showed indications of heteroscedasticity and autocorrelation. This condition indicates that a high coefficient of determination does not always indicate good model quality. Therefore, only models that met all regression assumptions proceeded to the validation stage. This approach is crucial to ensure that the selected model not only has a strong statistical relationship but also produces consistent estimates when applied to spatial data.

Models that meet all regression assumptions are then evaluated through a validation process to determine their accuracy in estimating aboveground biomass. This stage is crucial because a high coefficient of determination does not necessarily result in a model with good predictive ability when applied to data outside the calibration process. Therefore, the assessment is based not only on the closeness of the statistical relationship but also takes into account the magnitude of the deviation between the estimated biomass and the actual biomass in the field. In this study, validation was conducted using five parameters: Aggregate Deviation (SA), Mean Deviation (SR), Root Mean Square Error (RMSE), bias (e), and chi-square (χ^2). The combination of these five parameters provides a more comprehensive picture of the accuracy, consistency, and error tendency of each regression model.

Model	Code	SA	SR %	RMSE %	e%	χ^2 Calculate	χ^2 Table
Linear NDVI	M1	0.0319	1,3002	10,0093	2.2295	12,8203	22,3620
Linear GNDVI	M2	0.0604	7,7391	32,1938	13,8030	56,9199	22,3620
Linear SAVI	M3	0.0319	1,2994	10,0092	2,2287	12,8194	22,3620
Exponential GNDVI	M5	0.1226	17,8384	72,2939	38,8782	203,7186	22,3620
GNDVI Polynomial	M8	0.1351	18,9253	82,1809	44,0577	257,9972	22,3620
Power GNDVI	M11	0.1124	16,7252	63,6033	34,2619	162,1195	22,3620

Validation results indicate that a high coefficient of determination (R^2) does not always yield the best predictive ability. Therefore, model selection was carried out by considering all validation parameters, including SA, SR, RMSE, bias, and the χ^2 test. The Linear SAVI and Linear NDVI models were proven to meet all validation criteria with low prediction error values and showed no significant differences between estimated biomass and field-measured biomass. In contrast, several GNDVI-based models, despite having a strong relationship with biomass, were unable to meet all validation parameters, resulting in less stable estimates. This difference in performance is influenced by the spectral characteristics of each index. SAVI is more stable because it has a soil adjustment factor suitable for heterogeneous land use conditions such as in Banjarbaru City, while NDVI is more sensitive to the influence of soil and saturation at high biomass. In addition, the vegetation masking process before modeling also improves estimation accuracy by eliminating non-vegetation pixels, making the Linear SAVI model the most reliable model in estimating aboveground biomass in the study area.

To objectively determine the best model, all statistical and validation parameters are integrated through a scoring method. This approach allows each model to be compared based on its overall performance, rather than just one specific indicator. The model with the lowest score is considered to have the highest accuracy because it meets the majority of the evaluation parameters.

Code	R^2	R^2adj	s	SA	SR	RMSE	e	χ^2	Total
M1	1	1	1	1	1	1	1	1	8
M2	6	6	6	2	3	3	2	2	30
M3	1	1	1	1	1	1	1	1	8
M5	4	4	3	5	6	5	5	5	38
M8	3	4	4	6	6	6	6	6	41
M11	5	5	4	5	5	5	5	4	37

The scoring results show that the Linear SAVI model is the best model for mapping aboveground biomass in Banjarbaru City with the equation B = -287.341 + 517.664 SAVI. This model is able to explain approximately 90.5% of the variation in biomass, thus indicating that the SAVI value has a very strong relationship with biomass, while the rest is influenced by other factors such as vegetation composition, stand age, soil conditions, and the environment. The linear relationship obtained indicates that an increase in the SAVI value is followed by a proportional increase in biomass, making it suitable for the characteristics of heterogeneous urban vegetation. In addition to having high accuracy, the linear model is also simpler and easier to implement in Geographic Information Systems (GIS) and Sentinel-2 image processing for regular biomass monitoring. These results confirm that SAVI is more effective than other vegetation indices in estimating biomass in urban areas because it is able to reduce the influence of soil reflectance, resulting in a more representative estimate.

The SAVI-based linear model, selected as the best model, was then applied to Sentinel-2 imagery to generate a map of aboveground biomass distribution in Banjarbaru City. The mapping

International Journal Of Health, Engineering And Technology (IJHET) E-ISSN 2829 - 8683
Volume 5, Number 2, July 2026, Page. 2178 - 2188
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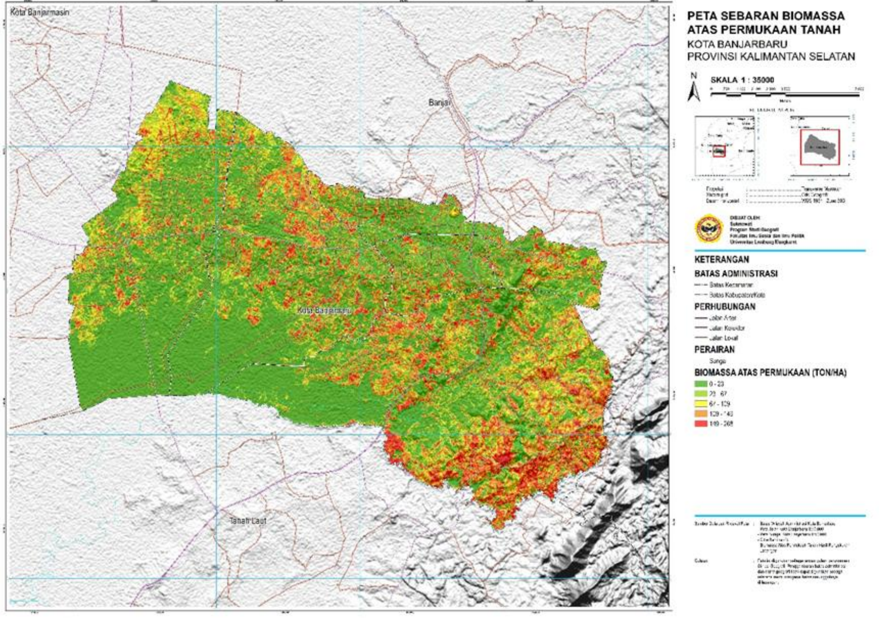
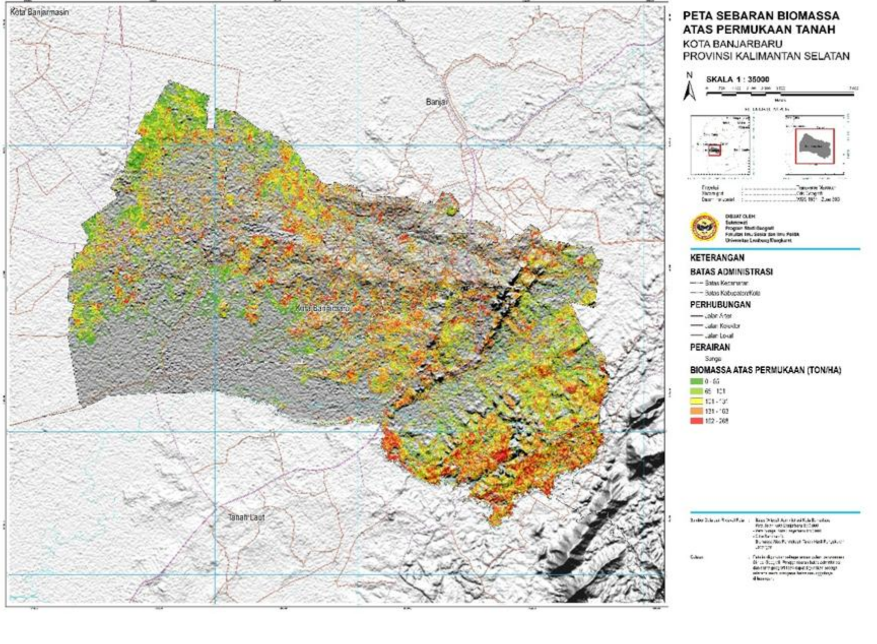
process was conducted using two approaches: one without masking and the other after masking based on the Maximum Likelihood classification results. The comparison of the two approaches aimed to evaluate the influence of non-vegetation objects on biomass estimation results and to determine the extent to which the masking process improved the representation of biomass distribution in the study area.



The results of biomass mapping without masking process show that biomass values still appear in all image pixels, including built-up areas, water bodies, and open land, because the regression model is applied to all SAVI values without distinguishing vegetation and non-vegetation objects. This condition causes the biomass distribution to be less realistic, with the dominance of the 0–23 ton/ha biomass class covering an area of 16,231.19 ha (53.15%), and produces a lower average biomass compared to the results of field measurements. To improve accuracy, a masking process was carried out using the Maximum Likelihood classification results so that only woody vegetation pixels were processed, while non-vegetation objects were eliminated. The application of masking resulted in a more realistic and representative biomass distribution because each mapped biomass value truly describes the presence of woody vegetation in the study area.



The masking process not only improved the spatial appearance of the biomass map but also enhanced the statistical quality of the mapping results. The minimum and maximum biomass values remained relatively constant due to the use of the same regression model, while the average biomass increased from approximately 50 tons/ha to 116 tons/ha after masking. This increase occurred because non-vegetation pixels were eliminated, allowing estimation to be performed only on woody vegetation. These results indicate that image preprocessing, specifically vegetation masking, plays a crucial role in producing more representative biomass maps. This finding confirms that the success of biomass mapping is determined not only by the regression model used but also by the quality of the input data, especially in urban areas with heterogeneous land use such as Banjarbaru City.

Parameter	No Masking	Masking Results
Minimum	0	0
Maximum	267.97	267.97
Average	50.63	116.92
Standard Deviation	61.02	40.52

A more interesting change is seen in the distribution of each biomass class. In the unmasked results, the biomass class of 0–23 tons/ha was the most dominant class, covering more than half of the study area. This dominance was primarily due to the large number of non-vegetation pixels that were still processed by the model, resulting in biomass values close to zero. After the masking process, this distribution pattern changed significantly. The low biomass class no longer dominated the study area because non-vegetation pixels had been eliminated. Instead, the biomass distribution shifted toward the medium to high biomass classes, which more closely matched actual vegetation conditions in the field. This shift indicates that most vegetation in Banjarbaru City actually has a higher biomass storage capacity than indicated by the unmasked mapping results. Thus, the use of masking not only improves the spatial appearance of the map but also enhances the quality of ecological interpretation of biomass distribution.

Class	Biomass (Without Masking)	Area (ha)	Wide (%)	Biomass (After Masking)	Area (ha)	Wide (%)
1	0–23	16,231.19	53.15	0–65	1,383.77	11.47
2	23–67	3,291.41	10.78	65–101	2,722.92	22.57
3	67–109	3,856.77	12.63	101–131	3,259.34	27.01
4	109–149	4,416.02	14.46	131–163	3,174.24	26.31
5	149–268	2,741.19	8.98	163–268	1,526.27	12.65
Total	–	30,536.58	100	–	12,066.54	100

The classification results after the masking process show that the biomass classes 101–131 tons/ha and 131–163 tons/ha have the largest area, indicating the dominance of woody vegetation with medium to high biomass in Banjarbaru City. This result differs from the mapping without masking, which is dominated by very low biomass classes, thus emphasizing the importance of the masking process to eliminate the influence of non-vegetation pixels. Ecologically, the dominance of medium biomass indicates that urban vegetation still has good biomass storage capacity, supported by the presence of green open spaces, urban forests, and woody vegetation. Meanwhile, very high biomass is only found in certain locations that still have large-diameter vegetation. Biomass distribution also varies between sub-districts, reflecting differences in land use, vegetation density, and development levels in each region.

Based on mapping results, Cempaka District has the highest biomass accumulation in Banjarbaru City, characterized by a dominance of high to very high biomass classes. This condition is influenced by the extensive natural vegetation cover, shrubs, and large-diameter tree stands, as well as a low rate of land conversion compared to other districts. The relatively intact vegetation structure makes this area a prime location for biomass and carbon storage.

Landasan Ulin District also exhibits relatively high biomass, despite some areas having been developed into built-up areas. The presence of green open spaces and remaining pockets of vegetation contribute to moderate to high biomass, although its distribution is becoming fragmented due to regional development.

In Liang Anggang District, biomass distribution is more heterogeneous due to the combination of land uses, including agriculture, shrubs, natural vegetation, and settlements. This variation results in an alternating pattern of low and high biomass distribution, reflecting the direct influence of land cover heterogeneity on biomass accumulation.

In contrast, the districts of North Banjarbaru and South Banjarbaru are dominated by low to moderate biomass. High development intensity, dense settlements, road networks, commercial areas, government centers, and public facilities have limited and fragmented woody vegetation, resulting in relatively low biomass storage capacity. This situation suggests that increased urban development tends to reduce biomass accumulation if not balanced by adequate green open space.

In general, biomass distribution shows a strong correlation with land-use characteristics. Areas with dense vegetation cover have higher biomass than built-up areas, consistent with various studies showing that urbanization contributes to the decline of biomass and carbon stocks in urban areas. Therefore, spatial biomass information can be used as a basis for green space planning, carbon inventories, and sustainable urban development.

The results also show that the integration of field data, Sentinel-2 imagery, the SAVI vegetation index, and a Maximum Likelihood classification-based masking process produces more accurate aboveground biomass estimates than the non-masking approach. In addition to improving statistical accuracy, this method produces a spatial distribution of biomass that is more representative of actual vegetation conditions in Banjarbaru City. These findings confirm that the accuracy of biomass mapping is influenced not only by the regression model but also by the quality of image preprocessing before the estimation process is carried out.

CONCLUSIONS

This study shows that aboveground biomass estimation based on Sentinel-2 imagery is able to depict the vegetation condition of Banjarbaru City with a high level of accuracy. Field biomass in 45 plots ranged from 23.15 to 199.71 tons/ha with an average of 129.54 tons/ha, reflecting the high variation in vegetation structure due to differences in land use. All three vegetation indices had a very strong positive relationship with biomass, but the Linear SAVI model was selected as the best model with the equation B = -287.341 + 517.644 SAVI because it met all statistical criteria, regression assumptions, and validation parameters. This model was able to explain 90.5% of the biomass variation and produced more stable estimates than the NDVI and GNDVI-based models. The application of masking based on Maximum Likelihood classification was also proven to improve the spatial representation of biomass by eliminating non-vegetation pixels, so that the average biomass of the mapping results increased from 50.63 tons/ha to 116.92 tons/ha. Practically, this model can be used as a basis for carbon inventory, biomass monitoring, and green open space planning and climate change mitigation policies in Banjarbaru City.

Despite yielding good results, this study still has several limitations. The model was developed based on 45 observation plots and a single Sentinel-2 image acquisition period, so it does not fully represent seasonal variations or vegetation growth dynamics over time. Furthermore, the biomass estimation only utilizes optical vegetation indices, thus failing to consider three-dimensional canopy structure information that can be obtained from LiDAR, UAV, or radar data. Future research is recommended to use a larger number of plots, multitemporal data, and integrate various remote sensing data sources and more advanced modeling approaches, such as machine learning, to improve the accuracy of biomass estimation in heterogeneous urban areas. This approach is expected to produce more precise biomass information and support environmental management and sustainable urban development more effectively.

REFERENCES

Badan Pusat Statistik Kota Banjarbaru. (2025). *Kota Banjarbaru dalam angka 2025*. Badan Pusat Statistik.

Bindu, G., Rajan, P., Jishnu, E. S., & Ajith Joseph, K. (2020). Carbon stock assessment of mangroves using remote sensing and geographic information system. *Egyptian Journal of Remote Sensing and Space Science, 23*(1), 1–9. https://doi.org/10.1016/j.ejrs.2018.04.006

Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M. S., Delitti, W. B. C., Duque, A., Eid, T., Fearnside, P. M., Goodman, R. C., Henry, M., Martínez-Yrízar, A., Mugasha, W. A., Muller-Landau, H. C., Mencuccini, M., Nelson, B. W., Ngomanda, A., Nogueira, E. M., Ortiz-Malavassi, E., ... Vieilledent, G. (2014). Improved allometric models to estimate the aboveground biomass of tropical trees. *Global Change Biology*, *20*(10), 3177–3190. https://doi.org/10.1111/gcb.12629

Firmansyah, A., Hamzah, H., & Achmad, E. (2022). Pemodelan penginderaan jauh untuk estimasi simpanan karbon di Blok 1 PT Alam Bukit Tigapuluh. *Journal of Science and Applicative Technology*, *6*(2), 99–108. https://doi.org/10.35472/jsat.v6i2.964

Muhaimin, M., & Ramali, A. (2021). Development of leading sectors and competitiveness of animal husbandry commodities in Banjarbaru City. *Advances in Social Science, Education and Humanities Research*, *525*, 399–403.

Netsianda, A., & Mhangara, P. (2025). Aboveground biomass estimation in a grassland ecosystem using Sentinel-2 satellite imagery and machine learning algorithms. *Environmental Monitoring and Assessment*, *197*(2), 1–16. https://doi.org/10.1007/s10661-024-13610-1

Nirwana, H. D., Saidy, A. R., Hatta, G. M., & Nugroho, A. (2024). Design of a green city with lower carbon based on vegetation in Banjarbaru using Sentinel-2. *Journal of Applied Data Sciences, 5*(2), 583–599.

Patty, S. I., Nurdiansah, D., Rizqi, M. P., & Huwae, R. (2022). Analysis of mangrove vegetation and distribution using Landsat 8 images in Bolaang Mongondow East, North Sulawesi. *Jurnal Ilmiah PLATAX*, *10*(2), 251–260. https://doi.org/10.35800/jip.v10i2.41069

Phiri, D., Simwanda, M., Salekin, S., Ryirenda, V. R., Murayama, Y., Ranagalage, M., Oktaviani, N., Kusuma, H. A., Zhang, T., Su, J., Liu, C., Chen, W. H., Liu, H., Liu, G., Cavur, M., Duzgun, H. S., Kemec, S., Demirkan, D. C., Chairet, R., ... Peerbhay, K. (2020). Sentinel-2 data for land cover/use mapping: A review. *Remote Sensing*, *12*(14), Article 2291. https://doi.org/10.3390/rs12142291

Pietersz, J. H., Pribadi, R., Pentury, R., & Ario, R. (2024). Estimasi tutupan kanopi berdasarkan NDVI dan kondisi tutupan tajuk pada ekosistem mangrove Negeri Passo, Teluk Ambon Dalam. *Jurnal Kelautan Tropis*, *27*(2), 197–208. https://doi.org/10.14710/jkt.v27i2.22090

Rosianty, Y., Lensari, D., & Syachroni, S. H. (2020). Memotivasi masyarakat untuk menanam pohon dalam mendukung terbentuknya kota hijau di Kelurahan Sukamulya Kecamatan Sematang Borang Kota Palembang. *Altifani: International Journal of Community Engagement*, *1*(1), 40–45. https://doi.org/10.32502/altifani.v1i1.3009

Santoso, N., Sutopo, Pambudi, G. P., Danarta, V. F., Wibisono, R. A., Astuti, T. P., & Wicaksono, D. A. (2021). Pendugaan biomassa dan serapan karbon di beberapa areal taman hutan kota Jakarta, Bekasi dan Bogor. *Jurnal Penelitian Hutan Tanaman*, *18*(1), 167–186.

Wai, P., Su, H., & Li, M. (2022). Estimating aboveground biomass of two different forest types in Myanmar from Sentinel-2 data with machine learning and geostatistical algorithms. *Remote Sensing*, *14*(9), Article 2146. https://doi.org/10.3390/rs14092146