

Spatial Estimation of Mangrove Carbon Reserves Using Random Forest Algorithm and NDVI Index from Sentinel-2 Imagery

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ABSTRACT

This study aims to evaluate the effectiveness of the Random Forest (RF) algorithm in classifying mangrove cover using Sentinel-2 imagery, to develop a regression model between NDVI values and carbon stock, and to estimate the total spatial carbon stock and its economic value. A quantitative approach was employed by combining RF-based classification of Sentinel-2 imagery with field data collected from 35 sample plots to estimate above- and below-ground biomass using species-specific allometric equations. This study concludes that the integrative method is effective for spatial estimation of mangrove carbon stocks and supports NDVI as a reliable predictor. Future implications include the development of temporal analysis and integration with drone-based imagery for higher spatial resolution.

INTRODUCTION

Climate change is an increasingly urgent global phenomenon, mainly caused by greenhouse gas (GHG) emissions sourced from human activities, such as land-use change, deforestation, and fossil fuel use (Fawzy et al., 2020; Karl & Trenberth, 2003; Weiss & Leip, 2012). Increasing concentrations of GHG in the atmosphere lead to an increase in the earth's temperature, a rise in sea level, and an increase in the frequency and intensity of extreme climate disasters (Palinkas & Wong, 2020). In Indonesia, the symptoms of climate change are evident with an average temperature increase of 0.03 °C per year during the period 1981–2018 (Meteorology, Climatology and Geophysics Agency, 2024), which contributes to the threat of flash floods, droughts, and the potential for subsidence of coastal areas such as Jakarta and Semarang in 2050 (Pradana et al., 2023). Rising temperatures also have a significant impact on archipelago areas, such as the Thousand Islands, which are experiencing sea level rise and are at risk of losing islands (Setiawati et al., 2023).

In response to this challenge, Indonesia has demonstrated a global commitment through the ratification of the Paris Agreement in Law No. 16 of 2016, with a target of reducing emissions of 31.89% with its own efforts and up to 43.20% with international support by 2030 (Climate Action Tracker, 2022). One of the main contributors to national emissions is the *Forest and Other Land Use* (FOLU) sector, which accounted for around 42.95% of total national emissions in 2018 (Feng et al., 2022; KataData Insight Center, 2022). Therefore, conservation and restoration strategies for forest ecosystems, especially mangroves, are very important to achieve national climate targets.

Mangrove ecosystems are known to be very effective carbon sinks compared to other types of forests. Mangroves have up to 50 times greater carbon storage capacity than tropical rainforests, thanks to their high biomass density, rapid sediment accretion and burial processes, and significant underground carbon storage capabilities (Alongi, 2012; Maulana et al., 2021; Sanderman et al., 2018). Based on estimates, Indonesia's mangroves can store up to 33 billion tons of carbon, exceeding the potential of tropical rainforests (25.18 billion tons) and competing with peatlands (55 billion tons) efficiently per hectare (KataData Insight Center, 2022). With this potential, mangroves are not only ecologically important, but also strategic in the context of carbon markets and emissions trading.

In West Nusa Tenggara Province (NTB), the Gili Lawang–Gili Sulat Aquatic Tourism Park (TWP) area is one of the important mangrove conservation areas. Based on the Ministry of Agriculture No. 92 of 2018, this area has an area of 10,000 ha with a mangrove cover of up to 80% and is included in the category of high density class (Rudiastuti et al., 2018). In addition to having high ecological value, this region also has great potential for the development of ecotourism and carbon trading schemes (Aziz et al., 2022; Hartini & Lestari, 2019; Huda & Sari, 2017). However, the management of this area is still considered to be not optimal, both in terms of institutions, monitoring data, and community involvement (Rahmani et al., 2023; Subhan &

Astarini, 2014). If not addressed in an integrated manner, the sustainability of the ecological function of the area can be disrupted (Maxwell et al., 2020).

Previous studies in this region have mostly focused on mapping mangrove areas using satellite imagery, or only limited to Above Ground Biomass (AGB) estimates (Firmansyah et al., 2019; Prasetyo, Valentino, & Shabrina, 2023; Rudiastuti et al., 2018). The other study only examines the carbon potential in Gili Sulat with an allometric approach without integrating with remote sensing technology (Diniyatushoaliha et al., 2023). There has not been much research that comprehensively examines the potential of carbon stocks for both AGB and Below Ground Biomass (BGB), and statistically links them to vegetation indices such as NDVI (*Normalized Difference Vegetation Index*), including evaluating the accuracy of satellite image classification using machine learning algorithms such as *Random Forest* (RF).

This study aims to fill this gap through an integrative approach between remote sensing methods and field allometric approaches in spatial estimation of mangrove carbon stocks. Specifically, the objectives of this study are: (1) to evaluate the effectiveness of RF algorithms in the classification of mangrove cover based on Sentinel-2 imagery; (2) build a linear regression model for NDVI value-based carbon stock prediction; and (3) estimating total carbon stocks and sequestration spatially along with their economic potential through a spatial approach.

The novelty of this study lies in the combination of NDVI data from satellite imagery with biomass measurements in the field to form a holistic and more accurate carbon estimation model. In addition, this study also applies statistical correlation tests and evaluation of mapping accuracy using *Kappa* coefficients, which are still rarely done in mangrove carbon studies in this region (Diniyatushoaliha et al., 2023; Purwanto et al., 2022). With this approach, it is hoped that the research results can support data-based conservation policies, while strengthening the achievement of Indonesia's E-NDC targets and the 13th Sustainable Development Goals (SDGs) regarding climate change management.

THEORETICAL REVIEW

Mangrove Ecosystem and Carbon Storage

Mangrove ecosystems are coastal vegetation systems that function as an interface between terrestrial and marine environments and are characterized by their ability to adapt to high salinity, tidal fluctuations, and low oxygen conditions (Feller et al., 2010; Kusmana et al., 1995). These ecosystems play a significant role in climate change mitigation due to their capacity to store and sequester carbon, commonly referred to as blue carbon.

Mangroves have a higher carbon storage capacity compared to terrestrial forests because carbon is stored not only in above-ground biomass but also in below-ground biomass and sediments (Alongi, 2012; Sanderman et al., 2018). This characteristic makes mangroves one of the most effective natural carbon sinks in reducing greenhouse gas emissions (Cummings & Shah, 2018).

Studies conducted in Gili Lawang and Gili Sulat have examined various aspects of mangrove ecosystems. Prasetyo et al. (2023) analyzed mangrove distribution and density using satellite imagery, while Rahmani et al. (2023) and Valentino et al. (2023) investigated mangrove community structure and ecological characteristics. In terms of carbon estimation, Diniyatushoaliha et al. (2023) applied allometric methods to estimate biomass and carbon stock, while Rudiastuti et al. (2018) utilized satellite imagery combined with field measurements to estimate biomass. However, these studies have not comprehensively integrated above-ground and below-ground carbon estimation with remote sensing approaches.

This indicates that an integrated approach combining remote sensing and field-based estimation of both above-ground and below-ground carbon stocks in Gili Lawang and Gili Sulat is still limited.

Remote Sensing for Mangrove Mapping

Remote sensing is a widely used approach for environmental monitoring due to its ability to provide spatial and temporal data efficiently (Stoms & Estes, 1993). Satellite imagery, particularly Sentinel-2, offers high spatial and spectral resolution, including red-edge bands that are sensitive to vegetation characteristics, making it highly suitable for mangrove mapping.

Several studies have applied remote sensing techniques in the study area. Prasetyo et al. (2023) used Landsat imagery to classify mangrove distribution, while Firmansyah et al. (2019) compared classification algorithms for mangrove mapping using Sentinel-2 imagery. Additionally, Hilyana et al. (2020) conducted spatial zoning analysis using GIS to support coastal management. Although these studies provide important information on mangrove distribution and spatial patterns, they primarily focus on land cover mapping and do not extend to carbon stock estimation. This highlights a gap in integrating spatial mapping with carbon assessment in mangrove ecosystems.

Vegetation Index (NDVI) and Carbon Estimation

The Normalized Difference Vegetation Index (NDVI) is one of the most widely used vegetation indices to assess vegetation density and health. NDVI is derived from the difference between near-infrared (NIR) and red spectral bands and has been widely used as a proxy for vegetation biomass and productivity. Previous studies have demonstrated that NDVI is strongly correlated with vegetation biomass and can be used to estimate carbon stock (Muhsoni et al., 2018). NDVI-based models combined with regression analysis are widely applied to estimate vegetation biomass spatially, including in mangrove ecosystems.

However, studies in the Gili Lawang and Gili Sulat area rarely validate NDVI-based carbon estimation using field measurements and statistical approaches. For instance, Diniyatushoaliha et al. (2023) estimated carbon stock using allometric methods without integrating NDVI or conducting statistical correlation analysis. Similarly, Rudiastuti et al. (2018) combined remote sensing and biomass estimation but did not perform regression analysis to quantify the relationship between vegetation indices and carbon stock.

This indicates that statistical validation, particularly regression-based analysis linking NDVI and field-measured carbon stock, remains underexplored in the study area.

Random Forest Algorithm for Land Cover Classification

Random Forest (RF) is a machine learning algorithm widely used for classification and regression tasks due to its ability to handle complex and non-linear relationships. RF constructs multiple decision trees and aggregates their outputs to improve classification accuracy and reduce overfitting.

In remote sensing applications, RF has been shown to outperform traditional classification methods such as Maximum Likelihood Classification (MLC) and Support Vector Machine (SVM) in mapping vegetation, including mangroves (Soffianian et al., 2023). Several studies have reported that RF achieves classification accuracy above 90%, making it a reliable method for land cover classification.

In the context of Gili Lawang and Gili Sulat, previous studies have applied classification approaches; however, the application of Random Forest integrated with carbon stock estimation remains limited. Therefore, the use of RF in this study is expected to improve the accuracy of mangrove mapping and support spatial carbon estimation.

Allometric Approach for Carbon Stock Estimation

Allometric equations are widely used to estimate biomass and carbon stock based on measurable tree parameters such as diameter at breast height (DBH). This approach has been applied in mangrove ecosystems to estimate both biomass and carbon content (Komiyama et al., 2005).

In the study area, applied allometric methods to estimate biomass and carbon stock (Diniyatushoaliha et al., 2023; Rudiastuti et al., 2018). However, these studies tend to focus primarily on above-ground biomass, while below-ground biomass is not comprehensively included. This limitation can lead to underestimation of total carbon stock, considering that a significant portion of mangrove carbon is stored below ground.

The integration of allometric methods with remote sensing data has been recognized as an effective approach to upscale field measurements into spatial carbon estimation (Pandey & Sharma, 2021; Pettorelli, 2019). This integration improves both the accuracy and efficiency of large-scale carbon assessments, particularly in coastal ecosystems such as mangroves.

METHODOLOGY

This study uses a quantitative approach based on remote sensing and field surveys. The main data were in the form of Sentinel-2 L2A imagery and field measurement data using an allometric approach. The research flow is as follows:

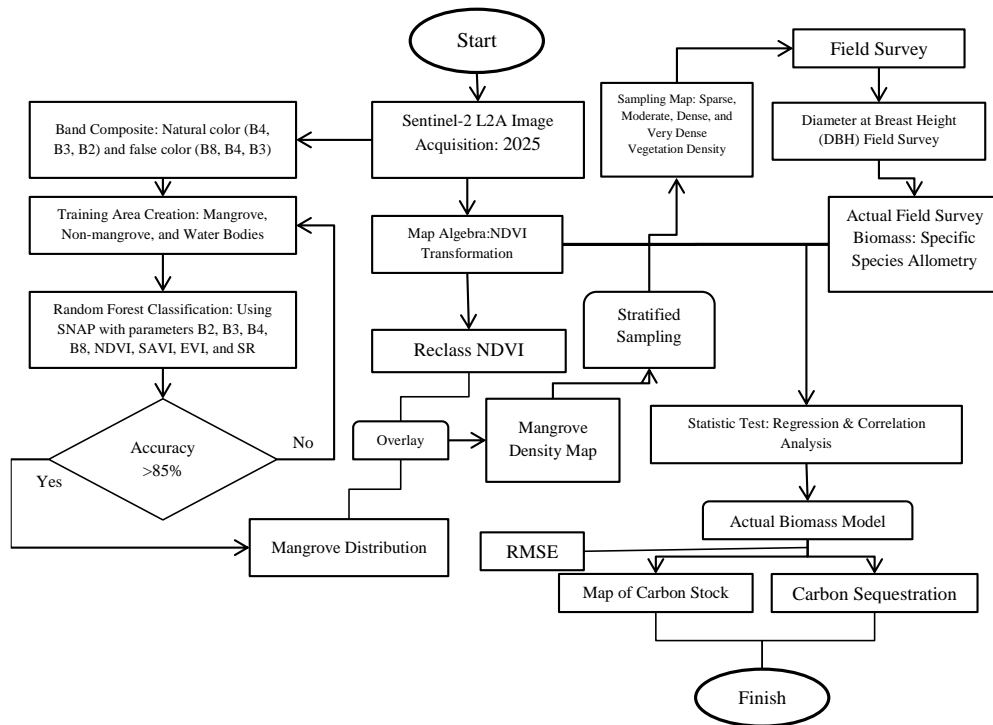


Figure 1. Research Flow

Data Acquisition and Pre-processing

The 2025 Sentinel-2 L2A image was obtained from the Copernicus site. The data has gone through geometric and atmospheric correction (BOA), so that the pre-processing carried out is only in the form of cutting the research area according to the boundaries of the Gili Lawang-Sulat TWP. Image composites are made in two formats, namely *true color* (B4, B3, B2) and *false color* (B8, B4, B3). Next, the NDVI vegetation index was calculated from the red and near-infrared bands, and then reclassified into six vegetation density classes, which were modified by the Ministry of Forestry (2005).

Image Classification and Validation

The classification was carried out using RF algorithms through the SNAP software. Eight input parameters were used, namely bands B2, B3, B4, B8 and the NDVI, SAVI, EVI, and SR indices. The results of the classification are divided into three classes: mangrove, non-mangrove, and water body (BA). Meanwhile, the validation of the classification results was carried out with 387 reference points, consisting of 137 points from field data and 250 random points generated through ArcGIS and confirmed through Google Earth. The accuracy of the model was calculated using *the confusion matrix and the Kappa coefficient* (Congalton & Green, 2008).

Biomass Field Surveys and Models

Field data collection was carried out using a stratified sampling method based on NDVI classes in mangrove areas. Data were taken from 35 plots measuring 20×20 meters (SNI, 2019). The trees measured include the stake

phase, the pole, and the mature tree. Measurements were made at chest-high diameters (DBH) using a tape measure (Howard et al., 2014), and then incorporated into species-specific allometric equations to calculate upper biomass (AGB) and lower biomass (BGB) (Komiyama et al., 2005).

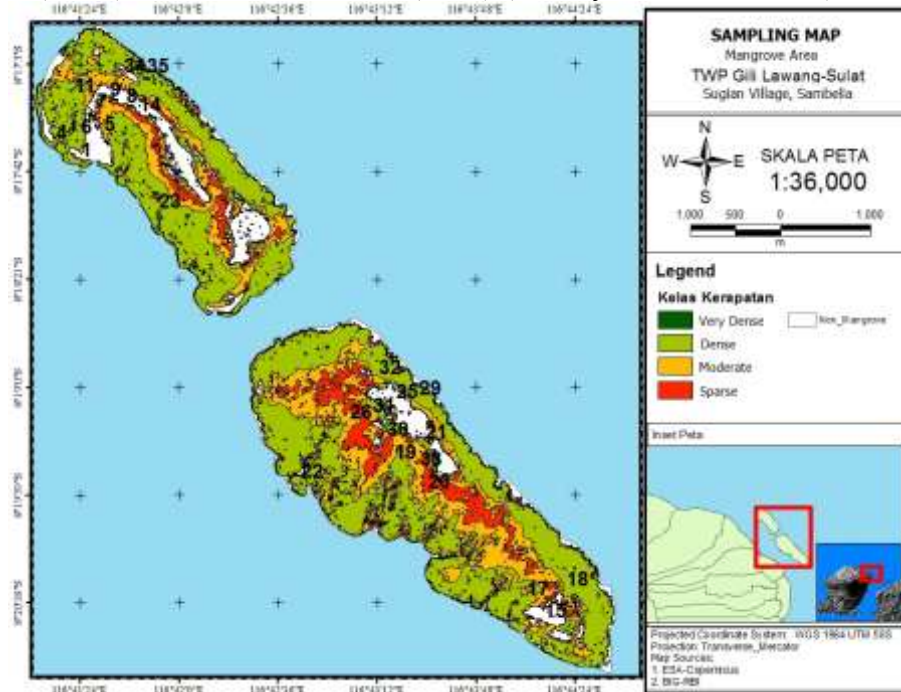


Figure 2. Research Location

In the measurement of AGB and BGB mangroves, a general equation was used by Komiyama et al. (2005) with the parameters of diameter (DBH) and wood density (ρ) based on species.

Table 1. Allometric Equation of AGB and BGB Mangrove

No	Mangrove Species	Wood Density (g/cm ³)
1	<i>Avicennia marina</i>	0.650
2	<i>Bruguiera cylindrica</i>	0.749
3	<i>Bruguiera gymnorhiza</i>	0.700
4	<i>Ceriops tagal</i>	0.746
5	<i>Exoecaria Agallocha</i>	0.450
6	<i>Lumnitzera racemosa</i>	0.710
7	<i>Rhizophora apiculata</i>	0.770
8	<i>Rhizophora mucronata</i>	0.701
9	<i>Rhizophora stylosa</i>	0.840
10	<i>Sonneratia alba</i>	0.475
11	<i>Xylocarpus granatum</i>	0.530

sources: (Kauffman & Donato, 2012; Komiyama et al., 2005; Zanne et al., 2009)

Data Analysis

The analysis was carried out in estimating carbon and CO₂ absorption of mangroves (Kauffman & Donato, 2012; SNI, 2019) and then statistical analysis was carried out. Statistically, NDVI and field carbon stock analysis were carried out which were tested by linear regression. The R² value is used to assess the strength of the relationship, and *the ANOVA test* is used to assess the significance of the model.

RESULTS AND DISCUSSION

Evaluation of the Effectiveness of RF Algorithms in Mangrove Cover Classification

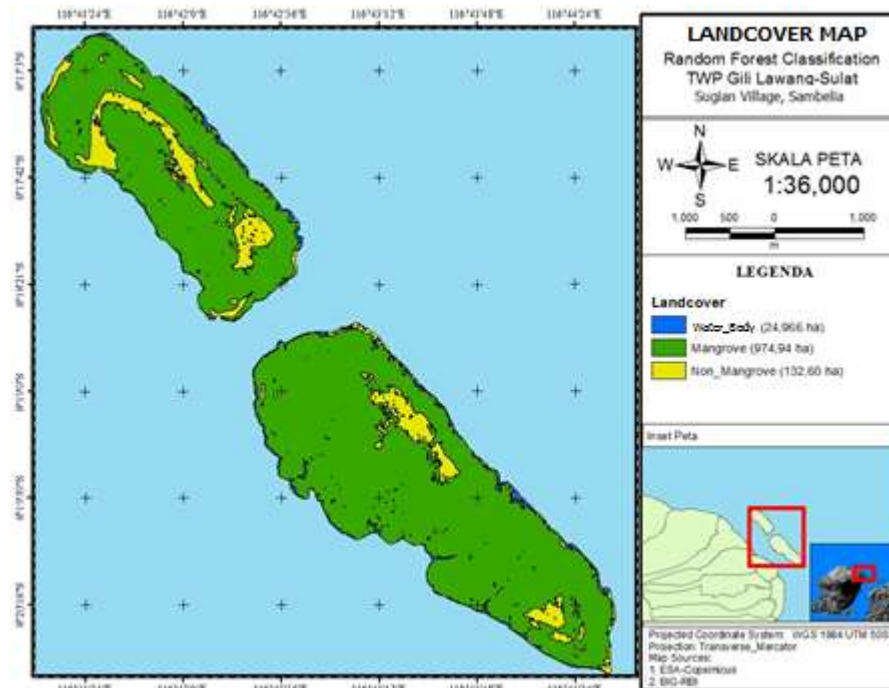


Figure 3. Results of Land Cover Mapping of Gili Lawang-Sulat TWP

The results of the classification of Sentinel-2 images using RF algorithms show a very high level of effectiveness in mapping mangrove cover in the Gili Lawang-Sulat TWP area. Based on Figure 3, the classification successfully identified three main cover classes, mangroves, non-mangroves, and water bodies, with strong dominance by mangrove vegetation covering an area of 974.94 ha or about 85.4% of the total area analyzed. This distribution indicates that the RF algorithm is able to capture the spectral characteristics of mangroves with high precision, in line with the findings of Rudiastuti et al. (2018) who also noted the dominance of mangrove ecosystems in this region.

Table 2. *Confusion matrix* Land Cover TWP Gili Lawang-Surat

Class Value	Mg	NMg	WB	Total	User Accuracy (UA)	OA (po)	EA (pe)	Kappa (κ)
Mg	250	5	6	261	0.9579	0.9587	0.499	0.9175
NMg	0	69	0	69	1			
WB	4	0	52	56	0.9286			
Total	254	74	59	387				
Producer Accuracy (PA)	0.9843	0.9324	0.8814					

The accuracy of the classification results was strengthened by accuracy analysis through *the confusion matrix* (Table 2), which showed an *Overall Accuracy* (OA) value of 95.87% and a *Kappa* coefficient of 0.9175. This value reflects a very strong degree of agreement between the classification results and the field reference data, and indicates *almost perfect agreement* (Landis & Koch, 1977). All classes showed excellent accuracy performance, with non-mangrove classes recording a perfect *User's Accuracy* (UA) (1.0000) and *Producer's Accuracy* (PA) of 93.24%. The mangrove and water body classes also had UA and PA values above 88%, which indicates that the classification runs consistently across categories.

The RF excellence in this study is supported by the rich spectral combination of Sentinel-2, which includes Band 2 (*Blue*), Band 3 (*Green*), Band 4 (*Red*), Band 8 (NIR), as well as a number of vegetation indices such as NDVI, SAVI, EVI, and SR. The use of NDVI as the primary index has proven to be effective, given its high correlation ($r \approx 0.91$) with mangrove canopy cover (Tran et al., 2022). In addition, the selection of RF model parameters, consisting of 120 trees (ntree) and 5 random variables per split, resulted in an optimal model, according to the recommendations of the latest literature (Nandika et al., 2023; Oshiro et al., 2012).

Compared to other methods, RF has proven to be competitive. Firmansyah et al. (2019) used SVM and *Decision Tree* for mangrove mapping in Gili Sulat and produced an area of 654.42 ha (SVM) and 625 ha (*Decision Tree*). The area of RF classification in this study is 622.75 ha, which is very close to that value and is in a difference of less than 5%. Meanwhile, in Gili Lawang, the area of mangrove cover from RF classification reached 352.19 ha, showing high precision compared to the results of Landsat 9-based classification (Prasetyo et al., 2023), which recorded 371.89 ha. The difference is more a reflection of the spatial resolution used, not the lack of method.

RF algorithms have proven to be reliable in processing multispectral image data, without requiring specific distribution assumptions, making them particularly suitable for complex and heterogeneous coastal environmental conditions (Belgium & Drăguț, 2016). Its resistance to *overfitting* and its ability to assess feature importance also make it a superior tool in satellite image-based classification.

NDVI-Based Mangrove Carbon Stock Prediction Model

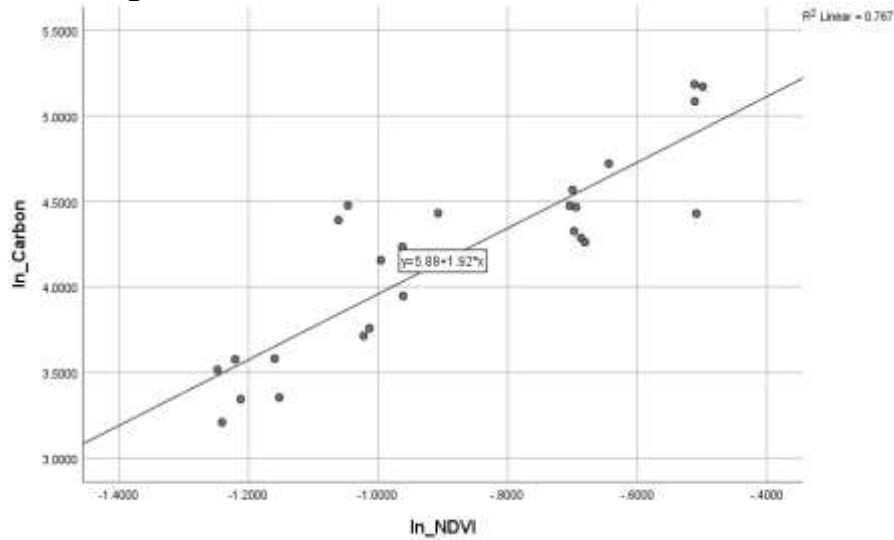


Figure 4. NDVI Plot Scatter Chart against Carbon Stocks

Regression analysis showed that the NDVI value of the Sentinel-2 image had a strong and significant positive relationship with the total mangrove carbon stock (above-ground carbon, AGC + subsurface carbon, BGC). Based on the distribution of data on the scatter plot graph (Figure 4), a consistent upward trend can be seen between the value of NDVI and carbon stocks. This indicates that the higher the vegetation reflectance (NDVI), the greater the carbon content stored in the area. This trend underlies the development of prediction models based on logarithmic linear regression.

The best regression model obtained is in the form of logs, with the following equations:

$$\ln(\text{Carbon}) = 5,88 + 1,92 \times \ln(\text{NDVI}) \quad (1)$$

This model has a coefficient of determination (R^2) of 0.767, which means that about 76.7% of the variation in carbon stocks can be explained by NDVI variations. The Pearson correlation value (R) of 0.876 also confirms a very strong and statistically significant relationship between the two variables. Thus, NDVI is proven to be a potential predictor in estimating the carbon reserves of mangrove vegetation spatially.

For the purpose of direct prediction in tC/ha, the above equation is converted to the following exponential form:

$$\text{Carbon} = 358,5 \times \text{NDVI}^{1,92} \quad (2)$$

Based on testing of test data (plots 26–35), this model shows a high level of predictive accuracy, with a *Root Mean Square Error* (RMSE) value of 9.79 tC/ha, or %RMSE of 12.33%. This means that the model has a low average prediction error against the actual carbon stock of the field. This value indicates that the model is reliable for NDVI-based carbon stock mapping in tropical mangrove regions. Compared to previous studies, this model shows superior performance. In the study of Putri (2023), which modeled the regression equation between carbon stocks and NDVI values, obtained an R^2 of 0.7409, while Ningsih (2024) noted a much weaker correlation ($r = 0.44$) and high prediction error (RMSE =

41.11 tC/ha). In fact, compared to the Suardana et al. (2023) model which has an RMSE between 11.09–13.63 tC/ha, this model is still more accurate.

Estimated Total Mangrove Stocks and Carbon Absorption

The mangrove ecosystem in the Gili Lawang-Sulat TWP, Sugian Village, Sambelia District, has great potential in storing and absorbing carbon, making it a strategic area for climate change mitigation. The survey results recorded the existence of 11 species of mangroves, namely *Avicennia marina*, *Bruguiera cylindrica*, *Bruguiera gymnorhiza*, *Ceriops tagal*, *Excoecaria agallocha*, *Lumnitzera racemosa*, *Rhizophora apiculata*, *Rhizophora mucronata*, *Rhizophora stylosa*, *Sonneratia alba*, and *Xylocarpus granatum*. These findings are in line with previous studies that reported the presence of 7–10 species in the region (Al Idrus et al., 2014; Rahmani et al., 2023; Valentino et al., 2023). Each species has different characteristics, both in dominance and morphology, where *Avicennia marina*, *Sonneratia alba*, and *Rhizophora mucronata* generally dominate in open areas near the sea with stagnant sandy clay substrates (Diniyatushoaliha et al., 2023; Frida et al., 2019; Valentino et al., 2023), while other species are more dominant in the central area or close to land.

The diversity of mangrove species in the Gili Lawang-Gili Sulat TWP contributes greatly to the carbon storage and sequestration capacity. The estimated results show that out of a total area of 974.94 ha, this area stores 73,513.84 tC (average 75.4 tC/ha) or equivalent to 269,553.20 tCO₂e. In detail, Gili Lawang contributed 28,738.78 tC (105,375.53 tCO₂e) and Gili Sulat 44,775.06 tC (164,176.82 tCO₂e).

Compared to previous studies at the same location, this value was much higher. Diniyatushoaliha et al. (2023) only recorded an average of 0.52 tC/ha and Rudiastuti et al. (2018) recorded 0.42 tC/ha. The difference is due to method: this study used an allometric-based total carbon (AGC + BGC) approach and NDVI Sentinel-2 data with a coverage of 35 points, whereas the previous study only calculated surface carbon with a limited number of plots. On the other hand, several national studies have recorded comparable or higher results, such as Fajri et al. (2023) in the Riau Islands (2,052.78 tC/ha), Dewiyanti et al. (2024) in Banda Aceh (81.37 tC/ha), and Ulqodry et al. (2025) in Maspari Island (573.90 tC/ha).

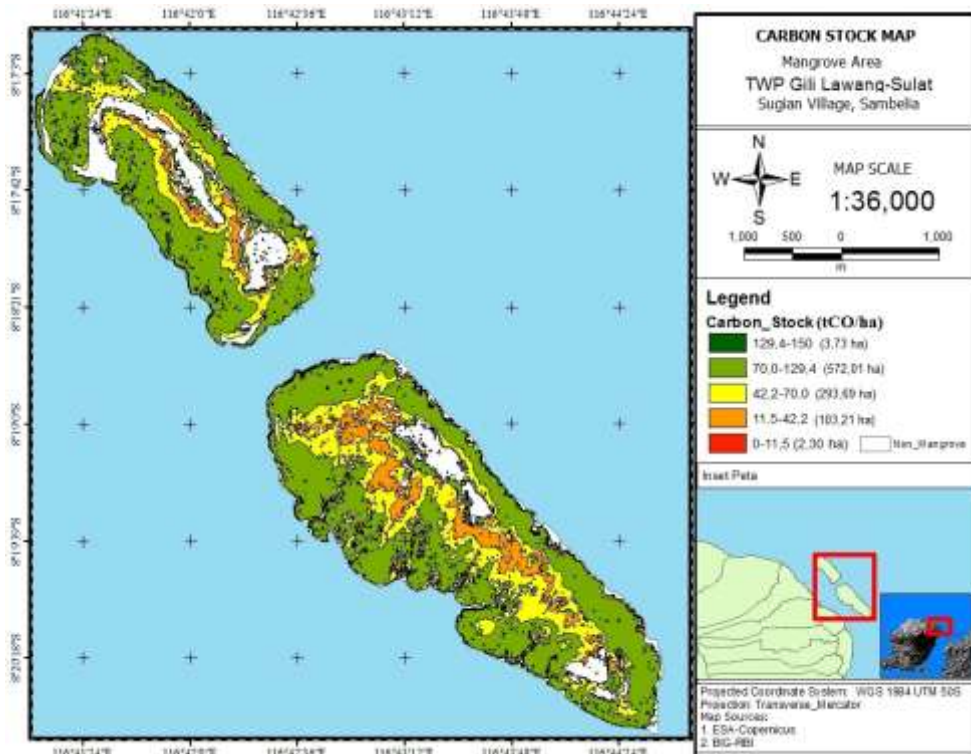


Figure 5. Mangrove Carbon Stock Map TWP Gili Lawang-Surat

Based on Figure 5, the distribution of carbon stocks varies according to vegetation density class. The "very dense" class (0.38% area) kept 91.5–120.4 tC/ha, the "dense" (58.67%) class kept 70.4–91.5 tC/ha, the "medium" (30.14%) kept 42.2–70.4 tC/ha, and the "rare" to "very rare" class (10.82% area) kept much lower stocks. These findings are consistent with Sapriyadi et al. (Sapriyadi et al., 2023) and Rahmat et al. (Rahmat et al., 2022), which shows that carbon stocks increase with vegetation density. However, density is not the only factor: growth phase, stem diameter (DBH), and species type are also highly determinative (Diniyatushoaliha et al., 2023; Zaman et al., 2023). *Rhizophora* spp., particularly *R. stylosa*, *R. apiculata*, and *R. mucronata*, are dominant in very dense classes with large DBH and high density (up to 0.840 g/cm³), thus storing higher carbon than species such as *Ceriops tagal* and *Lumnitzera racemosa* which dominate low-density areas.

Based on the potential carbon sequestration of 269,553.20 tCO₂e and the average voluntary carbon market price of 3.61 USD/tCO₂e, the economic value of this region reaches around USD 970,090 or Rp15.52 billion. Rizki et al. even estimate the combined carbon potential of Gili Lawang and Gili Sulat to reach 659,875 tCO₂e (Rp38.12 billion) (Rizki et al., 2024), even though using an area-wide approach without considering vegetation structure. This more holistic approach to research is considered to result in more conservative estimates but reflect the actual conditions of the ecosystem. With high ecological and economic value, the Gili Lawang–Gili Sulat TWP has great potential as a priority area for conservation and development of blue carbon initiatives. The combination of species diversity, the dominance of *Rhizophora* spp., and the influence of the diameter of the trunk and the density of wood make this area strategic in

supporting national GHG emission reduction targets and the achievement of the Sustainable Development Goals, especially SDG 13: Handling Climate Change.

CONCLUSIONS AND RECOMMENDATIONS

This study shows that *the Random Forest algorithm* is effective in classifying mangrove cover based on Sentinel-2 imagery with high accuracy, and that the NDVI index has a significant relationship with carbon stocks, making it a reliable predictor in spatial estimation. The regression model built was able to explain 76.7% of the variation in carbon stocks, with low prediction errors. The total estimated carbon stock of 73,513.84 tons C or equivalent to 269,553.20 tons of CO₂e shows the significant contribution of mangrove ecosystems to climate change mitigation. These findings have implications for the importance of utilizing remote sensing technology in conservation planning and carbon trading schemes, as well as opening up opportunities for the development of long-term monitoring with the integration of drone data and high-resolution temporal analysis.

FURTHER STUDY

Future research should integrate multi-temporal Sentinel-2 imagery, additional vegetation indices, and advanced machine learning models to improve the accuracy of spatial mangrove carbon stock estimation.

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