Aboveground mangrove carbon stock dynamics from 2016 to 2024 using PlanetScope imagery

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Abstract. This study aims to estimate and analyze aboveground mangrove carbon stocks in the Mandeh area, West Sumatra, from 2016 to 2024, by using Planetscope imagery. Specifically, the objectives are to map aboveground carbon (AGC) over the period 2016-2024, analyze changes in AGC over that period, and analyze spatiotemporal trends in mangrove carbon stock dynamics. This study examined temporal changes in carbon stocks from 2016 to 2024. Carbon stocks were estimated from the diameter at breast height (DBH) of tree stands measured in the field in 2024, and values for earlier years were reconstructed by deducting the corresponding annual diameter growth. Regression analyses were applied to develop a relationship between field AGC and vegetation indices derived from PlanetScope Image, including Normalized Difference Vegetation Index (NDVI). In 2016, the mangrove area was 10.421 ha, while in 2024, it was 8.699 ha, pointing to a change in the mangrove area of 1.722 ha at the study site. However, based on the estimated carbon stock results in 2024, which was 28.584 ton C ha^{-1}, compared to 2016, which was 27.416 ton C ha^{-1}, a difference of 1.168 ton C ha^{-1}. The SEE value in 2016 was recorded at 1.303 ton C ha^{-1}, while in 2024 it increased to 1.344 ton C ha^{-1}. This increase in the SEE value indicates differences in the accuracy of the estimation model between periods, which may be caused by variations in mangrove stand structure, changes in environmental conditions, or more complex spatial heterogeneity in 2024.

Keywords: carbon monitoring, coastal wetlands, NDVI, remote sensing, spatial modeling.

Introduction. Mangroves are globally recognized as highly productive coastal ecosystems that provide a wide range of ecological and socio-economic services. They act as natural buffers against coastal hazards, stabilize shorelines, support fisheries, and are among the most efficient blue carbon ecosystems, capable of storing carbon better than most terrestrial vegetation (Donato et al., 2011; Alongi, 2020). The ability of mangroves to absorb and store carbon in both aboveground and belowground biomass has made them central to global climate change mitigation strategies in various initiatives such as REDD+ (Howard et al., 2017). This is because global warming is currently one of the most discussed issues worldwide due to its significant impact on climate change (Hidayatullah et al., 2023).

Mandeh area is located in the western coastal region of Pesisir Selatan Regency, West Sumatra Province, Indonesia. Mandeh area has the potential for a fairly extensive coastal mangrove ecosystem, covering approximately 325 ha. This area is not only vital for biodiversity and fisheries, but also supports local livelihoods and tourism development. However, since 2016-2023 the mangrove area along the Mandeh coast has experienced extensive mangrove land conversion from 603.42 ha to 513.20 ha, a reduction of 90.22 ha (Suhaini & Prarikeslan, 2024). This can have an impact on ecological and economic functions. Mangrove land conversion and changes in annual

mangrove cover can sensitively affect the amount of carbon stocks (Zhu et al., 2015; Maeda et al., 2016; Li et al., 2019; Hidayatullah et al., 2023).

Mapping mangrove areas and calculating their carbon stocks in the Mandeh Region is crucial, and this can be achieved through remote sensing satellite imagery. This is done to support conservation and management initiatives, as well as climate change mitigation efforts. Therefore, mangrove areas are important in maintaining global climate stability (Hidayatullah et al., 2023). While traditional field-based measurements remain the gold standard, they are often hampered by limited accessibility, high labor costs, and difficulties in scaling measurements to the landscape level (Kauffman & Donato, 2012).

Remote sensing imagery data can address these challenges by enabling spatially explicit and temporally repeatable monitoring. One example of satellite imagery that can be used is Planetscope imagery, a high-resolution (3 m) commercial satellite imagery. Furthermore, Planetscope imagery has daily revisit capability, enabling the detection of small-scale changes and supporting detailed analysis of mangrove temporal dynamics (Hossain et al., 2023). However, the use of Planetscope imagery in temporally estimating aboveground mangrove carbon stocks is still limited (Giri et al., 2015; Murdiyarso et al., 2019). Furthermore, only a few studies have examined the temporal variation of mangrove aboveground carbon (AGC) in the Mandeh area.

Planetscope imagery has demonstrated its potential for estimating biomass and carbon stocks in mangrove ecosystems (Baloloy et al., 2018; Purnamasari et al., 2021; Gowda et al., 2025). The carbon stock in mangrove ecosystems can typically be estimated through spectral transformations such as vegetation indices that emphasize vegetation density parameters and are further correlated with field measured carbon values using allometric equations (Hidayatullah et al., 2023). Therefore, estimating mangrove carbon stocks using optical remote sensing data provides the best alternative that reduces costs, effort, and time (Kumar & Mutanga, 2017). This study aims to address this gap by utilizing Planetscope imagery to estimate and analyze aboveground mangrove carbon stocks in the Mandeh area, West Sumatra, from 2016 to 2024. Specifically, the objectives of this study are to: (1) map AGC over the period 2016-2024; (2) analyze changes in AGC over that period; and (3) analyze spatiotemporal trends in mangrove carbon stock dynamics. The results of this study may contribute to estimating blue carbon using high-resolution satellite imagery temporally, as well as providing actionable insights for mangrove conservation strategies and climate change mitigation in Indonesia.

Material and Method

Description of the study sites. This research was conducted in part of the Mandeh area located on the west coast of Sumatra, Pesisir Selatan Regency, West Sumatra Province (Figure 1). Geographically, Pesisir Selatan Regency is located at coordinates 0°59’ - 2°28.6’ South Latitude and 100°19’ - 101°18’ East Longitude, and covers an area of approximately 5794.89 km², or 13.70% of West Sumatra Province. The Mandeh area is part of the administrative area of Koto XI Tarusan District, Pesisir Selatan Regency.

The mangrove ecosystem in the Mandeh area, Pesisir Selatan Regency, West Sumatra is currently experiencing significant degradation, with nearly half of its coverage remaining in good condition, while the rest is classified as damaged or severely damaged. Spatial analysis using Geographic Information Systems (GIS) and remote sensing indicates that mangrove forests in this region are divided into three categories: undamaged (119.065 ha, 46.41%), damaged (105.325 ha, 41.05%), and severely damaged (32.164 ha, 12.54%) (Pasaribu et al., 2024). The highest level of degradation is observed in Sungai Nyalo Village, whereas in Teluk Raya Village, it still maintains relatively healthy (Pasaribu et al., 2024). Anthropogenic pressures such as land conversion, logging, and coastal development for tourism have been identified as the primary drivers of this decline (Shaw et al., 2019; Vancine et al., 2024). This ecological deterioration threatens the essential functions of mangroves, including shoreline protection, carbon sequestration, and provision of nursery grounds for marine biodiversity. Therefore, integrated rehabilitation and sustainable management strategies

are urgently required to restore the ecological resilience and socio-economic benefits of mangroves in the Mandeh coastal landscape.

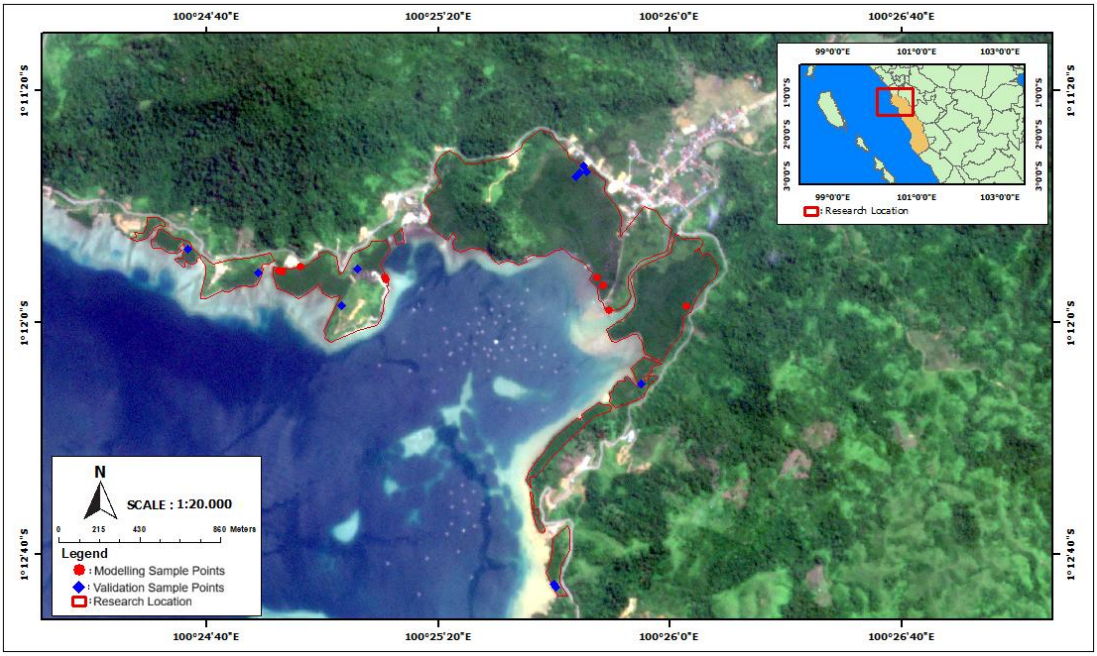


Figure 1. The location of the mangrove ecosystem in the Mandeh area of Pesisir Selatan Regency, West Sumatra, Indonesia.

Image dataset and pre-processing. This study used Planetscope imagery, a high-resolution remote sensing data sourced from Planet Labs' mini-satellite constellation, capable of capturing the Earth's surface daily with global coverage. PlanetScope captures multispectral imagery with a high spatial resolution of approximately 3–5 m, encompassing spectral channels such as red, green, blue, and near infrared (Table 1). This imagery has undergone geometric and radiometric correction, making it ready for accurate spatial and temporal analysis. The Planetscope imagery data used for multitemporal analysis spans from 2016 to 2024.

Table 1

Acquisition date of Planetscope imagery

Image type	*Acquisition date*	*Spectral bands (nm)*
Planetscope Dove-R	2016	Blue: ~465–515 nm Green: ~547–585 nm Red: ~650–680 nm Near-Infrared (NIR): ~845–885 nm
	2017	
	2018	
	2019	
	2020	
	2021	
	2022	
	2023	
	2024	

Planetscope imagery prepared for spatial and temporal analysis was transformed into a vegetation index. The vegetation index algorithm is calculated by combining various spectral bands from the imagery (Zhu et al., 2015). The vegetation index is a transformation of spectral values from several bands used to generate new images that highlight vegetation characteristics, such as leaf greenness, vegetation density, chlorophyll content, and biomass (Jensen, 2004; Wicaksono et al., 2016). This study used the Normalized Difference Vegetation Index (NDVI) vegetation index because it is considered capable of providing consistent accuracy (Rhew et al., 2011; Li et al., 2023).

Furthermore, in several previous studies, NDVI has good values for correlation and regression.

Field data collection and AGC calculation. Field data collection was conducted on August 26-29, 2024, using a purposive random sampling method to obtain representative mangrove biophysical samples. Field data collection used square plots, with plot sizes of 5 x 5 m quadrat, adjusted to the spatial resolution of the imagery used. At the sample plot locations, observations and data collection included: (i) measuring sample point coordinates using GPS, (ii) measuring mangrove stem diameter at breast height (DBH), (iii) identifying mangrove species, and (iv) measuring mangrove tree height using a laser rangefinder. This study was conducted to analyze carbon stocks temporally for 8 years from 2016 to 2024, so that the field carbon stock calculated from the diameter at breast height (DBH) of tree stands in 2024 will be reduced by the size of the tree diameter for the previous year. Each average tree diameter in one sample plot is reduced by 3.36 cm with the assumption that each year the average growth of mangrove tree diameter in Southeast Asia is 0.42 cm (Xiong et al., 2019). Therefore, from the reduction in DBH, the value of field carbon stock was estimated temporally from 2016 to 2024 based on the mangrove growth, and its spatial distribution was obtained.

Mangroves species were identified using an ecological approach, based on mangrove characteristics and growth zones. We found 2 species of mangroves, namely *Rhizophora apiculata* and *Sonneratia alba* in the study site. The data obtained were processed to estimate biomass in the field. This study focused on measuring above-ground biomass. We obtained 20 samples which were divided into two separate datasets: 10 samples for developing the model of the AGC map and 10 samples for validation of the model. Mangrove biomass estimation was carried out using an allometric species-specific approach adapted to the characteristics of each mangrove species (Table 2). We used the species-specific allometric equations for species *R. apiculata* and *S. alba*. The allometric equation produces aboveground biomass (AGB) values, but it does not directly produce AGC values (Kamal et al., 2022). Aboveground carbon stocks were calculated based on surface biomass estimates. This calculation follows SNI 7724:2011 guidelines, with the carbon formula: $C_b = B \times$ % organic C, where C_b represents the carbon stock contained in the biomass, B is the total aboveground biomass of mangrove vegetation, and % organic C is the carbon fraction of the biomass. Following the IPCC default guideline, a carbon conversion factor of 0.47 was applied, assuming that 47% of dry biomass consists of organic carbon.

Table 2

Species-specific allometric equations

Species	*Allometry*	*References*
Rhizophora apiculata	$B = 0.235DBH^{2.42}$	Ong et al. (2004)
Sonneratia alba	$B = 0.3841*\rho*D^{2.101}$ $\rho = 0.47$ ton m^{-3}	Kauffman & Cole (2010)

Note: B is aboveground biomass (kg), ρ is wood density (g cm^{-3}), D is diameter at breast height (DBH, cm).

Statistical analyses and AGC stock mapping. Regression analysis is used to identify relationships between two or more variables to map carbon stocks. These two variables include the dependent variable (AGC value in the field) and the independent variable (vegetation index pixel value). The NDVI vegetation index was correlated with field data in the form of biomass measurements or actual carbon content. The obtained field samples were subjected to correlation and regression analyses with vegetation index pixel values (Candra et al., 2016). Through regression analysis, the coefficient of determination (R^2) and regression equation were generated, then used as a model to estimate carbon distribution throughout the study area for each year of Planetscope imagery. This study uses the NDVI in carbon stock mapping because of its ability to represent the level of greenness and vegetation density from satellite imagery. The spatial carbon stock estimation model was built by linking NDVI values to biomass data

from field measurements through regression analysis. This approach allows a more efficient and accurate mapping in difficult-to-reach coastal areas and supports monitoring changes in mangrove carbon stocks over time.

The carbon stock information obtained represents the carbon value derived from the regression equation based on vegetation index inputs. In this context, each pixel value in the image corresponds to carbon value information. According to this equation, the pixel values of the vegetation index that reflect vegetation, particularly mangroves, are aggregated to estimate biomass at the research location. Consequently, the carbon stock information is obtained from the pixel values, where the number of pixels present at the research site indicates the carbon value.

Accuracy assessment. The accuracy of the regression model was evaluated using the Standard Error of Estimate (SE) method, which compares carbon values from field measurements with values predicted by the regression model. The smaller the SE value, the more accurate the model is in representing the actual data.

$$SEE = \sqrt{\frac{(y' - y)^2}{n - 2}}$$

Where: SEE is the standard error of estimate, y' is the carbon stock predicted in the field (ton C ha^{-1}), y is the carbon stock in the field (ton C ha^{-1}), and n is the sample size (Congalton & Green, 2019).

Results and Discussion

Field above ground carbon stock calculation. Table 3 shows the average DBH of mangrove trees measured in 2016 and 2024 across 20 sample plots. The data show a consistent increase in DBH values over time, indicating positive tree growth and potential stand development during the eight-year period. The average DBH in 2016 ranged between 0.09 cm and 9.00 cm, while in 2024 it increased to a range of 3.45 cm to 12.36 cm.

Table 3

Average diameter at breast height (DBH) of mangroves in 2016 and 2024 in the sample plots

No	*Average DBH 2016 (cm)*	*Average DBH 2024 (cm)*
1	8.81	12.17
2	6.72	10.08
3	5.64	9.00
4	7.22	10.58
5	3.10	6.46
6	9.00	12.36
7	7.44	10.80
8	2.33	5.69
9	1.64	5.00
10	1.83	5.19
11	2.86	6.22
12	0.09	3.45
13	4.60	7.96
14	3.46	6.82
15	1.57	4.93
16	4.43	7.79
17	1.80	5.16
18	4.16	7.52
19	5.83	9.19
20	5.37	8.73

Up to now, measurements of mangrove growth rates remain limited, while conventional methods typically applied to estimate tree age and growth rates in temperate regions—by counting and measuring annual growth rings—are almost impossible to implement in mangroves. Consequently, this study has not yet been able to accurately present the historical development of mangrove DBH growth in the study area.

The growth of DBH in this study was based on the findings of Xiong et al. (2019), which reported that, in general, the average DBH growth of non-plantation mangroves in Southeast Asia is 0.42 cm year^{-1}. Compared with results from several other studies conducted in different regions, the growth rate of mature mangroves in Malaysia recorded a diameter increment of 0.32 cm year^{-1} for *R. apiculata* (Putz & Chan, 1986). Mangrove forests in Micronesia reported a diameter increment of 0.96 cm year^{-1} for *S. alba* (Devoe & Cole, 1998). In Indonesia, a case study in Bunaken National Park reported diameter growth rates of 0.4 cm year^{-1} for *R. apiculata* and 0.6 cm year^{-1} for *S. alba*, respectively (Djamaluddin, 2004).

Mangrove growth rates vary seasonally and show a positive correlation with rainfall (Poungparn et al., 2025; Djamaluddin, 2019). The individual responses of mangroves to different habitat conditions also exhibit considerable variation, with indications that smaller trees grow faster than larger ones (Imai et al., 2009; Rajkaran & Adams, 2012). The analysis showed that the growth rates among mangrove species did not differ substantially. Growth tends to accelerate when young trees are released from open space formations or have grown tall enough to escape shading by neighboring trees (Whyte & Halpern, 2019; Chin et al., 2023). Subsequently, vertical growth proceeds rapidly over several years. Stem diameter expansion also becomes faster when light conditions are sufficiently favorable (Richards, 1996).

Table 4 shows the statistical summary of field-measured AGC in 2016 and 2024. The field AGC values increased from a mean of 0.013 ton C ha^{-1} in 2016 to 0.036 ton C ha^{-1} in 2024. The minimum and maximum values also increased during this period, from 0.000–0.066 ton C ha^{-1} in 2016 to 0.007–0.122 ton C ha^{-1} in 2024. The standard deviation increased from 0.017 to 0.030, indicating a wider variation in carbon storage among sampling plots as the mangrove stands matured.

Table 4

Mangrove aboveground carbon measurement results in the field

Statistics	*Field aboveground carbon (AGC) value (ton C ha^{-1}) in 2016*	*Field aboveground carbon (AGC) value (ton C ha^{-1}) in 2024*
Minimum	0.001	0.007
Maximum	0.066	0.122
Mean	0.013	0.036
Standard deviation	0.017	0.030

The observed increase in both DBH and AGC reflects enhanced biomass accumulation over time, which is closely related to vegetation growth and canopy development. Larger stem diameters contribute directly to higher aboveground biomass and carbon stocks, since stem volume is a major determinant of tree carbon content (Komiyama et al., 2008; Alongi, 2014). These results align with previous findings that emphasize the strong link between mangrove stand age, tree size, and carbon storage potential (Kauffman & Donato, 2012; Murdiyarso et al., 2015). Overall, the results demonstrate that mangrove stands in the study area experienced measurable structural and carbon stock growth from 2016 to 2024. This improvement supports the effectiveness of natural regeneration or management practices in maintaining mangrove productivity and carbon sequestration capacity. The combined analysis of DBH and AGC therefore provides a clear picture of mangrove ecosystem development and its role in long-term blue carbon dynamics.

Statistical analyses. Figure 2 shows the linear relationship between NDVI and field-derived aboveground carbon stock in mangrove areas for 2016 and 2024. In 2016, the regression model produced the equation y=2.2073x+2.5507 with a coefficient of

determination (R^2) of 0.8963. By 2024, the model improved slightly, with y=2.2529x+2.2774 and R^2 value of 0.9337. These coefficients indicate a strong and positive correlation between NDVI values and measured carbon stocks for both periods.

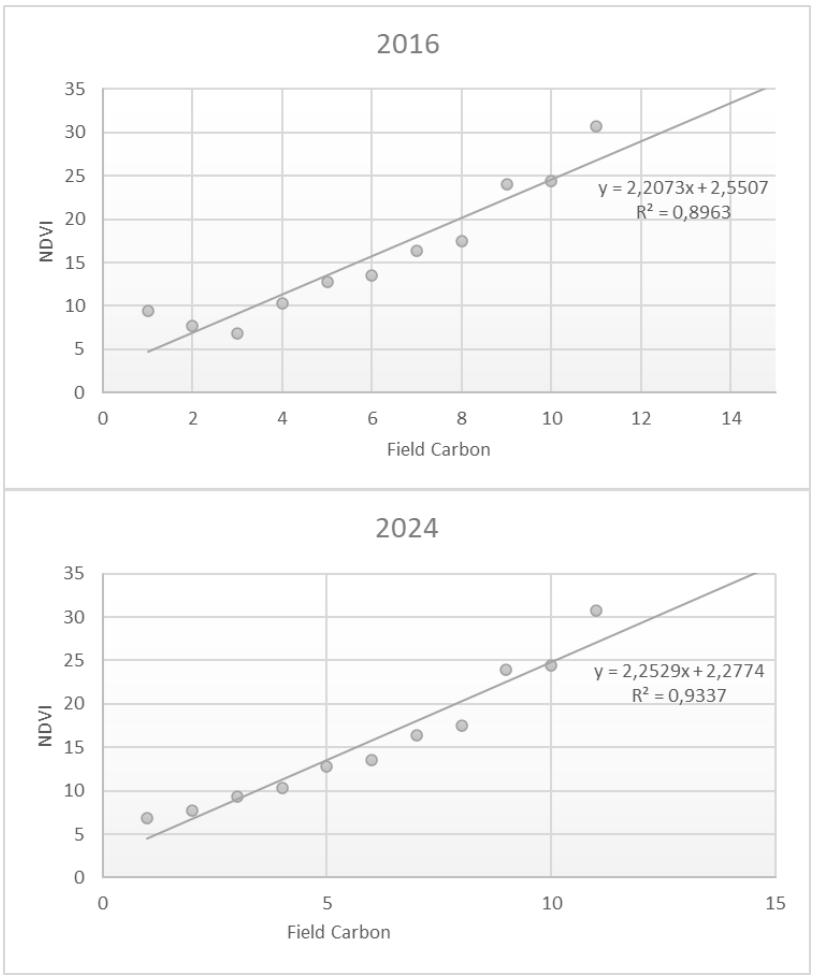


Figure 2. Linear regression between the NDVI and field measurement in 2016 (up), and 2024 (down).

The results suggest that NDVI can be used as a reliable spectral indicator for estimating mangrove aboveground carbon stock. Higher NDVI values generally represent denser vegetation cover and greater photosynthetic activity, which correspond to higher carbon storage capacity. The slight improvement in the 2024 model may reflect better data quality from recent PlanetScope imagery, improved canopy health, or more uniform field conditions during sampling. These findings are consistent with previous studies that have demonstrated strong correlations between spectral vegetation indices and mangrove biomass or carbon content (Kuenzer et al., 2011; Fatoyinbo & Simard, 2013; Rahman et al., 2021).

These regression equations can be applied to NDVI derived from PlanetScope images to produce a spatial model of carbon distribution across mangrove areas. This approach offers a practical and replicable way to estimate carbon stocks over large areas. Besides, this method also enables efficient estimation of carbon storage at landscape scales, particularly in regions where field sampling is limited (Otero et al., 2018; Pham et al., 2019). The results can be used for supporting long-term monitoring of mangrove ecosystem productivity.

AGC time-series. Figures 3 and 4 present the spatial distribution of estimated mangrove carbon stock within the study area. The map indicates heterogeneous carbon stock values, with higher and lower concentrations distributed unevenly across the mangrove

ecosystem. Such variability suggests that the spatial distribution and quantity of carbon stock changed over time, resulting in distinct carbon stock patterns between years.

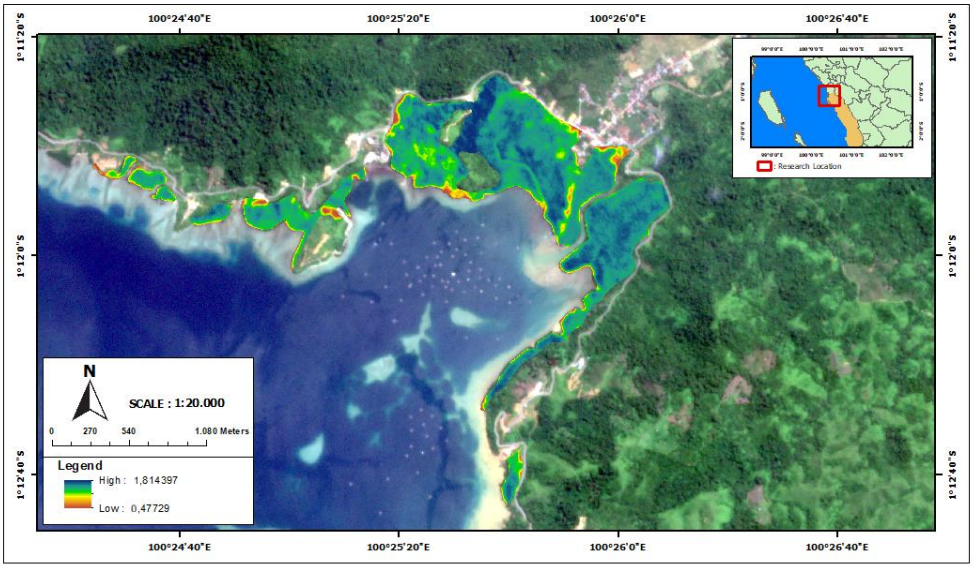


Figure 3. Map of estimated carbon stocks in 2016.

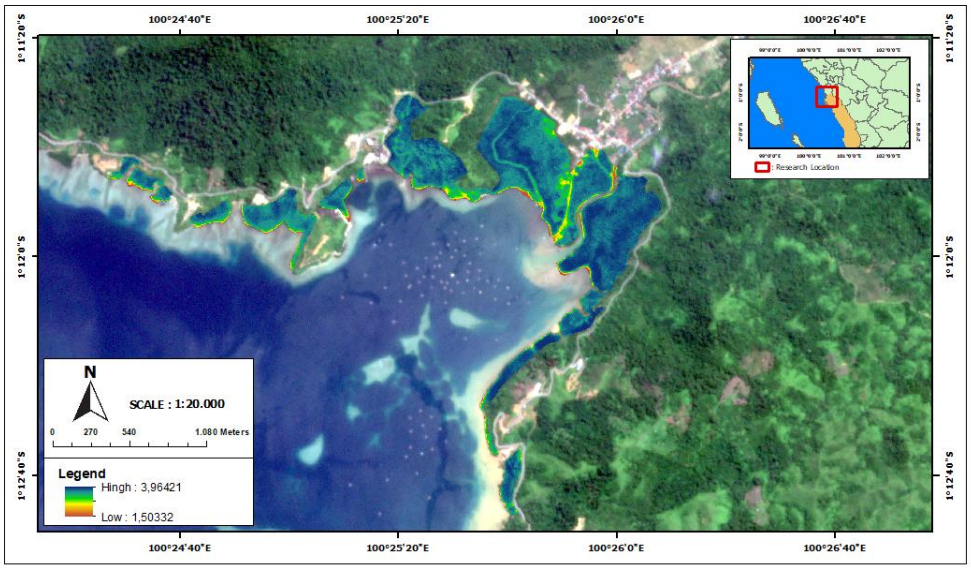


Figure 4. Map of estimated carbon stocks in 2024.

Based on the carbon stock map, spatial differences were observed due to changes in mangrove area between 2016 and 2024. In 2016, the mangrove area covered 10.421 ha, whereas in 2024 it decreased to 8.699 ha, indicating a reduction of 1.722 ha in the study site. According to carbon stock estimations, the total value in 2024 was 28.584 ton C ha^{-1}, with a minimum estimate of 1.193 ton C ha^{-1} and a maximum of 1.512 ton C ha^{-1}. These values were higher than the total carbon stock in 2016, which was 27.416 ton C ha^{-1}, with a minimum estimate of 1.217 ton C ha^{-1} and a maximum of 1.439 ton C ha^{-1}, as presented in Table 5. This variation is influenced by the diameter size of individual mangrove trees, even though the mangrove area in 2016 was larger. Thus, the increase in tree diameter in 2024 contributed to a higher estimated carbon stock compared to 2016.

Table 5

Carbon stock estimates for 2016 and 2024

Statistics	*Estimated aboveground carbon (AGC) value (ton C ha^{-1}) in 2016*	*Estimated aboveground carbon (AGC) value (ton C ha^{-1}) in 2024*
Minimum	1.217	1.193
Maximum	1.439	1.512
Mean	1.371	1.429
Standard deviation	0.069	0.080

Compared to field-based carbon stock values, remote sensing–derived estimates are often higher. Overestimation of mangrove carbon stocks in remote sensing analyses is generally attributed to the limitations of spatial resolution, the sensitivity of vegetation indices to canopy density, and the generalization of regression models used to link spectral data with biomass. A single pixel frequently represents a heterogeneous area that includes dense vegetation, soil, and water, yet algorithms may interpret the entire pixel as fully vegetated, resulting in inflated carbon values (Simard et al., 2019). Furthermore, vegetation indices such as NDVI are more responsive to leaf cover than to actual biomass structure (Tran et al., 2022), which leads to estimated carbon stocks exceeding field measurements. One possible explanation for discrepancies between field data and modelled data lies in the modelling approach itself (Canty et al., 2025; Carruthers et al., 2026). Additional contributing factors include the limited number and distribution of field plots used for calibration, as well as differences in the timing of data acquisition between satellite imagery and field surveys, which can introduce bias. Taken together, these factors explain why carbon stock estimates derived from remote sensing often exceed those obtained through direct field measurements.

Error and accuracy assessment. Accuracy testing using the standard error of estimate (SEE) approach is a statistical method used to assess the suitability of an estimation model to empirical data. In the context of mangrove forest carbon stock research, the SEE value in 2016 was recorded at 1.303 ton C ha^{-1}, while in 2024 it increased to 1.344 ton C ha^{-1}. In terms of accuracy, the results from 2016 were slightly better than those from 2024, with a difference of 0.041 ton C ha^{-1}, as lower error values are generally considered to indicate higher accuracy. However, when examined from the perspective of maximum estimation values, the 2024 results demonstrated superior accuracy compared to 2016. In 2024, the maximum estimation reached 1.512 ton C ha^{-1}, with an accuracy value of 1.344 ton C ha^{-1}, indicating an error of 1.344 ton C ha^{-1} relative to the maximum. By contrast, in 2016 the maximum estimation was 1.439 ton C ha^{-1} with an accuracy value of 1.303 ton C ha^{-1}, meaning that the error was nearly approaching the maximum estimation for that year. These findings suggest that while the 2016 dataset yielded lower error values, the 2024 dataset provided a more reliable estimation when considering the maximum carbon stock values.

The observed differences can be explained by the methodological approaches employed in each year. In 2024, data were collected directly in the field by measuring mangrove tree diameters, providing more up-to-date and reliable information. In contrast, the 2016 dataset relied on indirect estimation, where tree diameters were derived from reductions based on previous studies. Consequently, the 2024 dataset reflects actual field conditions more accurately, accounting for the variation in accuracy results. This emphasizes the importance of direct field measurements in enhancing the reliability of carbon stock assessments and reducing uncertainty in remote sensing–based models.

From an ecological perspective, these differences highlight the dynamic nature of mangrove carbon storage over time. The relatively lower error in 2016 suggests that the mangrove stands were more structurally homogeneous, making them easier to model with remote sensing data. In contrast, the higher reliability of maximum estimation in 2024 reflects the increasing complexity of mangrove growth and biomass accumulation, which may be better captured by newer datasets and improved modeling approaches.

This implies that long-term monitoring is essential to account for structural changes in mangrove ecosystems, as variations in accuracy can influence the reliability of carbon stock assessments used for climate mitigation strategies. Moreover, the ability of the 2024 dataset to provide more robust maximum estimates strengthens its potential application in carbon accounting frameworks, particularly for REDD+ initiatives and blue carbon management.

Conclusions. Based on the results of the carbon stock estimate in 2016, which was 27.416 ton C ha^{-1}, it is lower than in 2024, which was 28.584 ton C ha^{-1}, with a difference of 1.168 ton C ha^{-1}, even though the area of mangrove forest in 2016 was larger than in 2024. Likewise, the standard error of estimate (SEE) value in 2016 was 1.303 ton C ha^{-1} while in 2024 it was 1.344 ton C ha^{-1}, indicating a change in ecosystem complexity and higher data variability. This confirms that the accuracy of the carbon stock estimation model is influenced by temporal factors. Thus, continuous monitoring with more adaptive methods is needed to obtain more representative results. This study emphasizes the importance of evaluating the accuracy of estimates in supporting the management and conservation of mangrove forests as strategic carbon sinks.

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Conflict of Interest. The authors declare that there is no conflict of interest.

Data Availability. The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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