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Spatial and temporal study of estimating carbon stocks distribution of mangrove forest in coastal area of Teluknaga, Tangerang

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Abstract
Coastal mangrove forests play a crucial role in balancing carbon emissions in the atmosphere as they are a significant carbon store. Previous studies have shown that mangroves can absorb carbon four times more efficiently than terrestrial tropical forests. Unfortunately, the massive development and land use changes in Teluknaga District's coastal areas threaten these ecosystems' existence. To address this concern, efforts are being made to increase conservation, including estimating carbon stock. The aim of this study is to analyze the spatial distribution of biomass and carbon stock of mangrove forests in Teluknaga between 2016-2022 based on vegetation indices such as ARVI, EVI, and SAVI. Sentinel-2 was calculated into ARVI, EVI, and SAVI vegetation indices to model biomass. Statistical correlation analysis was also used to determine the best vegetation index to model biomass in the coastal area of Teluknaga District. This study found that the ARVI vegetation index had the best correlation (R = 0.60) for modeling biomass, with an RMSE value of 36.67 kg/pixel. Most mangrove forests in the coastal area of Teluknaga District showed an increase in biomass and carbon stock between 2016-2022, with significant growth in Muara and Lemo villages' mangrove forests, which is in line with an increase in the area and density of mangrove forests.
Keywords: biomass; carbon stock; mangrove; sentinel-2; vegetation indices

1. Introduction

Mangroves are crucial resources for improving human welfare and environmental stability in tropical nations like Indonesia. These ecologically beneficial plants provide erosion control, nursery grounds, and protection for coastal areas (Rizal, 2018). Additionally, they are effective carbon stores and absorbers, making them valuable for the environment (Otero et al., 2018). Mangrove forests have the highest carbon storage compared to other vegetation in coastal areas (Wicaksono, 2017), with an average of 1,023 mg of carbon per hectare (Jerath et al., 2016). This demonstrates that mangrove forests have more carbon stock than forests on land or terrestrial areas.

The significance of mangrove forests lies in their ability to store large amounts of carbon, which is crucial in combating global warming. The adverse effects of global warming threaten all living beings on Earth. Climate change and global warming are closely linked to the anthropogenic emission of CO_2 (Yoro, et al., 2020). As a greenhouse gas, CO_2 contributes significantly to global warming, and its concentration in the atmosphere is a major factor in climate change (Yoro, et al., 2020). The substantial carbon content in mangroves plays a vital role in offsetting anthropogenic CO_2 emissions (Macreadie et al., 2017). Therefore, preserving the extent of mangroves is a critical aspect of the REDD+ (Reducing Emission from Deforestation and Degradation) activities, which focuses on increasing carbon stocks (Ahmed, et al., 2016). Mangroves have the ability to convert atmospheric CO_2 into organic compounds that support the growth and development of their leaves, roots, branches, and stem tissue while creating carbon storage reserves (Hidayah, et al., 2019). Additionally, they can absorb carbon at a rate four times higher than terrestrial forests in tropical areas (Zulhalifah et al., 2021). Therefore, managing and preserving mangrove ecosystems effectively is essential to combat climate change (Sidik et al., 2018).

Teluknaga District in Tangerang is home to the mangrove ecosystem, which is a part of the larger mangrove forest area in Jakarta Bay. This area is spread over three administrative regions, including Teluknaga District, Penjaringan District, and Muara Gembong District, and spans across 9,749 hectares (Aini et al., 2015). The mangrove ecosystem in Teluknaga District is significant in Banten Province and has the potential for tourism, fisheries, and agriculture (Sari, et al., 2019).

The Teluknaga District's coastal area is a part of the Tangerang Regency's reclamation area. The plan for reclamation in the Teluknaga District area is based on the Regency Regulation of Tangerang No. 13 in 2011, which outlines the 2011-2031 Regional Spatial Planning (RT/RW) for Tangerang Regency. According to the regulation, Teluknaga District will have a reclamation area, which will become a protected forest area in the form of a mangrove forest. This is a significant concern because the reclamation activities in the Teluknaga District area must consider the mangrove ecosystem, which is part of a protected forest (RT/RW Tangerang Regency 2011-2013, 2011). The sediment deposition around the mangrove ecosystem caused by the reclamation activities can impact the mangroves (Slamet et al., 2020). High sediment deposits can cover mangrove roots and disrupt the mangrove respiration process (Zamani, 2019). Therefore, it is crucial to measure the carbon stocks in the mangrove forests in Teluknaga District, which are threatened by the reclamation activities (Slamet et al., 2020). One of the methods used to measure carbon stocks is remote sensing technology.

The use of remote sensing technology to measure carbon has the potential to produce more accurate and detailed research (Angelopoulou et al., 2019). This technology can provide data with higher spatial resolution and temporal data. It is also a cost-effective tool for analyzing mangrove features. Previous studies have used remote sensing technology to map mangrove carbon stocks (Muhsoni et al., 2018; Pham et al., 2021; Siddiq et al., 2020). Vegetation indices, such as the Atmospherically Resistant Vegetation Index (ARVI), Enhanced Vegetation Index (EVI), and Soil Adjusted Vegetation Index (SAVI), can be combined with field data to estimate carbon stocks (Candra et al., 2016). Medium-resolution satellite imagery data, like Sentinel-2, can estimate carbon stocks with a shorter recording visit time of 5 days (Baloloy et al., 2018). Sentinel-2 has a near-infrared and visible infrared sensor that provides 13 spectral bands with varying spatial resolution, namely 10 m, 30 m, and 60 m. Based on these features, Sentinel-2 satellite imagery can be used to estimate carbon stocks in mangroves using vegetation indices.

This research aims to examine the spatial arrangement of biomass and carbon stock in mangrove forests located in the Teluknaga coastal district during the years 2016 - 2022. The study utilizes the most effective vegetation index method, which involves three indices: ARVI, SAVI, and EVI, derived from Sentinel-2 imagery. The research also applies both spatial and statistical techniques to generate the optimum vegetation index that predicts the biomass and carbon stocks of mangrove forests in the Teluknaga coastal region.

2. Methods

2.1. Study Area

This research was conducted in a mangrove forest on Teluknaga District's coast, which spans four administrative areas: Tanjung Burung Village, Tanjung Pasir Village, Muara Village, and Lemo Village (see Figure 1). The research area is currently undergoing reclamation to construct residential and economic centers. These circumstances pose a threat to the survival of the mangrove forests in the study area.

2.2. Data Collection

For this study, two types of data were used: secondary and primary data. The secondary data included satellite imagery, while the primary data consisted of two components, such as species and diameter at breast height (DBH).

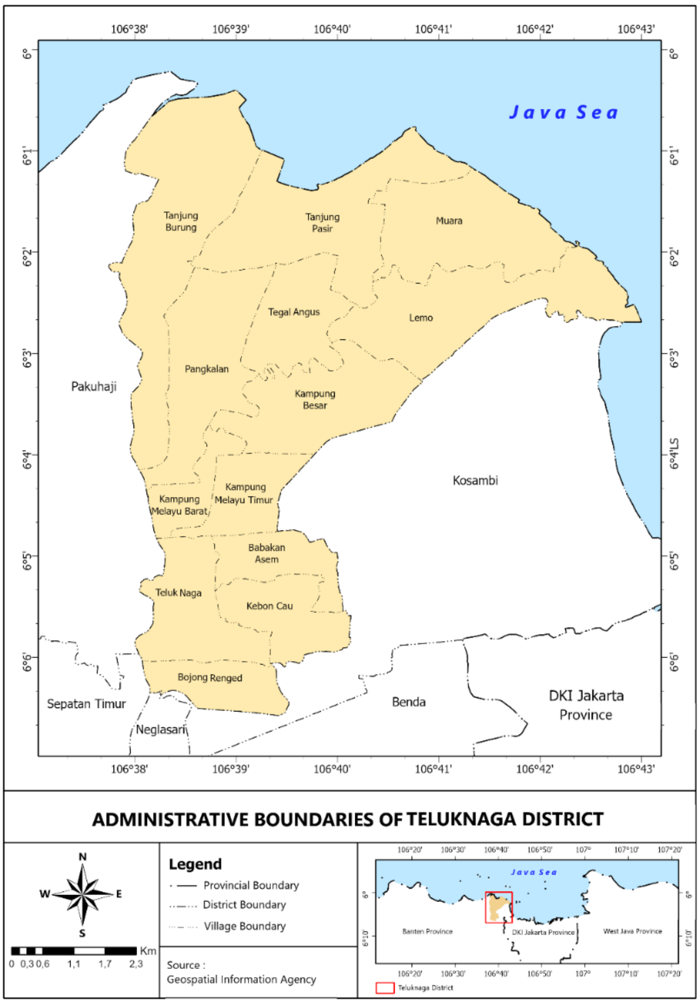

Figure 1. Administrative Boundaries of Teluknaga District

The satellite imagery used in this study is Sentinel-2 imagery. Further details regarding the Sentinel-2 imagery used are listed in Table 1. The Sentinel-2 satellite imagery used in this study was obtained from scihub.copernicus.eu. Sentinel-2 imagery is a satellite imagery developed by the European Space Agency (ESA) with a spatial resolution specification of 10, 30, and 60 meters with 13 spectral bands (Drusch et al., 2012). The red band and near-infrared (NIR) band used in processing the vegetation index have a spatial resolution of 10 m. The use of Sentinel-2 provides an advantage because it will produce a relatively high spatial resolution vegetation indices. The sentinel imagery used is taken every two years to see the dynamics of mangrove forests and reclamation activities from 2016 to 2022.

Table 1. Details of Sentinel-2 imagery data used

Imagery type	Recording date	Data level
Sentinel 2A	October 7, 2016	1C
Sentinel 2B	October 22, 2018	
Sentinel 2A	July 20, 2020	2A
Sentinel 2B	April 14, 2022	

Primary data collection in this study uses stratified random sampling. The number of samples collected will depend on the size of the mangrove area in the field. For this study, 30 samples of forest area will be used, following the guidelines in BIG Regulation Number 3 of 2014. This regulation sets the minimum number of sample plots based on the total mangrove area. Once the required number of plots has been obtained, they will be divided into a ratio of 8:2 (Liu et al., 2008), where 80% of the plots will be used as training data to build a biomass estimation model, and the remaining 20% will be used as testing data to check the accuracy of the model.

The variables in this study consist of independent variables and dependent variables. As for mangrove species variables and diameter at breast height will be used to calculate above-ground biomass as the dependent variable (Y). Then, the independent variable (X) of this study is the pixel value of the ARVI, SAVI, and EVI vegetation indices.

2.3. Mapping Mangrove Forest Distribution and Vegetation Indices

Mapping the distribution of mangrove forests is carried out using the supervised classification method. This method is carried out by utilizing available pixel information in the image, which generates parameters representing each class of land cover observed. In this research, supervised classification is carried out using the Google Earth Engine, where script code is entered into the processing process using the Javascript programming language. Making a map of the distribution of mangrove forests is done by dividing the research area into mangrove and non-mangrove forests.

To map the distribution of mangrove forests, a test was conducted to assess accuracy. Sample points from Sentinel-2 satellite imagery in 2022 were compared to the actual presence of mangrove forests in the field. Additionally, Sentinel-2 satellite imagery from 2016, 2018, and 2020 were compared to high-resolution Google Earth base maps. The Kappa coefficient was used to calculate accuracy (Sharma, 2018).

2.4. Vegetation Indices

After obtaining the mangrove forest distribution map, the next step is processing the vegetation index. This study's vegetation indices consisted of ARVI, SAVI, and EVI. This processing was done using ArcGIS Pro software by entering the ARVI, SAVI, and EVI vegetation indices equations.

ARVI is a type of vegetation index that is an improved version of NDVI (Xue, et al., 2017). It has greater resistance to atmospheric effects compared to NDVI. The ARVI formula uses the blue band to reduce the impact of atmospheric scattering caused by aerosols on the reflectance of the red band. Various studies have shown that ARVI is effective in reducing the brightness effect of atmospheric aerosols and is a reliable model for estimating AGB (Bordoloi et al., 2022; Siddiq et al., 2020). ARVI has the same range as NDVI, which is -1.0 to 1.0 (Kaufman, et al., 1992). The equation used to calculate ARVI is as follows: (Xue, et al., 2017)

$$ARVI = \frac{NIR - (R - \gamma(B - R))}{NIR + (R - \gamma(B - R))} \qquad (1)$$

where, NIR = reflectance in the near-infrared band; R = reflectance in the red band; B = reflectance in the blue band; γ = atmospheric self-correction factor that depends on the aerosol type (γ = 1, when an aerosol model is not available).

SAVI index is a useful tool that can help reduce the impact of soil brightness on the red and near-infrared (NIR) bands (Chen et al., 2019). It uses remote sensing data to model global soil-vegetation systems and can also analyze the transfer of NIR beams in non-vegetation areas (Rhyma et al., 2020). One advantage of using SAVI for AGB estimation is that it has a soil adjustment factor that helps minimize the effect of soil brightness on canopy reflectance (Das et al., 2021). Additionally, SAVI incorporates a ground brightness correction factor. The equation for SAVI is as follows: (Rhyma et al., 2020)

$$SAVI = \frac{NIR - R}{NIR + R + L} \times 1 + L \qquad (2)$$

where, NIR = reflectance in the near-infrared band; R = reflectance in the red band; B = reflectance in the blue band; L = adjustment factor to reduce the brightness of the soil (L = 0.5).

EVI was adopted by the Moderate Resolution Imaging Spectroradiometer (MODIS) Land Discipline Group as a vegetation index that can monitor photosynthetic activity in vegetation (Maeda et al., 2014). EVI is a feedback approach that includes background adjustment and the concept of atmospheric resistance into NDVI (Ahmad, 2012). It is an improved version of NDVI that enhances the ability to monitor vegetation in areas with high biomass and minimal atmospheric influence. EVI is more responsive to changes in vegetation canopy structure, canopy type, and vegetation physiology than NDVI (Yebra et al., 2013). The equation used in EVI is as follows: (Siddiq et al., 2020)

$$EVI = G \times \frac{NIR - R}{NIR + (C_1 \times R - C_2 \times B) + L} \qquad (3)$$

where, NIR = reflectance in the near-infrared band; R = reflectance in the red band; B = reflectance in the blue band; G = gain factor (G = 2.5); C_1, C_2 = aerosol coefficient (C_1 = 6, C_2 = 7.5); L = canopy calibration factor and soil effect (L = 1).

2.5. Carbon Stock Modelling

To estimate aboveground mangrove biomass, a three-step approach was followed. The first step involved conducting a normality test, followed by a linear regression test, and finally an accuracy test. IBM SPSS was used to perform the normality and linear regression tests. The accuracy test was conducted by calculating the Root Mean Square Error (RMSE) using Microsoft Excel.

Vegetation indices values of mangrove forests for 2016 - 2022 are obtained, tested for correlation, and then analyzed for correlation with biomass values obtained through field measurements by calculating the Diameter of Breast Height (DBH). This analysis was conducted using a linear regression test using IBM SPSS software, resulting in correlation values and a linear regression equation. The vegetation index that showed the strongest correlation with field biomass values will be used for biomass modelling. Carbon stock modelling will be derived from biomass modelling using the following equation: (Hastuti et al., 2017)

$$EC_b = B \times \%C_{organic} \qquad (4)$$

where, EC_b = above ground carbon stock (kg); B = above ground biomass (kg); $\%C_{organic}$ = the percentage value of carbon stock ($\%C_{organic}$ = 0.47).

2.6. Accuracy Test

A model accuracy test was conducted for the top regression model, utilizing the RMSE test. To perform this test, 20% of the overall field plot data was utilized for testing. A smaller RMSE value indicates that the predicted value from the model is closer to the actual measurement value of the field data. The formula for RMSE is as follows:

$$RMSE = \sqrt{\frac{(y - y')^2}{n}} \qquad (5)$$

where, y = field measurement data; y’ = vegetation indices modelling data; n = total number of samples.

3. Results and Discussion

3.1. Classification of Vegetation Indices

The study utilized several vegetation indices such as ARVI, SAVI, and EVI. The vegetation index was processed using ArcGIS Pro software, by applying Equation 1 for ARVI, Equation 2 for SAVI, and Equation 3 for EVI vegetation indices. Moreover, the vegetation indices were classified based on equal intervals into three classes as in Table 2.

Table 2. Vegetation index classification

Classification	Vegetation index values
Low	-0.163 – 0.146
Moderate	0.147 – 0.456
High	0.457 – 0.765

Throughout the study area, the ARVI vegetation index in the study area experienced fluctuations from 2016 - 2022. The southeastern coastal area of Teluknaga District saw an increase in the range of ARVI values from 2016 to 2018. During this time, the low vegetation index classification dominated the region in 2016, but shifted to the moderate class vegetation index classification by 2018. Meanwhile, the northwestern part of Tanjung Burung Village saw high vegetation index classification ARVI values in both 2016 and 2018 (see Figure 2). However, by 2020, most of the mangrove forests in the study area had fallen into the low vegetation index classification. This indicated a decrease in the range of ARVI values from 2018 in most parts of the study area. However, there was an increase in the ARVI value in mangrove forests to the medium class in 2020, particularly in Muara Village, Tanjung Pasir Village, and Lemo Village.

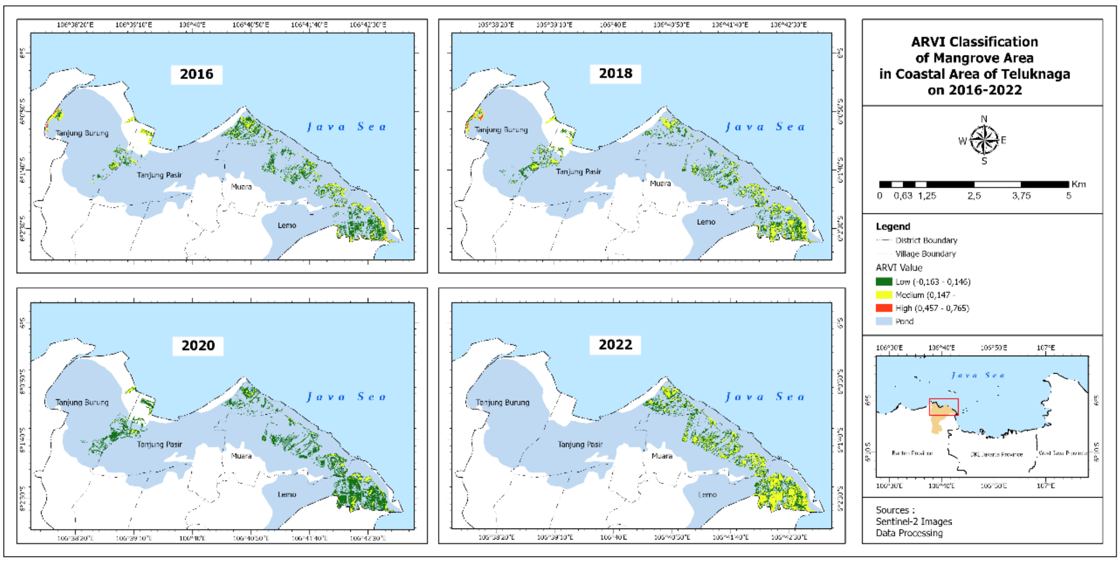

Figure 2. ARVI Classification Map of Mangrove Forests on the Coastal Area in Teluknaga District

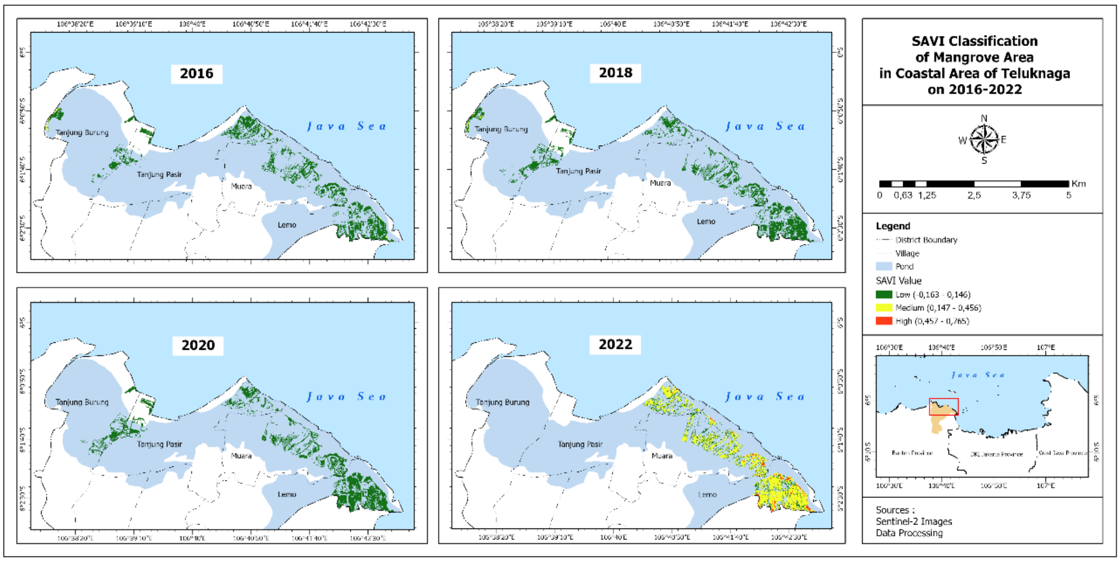

Figure 3. SAVI Classification Map of Mangrove Forests on the Coastal Area in Teluknaga District

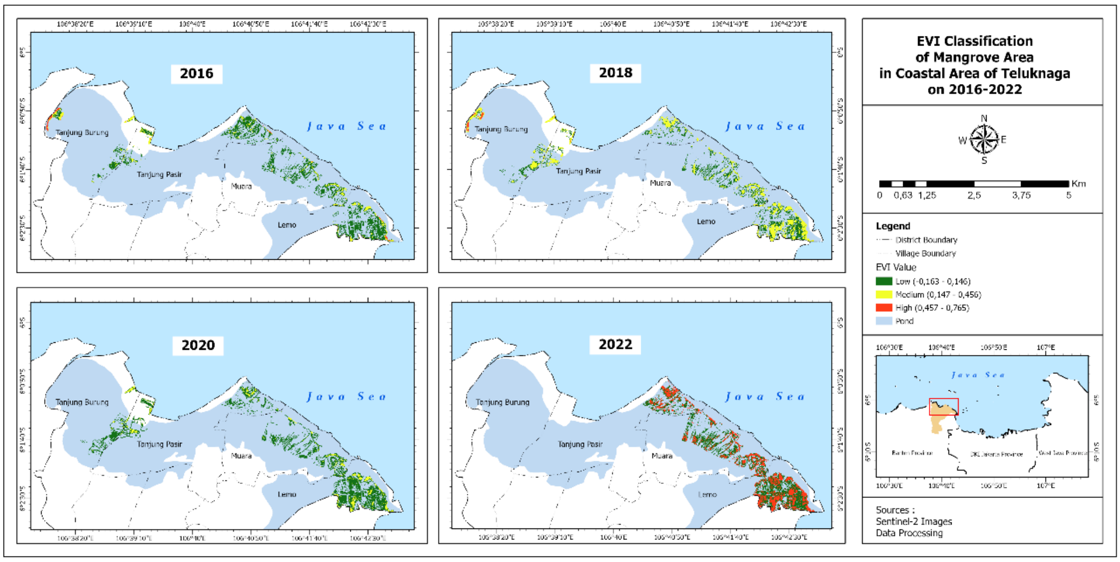

Figure 4. EVI Classification Map of Mangrove Forests on the Coastal Area in Teluknaga District

The fluctuation of ARVI values corresponds with the size of mangrove forests in the area (Hati et al., 2022). For instance, the mangrove forest in Lemo Village has seen a rise in ARVI value from a low vegetation index classification to a moderate low vegetation index classification class between 2016 and 2022. The reason for this change is the increase in mangrove forest size in Lemo Village over the same period.

Throughout the study area, it has been observed that the SAVI vegetation index range has increased (see Figure 3). This increase is attributed to a rise in the mangrove forests, which correlates with the increase in the SAVI value. The L (adjustment factor) value, employed in the SAVI calculation, can indicate the level of vegetation cover (see Equation 2). Higher L values signify lower vegetation cover within the study area. Thus, the L value can demonstrate the sensitivity of SAVI in detecting changes in mangrove forests. Consequently, an increase in SAVI value implies a greater vegetation cover within the area.

Regarding the EVI vegetation index, it has been observed that the largest changes occur within the established mangrove forests located in the eastern coastal region of Teluknaga District. Figure 3 illustrates this, showing that in 2016, most of the eastern coastal areas of Teluknaga District were categorized as being of low vegetation index classification. However, by 2018, most of mangrove forests in those areas had moved up to the moderate vegetation index classification, only to fall back to low vegetation index classification again from 2020 to 2022.

Based on figure 4, the EVI value in the study area is mostly low, indicating less dense mangrove forests in certain parts of the research area. This is due to the sensitivity of EVI in areas with dense vegetation cover. A higher EVI value corresponds to a higher density of vegetation cover (Zhu et al., 2021). It is evident that the low vegetation index classification dominates the overall EVI value.

3.2. Modelling of Aboveground Biomass

The data normality test was carried out to determine whether the dependent variable, which in this study is the biomass value from field measurements, has a normal distribution. Normality is one of the assumptions that must be fulfilled to perform a linear regression test. The data normality test used in this study is the Shapiro-Wilk test. This test was used because the number of samples used for the normality test was less than 50. Based on Table 3, it is known that the measured biomass data is normally distributed data. It is known that based on the Shapiro-Wilk test, the p-value obtained is 0.079, this value indicates that the p-value is > 0.05, which indicates that the biomass data is normally distributed.

Table 3. Results of the normality test for biomass data from field measurements

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Biomass	.162	30	.042	.938	30	.079

[a]Lillefors Significance Correction

A linear regression test was conducted to analyze the relationship between the independent variables, which are the pixel value of ARVI, SAVI, and EVI, and the dependent variable, which is the field biomass value. Based on the findings, the ARVI vegetation index has the highest R-value (0.60) compared to SAVI and EVI (see Table 4). As a result, the linear regression equation derived from ARVI was utilized to model biomass and estimate carbon stocks.

Table 4. Results of linear regression tests and accuracy tests

Vegetation indices	Linear regression equations	R	RMSE
ARVI	$Biomass = 1{,}119.634 \times (ARVI) - 93.130$	0.60	36.67
SAVI	$Biomass = 407.234 + 417.045 \times (SAVI)$	0.14	419.62
EVI	$Biomass = 23.892 + 4.129 \times (EVI)$	0.13	116.52

The calculations for Root Mean Square Error (RMSE) show that the biomass modeling using vegetation index has varying results. The model using SAVI has a high RMSE value, while the model using ARVI has a low RMSE value. The RMSE value indicates the difference between the modeled biomass value and the field measurement biomass value. The biomass modeling using ARVI pixel values has an RMSE value of 36.67 (see Table 4). This shows that the aboveground biomass modeling using ARVI pixel values differs from the biomass values obtained from field measurements by 36.67 kg/pixel.

3.3. Distribution of Carbon Stocks in 2016 – 2022

The aboveground carbon stock is obtained by calculating using Equation 4. The ARVI vegetation index regression model is then used to model the aboveground biomass, which is then input into a linear regression equation (see Table 4). This entire process is done using the raster calculation feature available in ArcGIS Pro. Upon testing the accuracy of the aboveground carbon stock modeling, it was found that the RMSE value is 17.22. This indicates that the carbon stock value obtained from the ARVI vegetation index modeling results differ by 17.22 kg/pixel from field measurements.

Furthermore, the results of the estimation of aboveground carbon stocks are classified into five classes as in Table 5. Each of these ranges is then calculated for the area of mangrove forest each year, assuming 1 pixel is 100 m^2.

Table 5. Carbon stocks classification

Classification	Carbon stocks values (kg/pixel)
Very low	0 – 55.25
Low	55.26 – 110.51
Moderate	110.52 – 165.76
High	165.77 – 221.02
Very high	221.03 – 276.27

As seen in Figure 5 and Table 6, it has been observed that most of carbon stocks in mangrove forests have been categorized as very low carbon stocks classification in all years analyzed. In 2016, 76.17% of the forest area, which is equivalent to 112.15 hectares, was classified as very low carbon stocks classification. The percentage of mangrove forests in the very low carbon stocks classification remained around 73% in 2018 and 2020. However, in 2022, it is expected that 66.53% or 120.54 hectares of mangrove forests will be classified in the very low carbon stocks classification. The data from 2016 to 2022 indicates a decline in the percentage of mangrove forests in the very low carbon stocks classification. The most significant decrease occurred between 2020 and 2022, with a 6.04% drop.

Between 2016 and 2018, there was a rise in the proportion of mangrove forest areas in the low carbon stocks classification. In 2016, the low carbon stocks classification made up 15.55% of the mangrove forest areas, which then increased to 19.35% in 2018, a growth of 3.8%. Moreover, the percentage of mangrove forest areas in the low carbon stocks classification continued to increase from 2020 to 2022, with the most significant rise occurring between 2018 and 2020. During this period, the percentage of land area for the low carbon stocks classification grew by 7.84%.

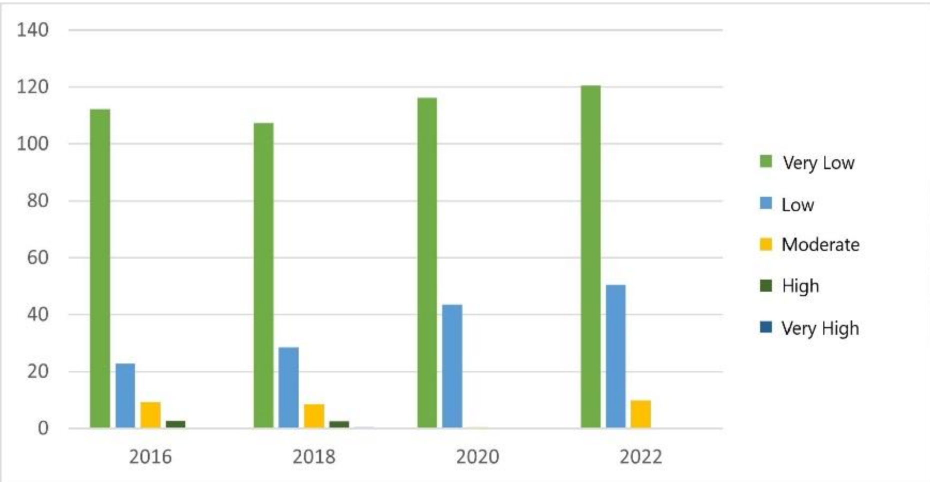

Figure 5. Diagram of Changes in the Value of Aboveground Carbon Stock Range

Table 6. The area of mangrove forests for each class of carbon stocks

Year	Classification	Carbon stocks values (kg/pixel)	Area (pixels)	Area (ha)	% area	Total area (ha)
2016	Very low	0 – 55.25	11,215	112.15	76.17	147.23
	Low	55.26 – 110.51	2,289	22.89	15.55	
	Moderate	110.52 – 165.76	921	9.21	6.26	
	High	165.77 – 221.02	277	2.77	1.88	
	Very high	221.03 – 276.27	21	0.21	0.14	
2018	Very low	0 – 55.25	10,726	107.26	72.84	147.25
	Low	55.26 – 110.51	2,849	28.49	19.35	
	Moderate	110.52 – 165.76	859	8.59	5.83	
	High	165.77 – 221.02	241	2.41	1.64	
	Very high	221.03 – 276.27	50	0.5	0.34	
2020	Very low	0 – 55.25	11,614	116.14	72.57	160.04
	Low	55.26 – 110.51	4,351	43.51	27.19	
	Moderate	110.52 – 165.76	39	0.39	0.24	
	High	165.77 – 221.02	0	0	0	
	Very high	221.03 – 276.27	0	0	0	
2022	Very low	0 – 55.25	12,054	120.54	66.53	181.18
	Low	55.26 – 110.51	5,048	50.48	27.86	
	Moderate	110.52 – 165.76	988	9.88	5.45	
	High	165.77 – 221.02	28	0.28	0.15	
	Very high	221.03 – 276.27	0	0	0	

Generally, the least amount of mangrove forest area can be found within the carbon stock range of 221.03 – 276.27 kg/pixel, which is classified as very high carbon stocks classification. Between 2018 and 2020, there was a notable decrease in the percentage of this category. As a result, no mangrove forests were left within the very high carbon stocks classification in 2020 and 2022.

The map in Figure 6 displays the spatial distribution of aboveground carbon stock values in mangrove forests along the Teluknaga District coast. It reveals that very low carbon stock values dominate all mangrove forests from 2018 to 2022. However, in 2016 and 2018, the northwestern region of Tanjung Burung Village exhibited very high carbon stock values. From 2016 to 2018, the southeastern areas of Muara Village and Lemo Village showed the range of carbon stock values between 55.26 to 110.51kg/pixel (low carbon stocks classification) and 110.52 to 165.76kg/pixel (moderate carbon stocks classification). In 2020, the same areas that were previously in the carbon stock classification were transformed into the low carbon stocks classification. However, the southeastern regions of Muara Village and Lemo Village are now categorized as moderate and high carbon stocks classification in 2022.

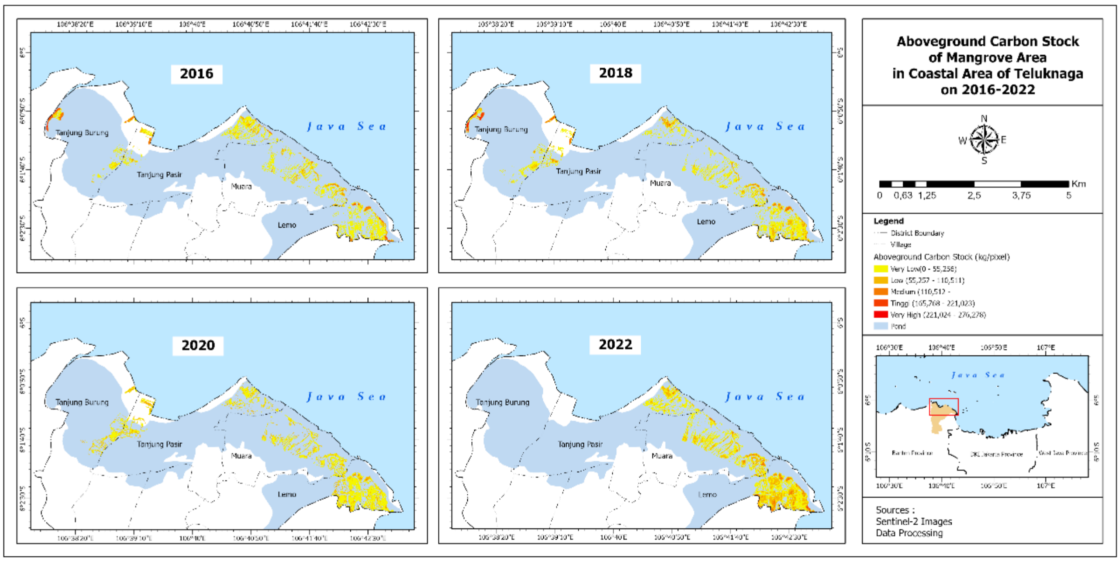

Figure 6. Distribution of Aboveground Carbon Stocks of Mangrove Forests on the Coastal Area in Teluknaga District

The value of carbon stock in Teluknaga's mangrove ecosystems is affected by reclamation activities (Slamet et al., 2020). Studies reveal that mangrove forests located close to settlements experienced reduced carbon stocks due to such activities. On the other hand, those mangrove that situated in the coastal areas showed increased carbon stocks (Slamet et al., 2020). Furthermore, the size of the mangrove forest plays a significant role in determining the fluctuation of carbon stocks (Mulyaningsih et al., 2017).

The largest reduction in carbon stocks in mangroves was observed in Tanjung Burung Village and the western region of Tanjung Pasir Village. This decline began in 2016 and continued until 2022 due to the loss of mangrove forests in the area. The primary reason for this loss is attributed to reclamation activities. Figure 9a illustrates the changes in the mangrove forests of these two villages. The loss of these forests has resulted in a significant decrease in the value of carbon stocks. In 2016, carbon stocks were recorded to have varying values from low to high carbon stocks classification. However, it is expected that these stocks would disappear entirely by 2022.

In contrast, the mangrove forests in Muara Village and Lemo Village have experienced an increase in carbon stocks. Figure 7b shows a significant change in the value of carbon stocks in the area from 2016 to 2022. Some mangrove forest areas in Muara Village and Lemo Village have transitioned from very low carbon stocks classification to moderate carbon stocks classification to high carbon stocks classification. The expansion of mangrove forests towards the coastal zone also contributes to the rise in carbon stocks. Previous studies have found that mangroves are most dominant in Muara Village and Lemo Village's coastal zone (Aini et al., 2015). The increase in the coastal zone's mangrove forest area due to reclamation is caused by a decrease in tidal prisms (Rusdiansyah et al., 2018). Tidal prisms refer to the amount of water that flows in and out of estuaries and bays due to tides (Schwartz, 2005). The decrease in tidal prisms results in weaker water circulation, which maximizes the distribution of nutrients to mangroves and promotes their growth.

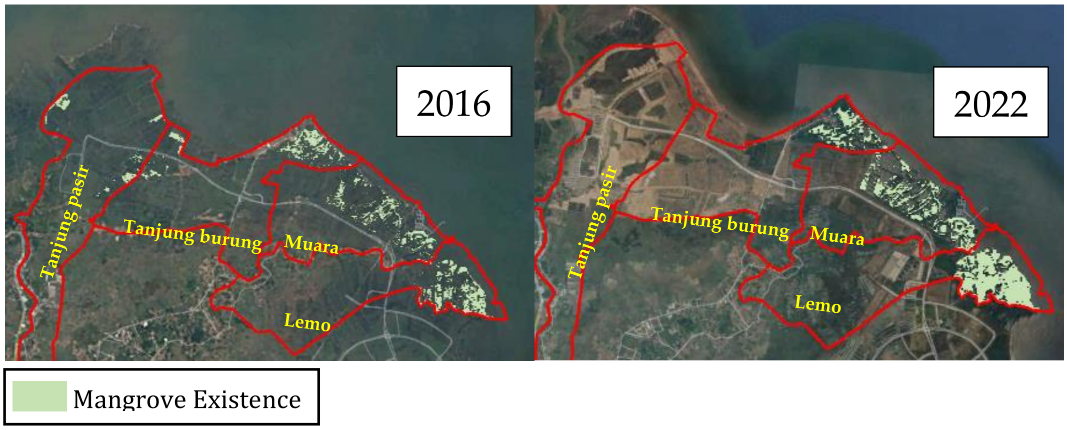

Figure 7. Mangrove Forests Changes Due to Reclamation in (a) 2016; (b) 2022

4. Conclusions

Between 2016 and 2022, the mangrove forest along the coast of Teluknaga District has grown in size. The most significant growth has taken place in Muara Village and Lemo Village. However, some of the mangroves in Tanjung Burung and Tanjung Pasir Villages have disappeared or are nearly nonexistent in 2022 due to extensive development in those areas. The expansion of the mangrove forest along the Teluknaga District coast affects the vegetation indices values. The wider the mangrove forest, the higher the ARVI, SAVI, and EVI values.

The ARVI vegetation index model is highly correlated with aboveground mangrove biomass as measured in the field. The relationship between field biomass measurements and ARVI pixel values shows a moderate correlation with an RMSE value of 36.67 kg/pixel. This indicates that there is a difference of 36.67 kg/pixel between the aboveground biomass values calculated using ARVI pixel values and those measured in the field.

According to the model, the aboveground biomass and carbon stock in mangrove forests along the Teluknaga District coast have increased in most study areas. This is in line with the expansion of mangrove forests in the district. As a result, areas with high mangrove forest density and coverage exhibit elevated carbon stocks.

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Author Contribution

Conceptualization, S.H.Y.; Data Curation, S.H.Y.; Formal Analysis, S.H.Y.; Investigation, S.H.Y.; Methodology, S.H.Y.; Software, S.H.Y.; Validation, S.H.Y.; Resources, S.H.Y.; Visualization, S.H.Y; Supervision, S. and T.G.P; Writing – Original Draft Preparation, S.H.Y.; Writing – Review & Editing, S.H.Y. and E.G.

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