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Analysis of Carbon Stock Estimation in Mangroves with Climate Variability in West Java 2019-2023

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***Abstract*— Mangrove ecosystems are important in carbon sequestration and climate regulation and contribute to climate change mitigation. However, carbon stock estimation is still mostly done manually, which is less efficient. This study utilizes remote sensing to investigate the correlation between mangrove carbon stocks and climate variability in West Java from 2019 to 2023. Mangrove land cover classification was performed using the Random Forest algorithm with NDVI and NDWI indices, while the relationship between carbon stock and climate factors was analyzed using linear regression. The results showed that increased precipitation was associated with higher carbon stocks (R^2=0.5514), while carbon stocks had a negative correlation with 2-meter temperature (R^2=0.8242) and sea surface temperature (SST) (R^2=0.7111). This study enhances our understanding of mangrove-climate interactions and provides valuable insights for developing remote sensing-based climate resilience and coastal ecosystem management policies.**

Keywords—2-meter Temperature, Biomass, NDVI, NDWI, Precipitation, Random Forest, Remote Sensing, SST

I. INTRODUCTION

Mangroves are essential ecosystems in coastal areas, serving as habitats for various species, coastal abrasion barriers, and natural carbon sinks [1]. Mangrove ecosystems are unique in their ability to thrive in high-salinity environments and play a vital role in maintaining the quality of coastal environments. In addition, mangroves also can sequester blue carbon, which is carbon stored in coastal ecosystems. [2]. One important indicator used to measure the carbon storage capability of mangrove ecosystems is carbon stock. Carbon stock refers to the amount of carbon stored in mangrove biomass, both above and below ground [3]. Mangrove carbon stocks can store three to four times more carbon than terrestrial forests, with most of the carbon stored in the soil [4]. However, man-grove deforestation threatens these ecosystems, making conservation and restoration efforts essential to maintaining mangrove carbon stocks and supporting adaptation to climate change impacts [5].

Indonesia has ±3.36 million hectares of mangrove forests, making it the country with the largest mangrove forest area in Asia and even in the world [6]. One of the provinces in Indonesia, namely West Java, has a large mangrove forest [7]. Areas in West Java have undergone restoration efforts, resulting in diverse mangrove ecosystems. Mangrove forests in West Java play an essential role in carbon sequestration, as shown by the Ciletuh mangrove forest, which has an estimated aboveground carbon storage of 14.93 t C ha^{-1} [8]. West Java's climate is influenced by tropical variability, including phenomena such as the El Niño Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), and the Asia-Australia Monsoon, which affect precipitation patterns [9].

The amount of carbon sequestration stored in mangroves must be calculated to address global climate issues and improve the function of this forest-type [10]. Some botanists still rely on manual estimation methods to assess carbon storage in mangroves, which takes a long time [11]. Therefore, the utilization of technology can be a solution to improve efficiency in the marine field [12]. One application of marine technology that can be done is remote sensing. Remote sensing is an effective method for monitoring and estimating the amount of mangrove carbon [10]. In addition, this study offers the novelty of integrating climate variability data (precipitation, 2-meter temperature, and sea surface temperature) to explore the relationship between carbon stocks and climate factors affecting mangrove ecosystems in West Java.

Remote sensing provides multi-temporal and multi-spectral data on land use and land cover [13]. After reviewing the literature on the advantages and limitations of various approaches, we used machine learning models to prepare man-grove land cover. Random forest was applied because it offers the best precision of all available classification techniques [14]. Random forest is a

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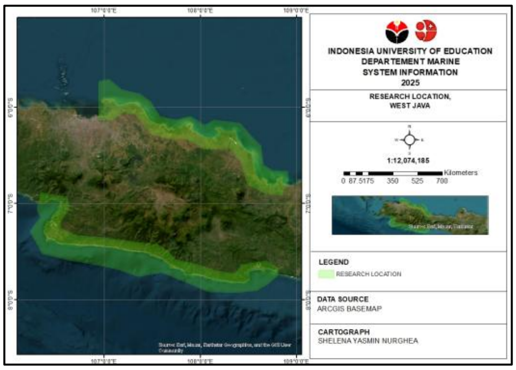

Figure. 1. Research Location Map

supervised learning algorithm that can be used in classification [15].

Therefore, the research aims to utilize remote sensing technology in classifying mangrove land cover. Mangroves possess unique characteristics that enable effective detection through satellite imagery. As vegetation grows in coastal environments with high salinity and humid conditions, mangroves respond significantly to certain spectral bands, particularly in the red and near-infrared (NIR) regions. The red (B4) and near-infrared (B8) bands are susceptible to vegetation conditions. In contrast, the green (B3) and far-infrared (SWIR) bands can identify moisture and water content in vegetation. After the mangrove land cover classification process, the next step is calculating mangrove biomass and carbon stock using estimation formulas based on previous research literature that utilizes remote sensing data. The results of these calculations will then be analyzed to explore the correlative relationship between measured carbon stocks and climate variability, which in this case is represented by Precipitation, 2-meter Temperature, and Sea Surface Temperature parameters in the West Java region.

II. Method

A. Research Location

This study covers the data period from 2019 to 2023. The research location is focused on mangrove ecosystems in the West Java region, as shown in Figure 1. The area has a diversity of climates and environmental conditions that can vary mangrove carbon stocks.

B. Data

The data used in this study include mangrove land cover obtained from Sentinel-2 satellite imagery, as well as climate variability data consisting of precipitation parameters, Sea Surface Temperature (SST), and air temperature at a height of 2 meters (2-meter Temperature), as listed in Table 1. Although allometric data from the Central Java region are not used directly in the analysis, they serve as a reference to inform and develop the carbon stock estimation method applied in this study.

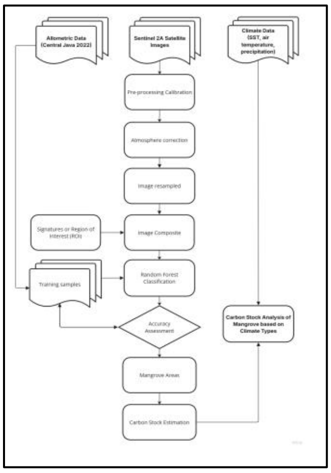

Figure. 2. Flowchart research

Climate data, which includes precipitation, air temperature at the height of two meters (2-meter Temperature), and Sea Surface Temperature (SST), is processed using Google Colab and visualized with the QGIS application. Meanwhile, Sentinel-2A image data were processed using Google Earth Engine (GEE) to produce multitemporal information on mangrove cover. The processing process includes radiometric correction, atmospheric correction, cloud and cirrus removal, and the addition of vegetation indices such as NDVI and NDWI to support further analysis.

C. Data Processing

Data processing in this study classifies mangrove land cover using the random forest method to obtain mangrove

TABLE 1.
DATA SOURCE

Data	Years		Source
Sentinel 2	2019 -2023	10 x 10 meter	Copernicus
Precipitation	2019 -2023	0,1° x 0,1°	GSMap
2-meter Temperature	2019 -2023	0,25° x 0,25°	ECMWF
Sea Surface Temperature	2019 -2023	0,25° x 0,25°	ECMWF

areas. After the mangrove land area is received, it is subclassified to determine its density class and calculate the carbon stock value, which will be analyzed with climate data. A flowchart of this research is presented in Figure 2.

The Normalized Difference Vegetation Index (NDVI) is a satellite image-based calculation method used to identify the greenness of vegetation [16]. NDVI can provide information on vegetation-related parameters, such as green leaf biomass and green foliage area, which aid in classifying vegetation types. Meanwhile, the Normalized Difference Water Index (NDWI) is a technique used to measure the moisture level or water content in satellite images. The equation between NDVI and NDWI is in Table 2.

This study employed the Random Forest algorithm, a machine-learning method that has demonstrated high accuracy in mangrove identification and mapping for mangrove cover classification. This method combines multiple decision trees to create a robust classifier and includes the ability to handle large datasets efficiently and select essential features for classification [17]. In Mangrove research, random forest has been used to predict intertidal wetland migration under sea level rise [18], assess mangrove leaf health [19], and map mangrove distribution [20]. In addition, this method can achieve high accuracy with a relatively small sample size, making it suitable for large-scale and long-term mangrove monitoring [17].

TABLE 2.
VEGETATION FORMULA

Spektral Indeks	Formula	Sentinel 2 Band	
Normalized Difference Vegetation Index	$NDVI = \frac{NIR-RED}{NIR+RED}$	$NDVI = \frac{B8-B4}{B8+B4}$	(1)
Normalized Difference Water Index	$NDWI = \frac{GREEN-NIR}{GREEN+NIR}$	$NDWI = \frac{B3-B8}{B3+B8}$	(2)

This study used Random Forest to classify Sentinel-2 satellite images, utilizing 100 decision trees. Five samples were required for each tree leaf, and a sample fraction of 70% was used to construct each tree. The model was trained on training data with mangrove and non-mangrove classes, using selected Sentinel-2 image bands, including B2, B3, B4, and B8.

Several metrics were used to evaluate the Random Forest model's performance, including recall, Precision, F1 Score, and Validation Accuracy. The metrics evaluate how effectively the model categorizes the classes in the image, particularly the mangrove class (class 1). Precision measures the accuracy of optimistic predictions, while Recal indicates the proportion of actual positives correctly identified. F1 score measures the harmonic mean of Precision and Recall, providing a balanced assessment of the model's performance, and Validation Accuracy reflects the model's correct classification across all classes [21]. These metrics are critical for evaluating model effectiveness in a variety of applications, including mathematical question classification, plant disease recognition, and attention level identification [22].

The equation between Precision, Recall, and F1 score is as follows [23]:

$$Precision = \frac{True\ Positives}{\text{True Positives}+False\ Positives} \quad (3)$$

$$Recall = \frac{\text{True Positives}}{\text{True Positives + False Negatives}} \quad (4)$$

$$F1\ Score = 2\ \times \left(\frac{Precision\ \times Recall}{Precission + Recall}\right) \quad (5)$$

The F1 score provides a more accurate representation of the model's performance in cases of an imbalance between precision and recall. This study calculated Recall, Precision, and F1 score values for the mangrove class (class 1) to assess the model's effectiveness in identifying and classifying mangroves on Sentinel-2 satellite images. These Recall, Precision, and F1 scores provide a more in-depth picture of the model's performance distinguishing mangroves from non-mangroves, which is essential for accurately mapping mangrove vegetation. Validation Accuracy measures the overall success of the model in classifying the validation data, which is calculated by comparing the number of correct predictions to the total amount of data in the validation set.

After the mangrove cover was identified, the mangrove area was calculated using the formula :

$$mangrove\ area = \sum(pixel\ \times\ resolution) \quad (6)$$

This calculation was done using the reduce region method, which sums all mangrove pixel values within the study area. The results obtained can be used to analyze changes in mangrove cover and their impact on environmental and climate variability in the region. At this stage, mangrove classification is based on the range of NDVI values used to determine the density level. The spectral value of mangroves based on their density level shows significant differences in reflectance characteristics

TABLE 3.
VEGETATION FORMULA

Density Class	Min NDVI	Max NDVI
Solid	0,782	0,876
Medium	0,139	0,392
Sparse	-0,030	0,293

[24]. Mangrove vegetation is characterized by high reflectance values in the near-infrared (NIR) band and the highest absorption values in the blue-to-red spectral range. The average values of NDVI for each classification class and mangrove density are presented in Table 3.

After determining the mangrove density, carbon stock Estimation was conducted through mangrove biomass conversion. Biomass estimation does not rely on direct allometric data calculations in the field in this study but instead uses estimation formulas developed from previous research. [25] :

$$Biomass = 17{,}4 - 110{,}2 \times NDVI + 220 \times NDVI^2 \quad (7)$$

This formula relates NDVI (Normalized Difference Vegetation Index) values to mangrove biomass, enabling biomass estimation from satellite imagery. NDVI is a vegetation index used to measure plant health, where higher NDVI values indicate better vegetation levels. In this case, the higher the NDVI value, the greater the biomass value that can be estimated for the mangrove cover.

Once the biomass is calculated, in Figure 5, carbon stocks can be estimated by multiplying the biomass value obtained by a carbon conversion factor. According to chemical composition analysis, the carbon fraction in mangrove biomass is close to 46.82%. For specific mangrove species, they recommended using 46.3% for B. gymnorrhiza, 45.9% for R. apiculata, and 47.1% for S. alba [26]. The study used a factor of 0.47 to convert carbon stocks; a factor of 0.47 is commonly used to convert biomass to carbon stocks in forest ecosystems [27].

$$Carbon\ Stock = Biomass \times 0{,}47 \quad (8)$$

Based on ratios found in mangrove ecosystem studies, a factor of 0.47 was used to convert mangrove biomass to carbon stock. This estimates the amount of carbon stored in the identified mangrove ecosystem.

After obtaining the carbon stock estimation results, the next step is to process climate data, which includes precipitation, air temperature at the height of two meters (2-meter Temperature), and Sea Surface Temperature (SST). These data were obtained from the GSMaP source for precipitation and ECMWF for 2m Temperature and SST. These three parameters are crucial because they significantly impact mangrove growth and vegetation density. The data obtained were then processed and visualized using QGIS software, which allows spatial analysis and integration with carbon stock data to understand the relationship between climate variability and mangrove ecosystem dynamics.

III. RESULTS AND DISCUSSION

The Random Forest method has been proven to be an effective technique for land cover classification using satellite imagery [28]. A study using Random Forest and Sentinel-2 imagery in Google Earth Engine demonstrated its effectiveness in rapid land cover mapping, with 88.32% accuracy for a 5-class classification scheme [29]. These studies collectively highlight the robustness and accuracy of the Random Forest method in classifying land cover across various geographical contexts.

The performance of this deep learning model is reflected in Table 4. The table shows that the model performance varies yearly, with different Recall, Precision, F1 Score, and Validation Accuracy values. The results differ annually, with lower F1 score values recorded in 2020 and 2021. In contrast, the highest F1 score was in 2022, reaching 0.8544. This variation in model performance indicates fluctuations in the quality of model predictions from year to year. This may be due to certain factors affecting the quality of input data and the estimation process.

The decrease in F1 scores in 2020 and 2021 may be attributed to several factors related to using secondary data from Sentinel-2A imagery. One of the leading causes is the potential error in the satellite data during this period. Several factors may contribute to these errors, including atmospheric effects such as scattering and absorption by aerosols or water vapor, as well as cloud contamination that can compromise the accuracy of NDVI values. In addition, sensor calibration issues, spatial resolution that may not be able to capture vegetation heterogeneity at small scales, and temporal resolution that may miss short-term changes in vegetation also pose challenges. All these factors can affect the biomass estimates calculated from

TABLE 4.
MODEL PERFORMANCE

Year	Recall	Precision	F1 Score	Validation Accuracy
2019	0.6605	0.9020	0.7626	0.87776
2020	0.5068	0.5237	0.5154	0.77098
2021	0.4975	0.6116	0.5486	0.79658
2022	0.7813	0.9437	0.8544	0.7784
2023	0.7790	0.8647	0.8190	0.8020

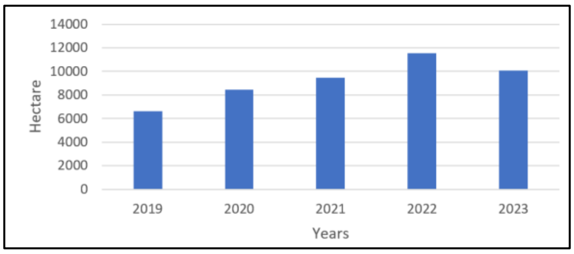

Figure. 3. Mangrove Distribution Area

the NDVI values, resulting in a decrease in model performance in specific years.

Despite the relatively low F1 score in 2020 and 2021, the model still showed good accuracy. Validation accuracy in both years was recorded at 0.77098 in 2020 and 0.79658 in 2021, indicating that the model could perform classification with a reasonably high success rate on the validation data. This shows that even as the balance between precision and recall, as represented by the F1 score, decreases, the model's accuracy remains a key indicator of good performance.

This validation accuracy value can be interpreted as the model successfully identifying common patterns in the data, even if the precision or recall is not always optimal. Thus, the model's overall performance remains reliable for mangrove cover analysis and biomass estimation despite technical challenges with the input data from satellite imagery in specific years. These results demonstrate the importance of considering multiple evaluation metrics simultaneously to get a comprehensive picture of model performance.

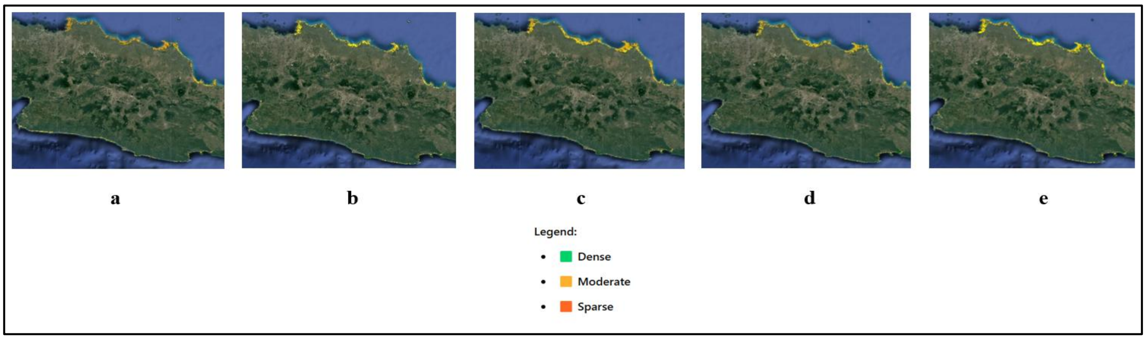

Figure. 4. Mangrove Density in West Java from 2019 to 2023 (a – e).

Figure 3 shows the development of the mangrove distribution area from 2019 to 2023. The mangrove area recorded a significant increase during this period. The most notable growth occurred in 2022, reaching more than 11,000 hectares. However, in 2023, it slightly decreased to 10,000 hectares. This indicates a significant effort in maintaining and restoring the mangrove ecosystem.

Figure 4 presents the dynamics of mangrove density change over the last five years, which can be used to identify patterns of mangrove degradation or regeneration in the coastal areas of West Java. Based on the data shown, mangrove density has increased yearly. In 2019, the sparse category still dominated the mangrove density class, but in subsequent years, the density increased to the moderate category. This increasing trend indicates the potential for mangrove regeneration in the area, which could indicate a successful rehabilitation program or natural factors that support mangrove growth. In addition, this information can serve as a basis for policy-making related to the conservation and rehabilitation of mangrove ecosystems in the area.

Mangroves exhibit varied responses to nutrient enrichment, with some species exhibiting increased growth while others experience adverse effects or no significant change [30]. Anthropogenic nitrogen and phosphorus inputs from agricultural, aquaculture, and urban runoff impact mangrove ecosystems, potentially affecting their resilience to climate change and carbon

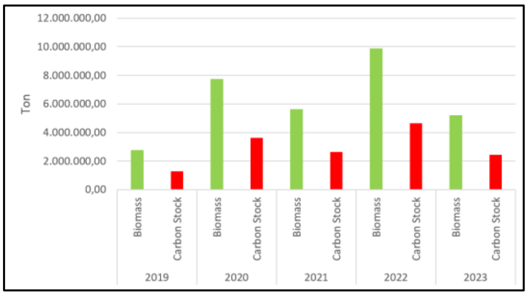

Figure. 5. Biomass and Carbon Stock Graph

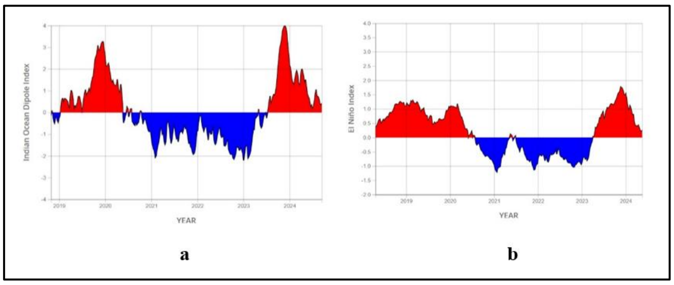

Figure. 6. (a) IOD Graph, (b) ENSO Graph
Source : *sealevel.jpl.nasa.gov*

storage capacity [31]. In coastal waters, nutrient profiles directly affect mangrove composition and growth, with lower nutrient content correlating with reduced mangrove growth [32]. Interestingly, bacteria isolated from mangrove environments show potential as plant growth-promoting inoculants, potentially reducing the need for synthetic fertilizers in agricultural applications [33].

Figure 5 compares mangrove biomass and carbon stocks over the same period. Biomass and carbon stocks exhibit a parallel pattern, where an increase in biomass always accompanies an increase in carbon stocks. Biomass fluctuated with the highest value recorded in 2022 at 9,883,964.17 tons, along with the largest area of 11,527 Ha. In contrast, 2019 recorded the lowest biomass of 2,780,307.83 tons in 6,597 Ha. Carbon stocks exhibited a similar pattern to biomass, with the highest value of 4,645,463.16 tons in 2022 and the lowest value of 1,306,744.68 tons in 2019. Despite the large size of the area, the decrease in biomass and carbon stocks by 2023 indicates the possibility of environmental change or degradation of mangrove vegetation. This highlights the importance of maintaining the ecosystem to maximize potential biomass and carbon stocks. Climate dynamics influence carbon stocks in mangrove ecosystems. Indonesia's climate is significantly influenced by the El Nino-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD). These phenomena primarily affect precipitation patterns, with impacts being most substantial during the dry season and weaker in the wet season [34]. ENSO impacts Indonesia's northern and eastern regions independently, while the IOD independently affects the southern and western areas [34]. Adverse IOD events are associated with higher precipitation and more extensive and longer mesospheric-scale convective complexes [35]. ENSO and IOD also affect sea surface temperature (SST) in Indonesian seas, with ENSO having a more substantial effect on the Java Sea [36]. These climate modes shape Indonesia’s weather patterns and hydrometeorological conditions. Figure 6 shows the diverse dynamics of IOD and ENSO. 2019 experienced a strong positive IOD, accompanied by a weak El Niño. In 2020, the IOD was neutral, while a moderate La Niña occurred. The La Niña trend continues in 2021 with weak to moderate intensity, while the IOD remains neutral. 2022 exhibits stable ENSO and IOD conditions in a neutral phase with no significant anomalies. Entering 2023, the IOD remains neutral, but a weak El Niño develops. The variations in IOD and ENSO during the 2019-2023 period certainly affected atmospheric and oceanic conditions in Indonesia. Changes in these two phenomena can be reflected in the three parameters used in the analysis: precipitation, 2-meter Temperature, and Sea Surface Temperature (SST).

The classification of precipitation parameters is as in Table 5, based on the Minister of Forestry Decree No. 837/UM/II/1980 and No. 683/KPTS/UM/1981.

In Figure 7, the dominance of lighter colors with an intensity of 2700 mm/year 2019 indicates precipitation in the medium category. Between 2020 and 2022, the intensity of the red color increased, reflecting a significant rise in rainfall due to La Niña, with intensities reaching 3300-3900 mm/year, falling within the high to very high category. However, in 2023, the color returns to a lighter shade, indicating a drastic decrease in precipitation with intensity to 1800 mm/year as El Niño returns. This pattern confirms the close relationship between ENSO dynamics and precipitation variability in the study area.

Figure 7 shows the pattern of annual temperature changes in the analyzed area. The color scale on the map indicates a temperature range of 21°C to 29°C, with lighter colors representing higher temperatures and darker colors representing lower temperatures. Generally, the temperature distribution pattern exhibits a relatively consistent trend from year to year, with high-temperature

TABLE 5.
THE CLASSIFICATION OF PRECIPITATION PARAMETERS

Class	Precipitation (mm/year)	Classification	Score
1	1500 - 2000	Very Low	10
2	2000 - 2500	Low	20
3	2500 - 3000	Medium	30
4	3000 - 3500	High	40
5	3500 - 4000	Very High	50

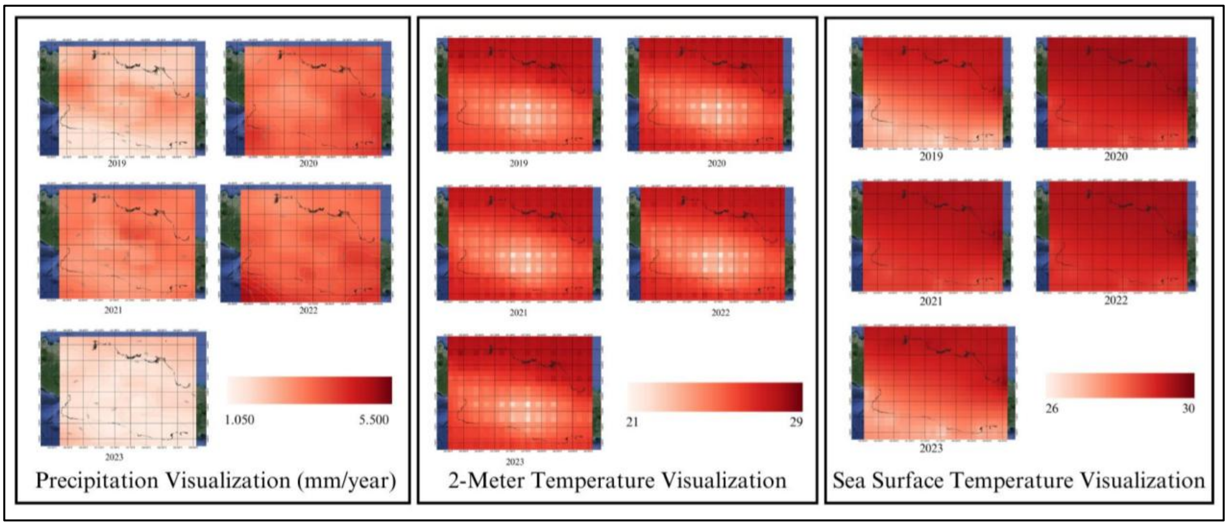

Figure. 7. Visualization

areas tending to stabilize in the central part of the region. In contrast, lower temperatures are scattered in the periphery, especially in areas bordering waters.

Figure 7 shows the SST distribution in West Java over five years from 2019 to 2023. The color scale ranges from 26 to 30 degrees Celsius, with lighter shades indicating lower temperatures and darker shades indicating higher temperatures. The map shows that this region's sea surface temperature (SST) tends to be higher in the north and slightly lower in the south. The SST distribution pattern generally shows consistency from year to year, although slight variations exist. Although global studies indicate a positive relationship between carbon density and precipitation, this correlation is not consistently observed in regional comparisons. Sediment depth, influenced by long-term geomorphological processes, is crucial in determining carbon stocks. [34].

Figure 8 shows the relationship between precipitation and average carbon stock. The linear regression results indicate a positive correlation, as shown by the equation y = 89.188x + 1069, with a coefficient of determination (R^2) of 0.5514. This suggests that the higher the average carbon stock, the higher the precipitation in the region, although other factors also influence this relationship. Figure 9 illustrates the relationship between average carbon stock and air temperature at a height of 2 meters. The linear regression results indicate a negative relationship, as the equation y =- 0.3165x + 29.48, with an R-squared value of 0.8242. This suggests that higher carbon stocks are generally associated with lower air temperatures, exhibiting a substantial correlation. Figure 10 illustrates the relationship between average carbon stock and sea surface temperature (SST). The relationship is also negative, with the equation y =- 0.2306x + 30.766 and R^2 = 0.7111. This suggests increased carbon stock is associated with lower sea surface temperatures (SST) in the study area.

This study discusses carbon stock estimation and employs a quantitative approach, using linear regression analysis, to determine the relationship between carbon stocks and climate variability in West Java. This area has not been widely studied in this context. Fluctuations in these factors can reflect the dynamics of mangrove growth and productivity in absorbing and storing carbon. In general, the results of this study indicate that carbon

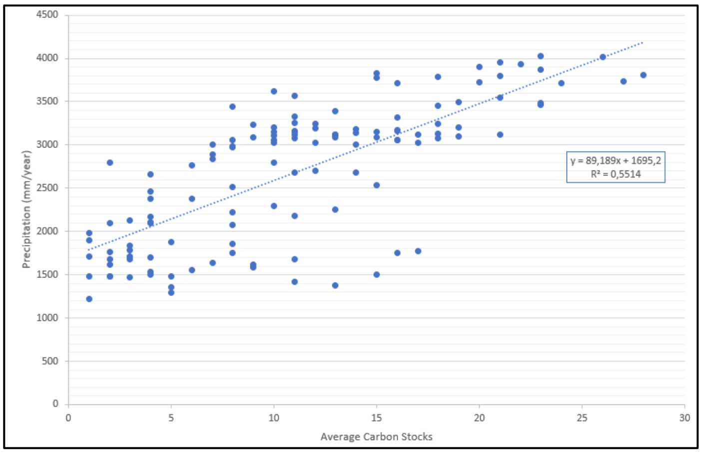

Figure. 8 Graph of the Correlation Carbon Stock and Precipitation

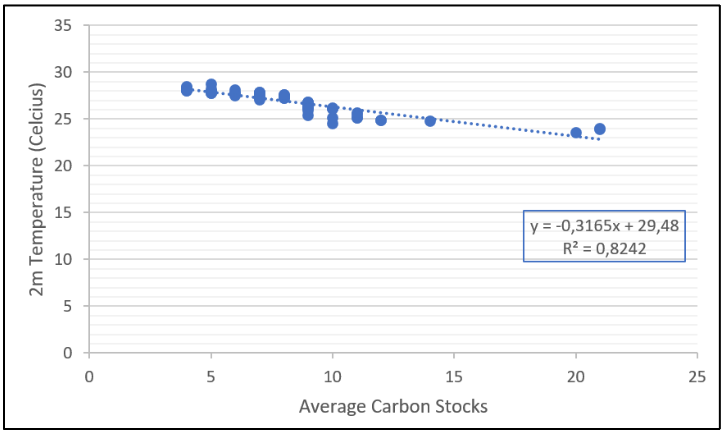

Figure. 9. Graph of the Correlation Carbon Stock and 2-meter Temperature

stocks tend to increase with increasing precipitation, with an R^2 of 0.5514, suggesting a moderate relationship between these two variables. However, other factors, such as environmental conditions and human activities, may also contribute to the dynamics of carbon stocks in mangrove ecosystems. However, there was an anomaly in 2021, when the mangrove area increased, but carbon stocks decreased. This may be influenced by a decrease in precipitation compared to the previous year and other factors, such as errors in data processing, which are reflected in the low F1-score values in 2020 and 2021.

Besides precipitation, air temperature at 2 meters height (2-meter Temperature) also relates to carbon stocks. The linear regression results show a negative correlation with the equation $y = -0.3165x + 29.48$, with an R-squared value of 0.8242. This indicates that the higher the carbon stock, the lower the air temperature in the region. This can be attributed to the role of mangrove ecosystems in sequestering carbon and lowering ambient temperatures through evapotranspiration, as well as the increased humidity generated by denser mangrove forests.

A similar negative relationship was also found between carbon stock and Sea Surface Temperature (SST), with the equation $y = -0.2306x + 30.766$ and an R^2 value of 0.7111. The higher the carbon stock, the lower the SST in the study area. The decrease in SST associated with higher carbon stocks can be attributed to increased mangrove cover, which reduces heat runoff into coastal waters and increases the infiltration of rainwater into the soil, ultimately helping to maintain thermal balance in the surrounding environment.

These results show that precipitation, 2-meter temperature, and Sea Surface Temperature influence carbon stocks in mangrove ecosystems. This suggests that mangrove ecosystems play a crucial role in regulating environmental temperatures and are a potential factor in mitigating climate change. However, the variability of the data also suggests that other contributing factors, such as environmental conditions, salinity, and human activities, can affect the balance of this ecosystem. Therefore, a comprehensive approach that considers various ecological factors is needed to holistically understand carbon stock dynamics in mangrove ecosystems.

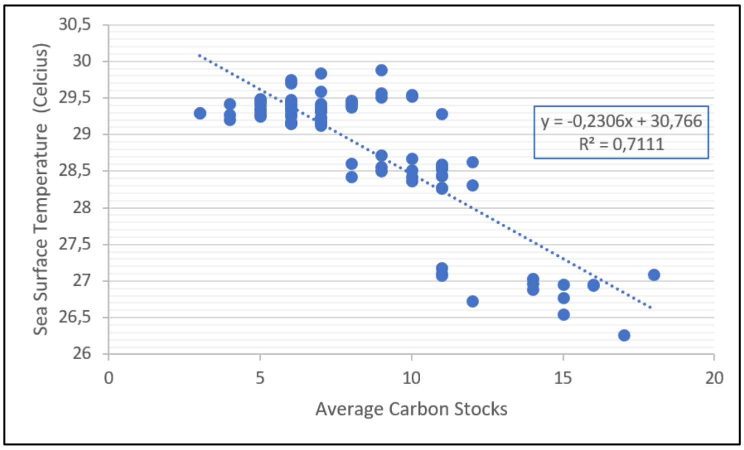

Figure. 10. Graph of the Correlation between Carbon Stock and SST

IV. Conclusion

This study utilized remote sensing and machine learning data to examine the relationship between mangrove carbon stocks and climate variability in West Java from 2019 to 2023. Land cover classification using the Random Forest algorithm and NDVI and NDWI indices accurately identified mangrove ecosystems. Carbon stock estimation results indicate that precipitation has a positive correlation with carbon stock ($R^2 = 0.5514$), while 2-m temperature ($R^2 = 0.8242$) and sea surface temperature ($R^2 = 0.7111$) exhibit a negative correlation, suggesting that rising temperatures can stress mangrove ecosystems and reduce their carbon sequestration capacity. Linear regression analysis demonstrated that climate variability plays a significant role in the dynamics of mangrove carbon stocks. Remote sensing and machine learning proved to be effective methods for large-scale and long-term mapping of mangrove ecosystems.

This study emphasizes the crucial role of stable climatic conditions in maintaining mangrove productivity and underscores the importance of integrated conservation strategies in enhancing mangrove resilience to climate variability. Using Random Forest algorithms and Sentinel-2 satellite imagery proved a practical approach for accurate mangrove classification and biomass estimation. The research also demonstrates that remote sensing technologies and machine learning models provide a reliable method for large-scale and long-term monitoring of mangrove ecosystems.

To ensure the sustainability of mangrove ecosystems and their carbon sequestration capabilities, it is crucial to implement and strengthen conservation and restoration programs, particularly in areas vulnerable to temperature stress and environmental degradation. Policymakers should integrate climate variability considerations into coastal management plans to mitigate the adverse effects of rising air and sea surface temperatures on mangroves. Advancements in remote sensing technology, combined with additional environmental parameters such as soil salinity and nutrient profiles, are recommended to enhance the accuracy of carbon stock estimations. Engaging local communities in mangrove conservation initiatives is crucial for promoting sustainable management practices and increasing awareness of the ecological benefits of mangroves. Furthermore, establishing long-term monitoring programs will facilitate the continuous assessment of climate impacts on mangrove carbon stocks, ensuring that comprehensive, real-time data inform adaptive management strategies. These measures will safeguard mangrove ecosystems, enhance their resilience to climate variability, and support their role in mitigating climate change and preserving coastal biodiversity.

The research highlights the urgent need for coordinated efforts to protect mangrove ecosystems as vital carbon sinks, ensuring their long-term contributions to climate change mitigation and coastal biodiversity preservation.

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