

# Spatial Analysis of the Economic Valuation of Mangrove Carbon Stocks in Banda Aceh City

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**Abstract:** Climate change or global warming is caused by an increase in Earth's surface temperature due to the greenhouse effect, with carbon dioxide (CO<sub>2</sub>) as the primary contributor. Rising CO<sub>2</sub> levels trigger atmospheric warming, sea level rise, agricultural disruptions, and more intense storms. Carbon absorption from the atmosphere can be achieved through mangrove forests, which serve as natural carbon sinks. However, mangrove deforestation leads to carbon release. This study aims to measure carbon stock and the economic value of mangroves along the coast of Banda Aceh City using NDVI analysis. The results indicate that the lowest carbon value is  $2.49505 \times 10^{-6}$  tons per hectare, demonstrating very limited carbon storage capacity in certain areas. The total economic value of carbon stocks in four mangrove areas is Rp 2,400,026,446. This study is expected to provide insights into global warming, support the role of mangroves as carbon sinks, and serve as a foundation for further research on climate change.

**Keywords:** Carbon; Climate change; Economic value; NDVI

## Introduction

Global warming is considered one of the key issues of climate change. It is defined as the increase in Earth's temperature caused by the entrapment of long-wave solar radiation due to the greenhouse effect. Greenhouse gases (GHGs) responsible for this effect include CO<sub>2</sub>, CFCs, N<sub>2</sub>O, CH<sub>4</sub>, and O<sub>3</sub>. Among these, CO<sub>2</sub> is believed to be the most significant contributor, accounting for 50% of the greenhouse effect (Bindu et al., 2020).

One of the mitigation strategies to reduce global warming caused by GHG emissions is enhancing the role of mangroves as carbon sinks. The carbon stored in biomass represents the potential of mangroves to sequester and store carbon (carbon stock) (Irsadi et al., 2015).

Reducing carbon emissions, which contribute to greenhouse gases (GHGs), can also be achieved through the carbon market economy. The value of carbon services reflects the willingness of society to pay in order to avoid the damage caused by rising carbon emissions

(Farahisah et al., 2021). The economic value of mangrove ecosystems can serve as a fundamental reference for formulating sustainable mangrove ecosystem management policies, ensuring the preservation of mangrove forest areas (Kepel et al., 2017).

Mangrove forests cover only 0.4% of the world's total forest area. However, according to the updated National Mangrove Map (PMN) in 2021, Indonesia has approximately 3.3 million hectares of mangrove forests, representing 23% of the global mangrove ecosystem (Giri et al., 2011).

Mangroves provide numerous benefits, including serving as a food source, wildlife habitat, coastal protection, and a highly efficient carbon sink. They absorb and store CO<sub>2</sub> from the atmosphere through photosynthesis at a significantly higher rate than other forest types (Hastuti et al., 2018).

The potential mangrove areas in Banda Aceh City are distributed across several regions, including Kuta Radja and Kuta Alam (Rahmah, 2014), Syiah Kuala (Utami et al., 2021), and Meuraksa (Rahmi et al., 2019).

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Before the 2004 tsunami, mangrove forests in Banda Aceh grew naturally along the coastline, contributing to the preservation of the ecosystem. However, after the tsunami, replanting efforts were carried out while maintaining the existing mangrove species. As a result, it is essential to assess the carbon stock in these mangrove areas (Saputra et al., 2016). This study employs a remote sensing approach (Rafdinal et al., 2022) and further analyzes the data using ArcGIS (Nesperos, 2021).

Traditional field measurement techniques are the most accurate method for collecting biomass data. However, this approach is often time-consuming and difficult to implement, especially in remote areas. Additionally, it does not provide the spatial distribution of biomass over large areas (Lu, 2006).

Therefore, remote sensing can serve as a highly effective tool for monitoring mangrove ecosystems, as it allows for large-scale coverage, is cost-efficient, and can be conducted periodically (Hendrawan et al., 2018). The use of remote sensing technology provides valuable information for estimating the potential of mangrove vegetation as a CO<sub>2</sub> sink, enabling effective and efficient monitoring (Cahyaningrum & Hartoko, 2014).

Research on estimating stored carbon stock in mangrove vegetation is essential to determine the capacity of mangrove forests in absorbing and storing carbon from the atmosphere. This information supports sustainable and long-term ecosystem management efforts in relation to mitigating the effects of global warming.

There is a strong correlation ( $R^2 = 0.728$ ) between vegetation indices derived from satellite data and estimated carbon stock calculated using allometric equations (Sugianto, 2016). This high coefficient of determination indicates that satellite data is reliable for estimating carbon stock. Numerous studies have already utilized remote sensing techniques to measure carbon stock in mangrove vegetation (Anand, 2020; Bindu, 2020; Hastuti et al., 2018; Schadu, 2021).

Therefore, this study aims to further explore the Valuation of Mangrove Carbon Stock in the Coastal Areas of Banda Aceh City.

## Method

Using remote sensing methods, we can monitor carbon in mangrove ecosystems through Vegetation Index Analysis (NDVI) and satellite imagery sourced from Google Earth Engine to detect changes in land cover and mangrove vegetation. Meanwhile, the economic valuation of carbon is conducted by applying Carbon Pricing, including emissions trading systems, to calculate the economic value of carbon storage or emission reduction derived from mangrove ecosystems.

This study will be conducted in Banda Aceh City, covering several districts, including Kuta Radja, Kuta Alam, Syiah Kuala, and Meuraksa (Figure 1).

The tools used in this study include a laptop and ArcMap software version 10.8 with ArcToolbox support. The materials used consist of a shapefile of the district boundaries of Kuta Radja, Kuta Alam, Syiah Kuala, and Meuraksa in Banda Aceh City, as well as Sentinel-2A satellite imagery (Surface Reflectance) obtained from Google Earth Engine (GEE).

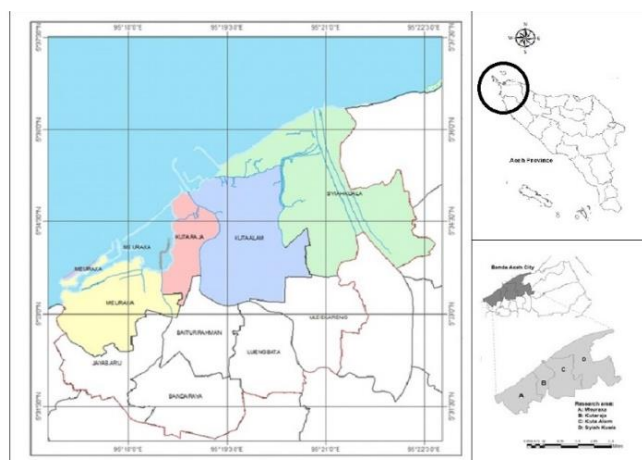


Figure 1. Research location

### *Accessing Sentinel-2A Satellite Imagery (Surface Reflectance) in Google Earth Engine (GEE)*

This study utilizes the Sentinel-2A dataset from January 1, 2023, to August 1, 2024, to generate a mangrove land cover map for four districts in Banda Aceh City. The data is accessed through Google Earth Engine (GEE) using JavaScript, which incorporates shapefiles of the four districts under study, Sentinel-2A imagery within the specified time range, and selected spectral bands essential for mangrove monitoring. These bands include Band 2 (Blue), Band 3 (Green), Band 4 (Red), Band 8 (Near-Infrared/NIR), and Band 11 (Shortwave Infrared 1/SWIR 1). The combination of these spectral bands allows for effective vegetation analysis, aiding in the identification and distinction of mangrove areas from other land cover types.

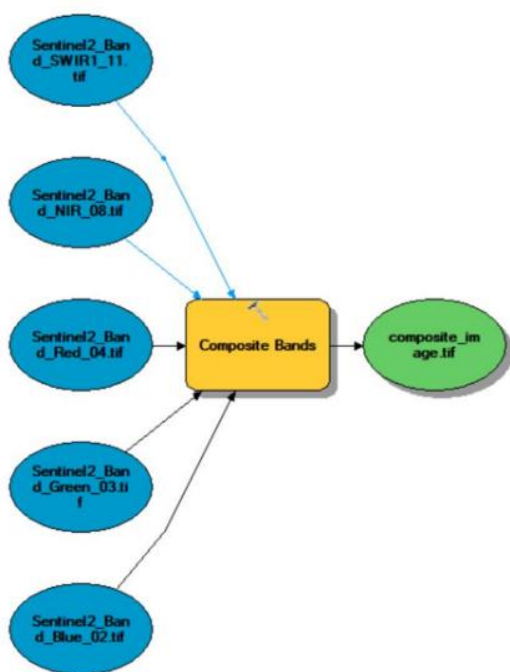
Radiometric correction is performed by combining and standardizing the colors of multiple images into a unified dataset, both digitally and visually. Raw satellite imagery is processed using ArcGIS software to enhance its quality. Meanwhile, atmospheric correction is carried out using the dark pixel correction method.

The Sentinel-2A imagery composite is generated using ArcGIS software. The process begins by importing the five downloaded spectral bands. Then, a composite image is created using the composite bands (data management) tool, where the raster bands are arranged in order from the shortest to the longest wavelength:



Band 2 (Blue), Band 3 (Green), Band 4 (Red), Band 8 (Near-Infrared/NIR), and Band 11 (Shortwave Infrared 1/SWIR 1). Once the bands are composited, three key bands (NIR, SWIR, and Red) are selected in the symbology menu within the properties settings to identify mangrove areas. Finally, mangrove classification is performed using the Iso Cluster Unsupervised Classification method.

Classification is used to distinguish mangrove land cover from other land types, such as fish ponds, settlements, land areas, shallow waters, and deep seas (Aswin et al., 2021). Additionally, the mangrove area calculation is processed in a distribution table, where the digitized mangrove polygons are automatically measured using the geometry calculate function (Irawan & Malau, 2016). The mangrove area is presented in the International System of Units (SI), specifically in hectares (ha).



**Figure 2.** Composite model builder of sentinel 2A image data was done using ArcGIS software

In remote sensing analysis, satellite image processing often requires the combination of multiple spectral bands to extract richer information. ModelBuilder in GIS software, such as ArcGIS, automates processing by structuring an efficient workflow. A recent study by Velamala et al. (2024) developed a new ArcGIS toolbox to automatically generate soil fertility distribution maps using ModelBuilder. Their research demonstrates that ModelBuilder enables non-GIS users to produce spatial maps more easily.

Through ModelBuilder, users can import various satellite image bands, merge them into a band composite, and systematically manage data. This process is highly beneficial for environmental analysis, such as mangrove ecosystem monitoring, where band composites are used to identify land cover changes and vegetation conditions. This approach enhances data analysis by making it faster, more accurate, and easily replicable for various research or natural resource management applications.

The composited satellite imagery remains in raster format, requiring conversion to vector format for further analysis. This is done using the Raster to Polygon tool found in the search menu. The processed mangrove area composite is then converted and stored as a vector file (shapefile/.shp) for further spatial analysis and mapping.

At this stage, image clipping is performed based on the Area of Interest (AOI) to reduce data size, making it easier for the computer to process (Syamsu et al., 2018). Additionally, AOI-based image clipping helps delineate the study area boundaries in Banda Aceh for more focused analysis.

A ground survey (ground check) is essential to verify real-world conditions and compare them with the mangrove cover detected from satellite imagery for data validation. The field survey also aims to assess the condition of the mangrove forest, surrounding buildings, and residential areas (Irawan & Malau, 2016). Ground checks are conducted using Global Positioning System (GPS) devices and cameras to document field observations (Fikri et al., 2021).

The NDVI analysis is conducted in ArcGIS using ModelBuilder, where the NIR band and Red band are incorporated into the toolbox directory. The NDVI calculation is then performed using the Raster Calculator, where the NDVI formula is applied to generate vegetation index values.

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

*Calculation of Land Cover Using the Normalized Difference Vegetation Index (NDVI)*

The NDVI (Normalized Difference Vegetation Index) is a calculation based on the reflectance of visible light and near-infrared (NIR) by vegetation. The pixel classification values for NDVI range from -1 to 1. Low NDVI values (negative) indicate areas such as water bodies, rocks, sand, and snow, while high NDVI values (positive) correspond to vegetated areas such as savannas, shrubs, and forests. NDVI values close to 0 typically represent bare land. The NDVI algorithm used in this study follows the approach of Huang et al. (2021).



### Calculation of Mangrove Carbon Stock Using Model Builder

The calculation of mangrove carbon stock is performed in ArcGIS by analyzing vegetation indices, below-ground biomass, above-ground biomass, total biomass accumulation, total carbon stock, and

mangrove carbon sequestration. The process involves integrating vegetation indices with biomass data to estimate the total carbon stock stored in mangrove ecosystems.

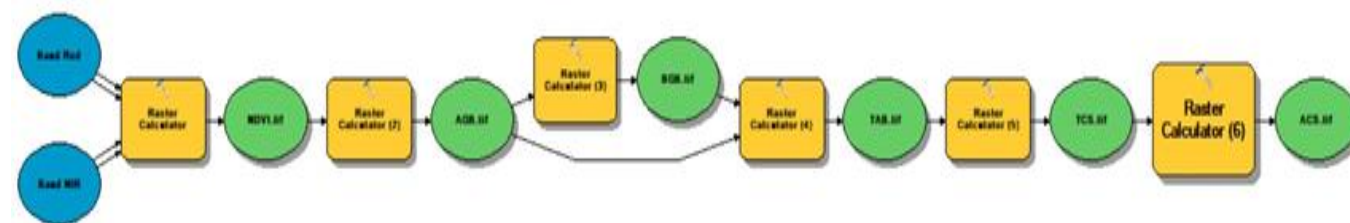


Figure 3. Calculation of mangrove carbon stock using model builder

#### Estimation of Above-Ground Biomass (AGB)

The estimation of above-ground biomass (AGB) is conducted using the NDVI-based correlation equation for mangrove biomass, with a coefficient of 0.787, as proposed by Jha et al. (2015):

$$AGB = 305.9 \times NDVI^{4.864} \quad (2)$$

Where:

NDVI = Vegetation Index value

AGB = Above-Ground Biomass value (ton ha<sup>-1</sup>)

#### Estimation of Below-Ground Biomass (BGB)

The below-ground biomass (BGB) is estimated from the calculated AGB using the following equation:

$$BGB = \text{Exp}(-1.0587 + 0.8836 \times \text{Ln}(AGB)) \quad (3)$$

Where:

AGB = Above-Ground Biomass (ton ha<sup>-1</sup>)

BGB = Below-Ground Biomass (ton ha<sup>-1</sup>)

#### Calculation of Total Accumulated Biomass (TAB)

The total accumulated biomass (TAB) is formulated as:

$$TAB = AGB + BGB$$

Where:

TAB = Total Accumulated Biomass (ton ha<sup>-1</sup>)

#### Calculation of Total Carbon Stock (TCS)

The total carbon stock (TCS) is calculated using the following formula:

$$TCS = TAB \times \%C_{\text{Organic}} \quad (4)$$

Where:

TCS = Total Carbon Stock (ton C ha<sup>-1</sup>)

TAB = Total Accumulated Biomass (ton ha<sup>-1</sup>)

%C<sub>Organik</sub> = Percentage of stored organic carbon (0.47) or based on laboratory measurements.

#### Economic Valuation of Mangrove Carbon Stock

The economic value of mangrove carbon stock is determined by integrating carbon sequestration data with carbon pricing models, including emissions trading systems and market-based carbon credit valuation. This approach helps assess the financial benefits of mangrove conservation in relation to global climate change mitigation.

The value of carbon traded in the global carbon market aims to offset greenhouse gas (GHG) emissions released into the atmosphere as a result of human activities. Through the purchase of carbon credits, buyers can compensate for their carbon emissions (Maharia et al., 2020).

The estimation of the economic value of carbon storage uses pricing approaches from both the voluntary and mandatory markets, including the Clean Development Mechanism (CDM). The global estimation of carbon storage's economic value varies depending on the market mechanisms applied.

The carbon price estimation used in determining the economic valuation of mangroves refers to the Global Social Cost of Carbon, with a fixed price of \$50 per ton of carbon (Hafli & Samiaji, 2024). The valuation formula is as follows:

$$\text{SUM} / 100 \times \$50 \times \text{Rupiah exchange rate} \quad (5)$$

Where:

SUM = Total carbon stock area measured in pixel units from Sentinel-2A imagery

100 = Conversion factor of Sentinel-2A pixels to hectares

\$50 = Carbon price, approximately \$50 per ton of carbon per hectare

## Result and Discussion

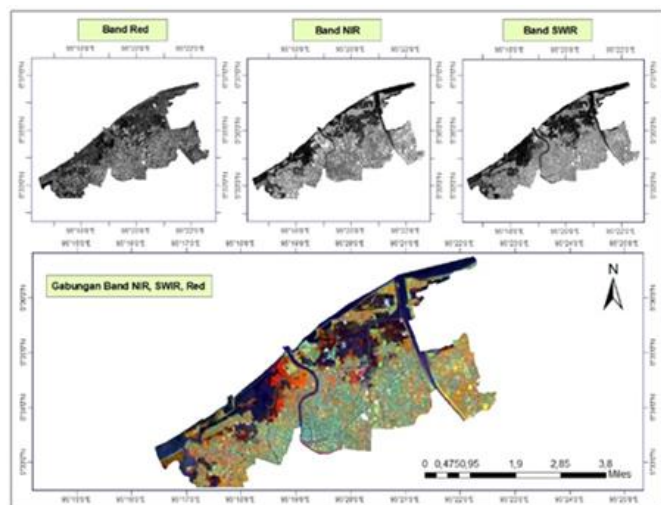
### Mangrove Area Image Processing

Sentinel-2B imagery was downloaded for free via Google Earth Engine (GEE), a comprehensive platform



for accessing global remote sensing data. In this study, the imagery was processed using ArcGIS software, which is widely recognized for its advanced spatial analysis capabilities.

The image processing workflow included several key stages, such as pre-processing, band combination, and spectral analysis. ArcGIS was utilized to extract more detailed information from the imagery, enabling accurate object identification for mangrove vegetation analysis. Figure 4 presents the results of Sentinel-2B image processing used in this study.



**Figure 4.** Band Combination for mangrove area processing with brick-red indication

After the image clipping process, the next step is to merge the images using the Composite Band technique. This technique involves combining two or more images with different spatial, spectral, or temporal resolutions to generate a more comprehensive and detailed image.

A method that enhances image quality by integrating the strengths of each original image (Wald, 1999). Using Composite Band, high-resolution images can be generated by merging multiple spectral bands, improving the accuracy of land cover classification and feature extraction.

The composite image is created by merging three spectral channels (bands) to produce red, green, and blue (RGB) colors. In this study, the image combination was performed using Band 4 (Red), Band 3 (Green), and Band 2 (Blue) to effectively separate vegetation from other objects. These three bands share the same spatial resolution of 10 meters, ensuring uniform image quality and analysis accuracy.

#### *Unsupervised Classification Processing*

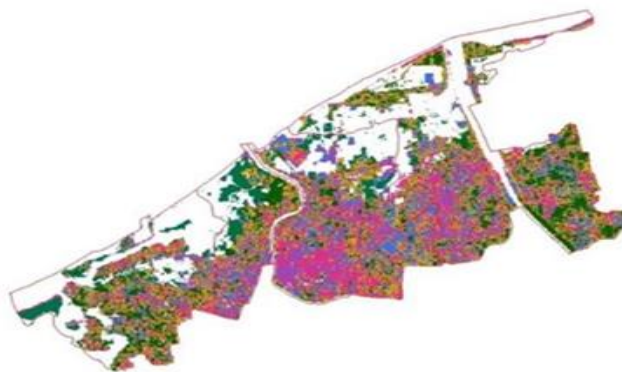
The distribution of mangrove areas resulting from Unsupervised Classification, as shown in Figure 2, indicates the presence of classification errors (bias). This

issue arises because non-mangrove vegetation is misclassified as mangrove.

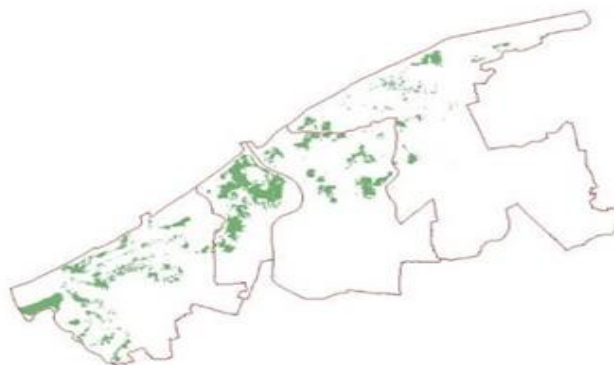
During the Unsupervised Classification process, the training area selection plays a crucial role in determining classification accuracy. However, since this method does not rely on pre-labeled training data, misclassification may occur, especially in areas where mangrove and non-mangrove vegetation share similar spectral characteristics.

In Unsupervised Classification, training areas are created on the imagery based on visual interpretation to group objects into specific classes. These training areas help in categorizing similar objects, ensuring better classification accuracy. The more training areas assigned to a particular class, the more precise the grouping becomes.

Training areas can be drawn in various polygon shapes, such as triangles, squares, or other polygons. From the classification results, only the mangrove areas are extracted to determine their distribution within the study area. The results of Unsupervised Classification (Figure 5) serve only as an initial reference for identifying key locations and guiding the selection of coordinate points for Supervised Classification, which provides a more accurate and refined classification of mangrove vegetation.



**Figure 5.** Unsupervised classification



**Figure 6.** Combined results of mangrove areas based on field verification



### Field Verification of Mangrove Conditions

Field verification of mangrove conditions was conducted by comparing vector-converted data with satellite imagery available on Google Earth. This process involves overlaying classified vector data onto Google Earth imagery to validate the accuracy of mangrove classification results. By using this method, we ensure that areas identified as mangrove in the image analysis genuinely correspond to actual mangrove areas, while also detecting potential misclassifications.

Field verification is crucial for improving mapping accuracy and supporting better decision-making in mangrove ecosystem management (Figure 6).

### Carbon Stock Distribution: High and Low Classes

The distribution of carbon stock classes was analyzed by focusing on mangrove areas with high and low carbon storage capacities. Carbon stock classes were categorized based on the intensity of carbon stored within different mangrove types. The analysis results are presented in Figure 7.

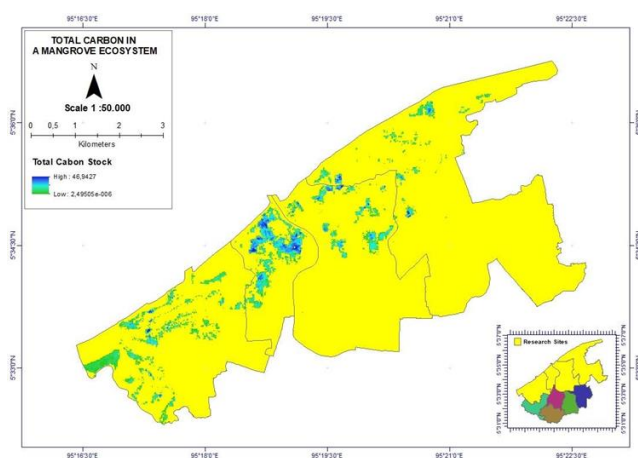


Figure 7. Distribution of high and low carbon stock classes

### Carbon Distribution in Mangrove Areas

Figure 7 provides a detailed visualization of carbon distribution within the mangrove ecosystem of Banda Aceh City. The low-carbon class has a total carbon stock of 46,927 tons, representing mangrove areas with reduced carbon storage capacity. These low-carbon areas often indicate declining mangrove health or productivity, leading to lower carbon sequestration potential.

The lowest carbon class recorded a value of  $2.49505 \times 10^{-6}$  tons per hectare (0.00000249505 tons per hectare), highlighting extremely minimal carbon storage capacity in specific mangrove regions. This category may include areas where the ecosystem is severely degraded or significantly affected by external factors, resulting in a limited ability to store carbon effectively.

Figure 7 clearly visualizes the contrast between low and the lowest carbon classes, offering essential insights into the carbon storage capacity of Banda Aceh's mangrove forests. This information serves as a critical reference for future conservation efforts and mangrove ecosystem restoration strategies.

### Stored Carbon Stock Value

Mangroves are vital ecosystems that play a crucial role in carbon storage and climate change mitigation. The economic value of carbon stock in the Kuta Alam mangrove area is Rp 470,622,878, demonstrating the area's significant contribution to total carbon stock valuation.

Meanwhile, the Kutaraja mangrove area recorded the highest economic carbon stock value, amounting to Rp 1,080,980,993. This indicates that Kutaraja's mangrove ecosystem holds the largest carbon storage potential, further emphasizing its importance in carbon sequestration and environmental sustainability (Figure 8).

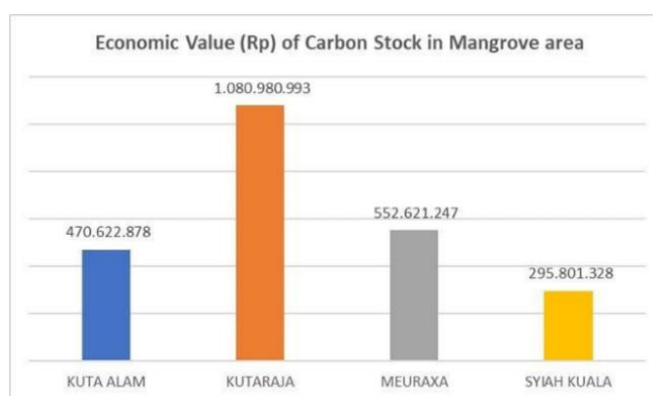


Figure 8. Economic value of mangrove carbon stock reserves

### Economic Value of Mangrove Carbon Stock

This value reflects the significant economic potential of carbon stock in Kutaraja, indicating its high carbon storage capacity. In Meuraxa, the economic value of carbon stock is recorded at Rp 552,621,247, demonstrating a substantial contribution to the total carbon stock value, although not as high as Kutaraja. Meanwhile, Syiah Kuala has the lowest economic carbon stock value among the analyzed areas, amounting to Rp 295,801,328. Despite being lower compared to other areas, this value still highlights the importance of Syiah Kuala in carbon storage efforts.

The total economic value of carbon stock across the four mangrove areas amounts to Rp 2,400,026,446. This comprehensive valuation provides an overview of the economic potential of stored carbon in the analyzed mangrove ecosystems. The data is crucial for mangrove conservation planning and management, emphasizing the significant economic benefits of these ecosystems.



and reinforcing the importance of conservation efforts to maintain and enhance their carbon storage capacity.

## Conclusion

For the lowest carbon class, the measured value is  $2.49505 \times 10^{-6}$  tons per hectare (0.00000249505 tons per hectare), indicating very low carbon storage capacity in certain mangrove areas. Meanwhile, the total economic value of carbon stock across the four mangrove areas is Rp 2,400,026,446, underscoring the economic significance of mangrove ecosystems in carbon sequestration.

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## Author Contributions

Writing—original draft, conceptualization, methodology, formal analysis, investigation, A.P.; writing—review and editing, validation, W.D. and D.S.; resources, data curation, preparation, A.P., W.D., and D.S. All authors have read and agreed to the published version of the manuscript.

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## Conflicts of Interest

The authors declare no conflict of interest.

## References

- Anand, A., Pandey, P. C., Petropoulos, G. P., Pavlides, A., Srivastava, P. K., Sharma, J. K., & Malhi, R. K. M. (2020). Use of hyperion for mangrove forest carbon stock assessment in Bhitarkanika forest reserve: A contribution towards blue carbon initiative. *Remote Sensing*, 12(4), 597. <http://dx.doi.org/10.3390/rs12040597>
- Aswin, Damar, A., & Yulianto, G. (2021). Kondisi Vegetasi Dan Perubahan Tutupan Lahan Ekosistem Mangrove Pulau Tanakeke Kabupaten Takalar Provinsi Sulawesi Selatan. *Jurnal Ilmu Dan Teknologi Kelautan Tropis*, 13(2), 305–318. <http://dx.doi.org/10.29244/jitkt.v13i2.33636>
- Bindu, G., Rajan, P., Jishnu, E. S., & Ajith Joseph, K. (2020). Carbon stock assessment of mangroves using remote sensing and geographic information system. *Egyptian Journal of Remote Sensing and Space Science*, 23(1), 1–9. <https://doi.org/10.13057/biodiv/d250941>
- Cahyaningrum, S., & Hartoko, A. (2014). Biomassa Karbon Mangrove pada Kawasan Mangrove Pulau Kemujan Taman Nasional Karimunjawa Mangrove Carbon Biomass at Kemujan Island, Karimunjawa Nasional Park Indonesia. *Management of Aquatic Resources Journal*, 3(3), 34–42. <https://doi.org/10.14710/marj.v3i3.5513>
- Farahisah, H., Yulianda, F., & Effendi, H. (2021). Struktur Komunitas, Cadangan Karbon, dan Estimasi Nilai Ekonomi Mangrove di Muara Sungai Musi. *Jurnal Ilmu Pertanian Indonesia*, 26(2), 228–234. <https://doi.org/10.18343/jipi.26.2.228>
- Fikri, A. S., Setiawan, F., Violando, W. A., Muttaqin, A. D., & Rahmawan, F. (2021). Analisis Penutupan Lahan menggunakan Google Earth Engine (GEE) dengan Metode Klasifikasi Terbimbing (Studi kasus: Wilayah Pesisir Kabupaten Lamongan, Provinsi Jawa Timur). *Prosiding FIT ISI*, 89–98. Retrieved from <https://proceedings.undip.ac.id/index.php/isiundip2021/article/view/627>
- Giri, C., Ochieng, E., & Tieszen, L. L. (2011). Status and distribution of mangrove forests of the world using earth observation satellite data. *Global Ecology and Biogeography*, 20(1), 154–159. <http://dx.doi.org/10.1111/j.1466-8238.2010.00584.x>
- Haflil, R. D. M., & Samiaji, J. (2024). Profil Stok Karbon dan Valuasi Ekonomi Ekosistem Mangrove di Kabupaten Tapanuli Tengah, Provinsi Sumatera Utara. *Proceeding Technology*, 4(1), 84–93. <https://doi.org/10.31258/jipas.13.1.74-81>
- Hastuti, A., Suniada, K., & Islamy, F. (2018). Carbon Stock Estimation of Mangrove Vegetation Using Remote Sensing in Perancak Estuary, Jembrana District, Bali. *International Journal of Remote Sensing and Earth Sciences*, 14(2), 137. <http://dx.doi.org/10.15578/jkn.v14i1.6864>
- Hendrawan, Gaol, J., & Susilo, S. B. (2018). Studi Kerapatan dan Perubahan Tutupan Mangrove Menggunakan Citra Satelit di Pulau Sebatik Kalimantan Utara. *Jurnal Ilmu Dan Teknologi Kelautan Tropis*, 10(1), 99–109. <https://doi.org/10.29244/jitkt.v10i1.18595>
- Huang, S., Tang, L., Hupy, J. P., Wang, Y., & Shao, G. (2021). A Commentary Review on the use of Normalized Difference Vegetation Index (NDVI) in the Era of Popular Remote Sensing. *Journal of Forestry Research*, 32(1), 1–6. <https://doi.org/10.1007/s11676-020-01155-1>
- Irawan, S., & Malau, A. O. (2016). Analisis Persebaran Mangrove di Pulau Batam Menggunakan Teknologi Penginderaan Jauh. *Jurnal Integrasi*, 8(2), 179



- 80-87. Retrieved from <https://jurnal.polibatam.ac.id/index.php/JI/article/view/33>
- Irsadi, A., Martuti, N. K. T., & Nugraha, S. B. (2015). Estimasi Stok Karbon Mangrove di Dukuh. *Jurnal Sain Dan Teknologi*, 2, 119-128. <https://doi.org/10.22219/avicennia.v5i1.20569>
- Jha, C. S., Madugundu, R., Al-Gaadi, K. A., Tola, E., & Kayad, A. G. (2015). Estimation of gross primary production of irrigated maize using Landsat-8 imagery and Eddy Covariance data. *Saudi Journal of Biological Sciences*, 24(2), 410-420. <https://doi.org/10.1016/j.sjbs.2016.10.003>
- Kepel, T., Suryono, D. D., & Salim, H. (2017). Nilai Penting Dan Estimasi Ekonomi Simpanan Karbon Vegetasi Mangrove Di Kecamatan Kema, Sulawesi Utara. *Jurnal Kelautan Nasional*, 12(1), 19. <http://dx.doi.org/10.15578/jkn.v12i1.6170>
- Lu, D. (2006). The potential and challenge of remote sensing-based biomass estimation. *International Journal of Remote Sensing*, 27(7), 1297-1328. <https://doi.org/10.1080/01431160500486732>
- Maharia, A. S., Muhdar, M., & Hidayah, R. A. I. (2020). Penggunaan Certified Emission Reductions sebagai Bukti Objek Transaksi Carbon Crediting. *Jurnal de Jure*, 12(2), 18-31. <http://dx.doi.org/10.36277/jurnaldejure.v12i2.467>
- Nesperos, V. J. C., Villanueva, C. M. M., Garcia, J. E., & Gevaña, D. T. (2021). Assessment of blue carbon stock of mangrove vegetation in Infanta, Quezon, Philippines. *Ecosystems and Development Journal*, 11(1), 48-60. Retrieved from <https://ovcre.uplb.edu.ph/journals-uplb/index.php/EDJ/article/view/618>
- Rafdinal, Linda, R., & Raynaldo, A. (2022). Struktur Komunitas dan Potensi Cadangan Karbon di Kawasan Hutan Mangrove Desa Malek, Kecamatan Paloh, Kabupaten Sambas, Indonesia. *Aquatic Science & Management*, 10(1), 16-22. <https://doi.org/10.35800/jasm.v10i1.40062>
- Rahmah, F., Basri, H., & Sufardi. (2014). Potensi Karbon Tersimpan Pada Lahan Mangrove Dan Tambak Di Kawasan Pesisir Kota Banda Aceh. *Jurnal Manajemen Sumberdaya Lahan*, 4(1), 527-534. Retrieved from <https://jurnal.usk.ac.id/MSDL/article/view/7124>
- Rahmi, M. M., Najmi, N., Bahri, S., & Suriani, M. (2019). Analisis Alih Fungsi Lahan Mangrove di Kawasan Pesisir Kota Banda Aceh. *Journal of Aceh Aquatic Science*, 5(2), 40-51. <https://doi.org/10.35308/.v3i1.1705>
- Saputra, S., Sugianto, & Djufri. (2016). Sebaran Mangrove Sebelum Tsunami dan Sesudah Tsunami di Kecamatan Kuta Raja Kota Banda Aceh. *Jurnal Edukasi dan Sains Biologi*, 5(1). Retrieved from <http://jkip.umuslim.ac.id/index.php/jesbio/article/view/155>
- Schaduw, J. N. W. (2021). Estimasi Karbon Tersimpan Pada Vegetasi Mangrove Pulau-Pulau Kecil Taman Nasional Bunaken. *Jurnal Ilmiah Platax*, 9(2), 289-295. <https://doi.org/10.35800/jip.v9i2.35746>
- Sugianto, S. (2016). Estimation of Carbon Stock Stands using EVI and NDVI Vegetation Index in Production Forest of Lembah Seulawah Sub-District, Aceh Indonesia. *Aceh International Journal of Science and Technology*, 5(3), 126-139. <http://dx.doi.org/10.13170/aijst.5.3.5836>
- Syamsu, I. F., Nugraha, A. Z., Nugraheni, C. T., & Wahwakhi, S. (2018). Kajian Perubahan Tutupan Lahan di Ekosistem Mangrove Pantai Timur Surabaya. *Media Konservasi*, 23(2), 122-131. Retrieved from <https://shorturl.at/8sKc2>
- Utami, W. A., Sarong, M. A., Asiah M. D., Abdullah, & Safrida. (2021). Shrimp Presence Level in the Mangrove Ecosystem Area Gampong Alue Naga Syiah District, Kuala City, Banda Aceh. *Jurnal Ilmiah Mahasiswa Pendidikan Biologi*, 6(3). Retrieved from <https://jim.usk.ac.id/pendidikan-biologi/article/view/18888>
- Wald, D. J., Quitoriano, V., & Kanamori, H. (1999). Relationships between Peak Ground Acceleration, Peak Ground Velocity, and Modified Mercalli Intensity in California. *Earthquake Spectra*, 15(3), 557-564. <https://doi.org/10.1193/1.1586058>