

Mapping the Estimation of Blue Carbon Stock in Mangrove Areas on the Banyuasin Coast, South Sumatra

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ABSTRAK

Ekosistem mangrove merupakan habitat pesisir penting yang menyimpan karbon biru dan memiliki relevansi bagi perencanaan mitigasi perubahan iklim berbasis ekosistem. Penelitian ini bertujuan memetakan sebaran mangrove serta mengestimasi karbon biomassa atas permukaan (*above-ground biomass carbon*, AGC) dan stok karbon organik sedimen pada profil 0–30 cm di Pesisir Banyuasin, Sumatera Selatan, menggunakan platform Google Earth Engine (GEE). Data yang digunakan meliputi citra Sentinel-2 MSI Level-2A periode 1 Januari 2022 hingga 31 Desember 2023 serta data *soil organic carbon* (SOC). Klasifikasi mangrove dilakukan menggunakan algoritma Random Forest, sedangkan kondisi vegetasi dianalisis menggunakan indeks NDVI, IRECI, dan TRVI. Pengukuran diameter setinggi dada (*diameter at breast height*, DBH), pengambilan sampel sedimen, dan titik pemeriksaan lapangan digunakan untuk mendukung estimasi karbon dan evaluasi klasifikasi. Hasil klasifikasi menunjukkan luas mangrove sebesar 4.068 ha, dengan akurasi keseluruhan 86,67% dan koefisien kappa 0,70. Karbon biomassa atas permukaan diperkirakan berkisar antara 54,3–246,0 Mg C ha⁻¹, dengan total sekitar 463.600 Mg C. Stok karbon organik sedimen pada profil 0–30 cm didominasi oleh kisaran 29,0–39,0 Mg C ha⁻¹, dengan total sekitar 144.500 Mg C. Secara gabungan, karbon biomassa atas permukaan dan karbon organik sedimen pada profil 0–30 cm mencapai sekitar 608.100 Mg C. Nilai tersebut merupakan estimasi parsial karena tidak mencakup karbon biomassa bawah permukaan atau akar, kayu mati, serasah, maupun karbon sedimen pada kedalaman lebih dari 30 cm. Hasil penelitian menyediakan informasi spasial awal mengenai distribusi stok karbon mangrove yang dapat mendukung prioritas konservasi, restorasi, dan perencanaan mitigasi perubahan iklim berbasis ekosistem.

Kata kunci: Mangrove, Karbon biru, Google Earth Engine, Sentinel-2, Random Forest

ABSTRACT

Mangrove ecosystems are important coastal habitats that store blue carbon and are relevant to ecosystem-based climate-mitigation planning. This study aimed to map mangrove distribution and estimate above-ground biomass carbon (AGC) and sediment organic carbon stock in the 0–30 cm profile along the Banyuasin Coast, South Sumatra, using the Google Earth Engine (GEE) platform. The analysis used Sentinel-2 MSI Level-2A imagery acquired from January 1, 2022, to December 31, 2023, together with soil organic carbon (SOC) data. Mangrove cover was classified using the Random Forest algorithm, while vegetation condition was characterized using NDVI, IRECI, and TRVI. Diameter at breast height (DBH) measurements, sediment sampling, and field ground-check points were used to support carbon estimation and classification evaluation. The classification identified 4,068 ha of mangroves, with an overall accuracy of 86.67% and a kappa coefficient of 0.70. Above-ground biomass carbon ranged from 54.3 to 246.0 Mg C ha⁻¹, totaling approximately 463,600 Mg C. Sediment organic carbon stock in the 0–30 cm profile was dominated by values between 29.0 and 39.0 Mg C ha⁻¹, totaling approximately 144,500 Mg C. The combined above-ground biomass carbon and sediment organic carbon stock in the 0–30 cm profile was approximately 608,100 Mg C. This value is a partial estimate because it excludes below-ground biomass (root carbon), dead wood, litter, and sediment carbon stored below 30 cm. The study provides preliminary spatial information on mangrove carbon stock distribution that may support conservation, restoration, and ecosystem-based climate mitigation planning.

Keywords: Mangrove, Blue carbon, Google Earth Engine, Sentinel-2, Random Forest

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1. INTRODUCTION

Mangrove ecosystems are vital coastal habitats that play an essential role in blue carbon sequestration, thereby supporting global efforts to mitigate climate change (Cinar et al., 2024; Ndhlovu et al., 2024; Song et al., 2025). Indonesia, in particular, harbors some of the most extensive mangrove forests globally and plays a pivotal role in both national and global carbon budgets (Hallegatte, 2014; Murdiyarso et al., 2015).

Estuaries are complex transitional zones between freshwater and seawater, characterized by highly dynamic physical and chemical conditions. These environments support high biodiversity and play a crucial role in the global carbon cycle (Alongi, 2023; Laignel et al., 2023; Rotter et al., 2021). In estuarine ecosystems, blue carbon is stored in coastal vegetation biomass and in underground sediments, where it can absorb and sequester large amounts of carbon, thereby contributing to climate change mitigation (Jordan & Fröhle, 2022; Neogi et al., 2017). Mangroves, as a key component of this ecosystem, can store up to three times more carbon than tropical terrestrial forests, with carbon stored both above ground (AGC) and below ground (BGC). Beyond carbon storage, mangroves also protect coastlines from erosion and storms (Pham et al., 2023; Sutton-Grier et al., 2015).

Recent advances in satellite remote sensing and machine learning have improved the accuracy of assessments of mangrove biomass and blue carbon stocks, enabling more effective monitoring and management (Giri, 2023; Tran et al., 2022; Wang et al., 2019). These advances, combined with field validation, support the development of robust blue carbon inventories needed for ecosystem-based climate mitigation strategies (Alongi et al., 2015). Multispectral Sentinel-2 imagery and the Google Earth Engine (GEE) platform have enabled efficient and accurate mangrove mapping and blue carbon assessment (Fariz et al., 2021).

Studies have demonstrated the potential of this approach in regions such as Papua (Kamal et al., 2020) and Bali (Suardana et al., 2023). However, many previous studies have focused primarily on above-ground carbon estimation or have relied on conventional approaches that do not fully leverage multispectral satellite data and cloud computing platforms (Alviana et al., 2023; APHA, 2017; Banuwa et al., 2019; Melki & Isnaini, 2014; T. Vashum, 2012). Comprehensive field validation of belowground biomass and sediment organic carbon pools also remains limited, despite the high spatial variability and substantial contribution of these components to total blue carbon storage (Song et al., 2023; Yanuar et al., 2023).

Various studies on mangrove blue carbon stock mapping have been conducted in Indonesia and globally using different approaches. For example, Suardana et al. (2023) mapped mangrove carbon

stocks in Benoa Bay, Bali, using Sentinel-2 and the Random Forest algorithm, focusing on above-ground carbon, but with limited field validation and without comprehensive integration of below-ground carbon estimation. In Papua, Kamal et al. (2020) combined remote sensing and field data to map mangrove blue carbon, highlighting the importance of blue carbon within total carbon stocks, although their approach relied on lower-resolution or more conventional workflows compared with Sentinel-2 and GEE-based processing. Globally, Adame et al. (2021) emphasized that accurate blue carbon mapping is important for climate change mitigation and that BGC can vary strongly in space, requiring comprehensive field validation; thus, integrative approaches that combine remote sensing with field measurements are recommended.

On the Banyuasin Coast of South Sumatra, which has substantial mangrove potential, studies that integrate cloud-based remote sensing with field measurements to estimate comprehensive blue carbon stocks remain limited. This gap constrains current understanding of the spatial distribution and magnitude of blue carbon in the region, while anthropogenic pressures (e.g., land conversion, aquaculture, and logging) increase the urgency for accurate, timely, and spatially explicit information for management. Earlier work in the same estuarine system, notably Melki and Isnaini (2014), estimated mangrove carbon stocks in the Musi and Banyuasin estuaries using conventional field-based biomass allometry without satellite remote sensing or cloud-computing platforms, so the spatial distribution of carbon across the wider coastal landscape could not be mapped. More recent Indonesian applications of Sentinel-2 and Random Forest, such as Suardana et al. (2023) in Benoa Bay, Bali, focused on above-ground carbon alone and did not incorporate field-based sediment organic carbon into an integrated blue carbon stock estimate.

This study addresses that gap by combining multi-index (NDVI, IRECI, and TRVI) Random Forest classification on Google Earth Engine with satellite-derived above-ground biomass carbon estimates evaluated against limited plot-scale field measurements and depth-resolved sediment organic carbon measurements (0–30 cm) following Indonesian National Standards (SNI 7724:2011; SNI 7717:2020). This approach provides a spatially explicit assessment of above-ground biomass carbon and sediment organic carbon stock in the 0–30 cm profile across the Banyuasin Coast. Therefore, this study aims to map mangrove extent and estimate above-ground biomass carbon and sediment organic carbon stock in the 0–30 cm profile along the Banyuasin Coast using Sentinel-2 MSI Level-2A data processed in Google Earth Engine with a Random Forest classifier, complemented by field vegetation measurements and sediment organic carbon data.

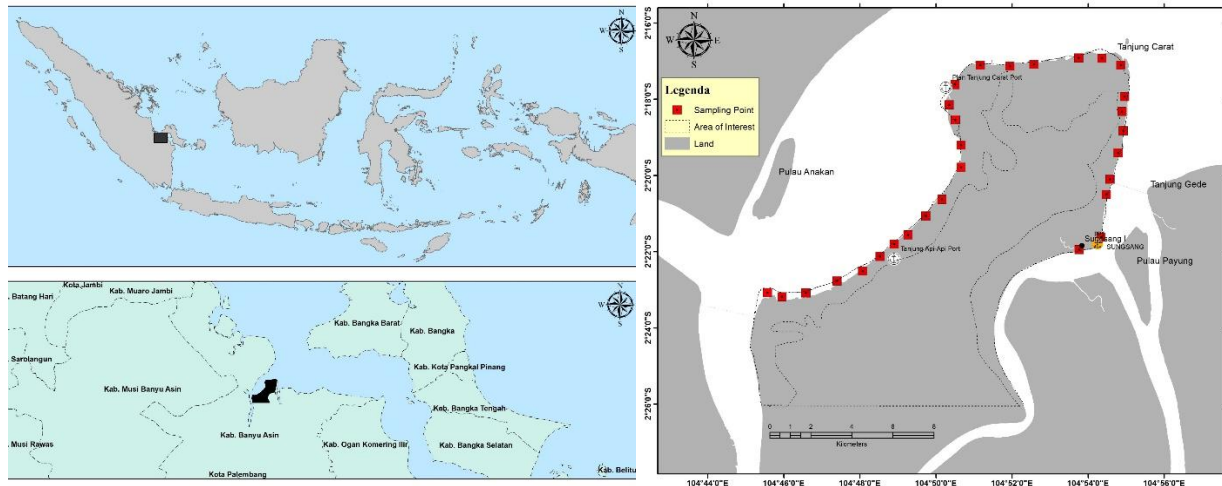


Figure 1. An Outline of an Area of Interest Located in the Banyuasin Coast, Banyuasin District, South Sumatra

2. STUDY AREA AND TIME

This study was conducted along the Banyuasin Coast in South Sumatra, bounded by the east bank of the Banyuasin River and the west bank of the Musi River (Figure 1). Field data collection took place in October 2024, and image processing and data analysis were completed in November 2024 at the Remote Sensing and Marine Geographic Information Systems Laboratory, Sriwijaya University.

2.1. Data and Equipment

- Satellite Imagery:** Sentinel-2 MSI Level-2A from January 1, 2022, to December 31, 2023, with 10 m spatial resolution.
- Soil Organic Carbon Data:** From OpenLandMap at depths of 0 cm, 10 cm, and 30 cm with 250 m resolution.
- Field Data:** DBH measurements, sediment sampling (0–10 cm and 11–30 cm depths), and ground check points for validation.
- Software:** Google Earth Engine (GEE) for data processing and classification; ArcGIS 10.8 for mapping.

2.2. Field Data Collection and Processing

Purposive sampling was used to select 30 observation stations across the mangrove area to serve as ground-check points for classification accuracy assessment, distributed to represent the range of canopy density, tidal position, and accessibility across the study area. Of these, three stations were purposively selected for intensive vegetation and sediment sampling, following the minimum sampling intensity for biomass and sediment carbon assessment recommended in the Indonesian National Standard SNI 7724:2011; these three stations were chosen to capture contrasting canopy conditions (sparse, moderate, and dense) so that the resulting regression and sediment carbon relationships would not be confined to a single vegetation condition. We acknowledge that intensive sampling at only three of the 30 stations limits the spatial representativeness of field-based AGC and

sediment organic carbon estimates, particularly given the high spatial heterogeneity typical of mangrove sediments; this constraint, along with the corresponding need for a larger network of intensive plots in future work, is discussed further in Section 3.3. Mangrove species (*Avicennia alba*, *Kandelia candel*, *Sonneratia alba*, and *Sonneratia caseolaris*) were identified directly in the field during vegetation surveys at these sampling stations, based on morphological characteristics of leaves, bark, and root systems; the Random Forest classification applied to the Sentinel-2 imagery was used only to distinguish mangrove from non-mangrove land cover and was not used to discriminate among mangrove species. Each station consisted of three plots measuring 10 × 10 meters. Diameter at breast height (DBH) was measured on all trees with DBH ≥ 10 cm using a calibrated tape measure to estimate above-ground biomass (Yanuar et al., 2023).

Sediment samples were collected using a 6 cm diameter corer to a depth of 50 cm and divided into two depth intervals (0–10 cm and 11–30 cm). Samples were transported in airtight containers for laboratory analysis of organic carbon content using the Loss on Ignition (LOI) method, following the Indonesian National Standard SNI 7717:2020, which is widely recognized for accurate estimation of organic carbon in mangrove sediments (Choudhary, Dhar, & Anil S. Pawase, 2024).

Sediment samples were processed in the laboratory using the Loss on Ignition (LOI) method. Approximately 100 g of sediment was oven-dried at 60°C for 48 h, homogenized, and a 3 g subsample was placed in a pre-weighed porcelain crucible. The subsample was combusted in a muffle furnace at 450°C for 4 h, cooled to near room temperature, and reweighed to quantify mass loss during ignition. Organic matter content (OM, %) was calculated as:

$$OM(\%) = (m_{dry} - m_{ash}) / m_{dry} \times 100$$

where m_{dry} is the oven-dry mass (g) and m_{ash} is the post-ignition mass (g).

Organic carbon content was then estimated from LOI-derived organic matter using a conversion factor of 0.58, i.e., $C_{org}(\%) = OM(\%) \times 0.58$.

2.3. Satellite Data and Image Processing

Multispectral Sentinel-2 MSI Level-2A imagery, with a spatial resolution of 10 meters and covering January 1, 2022, to December 31, 2023, was composited on Google Earth Engine using a median reducer after cloud masking, producing a stable surface reflectance mosaic for classification and index derivation. The imagery underwent atmospheric correction using the Sen2Cor processor embedded within the Level-2A products, and cloud masking was performed on the Google Earth Engine (GEE) platform to ensure high-quality reflectance data (Gorelick et al., 2017). Vegetation indices, including the Normalized Difference Vegetation Index (NDVI), Inverted Red-Edge Chlorophyll Index (IRECI), and Transformed Red-Edge Vegetation Index (TRVI), were calculated to assess mangrove health and canopy density (Suardana et al., 2023; Tran et al., 2022).

Land cover classification was conducted using the Random Forest (RF) algorithm with 100 decision trees and the Gini impurity criterion, which is effective for high-accuracy classification of multispectral images (Breiman, 2001; Zhou et al., 2024). Training data were collected through purposive field sampling and supplemented with high-resolution reference imagery and existing land cover maps to ensure a balanced representation of mangrove and non-mangrove classes (Kamal et al., 2020).

2.4. Blue Carbon Stock Estimation

Above-ground biomass carbon (AGC) stocks were estimated using a linear regression model that combines the IRECI and TRVI indices, calibrated by Suardana et al. (2023):

$$AGC = 13.99 + 104.471 \times IRECI + 3.025 \times TRVI$$

This model leverages the sensitivity of Sentinel-2's red-edge spectral bands to chlorophyll concentration and canopy structure, providing robust biomass estimates (Suardana et al., 2023; Tran et al., 2022).

Sediment organic carbon stock was estimated for the 0–30 cm sediment profile using laboratory-derived organic carbon content and sediment bulk density. Below ground biomass, or root carbon, was not measured in this study. Organic matter content (OM, %) obtained by the Loss on Ignition method was converted to organic carbon content as $C_{org}(\%) = OM(\%) \times 0.58$. Sediment bulk density (ρ_b , Mg m⁻³) was calculated as the ratio of oven-dry sediment mass to sampled core volume: $\rho_b = M_{dry}/V$, where M_{dry} is the oven-dry mass (Mg) and V is the core volume (m³) derived from the corer radius and layer thickness. Carbon stock for each layer was calculated

as $SOC_{layer} = \rho_b \times d \times C_f \times 10,000$, where d is sediment layer thickness (m) and C_f is the organic carbon fraction, calculated as $C_{org}(\%)/100$. The total sediment organic carbon stock for the 0–30 cm profile was calculated as $SOC_{0-30} = SOC_{0-10} + SOC_{11-30}$ and expressed in Mg C ha⁻¹.

To support spatial mapping of sediment organic carbon variability, Soil Organic Carbon (SOC) layers available in Google Earth Engine from OpenLandMap were extracted for the 0 cm, 10 cm, and 30 cm depth intervals at 250 m spatial resolution (Hengl et al., 2017). These layers were used to complement field-based estimates and generate the mapped sediment organic carbon stock component for the study area.

2.5. Validation and Accuracy Assessment

Classification accuracy was evaluated using a confusion matrix based on independent field validation points, yielding metrics such as producer's accuracy, user's accuracy, overall accuracy, and the kappa coefficient to assess the reliability of mangrove mapping (Zhou et al., 2024). Validation of carbon stock estimates was performed by comparing remote sensing-derived AGC values at the three intensively sampled stations with field-based AGC calculated from DBH measurements, and by comparing spatially derived estimates of sediment organic carbon for the 0–30 cm profile with laboratory-measured values at the same stations. Model performance was quantified using the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean bias (predicted minus observed), together with the corresponding sample size, to evaluate the consistency and precision of the estimates, accounting for spatial heterogeneity and scale differences (Choudhary, Dhar, & Anil S. Pawase, 2024).

Classification accuracy was evaluated using a confusion matrix based on 30 independent ground-check points (22 mangrove and 8 non-mangrove). The confusion matrix yielded 18 true positives, 4 false negatives, 8 true negatives, and 0 false positives, from which producer's accuracy, user's accuracy, overall accuracy, and Cohen's kappa were calculated.

3. RESULTS AND DISCUSSION

3.1. Spatial Distribution of Mangroves

Classification using Random Forest on Sentinel-2 MSI Level-2A imagery data identified 4,068 hectares of mangrove area, distinguishing mangrove from non-mangrove cover; species-level composition was not derived from this classification. Based on field surveys at the sampling stations, mangrove species identified include *Avicennia alba*, *Kandelia candel*, *Sonneratia alba*, and *Sonneratia caseolaris*. Accuracy assessment yielded an overall accuracy of 86.67% and a kappa coefficient of 70.59%, confirming the classification's reliability. The accuracy assessment for mangrove classification is presented in Table 1.

Table 1. Accuracy Assessment of Mangrove Classification (based on independent ground-check points)

No.	Class	n	Producer Accuracy (%)	User Accuracy (%)
1	Mangrove	22	81.82	100.00
2	Non mangrove	8	100	66.67
	Overall Accuracy	30	86.67	
	Kappa Coefficient	30	70.59	

The estimated mangrove extent of 4,068 hectares on the Banyuasin Coast aligns closely with prior regional assessments, confirming the robustness of the Random Forest classification applied to Sentinel-2 MSI Level-2A imagery. The overall classification accuracy of 86.67% and the kappa coefficient of 0.70 indicate a reliable model fit, comparable to results reported in other Indonesian mangrove studies using similar methodologies. For example, Suardana et al. (2023) achieved an even higher overall accuracy (98.4%) and kappa coefficient (0.96) in mapping mangroves in Benoa Bay, Bali, using Sentinel-2 data and Random Forest classification, indicating that classification accuracy in this study, while reliable, may benefit from a larger and more spatially distributed set of ground-check points in future work. This consistency underscores the suitability of machine learning algorithms, combined with high-resolution multispectral satellite data, for effective mangrove cover mapping (Dutta Roy et al., 2024; Giri, 2023; Zhou et al., 2024). The high classification accuracy supports estimating carbon stocks for ecosystem monitoring and management, which is critical for conserving mangrove habitats threatened by anthropogenic pressures (Fakhrurrozi et al., 2023). This approach addresses the gap in up-to-date, extensive spatial data for the Banyuasin Coast.

3.2. Vegetation Indices

Analysis of the vegetation indices provided information on the spatial condition of mangrove vegetation in the study area (Figure 2). NDVI values ranged from 0.52 to 0.98, with high values predominantly observed in the southwestern part of the Banyuasin River, indicating dense vegetation cover. The IRECI index showed relatively high values in the southern area, suggesting better chlorophyll-related canopy conditions and higher photosynthetic activity. TRVI values ranged from 1.77 to 7.01, with higher values generally associated with more open canopy conditions or potential vegetation degradation. Together, these indices describe spatial variation in mangrove greenness, canopy condition, and canopy openness.

NDVI is useful for identifying vegetation greenness and dense mangrove cover but has limited sensitivity to canopy structure and biochemical properties (Fariz et al., 2021). IRECI incorporates Sentinel-2 red-edge bands and is sensitive to chlorophyll-related canopy properties and biomass variation, whereas TRVI

complements this information by helping to identify canopy openness and potentially degraded vegetation conditions (Suardana et al., 2023; Tran et al., 2022). Previous research in Benoa Bay, Bali, reported that the IRECI-TRVI combination produced the most accurate above-ground biomass carbon model among the vegetation-index combinations tested, with an RMSE of approximately 11.09 Mg C ha⁻¹ (Suardana et al., 2023). Accordingly, this study adopted the IRECI-TRVI combination to estimate above-ground biomass carbon and used NDVI to support interpretation of broader mangrove greenness and canopy condition.

The integrated use of NDVI, IRECI, and TRVI provides complementary information for interpreting spatial patterns of mangrove condition and their relationship with mapped above-ground biomass carbon. This approach is consistent with the use of multispectral and red-edge information for mangrove and blue-carbon monitoring (Adame et al., 2021; Alongi, 2023; Tran et al., 2022). However, the comparative predictive performance of alternative index combinations was not independently tested in Banyuasin because only three intensive field stations were available. Therefore, the indices are interpreted primarily as complementary spatial indicators rather than as independently validated predictors of above-ground biomass carbon in the study area.

3.3. Blue Carbon Stock Estimation

Above-ground biomass carbon (AGC) was estimated using the IRECI-TRVI regression model derived from Sentinel-2 imagery. AGC values ranged from 54.3 to 246.0 Mg C ha⁻¹, with a total estimated stock of approximately 463,600 Mg C across the 4,068 ha mangrove area. Sediment organic carbon stock in the 0–30 cm profile, estimated from laboratory sediment measurements and complemented by OpenLandMap SOC data, ranged predominantly from 29.0 to 39.0 Mg C ha⁻¹ and totaled approximately 144,500 Mg C. The combined assessed carbon stock, comprising above-ground biomass carbon and organic carbon in the 0–30 cm sediment profile, was approximately 608,100 Mg C (Figure 3; Table 2).

This combined value should be interpreted as a partial estimate of the mangrove carbon pool. It includes only above-ground biomass carbon and sediment organic carbon in the 0–30 cm profile; it does not include below-ground biomass (root carbon), standing dead wood, litter, or sediment carbon stored below 30 cm. Mangrove carbon accounting should distinguish biomass pools from sediment carbon pools because they differ in their storage mechanisms, spatial variability, and sampling requirements (Alongi, 2020, 2023; Choudhary et al., 2024). Therefore, the estimated 608,100 Mg C represents the assessed carbon components in this study and should not be interpreted as the complete ecosystem carbon stock of Banyuasin mangroves.

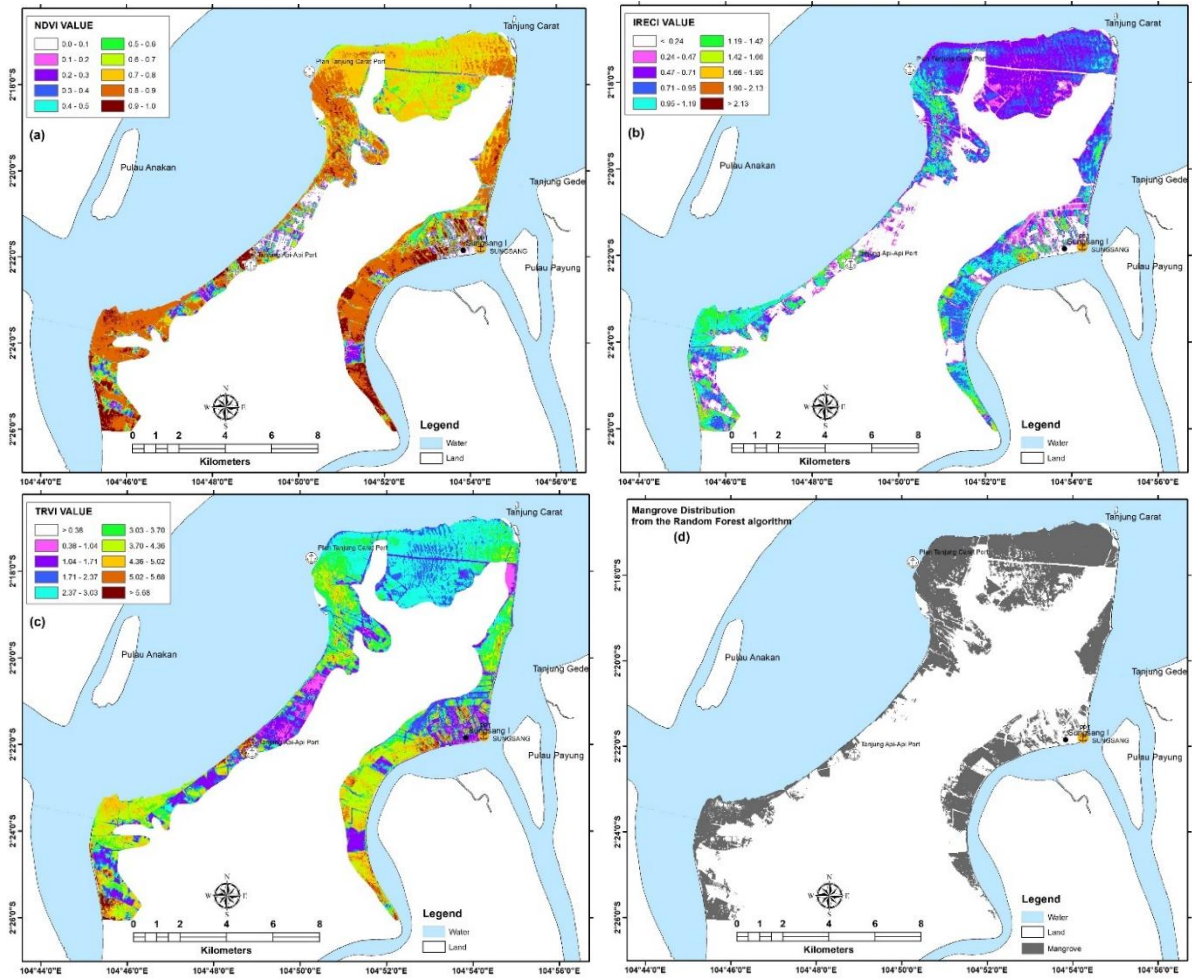


Figure 2. Vegetation Indices Distribution. (a) NDVI; (b) IRECI; (c) TRVI; (d) Mangrove Distribution from the Random Forest Algorithm

Table 2. Estimated Above-Ground Biomass Carbon and Sediment Organic Carbon Stocks in Banyuasin Mangroves

No.	Carbon Stock Component	Range (Mg C ha ⁻¹)	Total Stock (Mg C)
1	Above-ground biomass carbon (AGC)	54.3 – 246.0	463,600
2	Sediment organic carbon stock, 0–30 cm	29.0 – 39.0	144,500
	Assessed carbon stock: AGC + sediment organic carbon (0–30 cm)		608,100

Satellite-derived AGC estimates were compared with field-based AGC derived from DBH measurements at the three intensive sampling stations (n=3). The comparison produced an out-of-sample coefficient of determination (R^2) = -15,033.3, RMSE = 101.11 Mg C ha⁻¹, MAE = 99.73 Mg C ha⁻¹, and a mean bias of +99.73 Mg C ha⁻¹, where bias was calculated as predicted minus observed. These results indicate that satellite-derived AGC substantially exceeded the corresponding field-based AGC estimates at the sampled stations.

For sediment organic carbon stock in the 0–30 cm profile, comparison between the spatially derived estimates and laboratory-based sediment measurements at the same three stations produced an out-of-sample coefficient of determination of R^2 =

-28.25, RMSE = 4.49 Mg C ha⁻¹, MAE = 3.41 Mg C ha⁻¹, and a mean bias of -3.25 Mg C ha⁻¹. Although the absolute errors and bias were lower for sediment organic carbon than for AGC, the evaluation sample was limited to three stations and therefore does not support robust statistical inference regarding regional model performance.

Given the very small evaluation sample (n=3) and the mismatch in spatial support between the 10 m Sentinel-2 pixels and plot-scale field measurements, RMSE, MAE, and mean bias values are interpreted only as descriptive agreement metrics. Each station comprised three 10 × 10 m plots, totaling 0.03 ha, whereas Sentinel-2 products represent reflectance at a 10 m pixel scale. Remote-sensing estimates and plot-based biomass measurements can diverge when their spatial support, sampling design, and observation scale differ, especially in structurally heterogeneous mangrove ecosystems (Dutta Roy et al., 2024; Pham et al., 2023). The coefficient of determination reported here was calculated for out-of-sample predictions and can become negative when prediction errors exceed the variability around the observed mean. Accordingly, the strongly negative R^2 values are not interpreted as stable measures of model explanatory performance.

The substantial disagreement between satellite-derived and field-based AGC estimates likely reflects several interacting sources of uncertainty. Field AGC was estimated only for trees with DBH ≥ 10 cm, excluding smaller stems and saplings that may contribute to stand biomass. In addition, the field plots covered a limited area relative to the spatial heterogeneity captured by satellite pixels and the broader mangrove landscape. The IRECI-TRVI regression coefficients were also transferred from a model calibrated in a different mangrove setting, and their applicability may vary with species composition, canopy structure, stand density, tidal setting, and local environmental conditions. The transferability of remotely sensed biomass models is a recognized source of uncertainty in mangrove carbon assessments and should be evaluated through locally representative calibration data (Dutta Roy et al., 2024; Pham et al., 2023; Suardana et al., 2023). Consequently, the field-based AGC values in this study should be interpreted as lower-bound, plot-scale references rather than as spatially matched ground truth for the satellite-derived AGC map.

The lower absolute disagreement observed for sediment organic carbon should also be interpreted cautiously. Sediment organic carbon was measured using point-scale sediment cores, whereas the OpenLandMap SOC product has a spatial resolution of 250 m. Coarse-resolution soil products can smooth fine-scale variation in sediment properties and may not fully resolve spatial heterogeneity in mangrove sediment carbon (Hengl et al., 2017; Dutta Roy et al., 2024). In addition, the Sentinel-2 composite covered January 2022 to December 2023, whereas vegetation and sediment sampling was conducted in October 2024. Differences in acquisition periods may introduce uncertainty if mangrove canopy conditions, sediment deposition, or local disturbances changed between image acquisition and field observation (Alongi, 2023; Pham et al., 2023).

Despite these limitations, the spatial estimates provide a preliminary overview of the distribution of above-ground biomass carbon and sediment organic carbon across the Banyuasin Coast. Spatially explicit blue-carbon assessments can help identify areas with relatively high and low carbon stocks, thereby supporting prioritization for mangrove conservation, restoration, and ecosystem-based climate-mitigation planning (Alongi, 2020, 2023; Sidik et al., 2023). However, the AGC map should be interpreted as a preliminary regional estimate rather than as a fully calibrated local biomass product. Future research should establish a larger and more spatially distributed network of field plots and sediment cores, include smaller stems where appropriate, align plot boundaries with Sentinel-2 pixel footprints, collect field and satellite data over comparable periods, and develop locally calibrated AGC models. These

improvements are necessary to reduce uncertainty and strengthen future mangrove carbon-stock estimates in Banyuasin (Dutta Roy et al., 2024; Pham et al., 2023).

3.4. Canopy Cover and Sediment Organic Carbon

Canopy cover, measured using hemispherical photography, ranged from 19.3% (sparse) to 74.7% (dense), with denser canopies correlating with higher carbon storage. Sediment organic carbon (SOC) in the top 0–10 cm layer reached a maximum of 43.477 Mg C ha⁻¹, reflecting active mangrove litter decomposition and organic matter enrichment. Variations in SOC corresponded with canopy density and local environmental factors, underscoring the ecological importance of healthy mangrove vegetation for sediment carbon accumulation.

Variations in mangrove canopy cover significantly affect carbon storage, consistent with ecological theory and prior research (Alongi, 2023; Yaqin et al., 2022). Denser canopy areas support higher biomass and increased deposition of organic matter, which in turn enhances sediment organic carbon (SOC) accumulation. In the Banyuasin region, SOC values in the upper 0–10 cm sediment layer reached as high as 43.477 Mg C ha⁻¹, indicating substantial sediment carbon accumulation associated with active litter decomposition and organic matter enrichment, both key indicators of high ecosystem productivity (Meena & Datta, 2021; Salomidi et al., 2012; Sarkar et al., 2019).

The Banyuasin mangrove canopy cover ranged widely from 19.3% to 74.7%, spanning conditions from sparse to dense as defined by national standards (SNI 7717-2020). Carbon stocks varied accordingly, with areas of denser canopy cover exhibiting higher sediment and biomass carbon stocks, reinforcing the role of vegetation structure in carbon storage. These findings align with observations from other Indonesian sites, such as Tugurejo Village in Semarang, where canopy cover ranges from 20% to 70% and top-layer sediment organic carbon ranges from 30 to 50 Mg/ha (Yaqin et al., 2022). Similarly, Indo-Pacific mangrove ecosystems with dense canopies can store up to 50 Mg C ha⁻¹ of organic carbon sediment in surface sediments, underscoring Banyuasin's significant blue carbon potential (Lovelock et al., 2015).

Local environmental factors, including hydrology, sediment texture, and anthropogenic disturbances, also influence organic carbon stocks in sediments and contribute to spatial variability (Kulesza et al., 2018; Salomidi et al., 2012; Yu et al., 2021). Variability in carbon stocks among sampling stations correlates not only with vegetation density but also with these site-specific environmental conditions, confirming that ecological quality and habitat integrity are key determinants of carbon storage capacity.

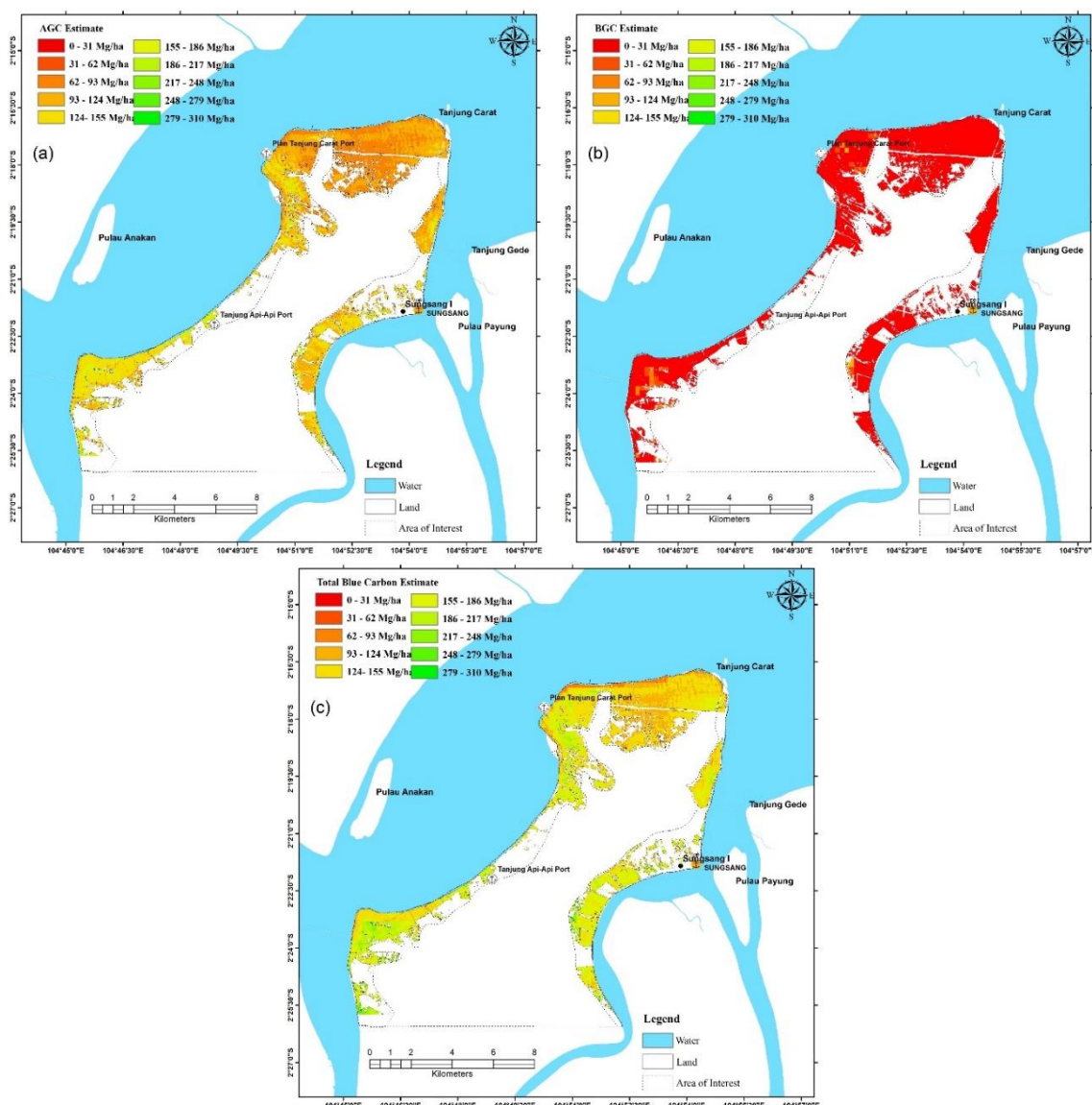


Figure 3. Spatial Distribution of Estimated Carbon Stocks in Banyuasin Mangroves: (a) Above-Ground Biomass Carbon (AGC); (b) Sediment Organic Carbon Stock in the 0–30 cm Profile; and (c) Assessed Carbon Stock, Calculated as AGC Plus Sediment Organic Carbon Stock (0–30 cm)

Given the strong linkages among canopy cover, sediment quality, and carbon stocks, preserving and restoring mangrove canopy structure is a primary strategy for protecting and enhancing blue carbon stocks and ecosystem resilience. Integrated management approaches that focus on canopy restoration may help maintain or enhance biomass and sediment carbon stocks over time, thereby supporting coastal ecosystem health and climate change mitigation efforts (Friess et al., 2019, 2023).

Estimated above-ground biomass carbon and sediment organic carbon stocks in Banyuasin align with global and regional ranges reported in recent studies (Adame et al., 2024; Alongi, 2023; Yaqin et al., 2022), further highlighting the substantial blue carbon stocks held by Indonesian mangroves. The observed variability in sediment organic carbon and canopy cover emphasizes the influence of both natural and anthropogenic factors on blue carbon potential. Overall, these results highlight the importance of

integrated management strategies that maintain canopy density and sediment quality to sustain blue carbon stocks effectively (Adame et al., 2024; Friedlingstein et al., 2020; Gattuso et al., 2018).

This study's integrative approach, combining remote sensing, machine learning, and field observations, offers a replicable framework for spatially explicit and timely monitoring of mangrove carbon stocks, subject to local calibration and expanded field validation. The substantial assessed carbon stocks in Banyuasin mangroves highlight their potential relevance to Indonesia's ecosystem-based climate-mitigation planning, aligning with national goals and global commitments under the Paris Agreement (Friess et al., 2019; Murdiyarso et al., 2015; Sidik et al., 2023).

Preserving and restoring dense mangrove stands should be prioritized to sustain blue carbon stocks and ecosystem resilience. The observed spatial variability of sediment organic carbon stocks further

suggests that targeted local interventions should be informed by detailed spatial data (Friess et al., 2019, 2023; Sidik et al., 2023). Overall, this study provides significant new data supporting ecosystem-based climate mitigation and highlights the value of advanced remote sensing technologies in informing policy and management decisions for coastal blue carbon ecosystems.

4. CONCLUSIONS

This study successfully mapped the spatial distribution and estimated the blue carbon stock of mangrove ecosystems along the Banyuasin Coast, South Sumatra, using Sentinel-2 multispectral imagery and a Random Forest algorithm on the Google Earth Engine platform. The mangrove area was estimated at 4,068 hectares, with dominant species including *Avicennia alba*, *Kandelia candel*, *Sonneratia alba*, and *Sonneratia caseolaris*. The classification achieved high accuracy, with an overall accuracy of 86.67% and a kappa coefficient of 0.70, demonstrating the effectiveness of the remote sensing and machine learning techniques used. The analysis estimated substantial above-ground biomass carbon and sediment organic carbon stocks in the 0–30 cm profile. Root carbon, dead wood, litter, and carbon stored below 30 cm were not assessed. Sentinel-2-derived above-ground carbon (AGC) ranged from 54.3 to 246 Mg C ha⁻¹, with a total stock of about 463,600 Mg C, while sediment organic carbon stock in the 0–30 cm profile contributed around 144,500 Mg C. The combined assessed carbon stock of above-ground biomass and organic carbon in the 0–30 cm sediment profile was approximately 608,100 Mg C. This estimate provides spatial information that may support mangrove conservation and ecosystem-based climate-mitigation planning, while recognizing that additional carbon pools were not quantified.

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