

EVALUATING MANGROVE CARBON BALANCE DYNAMICS IN THE KARIMUNJAWA ARCHIPELAGO UNDER SPATIOTEMPORAL LAND COVER CHANGE

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ABSTRACT. Mangrove ecosystems play a critical role in coastal resilience and long-term carbon storage, yet their spatiotemporal dynamics in small island systems remain poorly understood. This study analyzes mangrove land-cover change from 2000 to 2022 across four major islands in the Karimunjawa Archipelago (Karimunjawa, Kemujan, Parang, and Nyamuk) and projects future trends to 2042. Using multi-temporal satellite imagery and carbon stock-based estimates of CO₂ emissions resulting from mangrove land-cover change, the results reveal heterogeneous trajectories of degradation and recovery. Estimated CO₂ emissions were calculated by multiplying the change in carbon stock, the molecular weight conversion factor from carbon (12/44), and the area of mangrove land-cover change (ha). In 2015, Karimunjawa and Kemujan maintain the largest mangrove extents but are also associated with the highest estimated CO₂ emissions, reaching 273,899.30 t CO₂ ha⁻¹ as a consequence of land-use conversion, whereas Nyamuk exhibits relatively stable dynamics with localized carbon stock loss corresponding to estimated CO₂ emissions of up to 1,037.13 t CO₂ ha⁻¹, and Parang shows persistent decline with estimated CO₂ emissions of up to 587.97 t CO₂ ha⁻¹. Future projections indicate increasing carbon stock loss and associated estimated CO₂ emissions toward 2042, particularly on Kemujan, Nyamuk, and Parang, reaching 574,188.40, 2,551.95, and 1,953.84 t CO₂ ha⁻¹, respectively, highlighting growing risks to coastal ecosystem integrity and climate change mitigation efforts. These findings underscore the influence of geomorphology, anthropogenic pressure, and governance in shaping mangrove dynamics on small islands. Integrated, site-specific, and adaptive management strategies are therefore essential to conserve mangrove carbon stocks, minimize carbon losses associated with land-cover change, and strengthen coastal resilience in the Karimunjawa Archipelago.

KEYWORDS: Mangrove, CO₂ emissions, remote sensing, Karimunjawa

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INTRODUCTION

Mangrove ecosystems are among the most carbon-dense forests globally, functioning as long-term carbon sinks due to their capacity to store large amounts of carbon in both biomass and sediments. Global estimates indicate that mangroves store between 800 and 1,200 t CO₂-eq, substantially higher than most terrestrial tropical forests. However, carbon stocks vary across regions. For instance, mangroves in Southeast Asia exhibit some of the highest carbon densities, often exceeding 1,000 t C ha⁻¹, due to deep organic-rich soils and high productivity. In comparison, mangroves in the Caribbean and Latin America typically store around 600–900 t C ha⁻¹, while those in West Africa and parts of the Indo-Pacific range between 500 and 800 t C ha⁻¹. These regional differences are influenced by geomorphology, sedimentation rates, and climatic conditions. In addition to their large carbon stocks, mangroves also exhibit high CO₂ sequestration rates, typically ranging from 600,000 to 800,000 t CO₂ ha⁻¹, with some regions reporting even higher rates under favorable environmental conditions. This combination of high carbon storage and sequestration capacity reinforces their role as a key component of blue carbon ecosystems and a critical nature-based solution for climate change mitigation (Murdiyarso et al. 2015; Kauffman et al. 2020; Hadiyanto et al. 2021; Macreadie et al. 2021).

The Karimunjawa Archipelago, located in the northern Java Sea and administratively part of Jepara Regency, Central Java, Indonesia, comprises 27 islands, with four main inhabited islands: Karimunjawa, Kemujan, Parang, and Nyamuk. Karimunjawa and Kemujan function as socioeconomic centers with more developed infrastructure, whereas Parang and Nyamuk remain relatively rural and highly dependent on coastal resources. Ecologically, the archipelago is part of Karimunjawa National Park, encompassing interconnected coastal ecosystems, including mangrove forests that are primarily distributed along the shorelines of the four main islands and play critical roles in coastal protection and carbon storage (Wirasatriya et al. 2022). Mangrove ecosystems across Southeast Asia have experienced significant pressure from land-use change, particularly aquaculture expansion, coastal development, and tourism infrastructure, leading to widespread degradation. In small island systems, such pressures are often compounded by natural disturbances, resulting in highly dynamic and spatially heterogeneous mangrove trajectories (Howard et al. 2017; Lovelock and Duarte 2025). Previous studies in Indonesia have shown that these changes reduce mangrove extent and weaken key ecosystem functions, while also contributing to the release of substantial carbon stocks stored in biomass and soils (Macreadie et al. 2021; Syahid et al. 2020; Halim et al. 2023). Given the high carbon density of mangroves, even small-scale degradation can generate disproportionately large CO₂ emissions, reinforcing their importance in climate mitigation (Lee et al. 2014; Richards and Friess 2016; Bryan-Brown et al. 2020; Bhargava and Friess 2022).

Mangrove land conversion cannot be considered a carbon-neutral process due to the distinctive carbon storage characteristics of mangrove ecosystems compared with terrestrial tropical forests. In terrestrial tropical forests, approximately 80% of carbon is stored in aboveground biomass, particularly in stems and foliage. In contrast, mangrove ecosystems store approximately 70–80% of their carbon reserves within waterlogged sediments rather than vegetation biomass. The permanent inundation of mangrove soils creates anaerobic conditions that substantially limit microbial decomposition, allowing organic materials such as fallen leaves, branches, and roots to accumulate over millennia and form highly carbon-dense sediment layers. When mangrove areas are drained or converted, the carbon accumulated in these sediments over hundreds to thousands of years can be rapidly oxidized and released into the atmosphere within months to several years. Although ecological rehabilitation can restore mangrove vegetation structure, the re-accumulation and stabilization of sedimentary carbon stocks may require decades to centuries. Therefore, mangrove conversion can result in substantial carbon stock losses and associated CO₂ release, challenging the assumption that such land-use changes are carbon neutral. Within greenhouse gas inventory frameworks established by the Intergovernmental Panel on Climate Change (IPCC), mangrove conversion is recognized as an important source of carbon emissions rather than a carbon-neutral activity (Choudhary et al. 2024; Alongi 2014). The conceptual illustration of differences in carbon storage dynamics between mangrove ecosystems and terrestrial forests is provided in Figs. S1A and S1B in the Supplementary Materials.

Carbon stocks in mangrove sediments are higher than those in mangrove vegetation. According to the study conducted by Halim et al. (2023), mangrove stands in the Karimunjawa archipelago have an average carbon stock of 146.22 t C ha⁻¹ (28.8%) in the aboveground biomass, while the carbon content stored in the mangrove soil reaches 360.61 t C ha⁻¹ (71.2%). These findings indicate that carbon storage in mangrove ecosystems is substantially higher in the sediment/soil component than in the vegetation stands. This result is consistent with the blue carbon theory, which states that approximately 70–80% of carbon storage in mangrove ecosystems is retained within the sediment. The high carbon accumulation in mangrove soils is attributed to the continuous deposition of organic matter and the anaerobic soil conditions that slow down organic matter decomposition. Therefore, mangrove sediments play a crucial role as a long-term carbon sink and contribute significantly to climate change mitigation efforts.

In the Karimunjawa Archipelago, mangrove cover has fluctuated over time under increasing anthropogenic pressure, including land conversion, settlement expansion, and unregulated coastal development. Despite the presence of protected zones within the National Park, recent trends indicate spatially uneven dynamics, with some islands showing recovery potential while others continue to experience persistent degradation (Murdiyarso

et al. 2015; Bacar 2025). These contrasting patterns highlight the critical role of geomorphological settings, human pressure, and governance in shaping mangrove resilience on small islands (Ardhani et al. 2020). This study addresses these dynamics by integrating spatiotemporal analysis of mangrove change with carbon emission assessment across the four main islands. A comprehensive evaluation of how land-use change influences mangrove extent and associated CO₂ emissions has been estimated by multi-temporal satellite imagery and carbon stock-based emissions (Olofsson et al. 2014; Liao et al. 2025). However, no prior study has examined these dynamics through an integrated spatiotemporal and carbon-emission assessment across the four main islands of Karimunjawa. By focusing on island-scale variability and long-term trajectories, this study contributes to a more integrated understanding of mangrove dynamics and offers insights for adaptive, site-specific management to support climate mitigation and coastal resilience in small island systems.

MATERIALS AND METHODS

Inventory Data

A detailed analysis of land cover changes in the mangrove ecosystems of the Karimunjawa Archipelago is essential to assess historical trends, current conditions, and project future spatial dynamics of mangrove distribution. Temporal datasets representing mangrove extents for the years 2000, 2005, 2010, 2015, and 2022 are utilized as the basis for predicting changes through 2032 and 2042. Multispectral satellite imagery derived from Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI/TIRS, and Sentinel-2A MSI provides the primary source of remote sensing data (Adjovu et al. 2023). These datasets are subjected to preprocessing steps, including radiometric and geometric correction, atmospheric adjustment, and cloud masking. Subsequently, supervised classification using the maximum likelihood algorithm is performed within ArcGIS 10.8 and QGIS 2.16 environments to delineate mangrove land cover. Post-classification refinement involves accuracy assessment using ground truth data and confusion matrix metrics to ensure classification reliability. The resulting land cover maps are further analyzed using spatial overlay and change detection techniques to quantify mangrove gain and loss across time intervals.

Radiometric and Atmospheric Image Correction

Satellite imagery often contains noise and discrepancies relative to actual surface conditions, arising from various factors such as differences in solar zenith angles during data acquisition, geometric distortions, and atmospheric interference. To ensure the reliability and accuracy of spatial analysis, preprocessing corrections are required. Radiometric correction addresses distortions caused by variations in solar position and illumination. This process involves the conversion of Digital Number (DN) values to surface reflectance values, commonly referred to as Top-of-Atmosphere (ToA) reflectance (Imasu et al. 2023). The DN-to-reflectance transformation is performed using the following Eq. 1:

$$L\lambda = ((LMAX - LMIN) / (Qcalmax - Qcalmin)) \times (Qcal - Qcalmin) + LMIN \quad (1)$$

$L\lambda$: Radian value on the sensor for each band

$LMAX$: Maximum radian value of the sensor

$LMIN$: Minimum radian value of the sensor (RADIANCE_

MINIMUM_BAND)

$Qcalmax$: Maximum digital value (QUANTIZE_CAL_MAX_BAND)

$Qcalmin$: Minimum digital value (QUANTIZE_CAL_MIN_BAND)

$Qcal$: Digital number value (DN)

Following the conversion of Digital Number (DN) values, pixel reflectance values are further corrected based on the solar zenith angle to minimize reflectance variability caused by differences in solar position. The relative position of the sun with respect to the Earth varies depending on the acquisition time and the geographic location of the observed area. This correction is crucial to standardize surface reflectance across multi-temporal datasets. The solar angle correction is applied using the following Eq. 2:

$$ToA = (\pi \times L\lambda \times d^2) / (ESUN \times \cos\theta) \quad (2)$$

where $\theta = (90 - \text{sun elevation}) \times (\pi/180)$

Explanation of variables:

π : 3,14159

$L\lambda$: Radian value on the sensor for each band

d : Earth–Sun distance in astronomical units (AU), varies depending on acquisition date

$ESUN$: Mean solar exoatmospheric irradiance for the specific band

θ : Solar zenith angle (in degrees), calculated as 90° minus the solar elevation angle

The final stage of correction involves converting the radiance values into surface reflectance using the Dark Object Subtraction (DOS) method. This atmospheric correction technique assumes that certain pixels in the scene (typically deep water bodies or dense vegetation) should have near-zero reflectance values in specific spectral bands, especially in the shortwave and visible ranges (Imasu et al. 2023). The surface reflectance is estimated by subtracting the minimum path radiance from the observed radiance, as expressed by the following Eq. 3:

$$Rc = R - Rsi \quad (3)$$

where $Rsi = (Mean\ Rw - (2 \times StDev\ Rw))$

Explanation of Variables:

Rc : Surface reflectance

R : ToA reflectance

Rw : Deep and clear water body reflectance

$Mean$: Average

$Stdev$: Standard deviation

Geometric Correction

Geometric correction is performed to reduce geometric distortions inherent in satellite imagery and to ensure that the resulting image has a uniform coordinate system and scale that accurately corresponds to real-world geographic coordinates (Ogohara et al. 2017). The geometric correction process consists of the following steps:

- Reference Image Selection

A reference image with the highest geometric accuracy is selected as the base for correction.

- Ground Control Point (GCP) Identification

Ground Control Points (GCPs) are identified from stable and clearly distinguishable features that appear in both the imagery and a reliable topographic map.

- Geometric Transformation

Mathematical transformations, typically polynomial transformations, are applied to align the distorted image with the reference coordinates by adjusting pixel locations.

- Resampling

Resampling techniques are employed to assign new

pixel values after geometric transformation. Commonly used resampling methods include: Nearest Neighbor (for land classification), Bilinear Interpolation (for continuous data) or Cubic Convolution (for high visualization results).

- Error Evaluation (Root Mean Square Error – RMSE)

The geometric accuracy of the corrected image is assessed using the Root Mean Square Error (RMSE) metric, which quantifies the average deviation between the transformed Ground Control Points (GCPs) and their actual positions in the reference image. An image is considered to have acceptable geometric accuracy if the RMSE is less than 0.5 pixels, equivalent to approximately 15 meters for Landsat imagery.

Image Cropping and Overlay

Following the correction procedures, image overlay and cropping processes are carried out. Overlay refers to the capability of superimposing one map layer over another, allowing for spatial alignment and integration. In this study, the overlay process is used to combine specific spectral bands required for subsequent mangrove area analysis. Cropping, on the other hand, is performed to spatially constrain the imagery to the area of interest, thereby focusing the data processing on the relevant geographic extent (Raffay et al. 2025). This step also enhances computational efficiency by reducing the processing load on the software, as it limits the dataset to a smaller and more manageable spatial extent.

Mangrove Classification (Unsupervised Classification)

Unsupervised classification is a method that allows the computer algorithm to autonomously categorize image pixels into distinct spectral classes without prior training data. This classification approach is typically employed when the interpreter lacks sufficient knowledge about the specific land cover types present in the imagery or when detailed information about the study area is not readily available. In such cases, unsupervised classification provides an initial, data-driven segmentation of the image based on the spectral similarities of pixel values (Mahmood et al. 2023).

Mangrove Area

The results of the unsupervised classification are subsequently reclassified into two main categories: mangrove and non-mangrove, to facilitate the calculation of mangrove area. The spatial extent of mangrove vegetation is then quantified for each observation year. Once the mangrove areas have been delineated, the Normalized Difference Vegetation Index (NDVI) is computed to assess the density of mangrove canopy cover within the identified regions (Nguyen et al. 2020; Mahmood et al. 2023). The NDVI calculation utilizes the Near-Infrared (NIR) and RED bands that have been radiometrically corrected and is derived using the following Eq. 4:

$$NDVI = ((NIR - RED)) / ((NIR + RED)) \quad (4)$$

Mangrove Area Prediction (Cellular Automata – Artificial Neural Network)

Prior to conducting the land cover prediction process, several essential datasets must be prepared, including:

- Mangrove land cover data across three time points within a consistent temporal interval

- Explanatory variables such as existing mangrove builtup areas (2022), and existing roads and settlements (2022)

Cellular Automata (CA) is a raster-based computational technique that is widely used to simulate and predict land use changes over time. It effectively captures spatial dynamics by modeling the state of each pixel based on its neighborhood configuration. However, CA models are limited in that they can only simulate pixel-level transitions without explicitly accounting for the statistical relationships between independent and dependent variables (Fu et al. 2024).

On the other hand, an Artificial Neural Network (ANN) is a machine learning approach capable of identifying complex, non-linear patterns within input data (Try et al. 2020). In this study, the ANN model is implemented using the MOLUSCE (Modules for Land Use Change Simulation) plugin in QGIS. MOLUSCE is a widely used tool for land use prediction and simulation, although it is only available in QGIS versions below 3.x.

Several key considerations must be addressed when using the MOLUSCE (Modules for Land Use Change Simulation) plugin, including the following (Zimba et al. 2024):

- All input data must be in raster format and share the same spatial resolution, extent, and coordinate reference system to ensure consistency in model processing.
- Land use rasters must span three distinct years, representing the initial year, final year, and a separate year for model validation. This temporal structure allows for both model calibration and performance assessment.
- At least one explanatory (driving) variable must be included in the model, representing a factor that potentially influences land use change (e.g., distance to roads, settlements, or existing built-up mangrove areas).
- These requirements ensure that the simulation and prediction processes within MOLUSCE are executed accurately and yield reliable results for land use change modeling.

Estimating CO₂ Emissions

The carbon stock of mangroves per hectare was derived from field measurements conducted in 2022, yielding a value of 146.22 t C ha⁻¹ (Halim et al. 2023). Carbon stocks for 2000, 2005, 2010, 2015, 2032, and 2042 were estimated by multiplying the predicted mangrove area by this average value. CO₂ emissions resulting from mangrove changes were calculated based on differences in carbon stocks between time periods (ΔC) and converted using the molecular weight ratio of carbon to CO₂ (12/44), following Bu et al. (2022) (Eq. 5):

$$Emission\ CO_2\ (ton) = \Delta C \times (12/44) \times A \quad (5)$$

where ΔC is the change in carbon stock in year (2000, 2005, 2010, 2015, 2032, and 2042), 12/44 is the conversion factor from C to CO₂, and A is the area of mangrove change (ha). This approach estimates CO₂ emissions released due to carbon loss from mangrove ecosystems in year.

RESULTS AND DISCUSSION

Changes in Mangrove Ecosystem Extent from 2000 to 2022 in the Karimunjawa Archipelago

Karimunjawa and Kemujan Islands

Spatiotemporal analysis revealed distinct patterns of mangrove extent changes across Karimunjawa and Kemujan Islands from 2000 to 2022 (Fig. 1). Mangrove

areas in western Karimunjawa remained relatively stable, with limited expansion and minor losses, indicating sustained mangrove persistence under relatively low land-conversion pressure (Romañach et al. 2018; Friess et al. 2019; Akber et al. 2020). The National Park core zone exhibited no detectable changes, although approximately 32 ha of mangrove decline occurred immediately to the south of the protected area. In contrast, Kemujan Island experienced more pronounced mangrove loss, primarily associated with airport development, aquaculture expansion, and settlement growth (Richards & Friess 2016; Friess et al. 2019). Overall, 465.62 ha of mangrove area remained stable, while 99.03 ha expanded and 115.86 ha were lost. Mangrove extent remained relatively constant between 2005 and 2010 (~495.25 ha), indicating a period of limited spatial change.

Mangrove loss was concentrated in northern Karimunjawa (Nyamplungan) and southeastern Kemujan, primarily driven by aquaculture expansion (Richards & Friess 2016; Friess et al. 2019). Total losses (79.4 ha) slightly exceeded gains (68.4 ha), while canopy density remained high overall, particularly within the National Park core zone; lower-density areas likely indicate regeneration (Romañach et al. 2018). Between 2010 and 2015, losses (136.7 ha) far exceeded gains (53.82 ha), with ~95% occurring on Kemujan Island due to aquaculture and settlement

expansion (Akber et al. 2020). Continued degradation during 2015–2022 was observed in southern, southeastern, and northern Karimunjawa, including ~35 ha of additional loss near Bobi Beach and the western coast linked to pond development.

These trends corroborate previous findings (Wirasatriya et al. 2022) and align with broader regional patterns in Southeast Asia, where aquaculture accounts for up to 45% of mangrove loss (Basyuni et al. 2025). Despite these pressures, the Karimunjawa National Park core zone remains stable with high vegetation density, highlighting the effectiveness of protection measures. This underscores the need for adaptive management strategies, including community-based conservation and sustainable silvofishery systems, to reconcile ecosystem protection with local livelihoods (Baumgartner et al. 2016; Nuraini et al. 2021; Suryanti et al. 2025).

Parang Island

Parang Island exhibited a relatively unstable mangrove trajectory between 2000 and 2022, characterized by alternating periods of degradation and limited recovery (Fig. 2). Although mangrove cover remained relatively stable during 2000–2005 (50.24 ha), mangrove losses (17.34 ha) exceeded gains (7.22 ha), with approximately 78.3% of the decline concentrated along the northern coast. Degradation

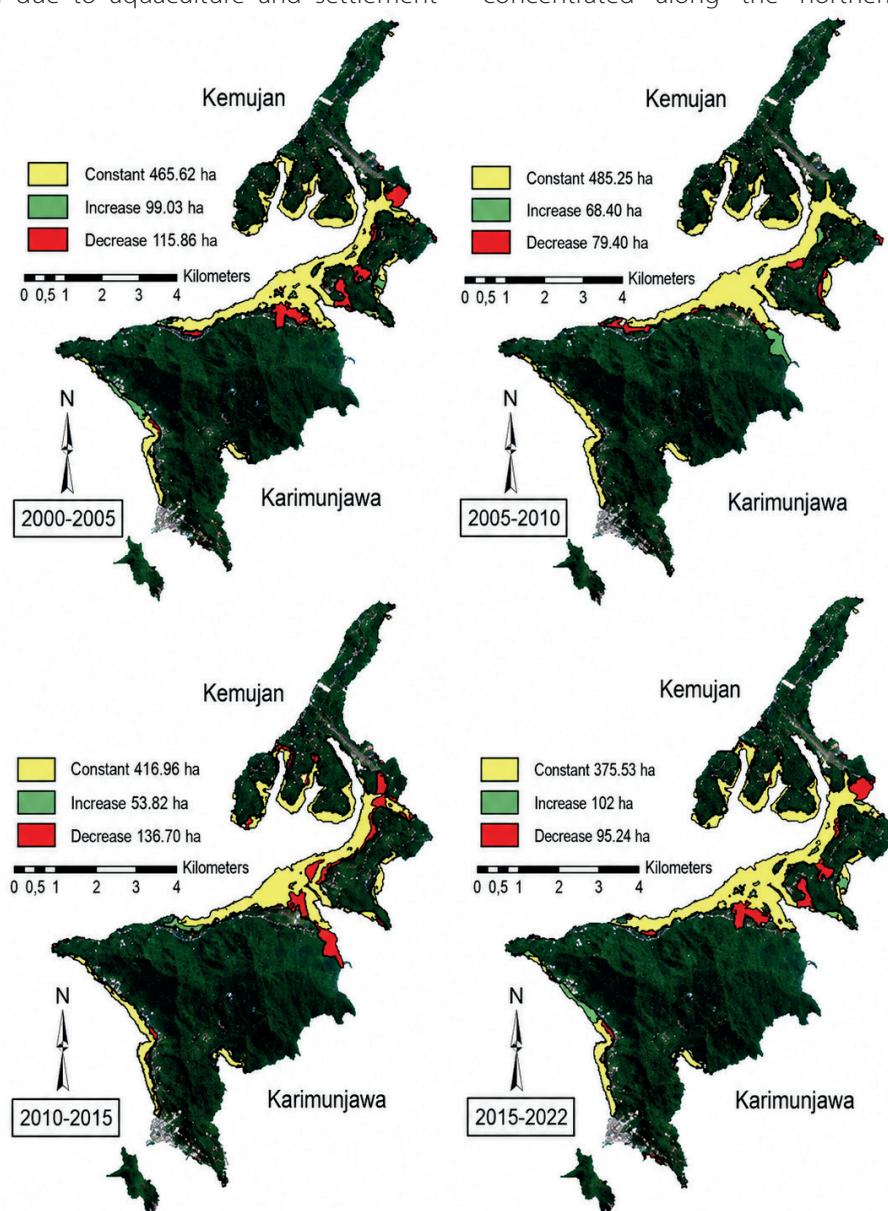


Fig. 1. Changes in the area of the mangrove ecosystem in Karimunjawa and Kemujan Islands from 2000 to 2022

intensified during 2005–2010, resulting in a net decline of 19.05 ha, potentially associated with extreme environmental events and increasing coastal exploitation, particularly in the northeastern region. Despite the initiation of community-based restoration efforts after 2010, mangrove losses continued through 2015. During 2015–2022, mangrove expansion (15.9 ha) partially compensated for ongoing losses (23.17 ha), indicating that recovery processes remained insufficient to offset persistent degradation pressures. Overall, the observed mangrove dynamics reflect the combined influence of natural disturbances and anthropogenic activities, highlighting the importance of integrated and adaptive coastal management strategies (Atwood et al. 2017; Cameron et al. 2019; Johnson and Lyman 2020; Akber et al. 2020; Suryanti et al. 2025).

Nyamuk Island

Nyamuk Island exhibited relatively limited overall mangrove change between 2000 and 2022, with a stable coastal mangrove belt despite localized areas of degradation and recovery (Fig. 3). The observed changes consisted of 2.01 ha of mangrove loss, 10.98 ha of gain, and 10.98 ha remaining stable throughout the study period. Notably, several loss areas occurred inland at approximately 250 m from the coastline, suggesting that land conversion rather than coastal erosion was likely responsible for these changes, while mangroves continued to maintain a relatively continuous coastal zone. Mangrove degradation

intensified during 2005–2010, followed by partial recovery during 2010–2015 with a net gain of approximately 11.14 ha. However, a pronounced decline occurred during 2015–2022 (–18.53 ha), indicating increasing pressure on mangrove persistence and potential limitations in maintaining long-term recovery trends. These dynamics highlight the vulnerability of small-island mangrove ecosystems to the combined influence of climatic disturbances and unsustainable land-use practices (Asbridge et al. 2019; West et al. 2025). Furthermore, the inland distribution of some degraded areas suggests a shift in dominant pressures from conventional coastal exploitation toward interior land transformation, a pattern increasingly reported in insular Southeast Asian environments (Syahid et al. 2023; Sahavacharin et al. 2022; Soeprbowati et al. 2024). Strengthening adaptive co-management approaches, integrating local ecological knowledge, and ensuring long-term policy continuity are therefore essential to maintain the ecological resilience of mangrove ecosystems on Nyamuk Island.

Changes in Mangrove Ecosystem Extent Based on Overlay Analysis (2000–2022)

Mangrove trajectories across the Karimunjawa Archipelago exhibited contrasting patterns between 2000 and 2022, reflecting differences in land-conversion pressure, conservation status, and environmental conditions (Fig.

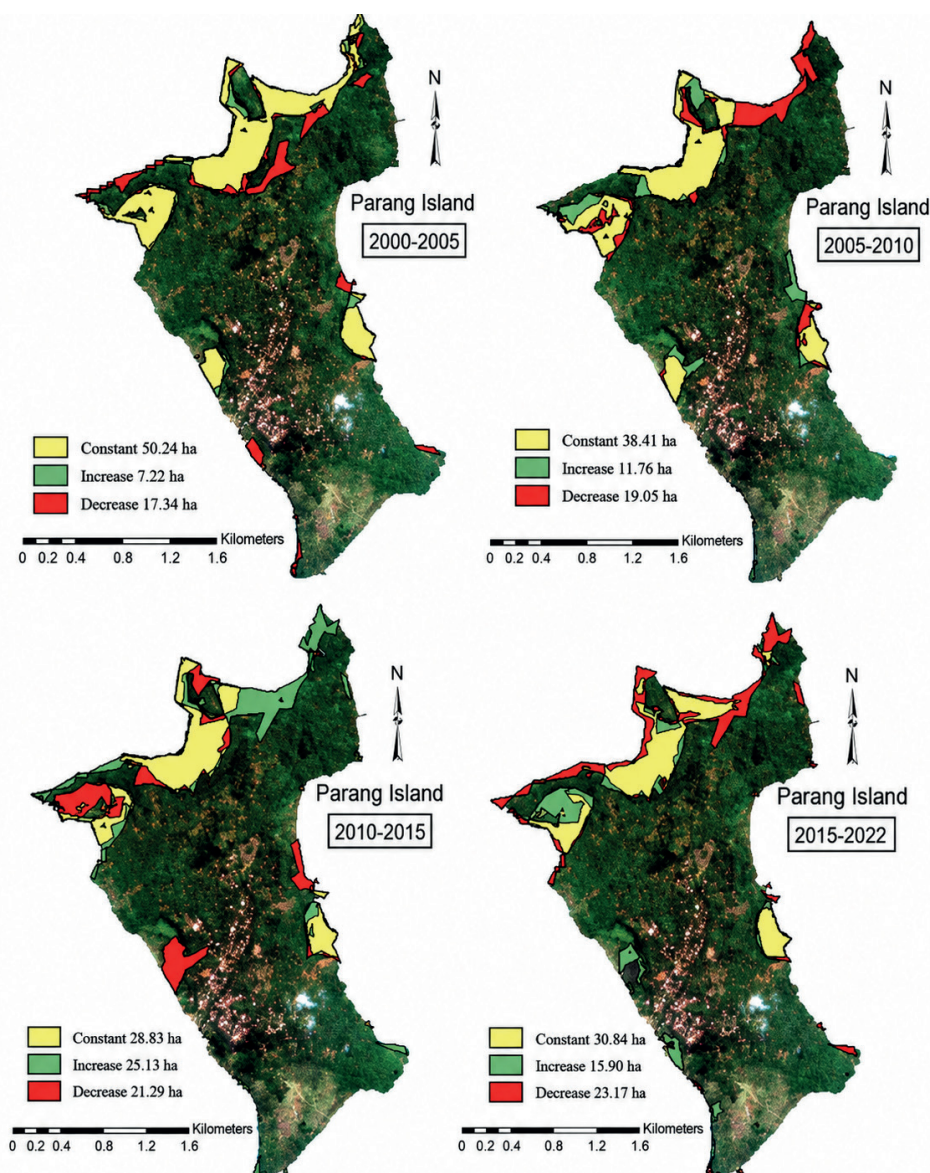


Fig. 2. Changes in the area of the mangrove ecosystem in Parang Island from 2000 to 2022

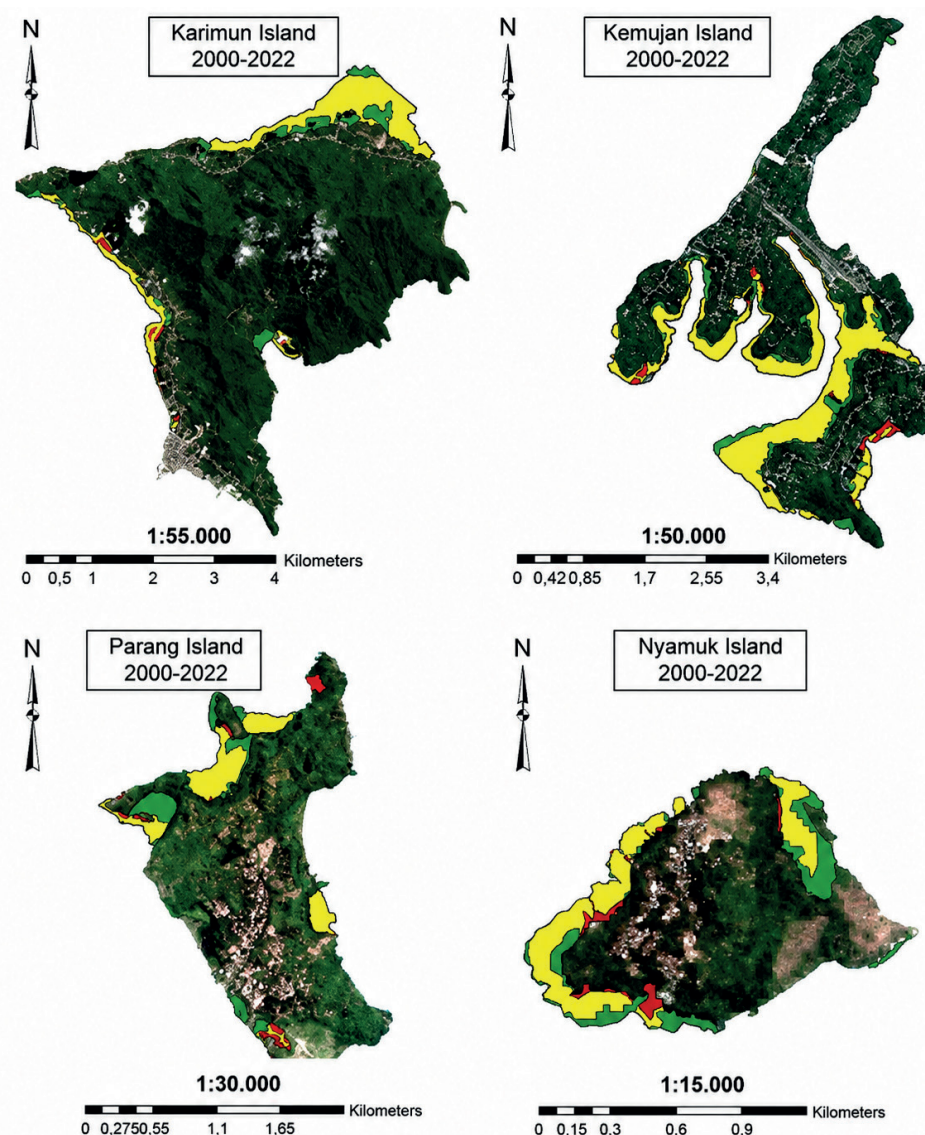


Fig. 4. Overlay Results of the Mangrove Ecosystem Area of Karimunjawa Island, Kemujan Island, Parang Island, and Nyamuk Island (2000–2022)

4). Karimunjawa and Kemujan Islands experienced net mangrove gains of 53.09 ha and 43.69 ha, respectively, with expansion mainly occurring in sheltered coastal environments and partly within protected areas. These patterns may be associated with the combined influence of restoration activities, conservation interventions, and favorable geomorphological conditions that support mangrove persistence and recovery (Bryan-Brown et al. 2020; Zhao et al. 2026). A temporary decline around 2015 suggests that short-term coastal development pressures affected mangrove extent; however, subsequent recovery by 2022 indicates the potential for mangrove persistence under relatively favorable management conditions. In contrast, Parang Island exhibited a persistent declining trajectory without clear evidence of recovery, potentially associated with continued land conversion and coastal disturbance, resulting in reduced ecosystem stability (Cameron et al. 2019; Rahim et al. 2024; Rahim et al. 2026). Nyamuk Island showed a non-linear pattern, characterized by early expansion followed by gradual and spatially dispersed degradation, suggesting the influence of sustained low-intensity anthropogenic pressures on small-island mangrove dynamics.

The comparative analysis of the four islands demonstrates varying mangrove trajectories shaped by a combination of natural geomorphological features, human activities, and institutional interventions

(Prihantono et al. 2022; Cahyaningsih et al. 2022; Suryanti et al. 2025; Subambang et al. 2025). While Karimunjawa and Kemujan Islands demonstrate the benefits of protection and active management (Suryanti et al. 2025), coral reefs in the Karimunjawa region, including around Kemujan Island, have reached a “bleaching alert” level, indicating ongoing environmental challenges despite management efforts (Trihatmoko et al. 2024). Parang and Nyamuk Islands reveal the consequences of unmanaged degradation and inconsistent conservation efforts (Santosa et al. 2023). This pattern echoes findings from regions such as the Philippines and Vietnam, where protected zones with enforcement capacity have shown net mangrove gains, while unprotected or informally managed areas continue to experience loss (Abino et al. 2014; Hoang et al. 2018).

Projected Spatio-Temporal Dynamics of Mangrove Extent in the Karimunjawa Archipelago Until 2042

Spatial projections (2022–2042) indicate heterogeneous mangrove trajectories across the Karimunjawa Archipelago. Aquaculture conversion has been identified as a significant driver of mangrove degradation (Purwanto et al. 2025). Karimunjawa shows near stability with slight gain (+1.45 ha), suggesting moderate resilience, while Kemujan is projected to experience the largest loss (–25.89 ha), driven by increasing land-use pressure from tourism and

aquaculture. Parang exhibits modest gain (+3.02 ha), whereas Nyamuk remains nearly stable (−0.46 ha) (Fig. 5), reflecting a balance between degradation and limited natural regeneration. These contrasting trends highlight the interaction of geomorphology, human pressure, and governance in shaping mangrove dynamics (Friess et al. 2022; Murdiyarso et al. 2023). Without targeted management, cumulative impacts may include increased coastal vulnerability, habitat fragmentation, and reduced ecosystem services. Conversely, islands with recovery potential provide opportunities for scaling up restoration, underscoring the need for adaptive, site-specific management strategies (Lovelock et al. 2015).

Although the CA-ANN model provides a useful approach for projecting future mangrove distribution, the predicted changes up to 2042 should be interpreted as scenario-based projections rather than deterministic forecasts. The reliability of the model depends on the quality of historical land-cover data, the selection of explanatory variables, and the assumption that past spatial patterns of mangrove change will continue in the future. Uncertainties may arise from factors that are difficult to represent spatially, including future policy interventions, changes in coastal development patterns, community-based conservation initiatives, climate variability, sea level rise, and extreme climatic events. In addition, the CA-ANN model

assumes that the relationships between environmental drivers and mangrove distribution remain relatively consistent over the projection period. However, future changes in anthropogenic pressures or conservation effectiveness may alter these relationships. Therefore, the projected increase or decline in mangrove extent should be considered an indication of potential future trajectories rather than an exact prediction. Future studies incorporating multiple scenarios, sensitivity analyses, and additional socioeconomic and climatic variables would further improve the robustness of long-term mangrove change projections.

Changes in Mangrove Area and CO₂ Emissions

Mangrove degradation can lead to substantial carbon stock losses because land-cover change disrupts the carbon stored in mangrove biomass and soils, resulting in associated CO₂ release (Arifanti et al. 2022; Jiang et al. 2022). Temporal analysis across the Karimunjawa Archipelago indicates that Karimunjawa and Kemujan exhibited the highest estimated CO₂ emissions associated with mangrove carbon stock losses, reaching approximately 273,899.30 t CO₂ ha^{−1} in 2015 and projected to increase to approximately 574,188.39 t CO₂ ha^{−1} by 2042. These patterns are primarily attributed to their larger mangrove

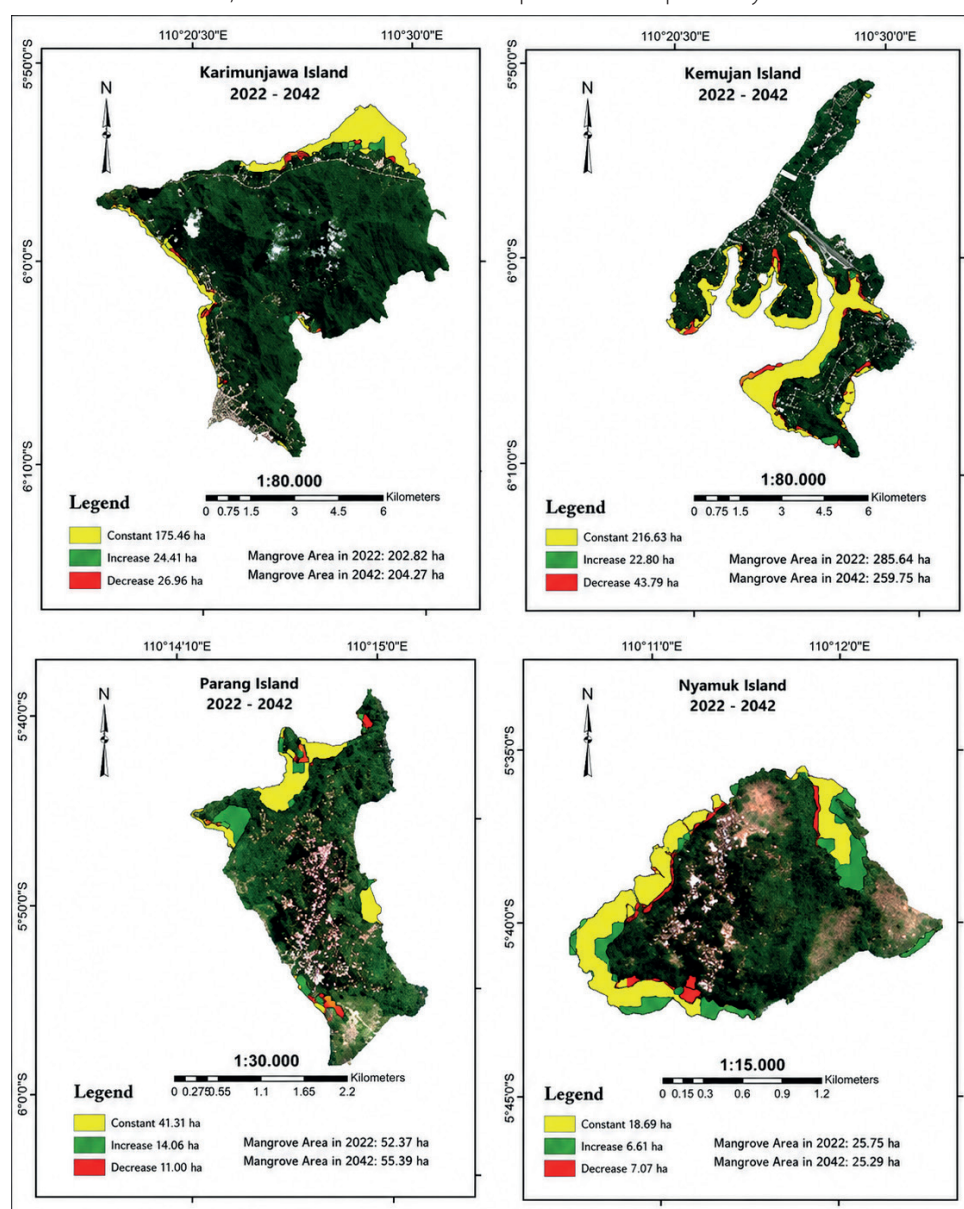


Fig. 5. Projected Changes in Mangrove Cover on Four Islands of the Karimunjawa Archipelago (2022–2042)

extent and greater carbon stocks exposed to land-cover conversion. In contrast, Parang and Nyamuk exhibited lower estimated CO₂ emissions associated with carbon stock losses, with Nyamuk reaching approximately 3,682.45 t CO₂ ha⁻¹ in 2022, although even small-scale mangrove degradation remains ecologically significant.

The temporal variation in estimated CO₂ emissions reflects the balance between mangrove degradation and recovery processes. Temporary reductions in carbon stock losses during certain periods (e.g., 2010 and 2022) may indicate short-term stabilization of mangrove extent or localized vegetation recovery. However, projected increases toward 2042 suggest continued anthropogenic pressure and potential future declines in mangrove carbon storage. Therefore, mangrove loss represents a dual impact by reducing ecosystem carbon stocks and weakening important ecosystem services that support climate change mitigation efforts (Arifanti et al. 2025). Continued degradation may also compromise progress toward sustainable development targets related to climate adaptation and ecosystem conservation (Fajeriadi et al. 2024; Rahmajati et al. 2026).

Interestingly, the results show that estimated CO₂ emissions associated with carbon stock losses decreased during certain periods, particularly in 2010 and 2022 (Fig. 6). This pattern may reflect temporary vegetation recovery or the influence of localized conservation interventions. However, without systematic protection, rehabilitation, and long-term monitoring, these short-term improvements may not compensate for the projected future carbon stock losses caused by continued land-cover change (Anisah et al. 2024). Mangrove rehabilitation should therefore extend beyond replanting activities by incorporating ecological

considerations, including substrate characteristics, tidal dynamics, and native species composition, to ensure long-term ecosystem recovery. Carbon storage capacity varies considerably among mangrove species and environmental conditions, including temperature and salinity (Hayati et al. 2023). Rehabilitated mangrove ecosystems may accumulate substantial carbon stocks, with reported values reaching 558.07 t CO₂ ha⁻¹ for total ecosystem carbon storage (Amelia et al. 2023).

These findings emphasize the importance of site-specific mangrove management strategies. Larger islands, such as Karimunjawa and Kemujan, should be prioritized for carbon conservation due to their extensive mangrove areas and substantial carbon stocks, while smaller islands such as Nyamuk require strict protection to prevent further carbon stock decline. Karimunjawa Island contains approximately 79,451 t CO₂ ha⁻¹ of total carbon stock, compared with 22,941 t CO₂ ha⁻¹ in the smaller Bawean Islands, supporting the prioritization of larger islands as important mangrove carbon storage areas (Asadi et al. 2024). Similarly, Nyamuk Island contains approximately 1,176.48 t CO₂ ha⁻¹ of mangrove carbon stock and has experienced mangrove area reduction due to land conversion, highlighting the need for stronger protection measures to prevent further carbon stock losses (Nuraini et al. 2021). Indonesian mangroves can accumulate approximately 1000 – 10,000 t CO₂ ha⁻¹ depending on management conditions, providing a scientific basis for optimizing conservation strategies across different island settings (Murdiyarso et al. 2021). Detailed calculations of carbon stock changes and associated CO₂ emissions are presented in Fig. 6 (a, b, c) and Tables S1–S5 in the Supplementary Materials.

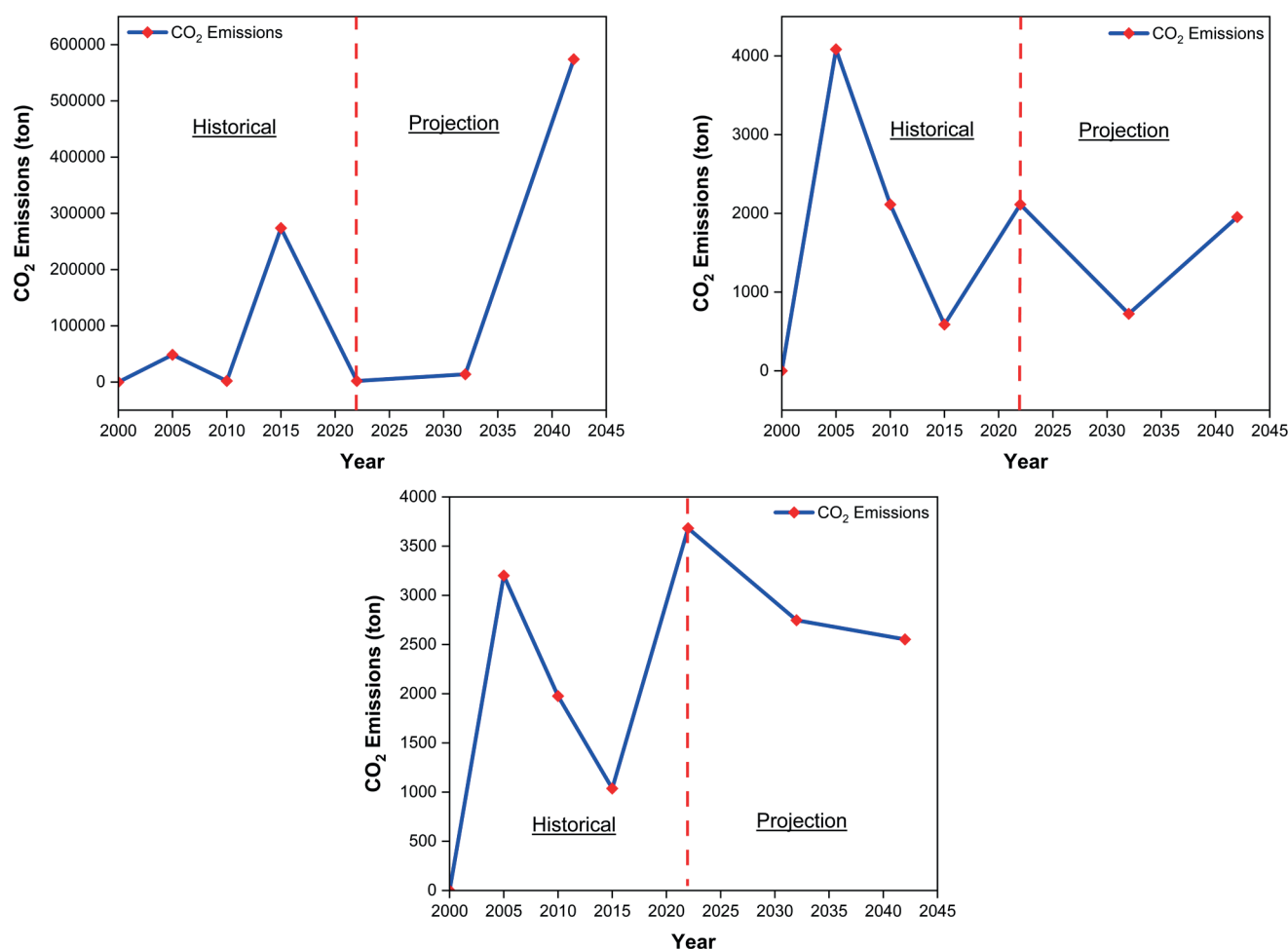


Fig. 6. Temporal distribution of CO₂ emissions from (a) Karimunjawa and Kemujan Islands, (b) Parang Island, (c) Nyamuk Island

CONCLUSIONS

This study highlights the spatiotemporal dynamics of mangrove ecosystems in the Karimunjawa Archipelago and their implications for carbon stock changes and coastal resilience. While Karimunjawa and Kemujan exhibit signs of recovery and expansion, Parang shows persistent decline, and Nyamuk reflects relatively stable but vulnerable conditions. These contrasting trajectories demonstrate that mangrove dynamics are shaped by the interaction of geomorphological characteristics, anthropogenic pressures, and governance conditions. By integrating long-term satellite image analysis, mangrove area prediction, and carbon stock-based CO₂ emission estimates, this study provides insights into how mangrove land-cover changes influence carbon storage patterns in small island systems. Projected increases in estimated CO₂ emissions associated with mangrove carbon stock losses by 2042, particularly on mangrove-rich islands, highlight potential risks to climate mitigation efforts and the sustainability of coastal ecosystem functions. These estimated emissions represent the potential release of carbon resulting from mangrove land-cover change and should not be interpreted as direct measurements of atmospheric CO₂ fluxes or as evidence

that mangroves no longer function as important carbon storage ecosystems.

The observed spatial variability underscores the importance of site-specific management approaches, where protected and effectively managed areas demonstrate greater potential for maintaining mangrove extent and carbon storage capacity compared with islands experiencing higher land-conversion pressure. Overall, these findings emphasize the need for integrated and adaptive mangrove management combining spatial planning, long-term monitoring, and restoration strategies to conserve carbon stocks, prevent further carbon losses, and strengthen coastal resilience in small island systems. Future research should incorporate more detailed field measurements of mangrove biomass carbon, soil organic carbon stocks, carbon accumulation rates, and greenhouse gas flux measurements to provide a more comprehensive understanding of mangrove carbon dynamics. The application of higher-resolution mapping approaches and further evaluation of local socio-economic drivers would also improve future projections and support more effective mangrove-based blue carbon management in the Karimunjawa Archipelago. ■

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