Long-Term Monitoring of Carbon Dynamics and Mangrove Health Using Remote Sensing: A Study of Balikpapan Bay, Indonesia

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Abstract

Mangrove ecosystems provide critical ecological services, including supporting coastal fisheries, protecting shorelines, and functioning as significant carbon sinks within the global carbon cycle. These ecosystems play a substantial role in climate change mitigation, as they are capable of sequestering up to three times more carbon dioxide (CO_2) than terrestrial forests. Given increasing anthropogenic pressures and environmental change, continuous monitoring of mangrove health is essential to sustain these ecological functions and ecosystem services. Remote sensing technology offers a cost-effective and efficient approach for large-scale assessment, spatial analysis, and long-term monitoring of mangrove conditions. This study utilized cloud-free Landsat-8 imagery from 2013 to 2020 to evaluate mangrove health in Balikpapan Bay using the Mangrove Health Index (MHI), which classifies conditions into three categories: excellent, moderate, and poor. Carbon storage was estimated using a model integrating vegetation indices with Above-Ground Carbon (AGC). The results revealed a fluctuating yet overall positive trend in mangrove health, with the "excellent" category increasing by 1.023% (174.78 ha), while the "poor" category decreased by 1.098% (187.67 ha) over the study period. AGC values exhibited a comparable pattern, reaching a peak of 375.54 Mg.ha^{-1} in 2018 (mean: 125.85 Mg.ha^{-1}). A strong positive correlation (r = 0.994) was observed between estimated mangrove health and AGC values, indicating that healthier mangrove ecosystems possess greater carbon sequestration potential. These findings highlight the importance of sustained monitoring and adaptive management strategies to support mangrove conservation and strengthen their contribution to climate change mitigation at regional and landscape management and policy scales.

Keywords: *Mangrove, Landsat–8, Above Ground Carbon, Mangrove Health Index*

Introduction

Mangrove ecosystems are essential in coastal regions, contributing to ecological, physical, and socio-economic functions. From an ecological perspective, mangrove ecosystems function as important habitats for the spawning and development of various marine species (Ramdhun and Appadoo, 2020) and offer significant carbon sequestration benefits (Fourqurean *et al.,* 2019; Sidik *et al.,* 2019). These forests are capable of storing large amounts of carbon within their biomass and other organic matter (Alongi, 2012).

In recent decades, the extent and health of mangrove ecosystems have deteriorated due to anthropogenic activities, including mangrove conversion and urban development (Richards and Friess, 2016; Nordhaus *et al.,* 2019). According to the data obtained from the National Mangrove Map, the mangrove area in 2023 was 3.44 million hectares (Nasional Mangrove Map, 2024). The loss of mangrove forests in Indonesia contributes to 42% of global carbon dioxide (CO_2) emissions (Murdiyarso *et al.,* 2015).

Monitoring the health of mangrove ecosystems is crucial for maintaining their ecological functions. This study utilizes remote sensing technology to evaluate mangrove health and estimate carbon storage. According to findings, carbon storage is estimated using a vegetation index-based model developed by Suardana *et al.,* (2023), which calculates Above Ground Carbon (AGC). The Mangrove Health Index (MHI) is used to assess health conditions, employing a spatial approach combining several mangrove indices (Nurdiansah and Dharmawan, 2021).

Balikpapan Bay is a strategically important mangrove area that is potentially subject to high anthropogenic pressure due to the development of

Indonesia's new capital city (IKN Nusantara), given its role as a primary logistical route to the capital region. Ongoing development activities are expected to affect mangrove ecosystem health as well as their capacity to store and sequester carbon. However, scientific studies addressing mangrove health conditions and carbon storage dynamics in Balikpapan Bay remain limited and fragmented. Previous research has predominantly focused on mangrove distribution and density (Pratama, 2018), carbon stocks and mangrove health within spatially restricted areas (Paputungan *et al.,* 2022), and specific ecological parameters and economic valuation, such as species diversity, stand productivity, and aboveground biomass (Kristiningrum *et al.,* 2019), while climate change mitigation has also been examined from a social perspective (Yuniarti *et al.,* 2023). To date, comprehensive studies integrating remote sensing–based monitoring to estimate carbon stocks and model CO_2 sequestration potential at the mangrove landscape scale in Balikpapan Bay are still lacking.

Therefore, monitoring mangrove health and estimating carbon storage capacity are critically important, particularly in regions experiencing intensive coastal development pressure. This study provides a novel contribution by utilizing remote sensing technologies that integrate the MHI and vegetation index–based modelling to assess mangrove health conditions and carbon storage potential in a spatially explicit and landscape-scale framework. Balikpapan Bay, East Kalimantan, was selected as the primary study area due to its strategic location and high vulnerability to the impacts of IKN Nusantara development. The objective of this study is to deliver a comprehensive assessment of mangrove health and potential carbon stocks in Balikpapan Bay, thereby providing a scientific basis to support adaptive mangrove conservation and management strategies under rapidly changing environmental conditions, while reinforcing the role of healthy mangroves in climate change mitigation through enhanced carbon sequestration capacity.

Materials and Methods

This study utilizes Landsat 8 satellite imagery as the primary data source for estimating AGC and the MHI, which are subsequently validated using field measurement data. A remote sensing approach is combined with a Random Forest machine learning classification method to accurately identify and map mangrove forest extent (Purwanto *et al.,* 2023; Behera *et al.,* 2021). Accuracy assessment is conducted to evaluate the reliability and suitability of the models prior to further analysis. All remote sensing analysis stages are implemented on the Google Earth Engine (GEE) platform, ensuring that the system is open-access, user-friendly, and freely available. A schematic overview of the methodological workflow is presented in Figure 1, while detailed explanations of each methodological step are provided in the following sections.

The mangrove ecosystem in Balikpapan Bay is located on the eastern coast of East Kalimantan Province, spanning the administrative areas of North Penajam Paser Regency, Kutai Kartanegara Regency, Balikpapan City, and the newly established national capital, IKN Nusantara (Figure 2).

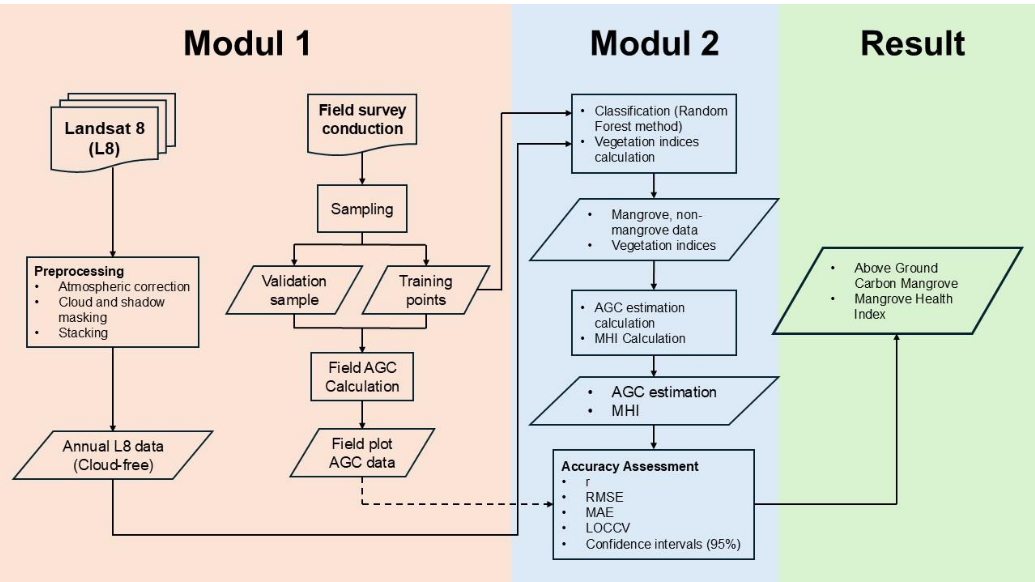

Figure 1. The flowchart of study methods used for mapping and calculating the AGC and MHI of mangrove forests

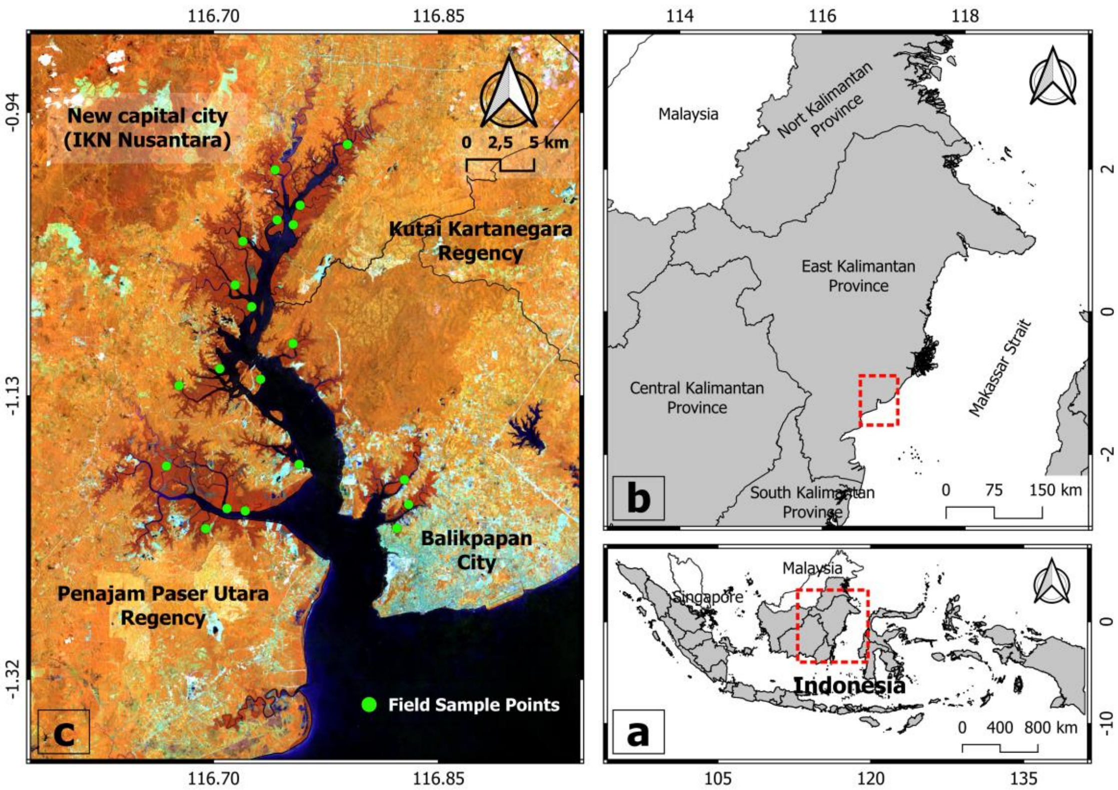

Figure 2. Study site: (a) the geographical location of East Kalimantan Province in Indonesia, (b) the geographical location of Balikpapan Bay in East Kalimantan Province, and (c) Balikpapan Bay is presented in a Landsat-8 standard false-color composite (RGB 5–6–4), where green dots denote field sample locations

The study conducted in Balikpapan Bay has identified significant mangrove biodiversity, with 20 to 36 species, including various types of trees, shrubs, and orchids found in this area. Mangrove species found in Balikpapan Bay are *Rhizophora apiculata*, *Rhizophora mocronata*, *Sonneratia alba*, *Acrosticum aureum*, *Ardisia sp.*, *Avicennia marina*, *Bruguiera gymnorhiza*, *Ceriops tagal*, *Dillenia suffruticosa*, *Dysoxylum sp.*, *Flagellaria sp.*, *Glochidion littorale*, *Guioa sp.*, *Heritiera littoralis*, *Lumnitzera littorea*, *Nypa fruticans*, *Pandanus odoratissima*, *Pouteria sp.*, *Xylocarpus granatum*, and *Cerbera manghas* (Warsidi and Endayani, 2007).

Remote Sensing Data

This study utilized Landsat 8 Operational Land Imager (OLI) Level-2 Surface Reflectance data (Collection 2, Tier 1) with spatial resolution 30x30 meters, which were accessed and processed using the GEE platform. The imagery was spatially filtered according to the study area (Balikpapan Bay) and temporally constrained to the defined analysis period. Cloud masking was performed using the quality assessment band (QA_PIXEL) generated by the CFMask algorithm, whereby pixels identified as cloud, cloud shadow, cirrus, and dilated cloud were excluded. In addition, invalid and radiometrically saturated pixels were removed to ensure that only high-quality surface reflectance observations were retained for subsequent analyses.

All cloud-free images that passed the quality screening were then grouped by year and aggregated to produce annual composite images (2013–2020) using the median reducer at the pixel level. The median compositing approach was selected because it effectively suppresses outliers, minimizes the influence of varying illumination geometry, and reduces residual atmospheric effects remaining after Level-2 correction. The resulting annual composites provide a temporally consistent and stable representation of surface conditions, supporting robust multi-temporal analyses and the extraction of environmental parameters.

Vegetation Indices Calculation

In calculating MHI and AGC, some vegetation indices are used based on Landsat-8 satellite images. The vegetation indices used can be seen in Table 1.

Mangrove carbon stock was estimated using a remote sensing–based model developed by

Suardana *et al.,* (2023). The model employs the optimal combination of vegetation indices, namely the TRVI and the DVI, to estimate AGC, with previously validated performance (R^2 = 0.95; RMSE = 13.63). The model is constructed based on species-specific allometric approaches for Asian mangroves, drawing on allometric equations from multiple prior studies (Clough and Scott, 1989; Komiyama *et al.,* 2005; Kangkuso *et al.,* 2015; Kangkuso *et al.,* 2018; Kusmana *et al.,* 2018; Analuddin *et al.,* 2020; Hasidu *et al.,* 2022). Given these characteristics, the model was applied to estimate mangrove carbon stocks in Balikpapan Bay. The model used is as follows:

$$AGC = -33.385 + (27.576 * TRVI) + (201.012 * DVI)$$

The AGC model results in carbon storage on the mangrove soil surface ($Mg.ha^{-1}$).

Mangrove Health Calculation

Mangrove health conditions were evaluated using the Mangrove Health Index (MHI) method developed by Nurdiansah and Dharmawan (2021), which is a remote sensing-based model demonstrating high accuracy (R^2 = 0.831). The vegetation indices applied include NBR, which is sensitive to living chlorophyll, soil and vegetation water content, lignin, mineral hydrates, ash, and charcoal are key factors for assessing mangrove health (Miller *et al.,* 2009). Furthermore, GCI estimates leaf chlorophyll content and reflects physiological conditions and overall vegetation health across species (Wu *et al.,* 2012). SIPI assesses the ratio of carotenoids to chlorophyll to characterize mangrove health (Chaube *et al.,* 2019); and ARVI, which exhibits a high correlation with MHI (Siddiq *et al.,* 2020). The MHI model applied in this study is as follows:

$$MHI = (102.12 * NBR) - (4.64 * GCI) + (178.15 * SIPI) + (159.53 * ARVI - 252.39$$

Mangrove health conditions are divided into three categories, such as poor (0–33%), moderate (33–66%), and excellent (66–100%) (Dharmawan, 2021).

Field Data and Accuracy Assessment

Field data collection was carried out in August 2020, selected specifically because it coincided with the dry season in Indonesia, minimizing the potential for rain to interfere with the survey. In this study, a total of 20 sampling points (Figure 2) were selected using a random sampling approach based on field conditions. At each sampling point, a 10 × 10 m plot was established for vegetation data collection. The collected data included tree species identification and measurements of diameter at breast height (DBH). Plot size and measurement procedures followed the standard protocol for mangrove forest structure and biomass assessment as proposed by Kauffman and Donato (2012). A total of nine mangrove species were identified during the field data collection, namely *Avicennia lanata*, *Bruguiera gymnorrhiza*, *Ceriops tagal*, *Lumnitzera littorea*, *Rhizophora apiculata*, *Rhizophora mucronata*, *Rhizophora stylosa*, *Sonneratia alba*, and *Xylocarpus granatum*. DBH was measured at 1.3 meters above ground level, which corresponds to the typical height of an adult's chest (Pearson *et al.,* 2005).

An accuracy assessment is necessary to evaluate how well the model results reflect field conditions. Validation is conducted by determining several parameters, including the correlation coefficient (r) to assess the strength of the relationship between the two variables. Error-values are then calculated using the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). In addition, Leave-One-Out Cross-Validation (LOOCV) was applied to evaluate model performance more comprehensively and to minimize potential bias arising from the relatively small sample size. In each iteration, one data point was used as the testing dataset, while the remaining points served as the training dataset, until all points had been sequentially

Table 1. Vegetation index formula used in the calculation of MHI and AGC

Vegetation Indices	Equation	References	Calculation Function
Normalized Burn Ratio (NBR)	$\frac{NIR - SWIR}{NIR + SWIR}$	Miller *et al.,* (2009)	MHI
Green Chlorophyll Index (GCI)	$\left(\frac{NIR}{Green}\right) - 1$	Wu *et al.,* (2012)	MHI
Structure Insensitive Pigment Index (SIPI)	$\frac{NIR - Blue}{NIR - Red}$	Haboudane *et al.,* (2002)	MHI
Atmospherically Resistant Vegetation Index (ARVI)	$\frac{NIR - 2 * Red + Blue}{NIR + 2 * Red + Blue}$	Kaufman and Tanre (1992)	MHI
Total Ratio Vegetation Index (TRVI)	$\sqrt{\frac{NIR}{Red}}$	Fadaei *et al.,* (2012)	AGC
Difference Vegetation Index (DVI)	$DVI = NIR - Red$	Hong-wei *et al.,* (2019)	AGC

used for validation. Furthermore, 95% confidence intervals for the regression coefficients were calculated to quantify uncertainty in the effects of the predictors. Prediction intervals for AGC estimates were also generated, providing a visual representation of the expected range of new observations based on the model.

Results and Discussion

Above Ground Carbon Storage

In this study, a vegetation index-based model was applied AGC estimation using TRVI and DVI. The model, originally developed for tropical mangrove ecosystems (Tahura Ngurah Rai, Bali), has demonstrated high accuracy in estimating AGC mangrove. An accuracy assessment using field measurements was conducted to evaluate its applicability to the Balikpapan Bay. The results revealed a consistent pattern between field-measured and estimated AGC values (Figure 3). Statistical analysis further indicated a strong correlation (r = 0.924), with an MAE of 23.510 $Mg.ha^{-1}$, and an RMSE of 39.182 $Mg.ha^{-1}$.

To further assess model robustness, additional cross-validation was performed using the LOOCV approach. The LOOCV analysis yielded an average RMSE of 40.91 $Mg.ha^{-1}$ and an average R^2 of 0.847, consistent with the performance observed in the independent validation dataset. On average, model predictions deviated by ±40.91 $Mg.ha^{-1}$ from field measurements. Considering the variability of mangrove carbon stocks within the study area, this level of accuracy is considered adequate for regional-scale estimation, although uncertainty at the individual plot scale remains relatively high due to ecosystem heterogeneity and the limited sample size. Overall, these findings indicate that the AGC estimation model reasonably represents field conditions, as reflected by strong correlation and acceptable error metrics. Therefore, the TRVI–DVI–based model is suitable for estimating mangrove AGC in Balikpapan Bay.

Meanwhile, the 95% confidence interval of the estimated AGC ranged from 165.588 to 236.491 $Mg.ha^{-1}$, with a mean value of 201.040 $Mg.ha^{-1}$ and a margin of error of ±35.45 $Mg.ha^{-1}$. This range indicates that the true population mean is likely to fall within these bounds at a 95% confidence level. The width of the confidence interval reflects inherent variability in mangrove structure and biomass. Nevertheless, the relative uncertainty of 17.63% remains acceptable for regional-scale carbon estimation in Southeast Asia. The observed variability is likely influenced by natural heterogeneity in stand structure, species composition, and environmental conditions within the study area.

The combined use of cross-validation and confidence interval analysis enhances the reliability of model performance evaluation, particularly given the relatively small sample size (20 plots). The consistent results obtained from the LOOCV approach indicate that the model demonstrates good generalization capability and does not exhibit significant overfitting, as reflected in the stability of RMSE and R^2 values across iterations. Furthermore, the 95% confidence interval analysis provides an estimate of parameter and prediction uncertainty, thereby reinforcing the robustness of predictor contributions in the AGC estimation model and reducing the likelihood that results are driven by sample-specific variation. The marginal uncertainty, which falls within a moderate range and remains within the commonly accepted threshold (10–30%), suggests that the model achieves an adequate level of precision for plot- to regional-scale applications. These findings are consistent with previous studies reporting that the integration of cross-validation and statistical uncertainty analysis is an effective strategy for improving the reliability of forest biomass and carbon estimation models in tropical regions (Belloli *et al.,* 2025; Gonçalves *et al.,* 2017; Chen *et al.,* 2015).

The estimation of mangrove carbon storage in Balikpapan Bay, East Kalimantan (2013–2020) demonstrated a fluctuating trend, with an average AGC of 118.42 $Mg.ha^{-1}$ (Figure 4). The lowest average AGC value was observed in 2016, at 111.89 $Mg.ha^{-1}$, with a value range from 0 to 222.45 $Mg.ha^{-1}$, while the highest average AGC occurred in 2018, at 125.85 $Mg.ha^{-1}$, with a value range from 0 to 375.54 $Mg.ha^{-1}$. The AGC values in this study were influenced by the application of near-infrared (NIR) spectrum in the vegetation index calculation, which is directly related to canopy cover and mangrove density (Hastuti *et al.,* 2017; Umarhadi and Syarif, 2018; Suardana *et al.,* 2022).

Mangrove ecosystems are among the most biodiverse globally and are integral to coastal communities (Worthington *et al.,* 2020; Iqbal, 2020). These forests can sequester CO_2 at a rate three times greater than other forest types (Donato *et al.,* 2011). According to the Indonesian National Standardization Agency (2011) in their ground-based forest carbon accounting guidelines (SNI 7724:2011), CO_2 absorbed through photosynthesis was converted into organic compounds, with 47% of the biomass consisting of carbon. The development of urban areas, such as Balikpapan City and the new national capital, IKN Nusantara, has the potential to exert significant pressure on the mangrove ecosystem in

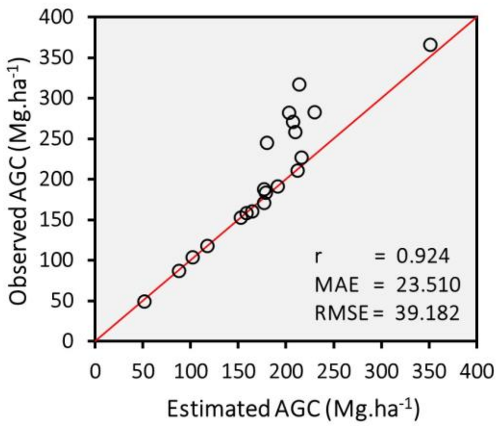

Figure 3. Scatter plots of observed and predicted AGC values. Scatter plots of observed and predicted AGC values. The red lines are 1:1 correspondence between observed and predicted AGC values

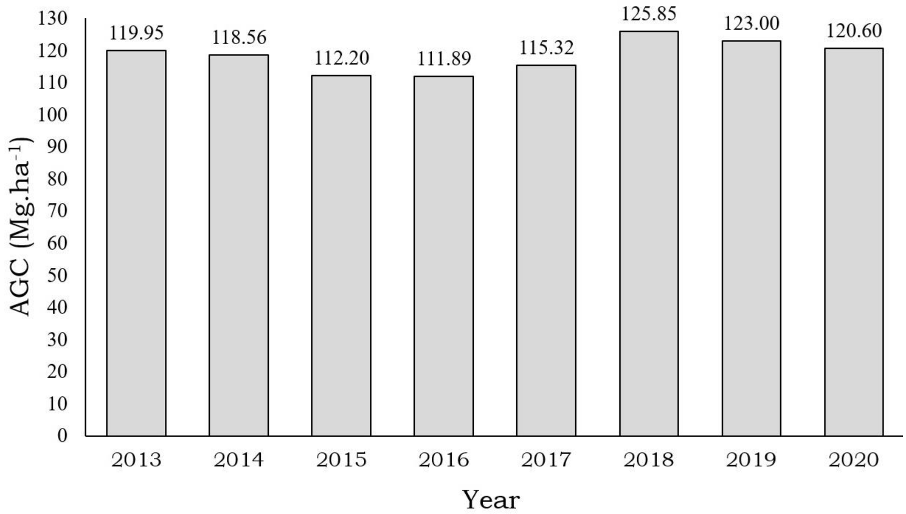

Figure 4. Temporal graph of average mangrove carbon storage estimation in the form of AGC (2013-2020)

Balikpapan Bay, possibly leading to increased carbon release into the atmosphere (Murdiyarso *et al.,* 2015).

Mangrove carbon storage estimation in terms of AGC is presented spatially (Figure 5). The carbon stock values were classified into five categories (Table 2) using the Natural Breaks (Jenks) method. This classification approach minimizes within-class variance and maximizes between-class variance, allowing the class boundaries to reflect the inherent distribution pattern of AGC values in the study area.

The spatial distribution of AGC shows a pattern consistent with mangrove health conditions identified in the previous results. The majority of mangrove AGC in Balikpapan Bay is classified from low to moderate, with only a few areas categorized as very low or very high. For instance, in the Jenebora region, between 2013 and 2020, several locations were classified as very low, likely due to prolonged exposure to anthropogenic disturbances, including oil spill events that have significantly affected parts of Balikpapan Bay.

The increase in mangrove AGC values from 2013 to 2020 was observed in the Balikpapan area. High to very high AGC categories remained consistent, although some locations still exhibited low to very low AGC categories. The presence of mangrove ecosystems advocacy groups, such as the Margomulyo Fishermen's Group and Graha Indah Mangrove Center, in addition to growing public awareness of the ecological importance of mangrove ecosystems, has positively influenced the development of these ecosystems as natural carbon sinks.

The Sepaku area has the closest distance to the IKN Nusantara from 2013 to 2020 and has a consistent mangrove AGC condition with a low to moderate category distribution. However, there was a

Table 2. Carbon stocks classification

Classification	Carbon stock values (Mg.ha^{-1})
Very low	0 – 55.25
Low	55.26 – 110.51
Moderate	110.52 – 165.76
High	165.77 – 221.02
Very High	≥ 221.03

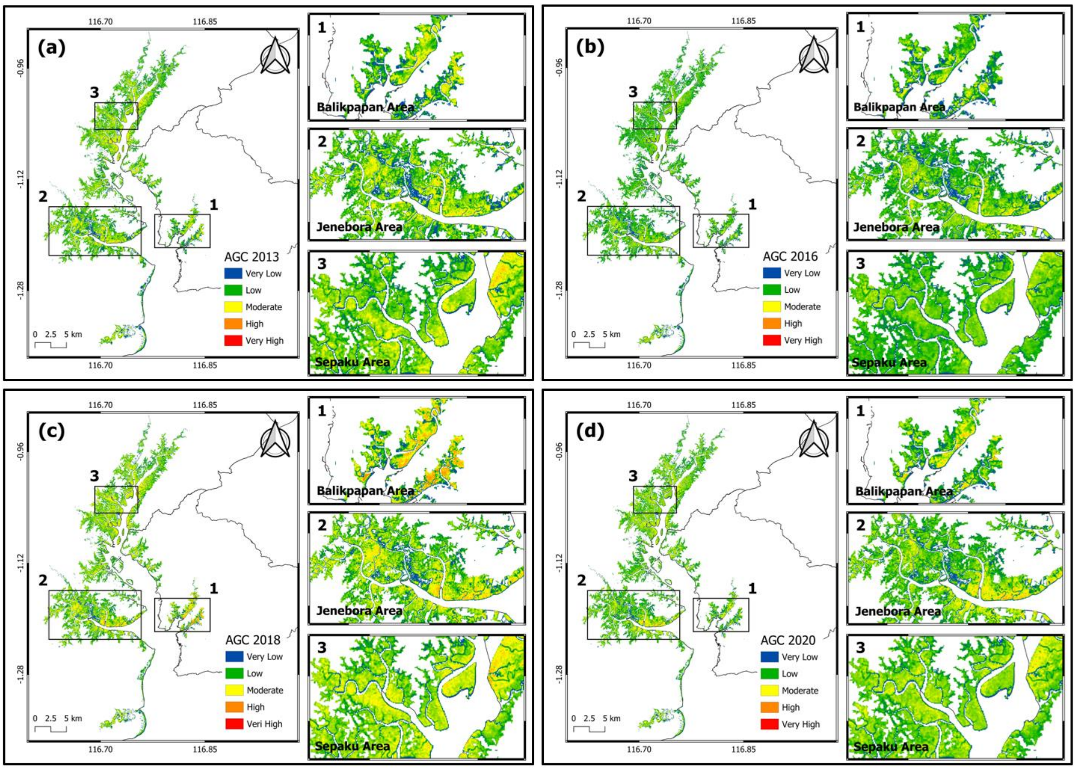

Figure 5. Spatial mangrove carbon storage estimation in the form of AGC: (a) in 2013, (b) in 2016, (c) in 2018, (d) in 2020

decline in mangrove AGC during 2016, but it increased again the following year. Improving the quality of mangrove ecosystems needs to be recommended in the Sepaku area, considering that the presence of new capital will impact the quality of the environment, such as pollution, human activities, land use, etc (Rahmadi *et al.,* 2023).

Mangrove Health Conditions

The mangrove health status in Balikpapan Bay, East Kalimantan, between 2013 and 2020 exhibited variability, typically categorized as “excellent,” with an average MHI of 75.35%. This trend is consistent with the findings related to mangrove carbon storage, where the MHI value reached its lowest in 2016 at 72.63%, and its highest in 2018 at 78.31%. The MHI values are influenced by factors such as canopy cover, tree diameter, and the abundance of saplings (Dharmawan *et al.,* 2020).

Based on the result presented in Figure 6, the mangrove health conditions were categorized into poor, moderate, and excellent. Over the eight years of observation, the "excellent" mangrove category increased by 1.023% (174.78 ha), while the "poor" category declined by 1.098% (187.67 ha). These results suggest a positive trend in the mangrove ecosystem health in Balikpapan Bay, with an average annual improvement of 0.128% (21.85 ha).

The mangrove health conditions, as evaluated using the MHI method, are represented spatially in Figure 7. The data indicates a decline in mangrove health from 2013 to 2016, likely due to the rapid industrial expansion in Balikpapan Bay (Figures 7a and 7b). These findings are supported by a study conducted by Mahdaleny (2015), which highlights that industrial growth in the region has led to adverse impacts on mangrove forests, including reclamation, water pollution, and the loss of marine biodiversity.

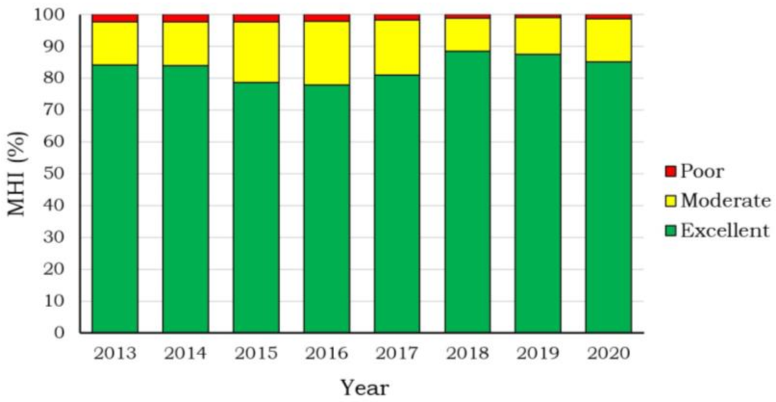

Figure 6. Temporal graph of mangrove condition (2013–2020) with three categories (poor, moderate, and excellent)

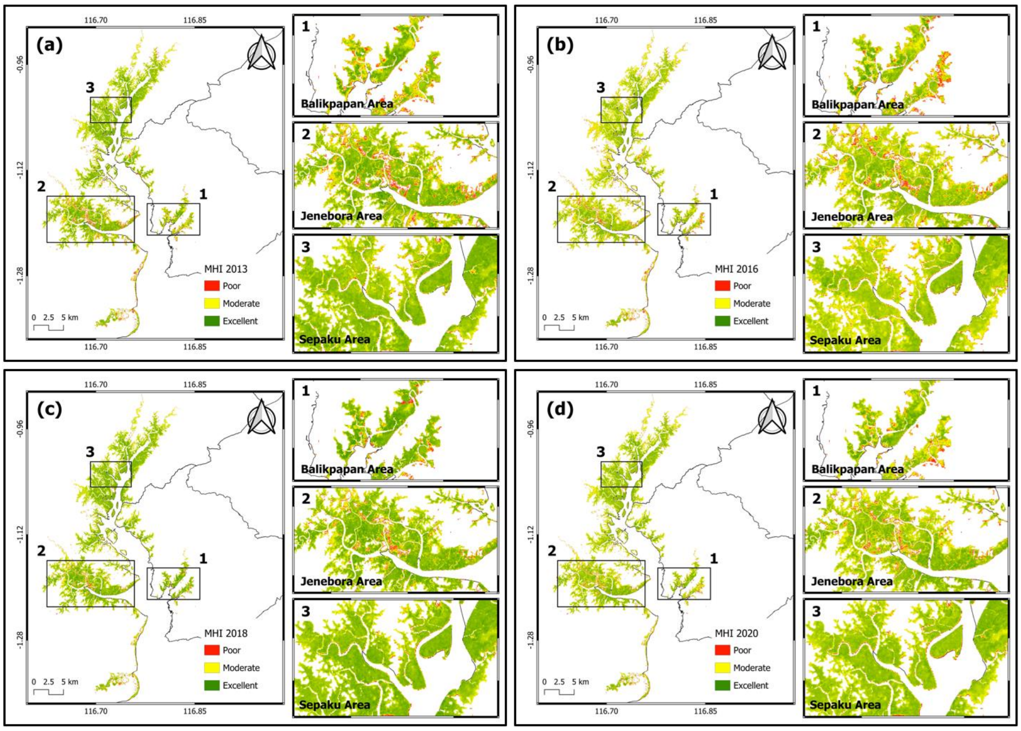

Figure 7. Spatial mangrove health condition with three categories (poor, moderate, and excellent): (a) in 2013, (b) in 2016, (c) in 2018, (d) in 2020

In addition to anthropogenic pressures, interannual climate variability such as El Niño and the positive phase of the Indian Ocean Dipole (IOD) during early 2015 to early 2016 (Figure 8) contributed to a significant reduction in rainfall in Balikpapan Bay. Rainfall decreased by 25.85% compared to 2014, representing the lowest annual precipitation recorded between 2010 and 2015 according to the Environmental Agency of Balikpapan City (2015) and the Central Bureau of Statistics for East Kalimantan Province (2015). Reduced precipitation likely increased salinity levels within the intertidal zone, imposing physiological stress on mangrove species with low salinity tolerance (Rahman, 2020; Ahmed *et al.,* 2022). Temporal patterns in mangrove vegetation indices indicate that these climatic anomalies coincided with measurable declines in vegetation health, suggesting that ENSO and IOD exerted indirect but significant effects on mangrove condition through altered hydrological and salinity regimes. Furthermore, the mixed semidiurnal tidal regime of Balikpapan Bay, as described by Nurjaya *et al.* (2018) may have amplified environmental stress by facilitating the retention of saline water within mangrove sediments during repeated tidal inundation cycles.

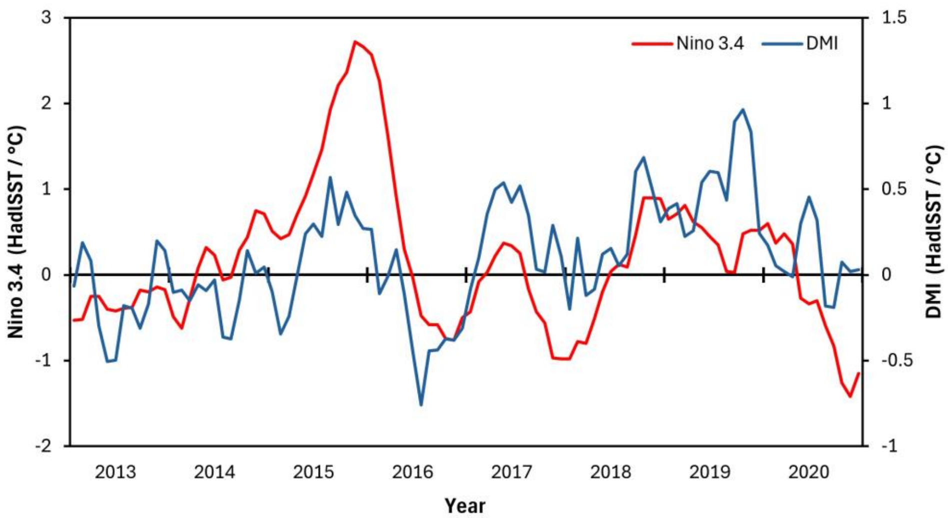

Figure 8. Seasonal mean Niño 3.4 sea surface temperature (SST) index and dipole mode index (DMI) derived from HadISST1.1 during the study period (2013–2020). Data source: NOAA physical sciences laboratory (PSL) derived from the HadISST dataset.

Following an observable recovery in mangrove condition in 2018, a subsequent decline from 2019 to 2020 (Figure 7c and 7d) corresponded with the March 29–31, 2018 oil spill originating from a leaking Pertamina submarine pipeline (Prastyani and Basith, 2018; Koto and Putrawidjaja, 2018; Widiawan, 2021; Amelia, 2022). The spill released approximately 6,995,411 liters of oil, primarily affecting Jenebora Village and damaging 34 hectares of mangroves, as well as multiple coral reef and seagrass areas (Amelia, 2022). Given the semi-enclosed morphology of the bay and its mixed semidiurnal tidal dynamics, oil residues were likely retained within intertidal sediments and mangrove root systems, prolonging exposure and ecological stress. Oil contamination in mangrove environments is known to persist for years within fine sediments, impairing root respiration and regeneration capacity (Lee *et al.,* 2013). These findings indicate that the observed decline in mangrove health cannot be attributed solely to natural climatic variability; rather, it reflects the combined and interacting effects of climate anomalies, tidal hydrodynamics, and anthropogenic disturbances. Such interactions underscore the need for integrated, data-driven monitoring to disentangle cumulative stressors affecting mangrove ecosystems in Balikpapan Bay.

Oil spills in mangrove ecosystems tend to intensify due to tidal dynamics within the intertidal zone (Astuti and Titah, 2020). In areas characterized by mixed predominantly semidiurnal tides, such as Balikpapan Bay, which experiences two tidal cycles per day (Supriyono *et al.,* 2015; Nurjaya *et al.,* 2018), hydrodynamic processes periodically drive oil into mangrove forests during high tide and subsequently trap it among root structures and muddy sediments during low tide. The relatively calm and semi-enclosed nature of the bay further reduces natural flushing capacity, thereby increasing the likelihood of oil accumulation and deposition within the intertidal substrate. Under certain conditions, oil residues may persist in sediments for more than four years,

significantly inhibiting mangrove growth and prolonging ecosystem recovery (Lee *et al.,* 2013; Ozigis *et al.,* 2018). This long-term retention amplifies ecological stress by impairing root respiration, reducing sediment stability, and limiting natural mangrove regeneration (Duke *et al.,* 2000; Alongi, 2002).

The growth of industrialization and the occurrence of oil spillages in Balikpapan Bay may also affect the capacity of mangrove ecosystems to function as carbon sinks. Onyena and Sam (2020) suggested that the overexploitation of mangrove ecosystems and pollution, such as oil spillages, diminishes their ecological services. Therefore, mangroves should not be regarded as worthless vegetation but as valuable resources that can be sustainably and responsibly developed.

Relationship between Health Condition and AGC Mangrove

This study calculated the correlation coefficient between the estimated mangrove health conditions and the estimated AGC values to evaluate the statistical relationship between the two variables (Figure 9). Both estimates were derived through a series of systematic data processing and analytical procedures conducted in this study. The results of the correlation coefficient indicate a strong positive

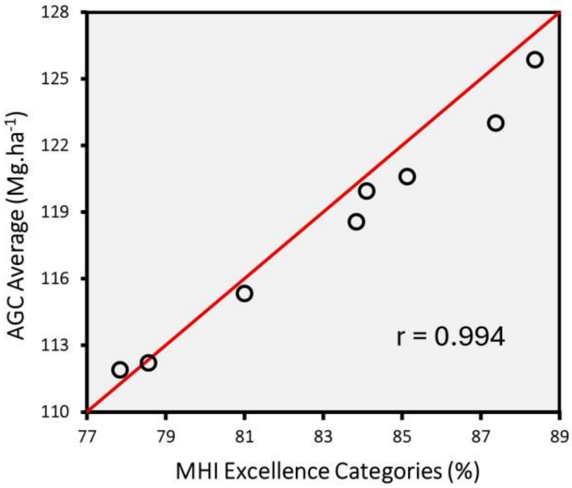

Figure 9. Scatter plots showing the relationship between estimated mangrove health (Excellent category) and mean AGC values (2013–2020)

relationship between mangrove health and AGC values, with a value of 0.994. Schaduw *et al*. (2021) explained that carbon storage in mangrove ecosystems is directly proportional to factors such as tree biomass, soil fertility, and the vegetation's capacity to absorb carbon. The carbon content in plants serves as an indicator of their capacity to capture CO_2 from the atmosphere (Dusenge *et al.,* 2019). A portion of the stored carbon is utilized as energy for physiological processes, while the rest is integrated into the plant's structural components (Bachmid *et al.,* 2020). Therefore, the healthier the mangrove ecosystem, the greater its carbon storage capacity.

The development of IKN Nusantara is likely to lead to population growth and an increase in anthropogenic activities, which can result in higher levels of household, industrial, and other forms of waste. According to Sinha *et al.,* (2014), waste accumulation can negatively impact soil and water quality, particularly in areas such as Balikpapan Bay, which serves as the estuary for the region's river systems. The increasing waste load in the bay poses a threat to mangrove growth and, if not effectively managed, could significantly damage the local ecosystem.

Conclusion

In conclusion, the mangrove health status in Balikpapan Bay between 2013 and 2020 showed fluctuating trends, though with an overall positive trajectory. The "excellent" mangrove category increased by 1.023% (174.78 ha), with an average annual increase of 0.128% (21.85 ha), while the "poor" category declined by 1.098% (187.67 ha), with an average annual decrease of 0.137% (23.46 ha). The potential carbon storage in the AGC of the mangroves in Balikpapan Bay reaches 375.54 $Mg.ha^{-1}$, with an average value of 118.42 $Mg.ha^{-1}$ during the study period. There was a strong positive correlation (r = 0.994) was observed between estimated mangrove health and AGC values, suggesting a close association between ecosystem condition and carbon storage potential. The primary threats to the mangroves of Balikpapan Bay include industrial expansion and oil spillages, which significantly diminish mangrove ecosystem services. These findings provide a valuable reference for policymakers to prioritize and manage mangrove ecosystems to preserve their functions. Immediate actions, such as protecting mangroves from existing waste, are crucial. This study used Landsat-8 data with a spatial resolution of 30 meters, which presents limitations for detailed mangrove analysis, particularly in heterogeneous or fragmented areas. Therefore, it is recommended that future investigations utilize higher-resolution data to enable more precise and comprehensive assessments. Another important consideration is that the AGC estimation model applied in this study was originally developed for a different site, although within the same biogeographical region (Asian mangroves), and has demonstrated satisfactory accuracy across multiple validation approaches. Nevertheless, cross-site model transferability may not fully account for site-specific ecological and structural variability. Future studies should therefore focus on developing region-specific models to enhance the representation of local characteristics and further improve AGC estimation accuracy.

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