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ASSESSING SPATIOTEMPORAL DYNAMICS OF MANGROVE HEALTH IN A TROPICAL ESTUARINE SYSTEM: A CASE STUDY FROM SEGARA ANAKAN, INDONESIA

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ABSTRACT

The Segara Anakan mangrove, one of Java's largest tropical mangroves, provides vital ecological and economic services. Its ability to protect Cilacap Regency from tsunamis, absorb atmospheric carbon and support community income is threatened by human and natural degradation. This study analyses spatiotemporal changes in mangrove distribution and health from 2018 to 2023. The aim is to identify key drivers of these changes. Sentinel-2A satellite imagery and a Support Vector Machine (SVM) algorithm were used to map mangrove distribution. Model validation with a confusion matrix showed high classification accuracies: 78.06% in 2018 and 86.39% in 2023. The Mangrove Health Index (MHI), which integrates SIPI, NBR, ARVI and GCI, was used to assess ecosystem health. Over five years, there was a net loss of 883.28 hectares. This represents 11.6% of the 2018 area. The main causes were conversion to aquaculture ponds and sedimentation. Degradation was greatest in the lagoon's west (Kampung Laut Sub-district), where heavy sedimentation comes from the Citanduy River. In contrast, good mangrove conditions improved in eastern sectors near industrial centres. In these areas, communities, companies and local governments collaborated on rehabilitation. The MHI proved highly effective for systematically monitoring mangrove health in tropical environments. This study demonstrates that integrated remote sensing is indispensable for directing targeted conservation. The proven impact of coordinated multi-stakeholder action sets a clear, practical benchmark for global mangrove protection, prompting the immediate adoption of similar robust strategies in all at-risk tropical mangrove regions.

Introduction

Mangrove ecosystems are vital to tropical and subtropical coastlines, delivering essential ecosystem services valued in the trillions of dollars each year. These services include protection from storms and erosion, support for biodiversity and fisheries, and significant global carbon sequestration. Mangroves are critical for climate change mitigation (Trégarot *et al*., 2021). Indonesia holds about 22.6% of the world's mangroves, making it essential for global mangrove conservation (Bunting *et al*., 2022). Despite this significance, Indonesia's mangroves face severe degradation — more than 54,000 hectares were classified as degraded in 2021, while another 756,183 hectares were listed as unsuitable habitat (Direktorat Pengelolaan DAS dan Rehabilitasi Hutan, 2025). This degradation impacts millions who rely on mangroves for fisheries, wood and shoreline protection; thus, livelihoods, food security and community resilience are all threatened (Mallick *et al*., 2021). In response to these threats, Indonesia has launched large-scale rehabilitation programmes that require effective, scalable monitoring tools to target and measure intervention success.

The global decline of mangroves is concerning, with a 3.4% loss recorded from 1996 to 2020 (Bunting *et al*., 2022). This global challenge reflects and helps frame the local pattern observed in the mangrove forest of Segara Anakan in Cilacap Regency, Java. It covered an area of 6,450 ha in 1903 but shrank to about 1,800 ha by 1992 (Wibowo & Handayani, 2006) and continues to decrease. Multiple drivers have contributed to this loss, including human-driven land conversion for agriculture and aquaculture, illegal logging and natural sedimentation (Ardli *et al*., 2022; Ismail *et al*., 2019). Consequently, as Java's largest mangrove area, the degradation in Segara Anakan significantly impacts both biodiversity and local economies. This underlines that the local issue is an urgent ecological and socio-economic problem with global repercussions. Given these challenges, it is vital to explore methods for effective assessment of mangrove conditions.

Assessing mangrove health across large, remote areas is logistically difficult and resource-intensive (Adinegoro *et al*., 2022). To address these challenges, satellite remote sensing (RS) — which uses sensors on satellites to collect information about the Earth's surface — offers a more efficient way to gather data. Early RS studies focused on mapping mangrove distribution (Everitt & Judd, 1989), and more recent research builds on these foundations by applying indices — quantitative values calculated from satellite images that reveal vegetation characteristics — to assess environmental health in greater detail. For example, the Normalised Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) estimate canopy structure and density, with NDVI reflecting green vegetation density and EVI improving sensitivity in high biomass regions (Hidayah *et al*., 2023; Prabakaran *et al*., 2014). In addition, Synthetic Aperture Radar (SAR), which creates images using microwave signals, helps analyse mangrove structure (Kovacs *et al*., 2013). Other indices also contribute to health assessment: the Photochemical Reflectance Index (PRI) gauges how efficiently plants use light energy (Song *et al*., 2011), and chlorophyll measurements indicate plant stress (Flores De Santiago *et al*., 2013). However, many of these methods often focus on just one health aspect.

A more holistic approach is the Mangrove Health Index (MHI), which combines four indices to provide a comprehensive assessment (Nurdiansah & Dharmawan, 2021). The Normalised Burn Ratio (NBR) indicates vegetation structure and fire impact by comparing near-infrared and shortwave infrared light reflectance. The Green Chlorophyll Index (GCI) measures leaf chlorophyll content, reflecting plant health and productivity. The Structure Insensitive Pigment Index (SIPI) assesses the balance of pigments such as carotenoids and chlorophyll to gauge physiological stress in plants. The Atmospherically Resistant Vegetation Index (ARVI) corrects for atmospheric distortion — such as haze or dust — when analysing vegetation. Together, these indices cover structure, chlorophyll, pigment balance (stress) and atmospheric effects. Within an ecological framework, the MHI highlights three key indicators of mangrove health: 1) ecosystem structure, 2) strength based on productivity, and 3) resilience related to habitat change (Li *et al*., 2014; Neres *et al*., 2024).

In the context of Indonesia's mangrove forests, prior remote sensing analyses have often been narrowed in focus compared to the holistic MHI approach described above. For example, studies typically used NDVI to assess structure (Akbar *et al*., 2020) or NDVI and DVI (Hilmi *et al*., 2022). Another Mangrove Index (MI) considered structure and soil moisture (Winarso *et al*., 2023). However, the simultaneous assessment of all three factors — structural integrity, chlorophyll as a proxy for productivity and pigment-based stress — is rare. Addressing this gap in the literature, our study applies the MHI for a detailed spatiotemporal analysis of mangrove health in Segara Anakan Mangrove.

This research introduces a significant advancement by applying the integrated MHI framework to Segara Anakan, a critical yet rapidly degrading mangrove ecosystem in Indonesia. Unlike previous studies in the area that relied on single indices (e.g., NDVI) or dual-index approaches, our work simultaneously evaluates structural, productive and stress-related health components. This multi-faceted assessment provides a more nuanced understanding of ecosystem dynamics, capturing both degradation drivers and recovery signals. Furthermore, while the MHI has been applied in other regions, such as Biak Island (Dharmawan, 2021) and Liki Island (Nurdiansah & Dharmawan, 2021), its application in a heavily sediment-impacted and anthropogenically pressured system like Segara Anakan is novel. This integrated, driver-aware approach sets our work apart from conventional mangrove mapping or health assessment studies, and provides a replicable model for complex tropical estuaries worldwide.

Accordingly, this research aims to analyse spatiotemporal changes in mangrove distribution and health from 2018 to 2023 and identify the drivers behind these changes. Building directly on the limitations of previous studies, the work makes three main contributions. First, it creates a detailed baseline to prioritise conservation and rehabilitation in Segara Anakan. Second, it demonstrates a comprehensive assessment method that others can apply in data-scarce regions. Finally, these contributions collectively aim to help local policymakers and managers make informed choices to boost both ecological resilience and socio-economic stability in coastal areas.

Materials and Methods

Study Area

Segara Anakan is in the Cilacap Regency, a large area bordered by the Indian Ocean to the south and Banyumas Regency in the north. It covers 225,361 Ha and contains 24 sub-districts.

Cilacap Regency's topography includes mountains, hills and lowlands. The mountainous northwest reaches elevations of over 1,000 meters at Mount Subang in Dayeuhluhur. The southeast contains two landscapes: A sloping plain that stretches south-southwest to Segara Anakan at about 100 meters elevation, and mountains in the north. The east and south are mostly lowlands.

Dayeuhluhur Subdistrict in Cilacap sits at 198 meters above sea level, the region's highest point. Kampung Laut Subdistrict, at one meter above sea level, is the lowest in the area. The mangrove ecosystem spreads through Cilacap's southern part near Nusa Kambangan Island, mainly along the Segara Anakan River. All mangroves grow in the brackish waters of Segara Anakan Lagoon. Administratively, the lagoon covers Ujung Alang, Panikel and Ujung Gagak Villages, together called "Kampung Laut". The study area is shown in Figure 1.

Data Acquisition and Preprocessing

Sentinel-2A MultiSpectral Instrument (MSI) Level-1C satellite images from 2018 to 2023 were used for this study. The Sentinel-2 mission, operated by the European Space Agency (ESA), provides global coverage with a high revisit frequency. It also offers spatial resolution up to 10 meters for its visible and near-infrared bands (Drusch *et al*., 2012). The year 2018 was selected as a baseline. It precedes several key regional conservation initiatives, allowing assessment of the ecosystem's state before these interventions. The year 2023 provides the most recent and cloud-free data available at the time

Figure 1: Location of the research area in Segara Anakan, Cilacap, Central Java

of analysis. This five-year interval is considered sufficient to observe significant spatiotemporal changes in mangrove extent and health (Du *et al*., 2023). The specific bands used were Band 2 (Blue, 490 nm), Band 3 (Green, 560 nm), Band 4 (Red, 665 nm), Band 8 (NIR, 842 nm) and Band 11 (SWIR, 1610 nm). To ensure consistency in all derived indices, all bands were resampled to a uniform 20-meter spatial resolution. The nearest-neighbour method was applied within the QGIS software environment.

Atmospheric correction is a critical pre-processing step. It converts the top-of-atmosphere radiance values (the intensity of light reaching the satellite from Earth's atmosphere) of Level-1C products to surface reflectance (the amount of light reflected by the ground), minimising atmospheric scattering and absorption. This study used the Dark Object Subtraction (DOS) method, implemented through the Semi-automatic Classification Plugin (SCP) in QGIS. The DOS method operates on the principle that certain pixels in the visible spectrum (such as deep water or shadow areas) should have zero reflectance. The algorithm identifies these "dark" pixels and subtracts their digital number values from all other pixels in the image. This effectively corrects for path radiance (light scattered by the atmosphere before reaching the satellite) (Chavez, 1996). Although simpler than more complex radiative transfer models, DOS is widely used and effective where atmospheric data may be unavailable (Chander *et al*., 2009). After atmospheric correction, images were cropped to the Segara Anakan study area boundary to streamline further processing.

Mangrove Classification

A supervised classification was performed to map mangrove distribution using the Support Vector Machine (SVM) algorithm. SVM is a non-parametric classifier known for its effectiveness in handling high-dimensional remote sensing data, even with a limited number of training samples (Mountrakis *et al*., 2011). The algorithm works by finding the optimal hyperplane that separates different classes with the maximum margin. For this study, a linear kernel was selected due to its computational efficiency and proven performance with multispectral data, where classes are often linearly separable in the feature space (Campos-Taberner *et al*., 2016). The regularisation parameter (C) was set to the default value of 1.0, as preliminary tests indicated stable performance without signs of significant over- or under-fitting.

Training samples, defined as Regions of Interest (ROIs), were manually digitised for three land cover classes: Mangrove, Non-Mangrove Vegetation and Water Body. A minimum of 30 polygons per class were created based on visual interpretation of a false-colour composite (FCC) using Band 8 (NIR), Band 4 (Red) and Band 3 (Green). This specific FCC combination effectively highlights mangrove vegetation in distinctive reddish-brown tones, facilitating accurate identification (Munandar *et al*., 2023). The classification was executed separately for the 2018 and 2023 images.

Post-classification (Accuracy Assessment)

The accuracy of the classified maps was assessed using a confusion matrix. For each year, 132 validation points were generated using a stratified random sampling scheme. These points were then compared against reference data derived from high-resolution Google Earth imagery.

Next, by using this confusion matrix, the overall accuracy and Kappa index was measured. The overall accuracy and Kappa Index was calculated based on the formula (1) until (4).

$$Overall\ accuracy = \frac{\Sigma \quad n_{ii}}{N} \tag{1}$$

$$Produce's\ accuracy\ for\ class\ i = \frac{n_{ii}}{ri} \tag{2}$$

$$Use's\ accuracy\ for\ class\ i = \frac{n_{ii}}{Ci} \tag{3}$$

$$Kappa = \frac{n\sum_{i=1}^{q} \ (nii) - \sum_{i=1}^{q} \ (ri\ Ci)}{n^2 - \sum_{i=1}^{q} \ ri\ Ci} \tag{4}$$

Where:

nii = Number of correctly classified samples in class I (diagonal of the confusion matrix)
N = Total sample for accuracy test
ri = Total number of reference samples in class *i* (row total)
ci = Total number of samples classified as class *i* (column total)
k = Kappa coefficient
q = Number of land-use classes

The overall accuracy was calculated to be 78.06% for 2018 and 86.39% for 2023. Both values exceed the widely accepted minimum threshold of 75% for land cover change studies, confirming the reliability of the classification output for subsequent analysis (Islami *et al*., 2022; Pande *et al*., 2024).

Mangrove Health Assessment (MHI)

Mangrove ecosystem health was assessed using the Mangrove Health Index (MHI), a composite model that integrates four spectral indices to provide a holistic view of ecosystem condition (Nurdiansah & Dharmawan, 2021). This model aligns with an ecological framework that assesses health based on structure, productivity and resilience (Li *et al*., 2014). The four constituent indices and their ecological rationale are as follows:

Normalised Burn Ratio (NBR): Sensitive to changes in vegetation moisture and plant stress, NBR is used here as an indicator of mangrove resilience and habitat condition (Alcaras *et al*., 2022). It is calculated as:

$$NBR = (B8 - B11) / (B8 + B11) \tag{1}$$

Green Chlorophyll Index (GCI): This index is strongly correlated with leaf chlorophyll content, serving as a proxy for mangrove photosynthetic activity and productivity (Wu *et al*., 2012). It is calculated as:

$$GCI = (B8 / B3) - 1 \quad (2)$$

Structure Insensitive Pigment Index (SIPI): Designed to minimise the influence of leaf surface and mesophyll structure, SIPI is sensitive to the carotenoid/chlorophyll ratio, which is useful for identifying vegetation structure and early signs of pigment-related stress (He *et al*., 2023). It is calculated as:

$$SIPI = (B8 - B2) / (B8 - B4) \quad (3)$$

Atmospherically Resistant Vegetation Index (ARVI): An enhancement of NDVI, ARVI incorporates the blue band to self-correct for atmospheric scattering effects from aerosols, making it more robust in humid, tropical coastal environments (Kaufman & Tanre, 1992). It is calculated as:

$$ARVI = (B8 - (2*B4) + B2) / (B8 + (2*B4) + B2) \quad (4)$$

The four indices were computed from the atmospherically corrected Sentinel-2 imagery. The final MHI was then computed using the established multiple linear regression equation:

$$MHI = (102.12*NBR) - (4.64*GCI) + (178.15*SIPI) + (159.53*ARVI) - 252.3 \quad (5)$$

Where:

B8 = Near-Infrared band
B11 = Shortwave Infrared band
B4 = Red band
B3 = Green band
B2 = Blue band

The resulting MHI values were classified into three health categories based on the thresholds defined by (Dharmawan, 2021), as shown in Table 1.

Spatiotemporal Change Analysis

Changes in mangrove distribution and health between 2018 and 2023 were analysed using overlay techniques in a GIS environment. This five-year interval is considered sufficient to observe significant spatiotemporal changes in mangrove extent and health (Du *et al*., 2023). The five-year study period from 2018 to 2023 was chosen due to the phenomenon of re-grown mangroves during this time. The re-growth of mangroves in the agricultural or pond areas of Segara Anakan is due to conservation efforts by the community and government that started in 2019 (Balai Data dan Informasi Sumberdaya Air Jawa Barat, 2020). Therefore, the effectiveness of mangrove conservation related to mangrove health can be identified during this period.

The post-classification comparison method was employed, where the 2018 and 2023 mangrove distribution maps were overlaid to quantify the total area of mangrove loss, gain and persistence. Similarly, the classified MHI maps for both years were overlaid to create a transition matrix, detailing the spatial dynamics and trajectories of mangrove health (e.g., areas that improved from “Moderate” to “Good”, or degraded from “Good” to “Degraded”). This allowed for a comprehensive quantification of changes over the five-year study period. The overall research workflow is summarised in Figure 2.

Table 1: MHI classification

Classification	MHI Value
Degraded	< 33,33
Moderate	33,33 to 66,67
Good	> 66,67

Source: (Dharmawan, 2021)

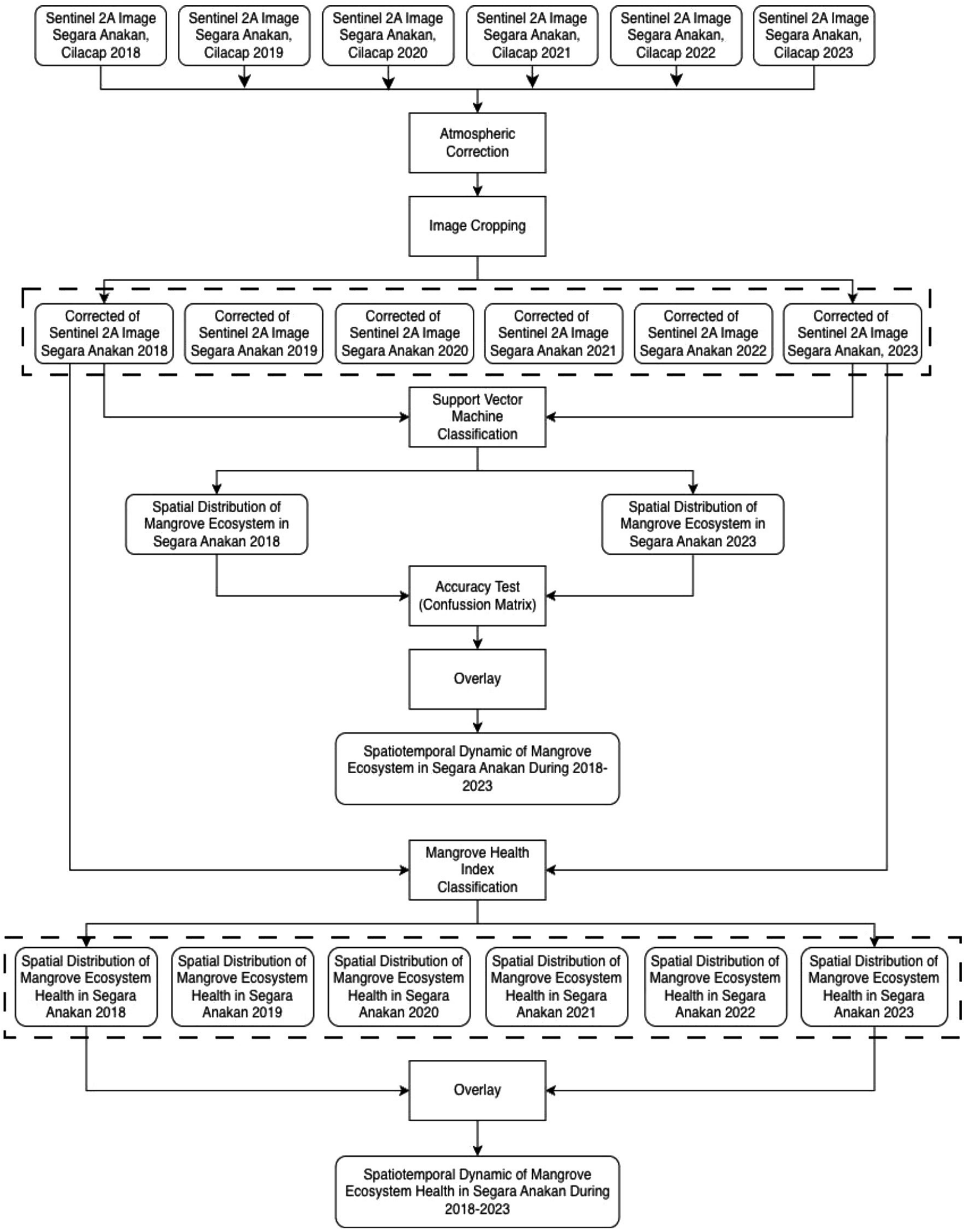


Figure 2: Research flow chart

Results and Discussion

Spatiotemporal Dynamics of Mangrove Distribution

The result of this study reveals a significant net loss of mangrove ecosystems in Segara Anakan between 2018 and 2023. The total mangrove area decreased by 883.28 hectares (Ha), from 7,623.05 Ha to 6,739.77 Ha (Table 2). However, a more detailed spatiotemporal overlay analysis reveals a dynamic process of both loss and gain, with a gross loss of 2,054.64 Ha and a gain of 1,171.35 Ha, resulting in the net decrease. A total of 5,568.41 Ha of mangrove area remained stable over the five-year period. The mangrove ecosystem distribution in every sub-district is shown in Table 2.

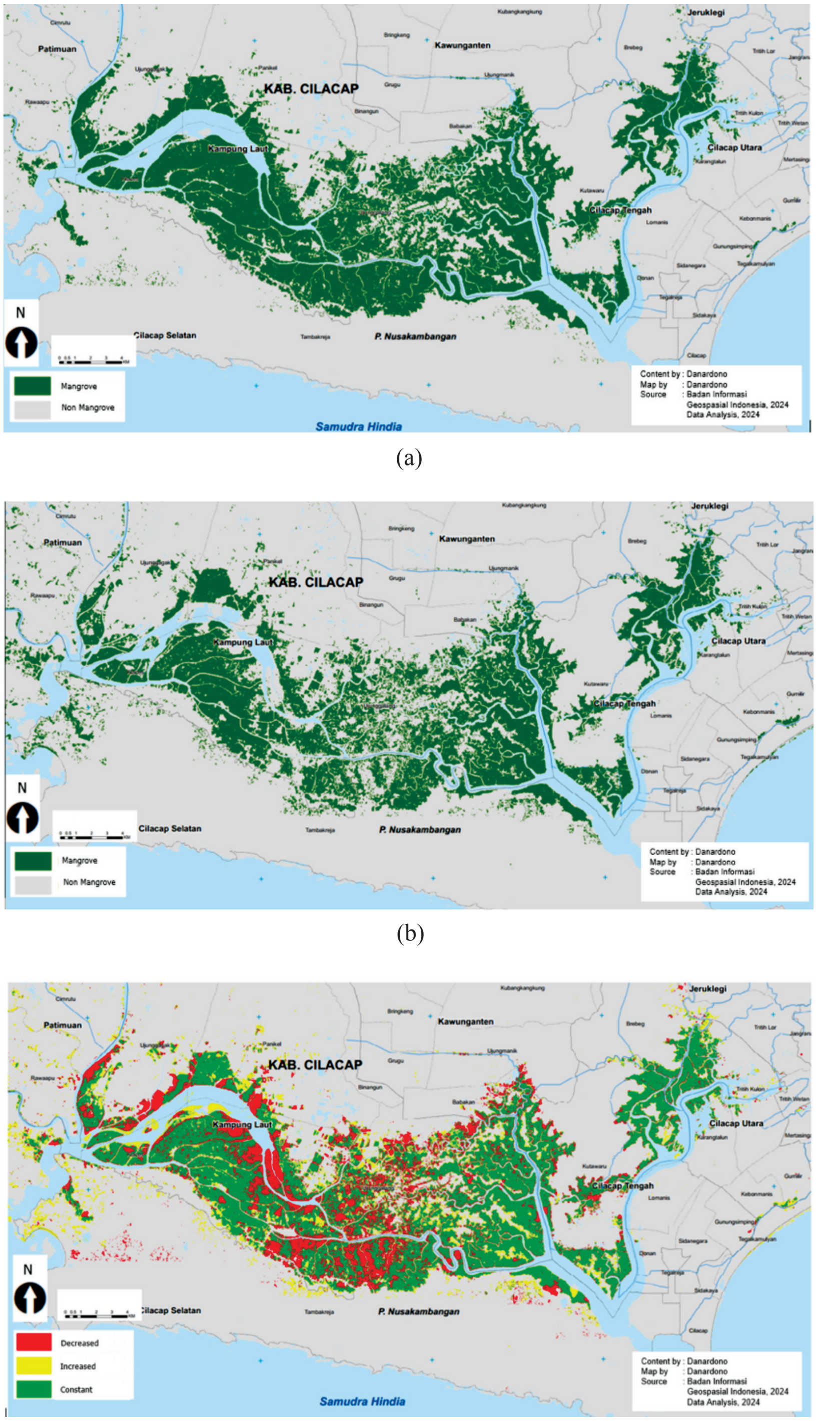
The spatial distribution of these changes was highly heterogeneous (Figure 3). Kampung Laut District, which holds the largest mangrove area, was the epicentre of loss, accounting for a gross decrease of 1,466.93 Ha. Spatially, this loss was concentrated on the western, seaward side of the lagoon (Figure 3), an area characterised by high sedimentation rates from the Citanduy River. In contrast, several eastern districts (e.g., North Cilacap, Jeruklegi, Patimuan) showed net gains, likely linked to local rehabilitation efforts and their proximity to established communities that facilitate conservation.

Accuracy Test of Spatial Distribution of Mangrove Ecosystem

The validation of SVM classification results was measured using a confusion matrix. The accuracy test result in 2018 was 78.06%, while in 2023, the result was 86.39%. The accuracy test results from 2018 and 2023 show values above 75%. The results of modelling the distribution of mangrove ecosystems using the SVM method in the study area can be used for further analysis, as the error value is below the standard threshold of 25% in physical environment research. The following are the results of the accuracy test conducted in 2018 and 2023, as shown in Tables 3 and 4.

Table 2: Dynamics of mangrove ecosystem distribution in Segara Anakan in 2018 and 2023

District	**Mangrove Ecosystem (Hectares)**		**Net Change (Ha)**
	2018	**2023**	
Bantarsari	0.03	2.94	+2.91
South Cilacap	807.33	735.56	-71.77
Central Cilacap	1,051.97	988.09	-63.88
North Cilacap	306.55	322.07	+15.52
Jeruklegi	83.24	105.86	+22.62
Kampung Laut	5,177.85	4,390.33	-787.52
Kawunganten	136.62	92.42	-44.20
Kesugihan	0.33	0.06	-0.27
Patimuan	59.14	102.44	+43.30
Total	**7,623.05**	**6,739.77**	**-883.28**



(a)

(b)

(c)

Figure 3: Spatiotemporal dynamics of mangrove ecosystems in Segara Anakan (2018–2023). (a) Distribution in 2018, (b) distribution in 2023, (c) changes between 2018 and 2023, highlighting areas of loss (red), gain (green), and stability (grey)

Table 3: SVM model accuracy test results in 2018

Land Cover 2018		Google Earth Interpretation			
		Water Body	**Mangroves**	**Non-Mangrove**	**Total**
SVM	Water body	33	4	4	41
	Mangroves	4	24	5	33
	Non-mangrove	5	7	46	58
Total		42	35	55	132

Accuracy test result = $\frac{corrected\ pixel\ numbers}{total\ pixel\ numbers}$ x 100% $= \frac{103}{132}$ x 100% = 78.06 %

Table 4: SVM model accuracy test results in 2023

Land Cover 2023		Google Earth Interpretation			
		Water Body	**Mangroves**	**Non-Mangrove**	**Total**
SVM	Water body	35	2	2	39
	Mangroves	0	28	3	31
	Non-mangrove	6	5	51	62
Total		41	35	56	132

Accuracy test result = $\frac{114}{132}$ x 100% = 86.39%

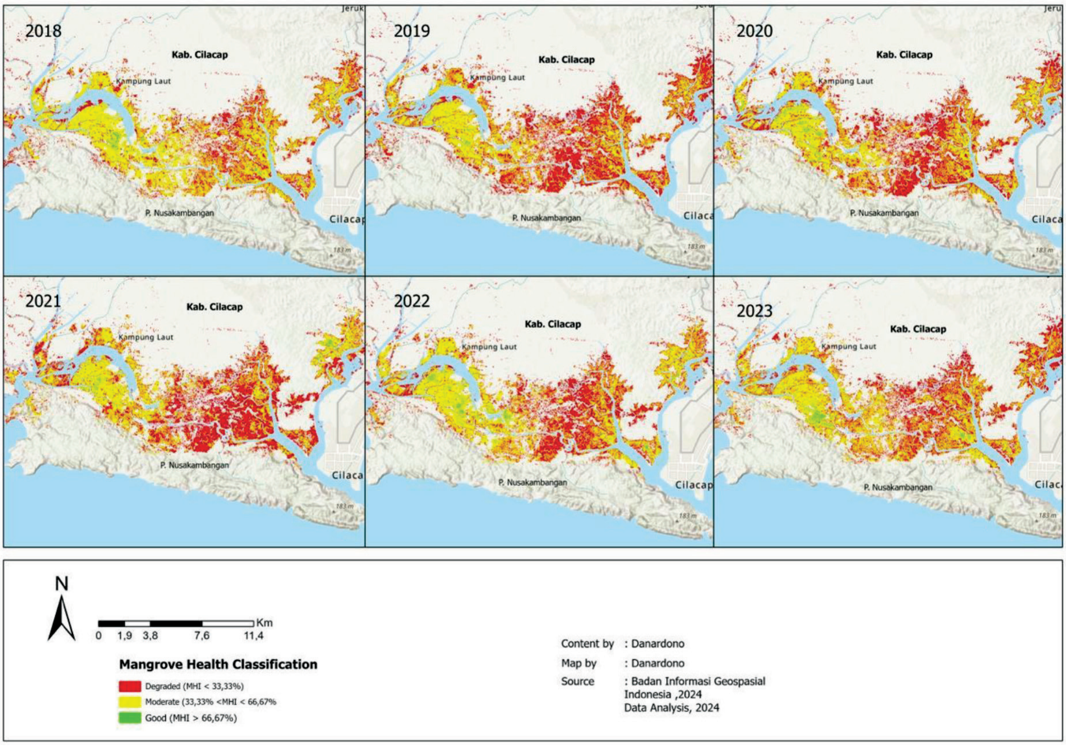
Dynamic of Mangrove Health Assessment Using the MHI

The MHI revealed significant shifts in the health of the remaining mangrove forest between 2018 and 2023 (Figure 4). In 2018, the ecosystem was predominantly (88.07%) in "Moderate" health. By 2023, while "Moderate" forests remained dominant (74.63%), "Good" mangroves had increased substantially from 6.90% to 21.53% of the total area. Concurrently, the "Degraded" class decreased from 5.03% to 4.84%.

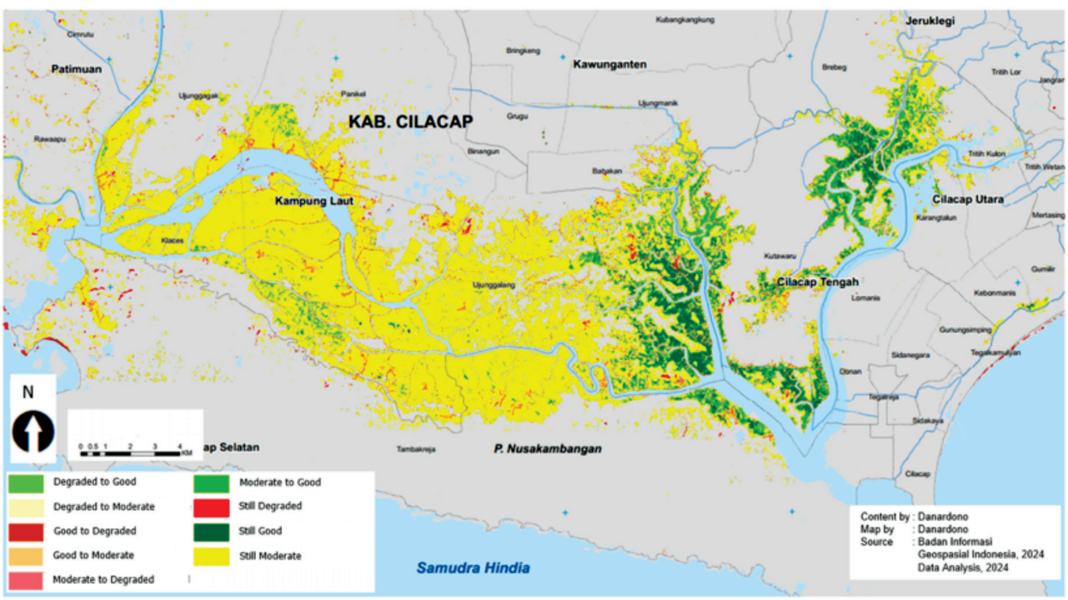
Analysis of health transitions (Table 5) shows a promising trend: 1,011.92 Ha of mangroves improved from "Moderate" to "Good". This improvement is spatially correlated with eastern districts where community-based rehabilitation has been active. Conversely, 158.01 Ha degraded from "Moderate" to "Degraded," primarily in the sediment-affected western regions.

Table 5: Transition matrix of mangrove health classes (2018-2023)

MHI Change	Size (Hectares)
Degraded to good	19.82
Degraded to moderate	149.48
Good to degraded	8.93
Good to moderate	67.22
Moderate to degraded	158.01
Moderate to good	1,011.92
Still degraded	352.48
Still good	486.38
Still moderate	6,696.45



(a)



(b)

Figure 4: Mangrove ecosystem health and its dynamics (a) health status from 2018 to 2023, (b) transition of health classes between 2018 and 2023, showing key trajectories of improvement (e.g., moderate to good) and degradation

The spatial pattern of health is stark. The western sectors, particularly in Kampung Laut, are dominated by "Moderate" to "Degraded" stands, often co-dominated by *Nypa fruticans* and *Avicennia marina*, which are more tolerant of the stressful, high-sedimentation environment. In contrast, the healthier eastern mangroves are typically dense stands of Sonneratia and Rhizophora species. This dichotomy underscores that the overall improvement in health metrics (increase in "Good" class) is occurring alongside a net loss of area, indicating that conservation efforts are effective in specific locales but are not yet counteracting the large-scale drivers of loss and degradation in the west.

In 2018, the "Good" mangroves on the west side of Segara Anakan were classified as moderate, while on the east side, the health conditions were good. Likewise, in 2023, mangroves in "Moderate" health are mostly scattered on the west. The good condition of mangrove ecosystems in 2023 is characterised by mangrove vegetation, particularly the Sonneratia and Rhizophora species, which have a reasonably high density. Meanwhile, the moderate and degraded mangrove ecosystems are dominated by *Nypa fruticans* and *Avicennia marina* mixtures.

Mangroves of moderate health decreased from 2018 to 2023 despite efforts to rehabilitate them by planting mangrove seedlings. Even so, many mangroves found in the field are still seriously degraded. The degradation is observed in mangroves that experience drought, causing the leaves to turn brownish-yellow and some to die. The number of mangrove ecosystems that experience drought is influenced by their overuse as household materials and high sedimentation.

Sedimentation can affect chlorophyll content and hinder mangrove growth, and depletion of oxygen through the root system will reduce mangrove ecosystem functions and services, including habitat, carbon and biodiversity losses (Sugiana *et al*., 2022). However, the area of mangroves has decreased significantly from 2018 to 2023. However, its health status, rated as excellent, has improved with the reduction of bad and moderate mangrove categories due to the development of seedlings and several rehabilitation programmes.

The results of this study show that mapping the extent and health of mangrove ecosystems using remote sensing technology is both effective and efficient. The value of the modelling accuracy test, which reached above 76% in both 2018 and 2023 modelling, indicates that it exceeds the accuracy threshold of 75% in abiotic research. Therefore, remote sensing can be utilised to monitor the condition of mangrove ecosystems both in terms of area and health, especially in areas with large coverage. The effectiveness of using remote sensing to observe the condition of mangrove ecosystems has also been widely studied by (Perdana *et al*., 2022; Priyono *et al*., 2022).

Discussions

The mangroves in Segara Anakan have decreased significantly over the past five years, reducing in area by 205.64 hectares. The sub-district in Segara Anakan that experienced the most significant loss was Kampung Laut, located close to the estuary. The decline in the mangrove forests in Segara Anakan is mainly due to the logging of several types of mangroves for wood. In addition, converting mangrove land into agricultural land and ponds changes the distribution pattern and mangrove population in the study area. These results are from research conducted by (Dwininta & Hartono, 2017) on mangroves in Segara Anakan, which identified that mangrove ecosystems changed into other land uses from 2000 to 2015.

This study revealed that many mangrove forests were turned into settlements, ponds and rice fields due to sedimentation and logging of mangrove vegetation during the five years under study. The anthropogenic factor is the main cause of changes to mangrove health in the study area. It is similar with the previous research, which showed that mangrove ecosystem degradation in Sierra Leone is triggered by human activities such as illegal logging (Huber *et al*., 2023), industrial development in mangrove forests in China (Jia *et al*., 2021), and large-scale exploitation in mangrove forests in Brazil (Kuenzer *et al*., 2011).

Another factor affecting mangrove health in the study area is hydrodynamics within the habitat. The sedimentation rate in the western part of Segara Anakan is higher than on the eastern side (Cahyo *et al*., 2024), resulting in more mangrove decline in the west. The high erosion rate in the Citanduy Watershed causes much sediment to be transported and deposited in western Segara Anakan (Hariati *et al*., 2024; Malawani *et al*., 2020). High sedimentation leads to changes in the mangrove habitat in the western part of Segara Anakan, resulting in mangrove degradation. This is consistent with previous research that found that high sedimentation causes mangrove degradation. Changes in soil conditions and inundation fluctuations due to sedimentation inhibit mangrove growth (Listyaningsih *et al*., 2013).

This study also proves that on the west side of the study area, annual water and salinity value changes tend to fluctuate due to high freshwater infiltration from the Citanduy River (Holtermann *et al*., 2009). In addition, mangroves in the west, which are relatively closer to the sea, tend to cause higher tides compared to the east, which are far from the sea. Fluctuations in water salinity during the rainy and dry seasons lead to the degradation of mangrove ecosystems due to extreme habitat changes. Previous studies mentioned that mangrove degradation is also caused by tidal changes in Cilamaya Mangrove habitat (Kurniawansyah *et al*., 2023). High tides increase salinity levels in mangrove forests in Bangladesh, causing mangrove degradation (Ahmed *et al*., 2022).

The findings of this study, which demonstrate a significant net loss of mangrove area alongside an improvement in the health of remaining stands, resonate with and are contextualized by regional and global research on mangrove dynamics. The net area loss in Segara Anakan (-883 ha over 5 years) aligns with the broader national trend in Indonesia, where deforestation and conversion to aquaculture remain primary drivers of mangrove loss (Arifanti *et al*., 2022; Murdiyarso *et al*., 2025). This pattern is consistent with global analyses showing that area-based metrics alone can understate functional decline, as coastal protection capacity can decrease by up to 25% even with minor area loss, primarily due to reductions in canopy height and health (Xu *et al*., 2024). Our detection of spatially heterogeneous health trends, with western sectors degrading and eastern sectors improving, mirrors findings from other stressed tropical estuaries and supports the utility of composite health indices, like the MHI, for detailed ecosystem diagnostics. For instance, a 2021 study in Segara Anakan using only NDVI also reported a declining health trend, attributing it to deforestation and natural stressors *(*Akbar *et al*., 2020).

Our application of the multi-faceted MHI, however, provides a more nuanced picture by differentiating between structural, productivity and pigment-stress components, revealing that "health" is not monolithic. This complexity is echoed in findings from Bunaken National Park, where MHI assessments showed a majority of mangroves in good condition, highlighting that ecosystem responses are highly site-specific and dependent on local pressure regimes (Schaduw *et al*., 2024). Furthermore, the dominance of species like Sonneratia and Rhizophora in healthier eastern zones of Segara Anakan is consistent with their recognised ecological role and high Importance Value Index (IVI) in other Indonesian mangroves, including those in Bunaken (Ismail *et al*., 2021; Schaduw *et al*., 2024). Conversely, the prevalence of *Nypa fruticans* and *Avicennia marina* in degraded western areas aligns with their known tolerance to high-stress, high-sedimentation environments (Yuwono *et al*., 2007). Collectively, these comparisons confirm that while the overarching threat of anthropogenic conversion is a global constant (Murdiyarso *et al*., 2025), the spatiotemporal patterns of mangrove health and species composition are dictated by a complex interplay of local geomorphic, hydrodynamic and conservation factors.

The findings of this study, which demonstrate a significant net loss of mangrove area alongside an improvement in the health of remaining stands due to targeted rehabilitation, resonate with and are contextualised by recent global research. The successful detection of mangrove health and recovery patterns using multispectral Sentinel-2 data in our study is strongly supported by (Maurya & Mahajan, 2025; Routhier *et al*., 2025), who similarly validated the efficacy of satellite remote sensing for monitoring post-hurricane recovery and assessing canopy-level biochemical properties, respectively.

However, the primary driver of mangrove loss identified here aligns more closely with the work of (Zhang *et al*., 2025), who emphasize that anthropogenic pressures, rather than single natural disasters, are the dominant force behind long-term mangrove alteration. This distinction underscores a critical interplay between natural and human-induced stressors. Collectively, this comparison situates our local findings within a global narrative, confirming that while remote sensing is a robust tool for monitoring mangrove dynamics, the specific drivers of change—be they acute anthropogenic conversion, chronic pollution, or the compounding effects of extreme weather—are highly region-specific and must be accurately diagnosed for effective conservation.

The results of identifying mangrove health using the MHI method show that this index is effectively used in tropical mangrove ecosystems. The MHI index can improve the accuracy of mangrove health mapping by utilising the NDVI (Nguyen & Nguyen, 2021) and EVI (Ishtiaque *et al*., 2017) vegetation indices, which are still predominantly used for this purpose (Tran *et al*., 2022). NDVI and EVI, which only consider vegetation structure and condition, ignore other indicators of mangrove health, such as ecosystem productivity and resilience related to sediment conditions in mangrove habitats. In the MHI model, using the NBR index can simulate the drought conditions of mangrove habitats, allowing it to describe mangrove resilience. The land drought indicator (NBR) was chosen because drought is one of the dominant triggers for mangrove degradation (Akram *et al*., 2023). Research (Winarso *et al*., 2023) shows that the NDVI vegetation index is not accurate for mapping mangrove health in areas near terrestrial vegetation, where mangroves have experienced succession. The presence of shrubs in the after-logged mangrove area was classified in good condition. The presence of the NBR index in the MHI method can reduce the inaccuracy of this finding in after-logged mangroves.

Other spectral indicators have also been developed, such as the Mangrove Recognition Index (Zhang & Tian, 2013) and the Mangrove Probability Vegetation Index (Kumar *et al*., 2017). However, these indicators are only sensitive to mangroves under constantly flooded conditions, which is not possible for mangroves in the tropics. A comprehensive assessment of mangrove health has also been developed by considering four factors: Mangrove canopy width, mangrove fragmentation, mangrove density, and mangrove plant diversity (Hai *et al*., 2022). However, this index requires a combination of remote sensing and field surveys to obtain data. It implements mangrove health monitoring activities that are ineffective in tropical mangroves with large areas located in remote areas. Therefore, the MHI index is considered adequate and efficient enough to monitor mangrove health at regular intervals, either monthly or annually.

However, the MHI has limitations. As a model based on optical remote sensing, its accuracy can be compromised by persistent cloud cover, a common issue in tropical regions. It also primarily reflects the condition of the mangrove canopy and may not fully capture below-ground carbon dynamics or subtle changes in soil properties, which are significant components of mangrove blue carbon stocks. Future research could strengthen this approach by integrating Synthetic Aperture Radar (SAR) data to overcome cloud limitations and by validating the MHI categories more rigorously against field-measured data on sediment carbon and biodiversity metrics.

A limitation of this study is its reliance on a five-year interval, which may miss shorter-term dynamics. Future research could employ a dense time-series analysis to better understand the seasonal and inter-annual drivers of health. Furthermore, while the MHI is comprehensive, integrating field-measured data on soil salinity, sedimentation rates and biodiversity would further validate and enrich the remote sensing model. Exploring the application of this integrated MHI and stakeholder approach in other tropical mangrove systems would also be a valuable contribution.

Based on these findings, we propose the following strategic recommendations for management and policy: 1) High-Priority Restoration: Kampung Laut District must be the highest priority for urgent restoration. The severe area loss and degraded health of mangroves demand targeted interventions, including pond rehabilitation and strategic replanting. Conservation Consolidation: The eastern districts (Central Cilacap, North Cilacap, and South Cilacap), which currently host healthier mangroves, should be designated as conservation priority zones. Efforts here should focus on protecting these forests from future conversion and sustaining the community-led initiatives that have proven successful. 2) Key Actions for Stakeholders in Local Government: Regulations against illegal logging and unsustainable pond expansion should be enforced, particularly in Kampung Laut. Spatial planning must formally integrate the MHI health maps to protect critical mangrove zones from land-use change. National Agencies (e.g., KLHK) can adopt the MHI methodology as a standardised, cost-effective tool for national mangrove monitoring.

The findings from Segara Anakan should inform the targeting of national rehabilitation programmes (e.g., PRLM) to the most vulnerable areas. NGOs and Community Groups play a vital role in facilitating community-based conservation and developing sustainable livelihood programmes (e.g., ecotourism, silvofishery) to reduce economic pressure on mangrove resources. To transition from periodic assessment to proactive management in Adaptive Management, the MHI monitoring system should be institutionalised. We recommend that local environmental agencies integrate annual MHI assessments into their monitoring and evaluation framework. This would enable 1) Rapid Detection: Early identification of degrading areas before they are lost; 2) Performance Tracking: Quantitative evaluation of the effectiveness of restoration projects; 3) Adaptive Management: Allowing managers to adjust conservation strategies based on near-real-time ecosystem health data.

Conclusions

This study documents a significant ecological decline in the Segara Anakan mangrove ecosystem, with a net loss of 883.28 hectares between 2018 and 2023, reducing the total area to 6,739.76 Ha. Spatially, this loss was concentrated in the western Kampung Laut District, which alone lost a gross of 1,466.93 hectares, primarily to aquaculture conversion. The Mangrove Health Index (MHI) reveals a predominant "Moderate" health status across 73.63% of the remaining forest, but a critical spatial disparity exists: Western sectors are severely degraded while eastern areas near settlements show "Good" health, likely supported by local conservation. Based on these findings, a targeted action plan is proposed. First, the western Kampung Laut sub-district must be the highest priority for restoration, requiring collaboration with upland managers to reduce erosion from the Citanduy Watershed. Second, the resilient eastern sectors should be formally protected from conversion, with their successful rehabilitation models documented and scaled up. Finally, the MHI methodology should be institutionalised by local government agencies using freely available Sentinel-2 data for annual, evidence-based monitoring. This spatially explicit roadmap — prioritising western restoration, conserving eastern forests and embedding the MHI tool — enables stakeholders to collaboratively reverse degradation. This approach provides a transferable model for evidence-based coastal management in other tropical regions. To build on this study, future research should integrate Synthetic Aperture Radar (SAR) data with optical indices, like MHI, to overcome cloud-cover limitations and improve health monitoring in perpetually cloudy tropical regions. In addition, ground-truthing MHI categories with field measurements of soil carbon, salinity, biodiversity and canopy biochemistry would enhance the index's ecological validity.

Author's Contribution

Danardono carried out the research and analysed the mangrove health modelling, and wrote and revised the article. Aditya Saputra provided the theoretical framework and criticised the article. Puspita Indra Wardhani provided the research workflow and also criticised the article. Nurul Fauzia Wardhani collected all data and conducted field surveys. Afif Ari Wibowo analysed the mangrove area using SVM modelling. Basyar Ihsan Arijuddin validated the mangrove area modelling and contributed to the writing. Fajar Yulianto criticised the article and anchored the review and revision. Favian Mafazi Giska Putra conducted field surveys and processed image data from Sentinel 2A. Hannah Khoirunnisa modelled mangrove health and criticized the article.

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Conflict of Interest Statement

The authors agree that this research was conducted in the absence of any self-benefits, commercial, or financial conflicts and declare absence of conflicting interests with the funders.

References

Adinegoro, R., Putra, I. N. N., & Putra, I. G. (2022). Pemetaan perubahan luasan mangrove menggunakan citra Sentinel-2A pasca kematian mangrove di Denpasar-Bali. *Journal of Marine and Aquatic Sciences*, *8*(1), 66–77. https://doi.org/10.24843/jmas.2022.v08.i01.p08

Ahmed, S., Sarker, S. K., Friess, D. A., Kamruzzaman, M., Jacobs, M., Islam, M. A., Alam, M. A., Suvo, M. J., Sani, M. N. H., Dey, T., Naabeh, C. S. S., & Pretzsch, H. (2022). Salinity reduces site quality and mangrove forest functions: From monitoring to understanding. *Science of the Total Environment*, *853*, 158662. https://doi.org/10.1016/j.scitotenv.2022.158662

Akbar, M. R., Arisanto, P. A. A., Sukirno, B. A., Merdeka, P. H., Priadhi, M. M., & Zallesa, S. (2020). Mangrove vegetation health index analysis by implementing NDVI (normalized difference vegetation index) classification method on Sentinel-2 image data: Case study Segara Anakan, Kabupaten Cilacap. *IOP Conference Series: Earth and Environmental Science*, *584*(1), 012069. https://doi.org/10.1088/1755-1315/584/1/012069

Akram, H., Hussain, S., Mazumdar, P., Chua, K. O., Butt, T. E., & Harikrishna, J. A. (2023). Mangrove health: A review of functions, threats, and challenges associated with mangrove management practices. *Forests*, *14*(9), 1698. https://doi.org/10.3390/f14091698

Alcaras, E., Costantino, D., Guastaferro, F., Parente, C., & Pepe, M. (2022). Normalized burn ratio plus (NBR+): A new index for Sentinel-2 imagery. *Remote Sensing*, *14*(7), 1727. https://doi.org/10.3390/rs14 071727

Ardli, E. R., Yuwono, E., & Purwanto, A. D. (2022). Land cover changes and impacts of massive siltation on the mangrove Segara Anakan lagoon system, Cilacap, Indonesia. *Journal of Ecological Engineering*, *23*(7), 29–41. https://doi.org/10.12911/22998993/149821

Arifanti, V. B., Kauffman, J. B., Subarno, J. B., Ilman, M., Tosiani, A., & Novita, N. (2022). Contributions of mangrove conservation and restoration to climate change mitigation in Indonesia. *Global Change Biology*, *28*(15), 4523–4538. https://doi.org/10.1111/gcb.16216

Bunting, P., Rosenqvist, A., Hilarides, L., Lucas, R. M., Thomas, N., Tadono, T., Worthington, T. A., Spalding, M., & Murray, N. J. (2022). Global mangrove extent change 1996–2020. *Remote Sensing*, *14*, 3657. https://doi.org/10.3390/rs14153657

Cahyo, T. N., Hartoko, A., Muskananfola, M. R., Haeruddin, & Hilmi, E. (2024). Mangrove density and delta formation in Segara Anakan Lagoon as an impact of the riverine sedimentation rate. *Biodiversitas*, *25*(3), 1276–1285. https://doi.org/10.13057/biodiv/d250344

Campos-Taberner, M., García-Haro, F. J., Camps-Valls, G., Grau-Muedra, G., Nutini, F., Crema, A., & Boschetti, M. (2016). Multitemporal and multiresolution leaf area index retrieval for operational local rice crop monitoring. *Remote Sensing of Environment*, *187*, 102–118. https://doi.org/10.1016/j.rse.2016.10.009

Chander, G., Markham, B. L., & Helder, D. L. (2009). Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Remote Sensing of Environment*, *113*(5), 893–903. https://doi.org/10.1016/j.rse.2009.01.007

Dharmawan, I. W. E. (2021). Mangrove health index distribution on the restored post-tsunami mangrove area in Biak Island, Indonesia. *IOP Conference Series: Earth and Environmental Science*, *860*(1), 012007. https://doi.org/10.1088/1755-1315/860/1/012007

Direktorat Pengelolaan DAS dan Rehabilitasi Hutan, Kementerian Kehutanan. (2025). *Peta mangrove nasional tahun 2024*.

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F., & Bargellini, P. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment*, *120*, 25–36. https://doi.org/10.1016/j.rse.2011.11.026

Du, C., Khan, S., Ke, Y., & Zhou, D. (2023). Assessment of spatiotemporal dynamics of mangrove in five typical mangrove reserve wetlands in Asia, Africa and Oceania. *Diversity*, *15*(2), 148. https://doi.org/10.3390/d15020148

Dwininta, A. C., & Hartono. (2017). Perubahan hutan mangrove tahun 2000–2015 di Segara Anakan Kab. Cilacap Jawa Tengah menggunakan citra Landsat 7 ETM+ dan 8 OLI. *Jurnal Bumi Indonesia*, *6*(1), 1–10.

Everitt, J. H., & Judd, F. W. (1989). Using remote sensing techniques to distinguish and monitor black mangrove (*Avicennia germinans*). *Journal of Coastal Research*, *5*(4), 737–745.

Flores De Santiago, F., Kovacs, J. M., & Lafrance, P. (2013). An object-oriented classification method for mapping mangroves in Guinea, West Africa, using multipolarized ALOS PALSAR L-band data. *International Journal of Remote Sensing*, *34*(2), 563–586. https://doi.org/10.1080/01431161.2012.715773

Hai, P. M., Tinh, P. H., Son, N. P., Van Thuy, T., Hanh, N. T. H., Sharma, S., Hoai, D. T., & Duy, V. C. (2022). Mangrove health assessment using spatial metrics and multi-temporal remote sensing data. *PLOS ONE*, *17*(12), e0275928. https://doi.org/10.1371/journal.pone.0275928

Hariati, F., Muhammad Libasut Taqwa, F., Alimuddin, A., Salman, N., & Fadhillah Sulaeman, N. H. (2024). Simulasi perubahan tata guna lahan terhadap laju erosi lahan menggunakan metode Universal Soil Loss Equation (USLE) pada daerah aliran sungai (DAS) Ciseel. *Tameh: Journal of Civil Engineering*, *11*(1), 52–61. https://doi.org/10.37598/tameh.v11i1.185

He, C., Sun, J., Chen, Y., Wang, L., Shi, S., Qiu, F., Wang, S., & Tagesson, T. (2023). A new vegetation index combination for leaf carotenoid-to-chlorophyll ratio: Minimizing the effect of their correlation. *International Journal of Digital Earth*, *16*(1), 272–288. https://doi.org/10.1080/17538947.2023.2168772

Hidayah, Z., Rachman, H. A., & As-Syakur, A. R. (2023). Pemetaan kondisi hutan mangrove di kawasan pesisir Selat Madura dengan pendekatan Mangrove Health Index memanfaatkan citra satelit Sentinel-2. *Majalah Geografi Indonesia*, *37*(1), 84–94. https://doi.org/10.22146/mgi.78136

Hilmi, E., Sari, L. K., Mahdiana, A., Junaidi, T., Muslih, M., Samudra, S. R., Prayogo, N. A., Baedowi, M., Cahyo, T. N., Putra, R. R. D., & Sari, F. A. (2022). Mapping of mangrove ecosystem in Segara Anakan Lagoon using normalized difference vegetation index and dominant vegetation index. *Omni-Akuatika*, *18*(2), 165–173. https://doi.org/10.20884/1.oa.2022.18.2.926

Holtermann, P., Burchard, H., & Jennerjahn, T. (2009). Hydrodynamics of the Segara Anakan lagoon. *Regional Environmental Change*, *9*(4), 245–258. https://doi.org/10.1007/s10113-008-0075-3

Huber, L. C., Sainge, M. N., Feka, Z. N., Kamara, R. A., Kamara, A., Sullivan, M., & Cuni-Sanchez, A. (2023). Human-driven degradation impacts on mangroves in southern Sierra Leone. *Trees, Forests and People*, *14*, 100445. https://doi.org/10.1016/j.tfp.2023.100445

Ishtiaque, A., Shrestha, M., & Chhetri, N. (2017). Rapid urban growth in the Kathmandu Valley, Nepal: Monitoring land use land cover dynamics of a Himalayan city with Landsat imageries. *Environments*, *4*(4), 72. https://doi.org/10.3390/environments4040072

Islami, F. A., Tarigan, S. D., Wahjunie, E. D., & Dasanto, B. D. (2022). Accuracy assessment of land use change analysis using Google Earth in Sadar watershed Mojokerto Regency. *IOP Conference Series: Earth and Environmental Science*, *950*(1), 012091. https://doi.org/10.1088/1755-1315/950/1/012091

Ismail, Sulistiono, Hariyadi, S., & Madduppa, H. (2019). Correlation between mangrove degradation in Segara Anakan and production of crab (*Scylla* sp.) in Cilacap Regency, Central Java Province. *Jurnal Ilmu Pertanian Indonesia*, *24*(3), 179–187. https://doi.org/10.18343/jipi.24.3.179

Ismail, Sulistiono, Hariyadi, S., & Madduppa, H. (2021). Diversity, density, and importance value index of mangroves in the Segara Anakan lagoon and its surrounding area, Cilacap Regency, Indonesia. *IOP Conference Series: Earth and Environmental Science*, *744*(1), 012034. https://doi.org/10.1088/1755-1315/744/1/012034

Jia, M., Wang, Z., Mao, D., Ren, C., Wang, C., & Wang, Y. (2021). Rapid, robust, and automated mapping of tidal flats in China using time series Sentinel-2 images and Google Earth Engine. *Remote Sensing of Environment*, *255*, 112285. https://doi.org/10.1016/j.rse.2021.112285

Kaufman, Y. J., & Tanré, D. (1992). Atmospherically resistant vegetation index (ARVI) for EOS-MODIS. *IEEE Transactions on Geoscience and Remote Sensing*, *30*(2), 261–270. https://doi.org/10.1109/36.134076

Kovacs, J. M., Lu, X. X., Flores-Verdugo, F., Zhang, C., Flores de Santiago, F., & Jiao, X. (2013). Applications of ALOS PALSAR for monitoring biophysical parameters of a degraded black mangrove (*Avicennia germinans*) forest. *ISPRS Journal of Photogrammetry and Remote Sensing*, *82*, 102–111. https://doi.org/10.1016/j.isprsjprs.2013.05.004

Kuenzer, C., Bluemel, A., Gebhardt, S., Quoc, T. V., & Dech, S. (2011). Remote sensing of mangrove ecosystems: A review. *Remote Sensing*, *3*(5), 878–928. https://doi.org/10.3390/rs3050878

Kumar, A., Stupp, P., Dahal, S., Remillard, C., Bledsoe, R., Stone, A., Cameron, C., Rastogi, G., Samal, R., & Mishra, D. R. (2017). A multi-sensor approach for assessing mangrove biophysical characteristics in coastal Odisha, India. *Proceedings of the National Academy of Sciences, India Section A: Physical Sciences*, *87*(4), 679–700. https://doi.org/10.1007/s40010-017-0441-y

Kurniawansyah, A., Susiloningtyas, D., Dwi, M., & Manessa, M. (2023). Suitability of mangrove tourism areas in Cilamaya Wetan District, Karawang Regency. *Forum Geografi*, *37*(1), 10–23. https://doi.org/10.23917/forgeo.v37i1.19852

Li, Q., Lu, W., Chen, H., Luo, Y., & Lin, G. (2014). Differential responses of net ecosystem exchange of carbon dioxide to light and temperature between spring and neap tides in subtropical mangrove forests. *The Scientific World Journal*, *2014*, 943697. https://doi.org/10.1155/2014/943697

Listyaningsih, D. D., Yulianda, F., & Ardli, E. R. (2013). Kajian degradasi ekosistem mangrove terhadap populasi *Polymesoda erosa* di Segara Anakan, Cilacap. *Forum Geografi*, *27*(1), 1–10.

Malawani, M. N., Mardiatno, D., & Haryono, E. (2020). Anthropogenic signatures in the context of landscape evolution: Evidence from Citanduy Watershed, Java, Indonesia. *ASEAN Journal on Science and Technology for Development*, *37*(1), 7–14. https://doi.org/10.29037/AJSTD.600

Mallick, B., Priodarshini, R., Kimengsi, J. N., Biswas, B., Hausmann, A. E., Islam, S., Huq, S., & Vogt, J. (2021). Livelihoods dependence on mangrove ecosystems: Empirical evidence from the Sundarbans. *Current Research in Environmental Sustainability*, *3*, 100077. https://doi.org/10 1016/j.crsust.2021.100077

Maurya, K., & Mahajan, S. (2025). Mangrove forest health assessment using hyperspectral remote sensing for Gulf of Kutch, Gujarat: A case study. *Discover Environment*, *3*(1), 21. https://doi.org/10.1007/s44274-025-003 21-8

Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *66*(3), 247–259. https://doi.org/10.1016/j.isprsjprs.2010.11.011

Munandar, E., Saverti Jasmine, A., & Khalifa, M. A. (2023). Identification of mangrove cover in Banten Bay using Google Earth Engine. *Journal of Applied Geospatial Information*, *7*(1), 796–804.

Murdiyarso, D., Sharma, S., & Sasmito, S. (2025). Editorial: Indonesian mangrove ecology and the changing climate. *Frontiers in Ecology and Evolution*, *13*, 1718325. https://doi.org/10.3389/fevo.2025.1718325

Neres, J. N., Strenzel, G. M. R., Mielke, M. S., & Barros, F. (2024). Mangrove forest health condition from space and the use of in situ data. *Marine Environmental Research*, *201*, 106704. https://doi.org/10.1016/j.marenvres.2024.106704

Nguyen, H. H., & Nguyen, T. T. H. (2021). Above-ground biomass estimation models of mangrove forests based on remote sensing and field-surveyed data: Implications for C-PFES implementation in Quang Ninh Province, Vietnam. *Regional Studies in*

Marine Science, *48*, 101985. https://doi.org/10.1016/j.rsma.2021.101985

Nurdiansah, D., & Dharmawan, I. W. E. (2021). Spatial and temporal analysis for mangrove community healthiness in Liki Island, Papua, Indonesia. *IOP Conference Series: Earth and Environmental Science*, *944*(1), 012017. https://doi.org/10.1088/1755-1315/944/1/012017

Pande, C. B., Srivastava, A., Moharir, K. N., Radwan, N., Mohd Sidek, L., Alshehri, F., Pal, S. C., Tolche, A. D., & Zhran, M. (2024). Characterizing land use/land cover change dynamics by an enhanced random forest machine learning model: A Google Earth Engine implementation. *Environmental Sciences Europe*, *36*(1), 90. https://doi.org/10.1186/s12302-024-00901-0

Perdana, P., Wiguna, K., Wayan, N., Sutari, S., Febriarta, E., & Permata, A. L. (2022). Spatial analysis of mangrove distribution using Landsat 8 OLI in Badung Regency and Denpasar City, Bali Province, Indonesia. *Forum Geografi*, *36*(1), 21–29. https://doi.org/10.23917/forgeo.v36i1.14711

Prabakaran, C., Singh, C. P., & Panigrahy, S. (2014). Assessment of the health status of Indian mangrove ecosystems using multi-temporal remote sensing data. *Tropical Ecology*, *55*(2), 245–253.

Priyono, K. D., Saifuddin, A., Nugroho, F. S., & Jumadi, J. (2022). Identification of mangrove changes in the Mahakam Delta in 2007–2017 using ALOS/PALSAR and Landsat. *International Journal of GEOMATE*, *23*(96), 77–84.

Routhier, M. R., Moore, G. E., Rock, B. N., Glidden, S., Duckett, M., & Zaluski, S. (2025). Assessing mangrove forest recovery in the British Virgin Islands after hurricanes Irma and Maria with Sentinel-2 imagery and Google Earth Engine. *Remote Sensing*, *17*(14), 2485. https://doi.org/10.3390/rs17142485

Schaduw, J. N. W., Tallei, T. E., & Sumilat, D. A. (2024). Mangrove health index, community structure and canopy cover in small islands of Bunaken National Park, Indonesia: Insights into dominant mangrove species and overall mangrove condition. *Tropical Life Sciences Research*, *35*(2), 187–210. https://doi.org/10.21315/tlsr2024.35.2.9

Song, C., White, B. L., & Heumann, B. W. (2011). Hyperspectral remote sensing of salinity stress on red (*Rhizophora mangle*) and white (*Laguncularia racemosa*) mangroves on Galapagos Islands. *Remote Sensing Letters*, *2*(3), 221–230. https://doi.org/10.1080/01431161.2010.514305

Sugiana, I. P., Andiani, A. A. E., Pradnyandari Dewi, I. G. A. I., Astawa Karang, I. W. G., As-Syakur, A. R., & Dharmawan, I. W. E. (2022). Spatial distribution of mangrove health index on three genera dominated zones in Benoa Bay, Bali, Indonesia. *Biodiversitas*, *23*(7), 3407–3418. https://doi.org/10.13057/biodiv/d230713

Tran, T. V., Reef, R., & Zhu, X. (2022). A review of spectral indices for mangrove remote sensing. *Remote Sensing*, *14*(19), 4868. https://doi.org/10.3390/rs14194868

Trégarot, E., Caillaud, A., Cornet, C. C., Taureau, F., Catry, T., Cragg, S. M., & Failler, P. (2021). Mangrove ecological services at the forefront of coastal change in the French overseas territories. *Science of the Total Environment*, *763*, 143004. https://doi.org/10.1016/j.scitotenv.2020.143004

Wibowo, K., & Handayani, T. (2006). Pelestarian hutan mangrove melalui pendekatan mina hutan (silvofishery). *Jurnal Teknik Lingkungan*, *7*(3), 227–233.

Winarso, G., Rosid, M. S., Kamal, M., Asriningrum, W., Margules, C., & Supriatna, J. (2023). Comparison of mangrove index (MI) and normalized difference vegetation index (NDVI) for the detection of degraded mangroves in Alas Purwo Banyuwangi and Segara Anakan Cilacap, Indonesia. *Ecological Engineering*, *197*, 107119. https://doi.org/10.1016/j.ecoleng.2023.107119

Wu, C., Niu, Z., & Gao, S. (2012). The potential of the satellite-derived green chlorophyll index for estimating midday light use efficiency in maize, coniferous forest and grassland. *Ecological Indicators*, *14*(1), 66–73. https://doi.org/10.1016/j.ecolind.2011.08.018

Xu, X., Fu, D., Su, F., Lyne, V., Yu, H., Tang, J., Hong, X., & Wang, J. (2024). Global distribution and decline of mangrove coastal protection extends far beyond area loss. *Nature Communications*, *15*(1), 54349. https://doi.org/10.1038/s41467-024-54349-0

Yuwono, E., Jennerjahn, T. C., Nordhaus, I., Riyanto, E. A., Sastranegara, M. H., & Pribadi, R. (2007). Ecological status of Segara Anakan, Indonesia: A mangrove-fringed lagoon affected by human activities. *Asian Journal of Water, Environment and Pollution*, *4*(1), 61–70.

Zhang, X., & Tian, Q. (2013). A mangrove recognition index for remote sensing of mangrove forest from space. *Current Science*, *105*(9), 1149–1154.

Zhang, Y., Zhao, G., Krauss, K. W., Pan, L., Xu, Y., & Meng, X. (2025). Anthropogenic activities have greatly altered mangroves over the last hundred years. *Global and Planetary Change*, *253*, 104950. https://doi.org/10.1016/j.gloplacha.2025. 104950