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Directions for Mangrove Forest Rehabilitation Based on Damaged Mangrove Mapping using a Remote Sensing Approach

Luisa Febrina Amalo[1]
Yudi Setiawan[1,2]
Cecep Kusmana[3]

[1]IPB University, Center for Environmental Research (CER), Bogor, Indonesia.
[2]IPB University, Faculty of Forestry and Environment, Conservation of Forest Resources and Ecotourism, Bogor, Indonesia.
[3]IPB University, Faculty of Forestry and Environment, Department of Silviculture, Bogor, Indonesia.

Abstract

Numerous mangrove forests in Indonesia have suffered significant losses. To develop rehabilitation programs, it is essential to conduct a spatial study to map the damaged mangroves. However, few research efforts have focused on mapping damaged mangroves using a canopy cover spatial model that refers to MoEF regulation criteria. An estimation of canopy cover using vegetation indices based on the regulation was assessed across the Coastal Area of Bekasi Regency, where most of the mangroves have been largely converted into ponds and agricultural land. The modeling results suggest that the NDMI is more effective in detecting damage to mangroves in the intertidal zone. The study's findings suggest directions for planting in mangrove rehabilitation efforts. The results of this study could be promising for monitoring damaged mangroves and implementing comprehensive rehabilitation programs in the Bekasi Regency and similar areas.

Keywords: Mangrove, regression model, rehabilitation, spatial model, vegetation index.

1. INTRODUCTION

The mangrove forest is a crucial ecosystem that thrives in the coastal region (Poedjirahajoe and Matatula 2019). This type of forest is found along the coast or river estuaries and is influenced by tidal movements (Nagelkerken et al. 2008; Agustini et al. 2016). Mangrove forests significantly contribute to the stability of the ecological and hydrological functions of the surrounding areas. Furthermore, mangroves act as breeding grounds, provide soil nutrients, protect coastlines against erosion, and serve as natural barriers against storm surges (Nordhaus et al. 2019).

Based on Rahadian et al. (2019), Indonesia's total area of mangroves in 2019 was approximately 3 million hectares (Rahadian et al. 2019). These mangroves are distributed throughout Banten, Greater Jakarta, West Java, Central Java, Yogyakarta, and East Java. Muaragembong, located on the coast of Bekasi Regency in West Java, is one of the largest mangroves in the region. However, out of the 10,481 hectares of protected forest designated in the Muaragembong District, 93.5% has been converted into aquaculture ponds and agricultural land (Bekasi Regency Government 2020). In 2019, the mangrove area extent only remained at 985.85 hectares (Maulani et al. 2021).

Several studies outline the mangrove damage based on mangrove density and/or canopy cover. First, Minister of Environment Decree No. 201 of 2004 categorizes good and damaged mangroves based on indicators of canopy cover and tree density as good/medium/damaged mangroves (Efriyeldi et al. 2020; Singgalen and Manongga 2022; Tharieq et al. 2023). Second, SNI 7717:2020 concerning geospatial information specifications–Mangroves, which divides canopy cover into dense, moderate, and sparse mangroves based on a scale of 1:25,000 or 1:50,000 (Setiyaningrum and Puspitasari 2022; Murdiyarso and Ambo-Rappe 2023). Third, the Mangrove Health Index from the National Research and Innovation Agency and COREMAP-CTI (Sugiana et al. 2022; Wasil and Muhsoni 2023). However, for this research, we have used the MoEF decree damaged mangrove based on canopy cover categorization cover in order to calculate the damaged mangrove based on governmental criteria for this judgment to be directly provided for short or long-term decisions.

Remote sensing is a relatively accessible approach for evaluating mangrove forest damage in a wider area. Various studies have been performed canopy cover and vegetation index model for mangrove mapping. For instance, Kamal et al. (2016) have been used Enhanced Vegetation Index (EVI) using ALOS AVNIR-2 to perform forest canopy fractional canopy in Karimunjawa islands. While, Ruslisan et al. (2018) used canopy density model with NDVI, SAVI, and EVI using IKONOS-2, WorldView-2, and WorldView-3. A comparison between several indices (NDVI, NDII, LAI, GARI, OSAVI, NDBI, NDWI) was also performed by Monsef and Smith (2017) in the Egypt Red Sea using Landsat 8. NDMI was performed by Prihantono et al. (2022) and Purwanto et al. (2023) to map the mangroves. However, from a literature review, there has been no research that measures the level of mangrove forest damage using spatial models of canopy cover and comparison of NDVI, SAVI, and NDMI based on the MoEF decree, particularly in Indonesia.

Therefore, an analysis of mangrove degradation, especially the assessment of damaged mangroves using several vegetation indices based on MoEF mangrove damage criteria must be carried out. The damaged mangrove assessment includes identifying periodic changes in mangrove forest area and mapping mangrove forest damage so that planting directions for mangrove forest rehabilitation can be more targeted and comprehensive. The aim of this research is to generate a map showing the extent of mangrove damage in the Coastal Area of Bekasi Regency, Southeast Asia, Indonesia, by utilizing various vegetation indices. The findings of this study will hold significant importance for land planning and policy-making at the local, regional, national, and international levels.

2. MATERIALS AND METHOD

The present study utilized Sentinel-2A satellite imagery to assess changes in mangroves and estimate canopy cover using several vegetation indices, namely NDVI, SAVI, and NDMI expressed in equation 1–3. These indices have been shown to exhibit a strong correlation with canopy cover (Huang et al. 2021). NDVI is a vegetation index that calculates the ratio of red and NIR wavelengths for vegetation index extraction. SAVI is a vegetation index that reduces the impact of the soil background. The NDMI is a vegetation index that mitigates atmospheric disturbances and soil reflection in vegetation areas, thereby enhancing the sensitivity of the index results to biomass and canopy cover density (Purwanto et al. 2023).

$$\text{NDVI} = \frac{nir - red}{nir + red} \quad (1)$$

$$\text{SAVI} = (1+\text{L}) \frac{nir - red}{(nir + red + L)} \quad (2)$$

$$\text{NDMI} = \frac{nir - swir}{nir + swir} \quad (3)$$

2.1. *Canopy Cover In-situ measurement*

The criteria for determining mangrove damage are predicated upon the guidelines established by Indonesia Minister of Environment Decree Number 201 of 2004, with the sample plot for which density and canopy cover will be calculated possessing a size of 10 × 10 meters, following the pixel size of the Sentinel-2A satellite image. In situ measurements of the mangrove canopy cover were obtained through hemispherical photography (Kamal et al. 2016; Meyer et al. 2019; Kuncahyo et al. 2020; Purnama et al. 2020). Hemispherical photography necessitates the utilization of a camera equipped with a fish eye lens and possessing a viewing angle of 180°, or a cellphone camera. The images were then analyzed using ImageJ software (https://imagej.net/ij/index.html) to calculate the percentage of mangrove canopy cover based on pixel values (equation 4) (Dharmawan et al. 2020; Kuncahyo et al. 2020).

$$mangrove\ canopy\ cover = \frac{Pcanopy}{\Sigma P} \text{ x } 100\% \quad (4)$$

Information:
P Canopy: Number of canopy pixels
ΣP: Total number of pixels

2.2. *Spatial model for estimating mangrove canopy cover from vegetation indices*

2.2.1. *Building a regression model*

The independent variables in developing the estimation model include vegetation indices NDVI, SAVI, and NDMI (equation 5-8), with canopy cover from in situ measurements as the dependent variable (y). Before conducting the regression analysis, certain prerequisites were fulfilled to ensure further analysis. The classical assumption test is a necessary step in developing a regression model. To construct this model, the data must meet certain conditions, such as being normally distributed and free from symptoms of heteroscedasticity, autocorrelation, or multicollinearity when using independent multivariable models. In this study, only normality and heteroscedasticity tests were conducted using the Kolmogorov–Smirnov test and Glejser Test, respectively, as only one variable was used (Saleh et al. 2021).

Once the regression model was built, the indicator used was the R2 value of R, which measures the strength of the linear relationship between two quantitative variables (Zahra et al. 2022). The R-value indicates the ability of the independent variable to explain the dependent variable and is represented by the correlation value. A canopy cover estimation model was constructed using the regression model simple linear, quadratic, and logarithmic.

2.3. Validation test

The construction of a regression model necessitated its validation to ascertain its accuracy. The validation testing entailed the calculation of various metrics, including error (e), aggregate deviation (AD), mean deviation (MD), and root mean square error (RMSE) (Yusandi and Jaya 2016).

$$e = \sum_{i=1}^{n} \left\{ \frac{\frac{y'-y}{y'}}{n} \right\} \quad (5)$$

$$AD = \frac{\sum_{i}^{n} y' - \sum_{i}^{n} y}{\sum_{i}^{n} y'} \quad (6)$$

$$MD = \left\{ \frac{\sum_{1}^{n} \frac{y'-y}{y'}}{n} \right\} \quad (7)$$

$$RMSE = \left\{ \sqrt{\frac{\sum_{i=1}^{n} \left(\frac{y'-y}{y'}\right)^2}{n}} \right\} \quad (8)$$

Description: y' model value; y: observation value.

2.4. Selection of the best regression model

The most appropriate regression model was chosen by evaluating the comparison metrics (R, AD, MD, RMSE, and e) (Yusandi and Jaya 2016). The model with the highest overall assessment score was deemed the best. The assessment criteria were based on equations (9-10).

$$Score\ r_{sq} = \left(\frac{r - r_{min}}{r_{\max} - r_{min}}\right) x\ (n-1) + 1 \quad (9)$$

$$Score\ validation\ indicator = \left(\frac{x - x_{max}}{x_{min} - x_{max}}\right) x\ (n-1) + 1 \quad (10)$$

Note: x: e/SA/SR/RMSE; min: minimum value; max: maximum value; n: number of models.

2.5. Mangrove damage mapping

The mapping of mangrove damage was analyzed by entering the best regression model equation results. Then, the values were categorized based on the Ministry of Environment Decree No. 201 of 2004. The criteria used were limited to the category of percentage canopy cover, with details: >75% good–dense canopy cover, 50-75% good–medium canopy cover, and <50% damaged.

3. RESULTS AND DISCUSSION

3.1. Spatial model for estimating mangrove canopy using vegetation index

Correlation and regression analyses were conducted using in situ canopy data as the dependent variable and various vegetation indices as independent variables. The vegetation indices employed, included the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), and Normalized Difference Moisture Index (NDMI). The NDVI is an indicator of green leaf biomass and leaf area index, and it is widely applied to mangrove forests, displaying a strong correlation with canopy coverage (Dharma et al. 2022). The SAVI, a modified version of the NDVI, reduces the influence of soil background on canopy brightness levels, resulting in a more accurate representation of vegetation conditions (Hardianto et al. 2021). The NDMI, on the other hand, has been widely used in previous research to identify open surface water and intertidal areas (Prihantono et al. 2022). In mangrove forests, which are periodically inundated by high tides, accurately identifying open water is crucial to understanding the tidal status.

This study used 37 plots dispersed throughout the research area (Figure 1). The data splitting process is widely utilized in model validation, where the data is divided into two distinct groups: training data and testing data. By having a separate dataset for validation unrelated to the training data, we can assess and compare the predictive performance of various models without the risk of overfitting the training data (Joseph 2022). In this study, a ratio of 75:25 is used, whereby 75% of the data is allocated for training purposes, and the remaining 25% is designated for testing.

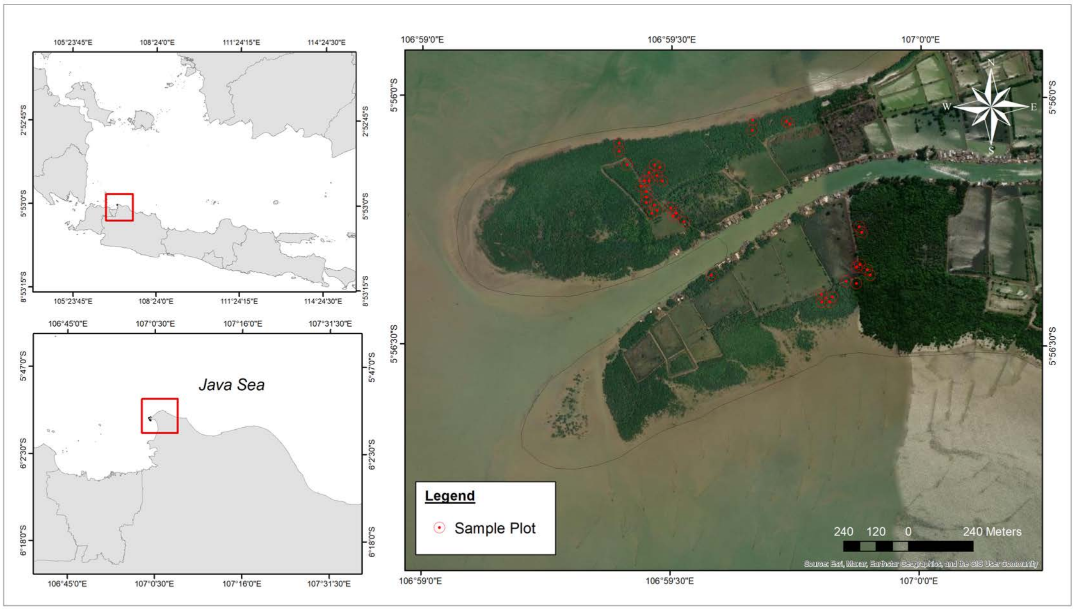

Figure 1. Study area and canopy cover plots.

3.2. Building a regression model

The initial step in constructing this regression model involved evaluating the assumptions of normality and heteroscedasticity. Normality testing is conducted regardless of the distribution of residual values to assess whether the regression model is appropriate, while heteroscedasticity testing assesses whether the variation in residual values remains constant throughout the range of predicted outcomes; in other words, it assesses if there is a pattern or correlation between residual and predicted values (Astivia and Zumbo 2019). The study utilized the K-S test for normality and the Glejser test for heteroscedasticity. The P-value obtained from the K-S test was greater than 0.05, indicating that the data followed a normal distribution. Similarly, the significance value obtained from the Glejser test was also greater than 0.05, indicating no evidence of heteroscedasticity in the regression model (Table 1). These results indicate that the classical assumptions of normality and homoscedasticity are met.

The regression model was fitted with the vegetation index using linear, logarithmic, and quadratic methods. The model results yielded various variables, including R, R2, and p-values (Table 2). The outcomes of spatial modeling involving linear and nonlinear regression were noteworthy in that the quadratic regression model demonstrated more effective predictive capabilities than the simple linear and logarithmic regression models. The coefficient of determination R2 achieved its peak value among these three models. Among the vegetation indices applied, the NDVI and SAVI models attained the highest R2 value of 0.974, which can be attributed to their shared algorithms that utilize the same bands, including the NIR and RED bands. The R2 value of the NDMI was 0.847. The statistical significance of all models was indicated by their respective P-values, which were all <0.05. The scatter plots for the linear, logarithmic, and quadratic regression models of the NDVI, SAVI, and NDMI indices in conjunction with mangrove canopy cover are illustrated in Figure 2.

Table 1. Normality and heteroscedasticity test results with canopy cover (%).

Model	Normality test (K-S) Asymp. Sig.	Heteroscedasticity Sig.
NDMI	0.188	0.096
SAVI	0.156	0.77
NDVI	0.156	0.77

Table 2. Regression statistics for canopy cover (%) for each vegetation index in the 28 training data plots.

Indeks Vegetasi	Regression	Equation	R	R^2	p value
NDMI	Simple linear	*y = 161.81NDMI + 3.7*	0.902	0.813	<0.001
	Logarithmic	*y = 12.613ln(NDMI) + 68.809*	0.812	0.659	<0.001
	Quadratic	*y = -340.431NDMI2 + 309.043NDMI - 7.690*	0.930	0.865	<0.001
SAVI	Simple linear	*y = 65.652SAVI + 4.442*	0.945	0.894	<0.001
	Logarithmic	*y = 15.320 ln(SAVI) + 58.922*	0.889	0.789	<0.001
	Quadratic	*y =-60.585SAVI2 + 128.908SAVI - 6.905*	0.974	0.949	<0.001

Table 2. Continued...

Indeks Vegetasi	Regression	Equation	R	R^2	p value
NDVI	Simple linear	*y = 93.747NDVI + 4.440*	0.945	0.894	<0.001
	Logarithmic	*y = 15.321 ln(NDVI) + 64.379*	0.889	0.789	<0.001
	Quadratic	*y = -123.511NDVI2 + 184.058NDVI -6.905*	0.974	0.949	<0.001

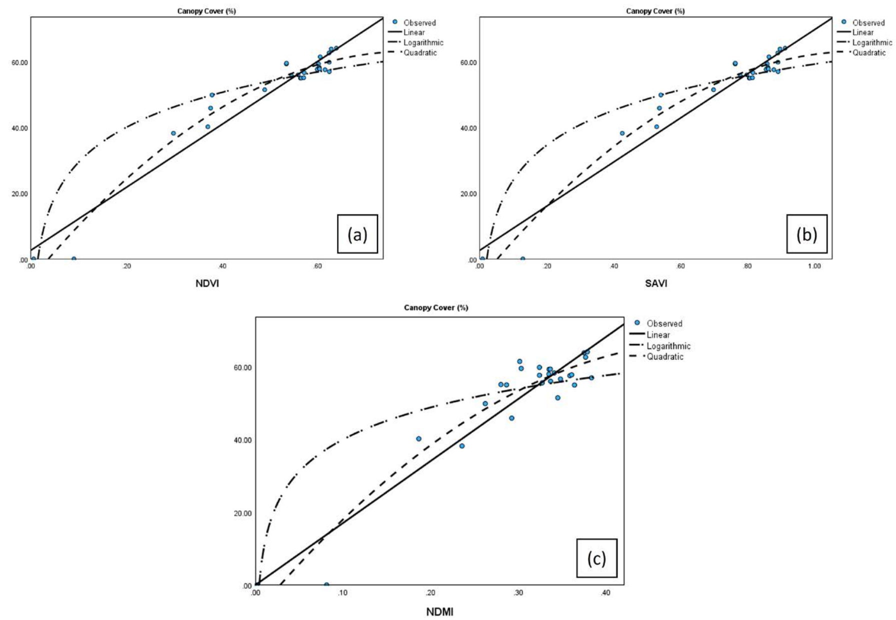

Figure 2. Scatter plot of linear, logarithmic, and quadratic regression models of (a) NDVI, (b) SAVI, and (c) NDMI with mangrove canopy cover.

3.3. Validation test

In the validation process, the model's accuracy in predicting the value of mangrove canopy cover was assessed by comparing in-situ measurement results with the model results. The validation test utilized 11 in-situ measurement data plots with corresponding predicted values from the model results. The indicators employed included e, AD, MD, and RMSE (Table 3). A decrease in the values of these four indicators indicates an improvement in the model. AD represents the difference between the in-situ measurement values and the predicted values, which is proportional to the predicted value, or the difference between the number of in-situ measurement values and the number of predicted values. The AD values obtained by all models ranged from -0.014 to 0.041, which falls within the theoretical range of -1 to 1 (Yusandi and Jaya 2016). A good model typically has an SR value below 0.1 (10%). The resulting data for the models ranged from 0.127 to 0.186, which is still within the range of 0.1.

Table 3. Validation test.

Model	Formula	Value			
		e	AD	MD	RMSE
M1	*CC = 161.81NDMI + 3.7*	0.142	0.006	0.142	0.444
M2	*CC = 12.613ln(NDMI) + 68.809*	0.127	-0.015	0.127	0.434
M3	*CC = -340.431NDMI2 + 309.043NDMI - 7.690*	0.150	-0.019	0.150	0.434
M4	*CC = 65.652SAVI + 4.442*	0.186	0.041	0.186	0.429
M5	*CC = 15.320 ln(SAVI) + 58.922*	0.150	-0.014	0.150	0.430
M6	*CC =-60.585SAVI2 + 128.908SAVI - 6.905*	0.179	0.001	0.179	0.428
M7	*CC = 93.747NDVI + 4.440*	0.186	0.041	0.186	0.429
M8	*CC = 15.321 ln(NDVI) + 64.379*	0.150	-0.014	0.150	0.430
M9	*CC = -123.511NDVI2 + 184.058NDVI -6.905*	0.179	0.001	0.179	0.428

Note: CC: Canopy cover

The model's error rate ranged from 0.127% to 0.186%, below 20%. A good model should have an error rate close to zero (Hodson 2022). Root Mean Squared Error (RMSE) is one of the most commonly used model evaluation indicators. A low RMSE value indicates that the predicted value is close to the field value. The validation test results in Table 3 show RMSE values ranging from 0.429 to 0.444 (43–44%). According to Alexander et al. (2015), a good RMSE value is close to 0 (fits perfectly), with the rule of thumb being RMSE <10%. However, in several studies, particularly in canopy cover models, it is rare to find models that approach <10%. Similar research by Yusandi and Jaya (2016) had a model RMSE range of 18–27%; Meyer et al. (2019) had 26–30%; Wang and Glenn (2008) had 25–50%; and Islami et al. (2021) had an RMSE range of 59–85%. Given this context, the model performance of the RMSE produced by this study can be considered satisfactory.

3.4. Best predictor model

The selection of the best model was based on its score using R, e, AD, MD, and RMSE. A well-performing model will have a high R and low e, AD, MD, and RMSE. Table 4 indicates that the most effective canopy cover estimation model is the M3 model, which is a quadratic regression model with the equation CC = -340.431NDMI^2 + 309.043NDMI - 7.690. This model has an R2 value of 0.865. Although not all validation values have the lowest, the overall results suggest that this model is the best predictor among other.

Table 4. Scoring model.

Model	R	e	AD	MD	RMSE	Total	Ranking
M1	5.444	6.870	5.618	6.870	1.000	25.802	7
M2	1.000	9.000	8.413	9.000	5.772	33.185	2
M3	6.827	5.900	9.000	5.900	5.780	33.408	1
M4	7.568	1.000	1.000	1.000	8.357	18.925	9
M5	4.802	5.916	8.257	5.916	8.024	32.917	3
M6	9.000	2.014	6.272	2.014	9.000	28.299	5
M7	7.568	1.000	1.001	1.000	8.357	18.927	8
M8	4.802	5.917	8.260	5.917	8.024	32.921	4
M9	9.000	2.014	6.272	2.014	9.000	28.300	6

3.5. Mangrove damage mapping

Mangrove damage mapping was performed using the model equation with the best performance. Model M3 is a quadratic regression model designed to assess the relationship between in situ canopy cover and Normalized Difference Moisture Index (NDMI), which utilizes NIR and SWIR bands in its algorithm. SWIR is particularly useful for assessing water status in plant canopies through satellite imagery (Suyarso and Avianto 2022). In green leaves, the NIR band exhibits a higher reflectance value than other bands, and the decrease in SWIR reflectance value relative to NIR is attributed to water absorption. As a result, NDMI is sensitive to soil and plant moisture, shade, leaf water content, and other factors that reflect the interplay of structure and water content (Prihantono et al. 2022).

The modeling results suggest that the NDMI is more effective in detecting damage to mangroves in the intertidal zone. Figure 3a shows an area of former ponds within the mangrove forest, which can be distinguished as damaged mangroves using NDMI modeling (Figure 3b). The mangroves in the study area have many former pond area, making it desirable for the model results to identify water in the middle of mangrove area. However, this approach may also identify mangroves that are vulnerable to high tides (low-high water stress) as damaged. Figure 3c shows mangroves growing on accretion land that are susceptible to sea tides, which the NDMI model identified as damaged, even though there were mangroves present (Figure 3d). The NDMI values in the emerging soil areas ranged from <0.25. According to Prihantono et al. (2022), an NDMI value <0.4 represents bare soil or medium-low canopy cover from vegetation with high-low water stress.

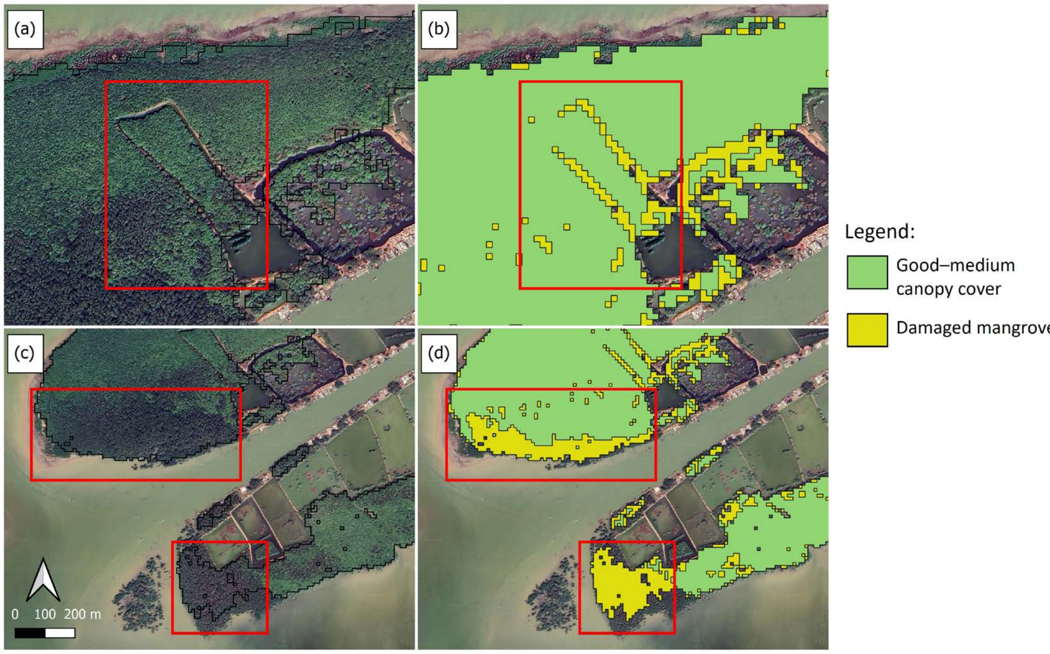

Figure 3. A comparison of the areas of former ponds and accretion land on Google Earth with the modeling result (a) Former pond area on Google Earth November 2023, (b) Former pond area based on produced map, (c) Accretion land in Google Earth November 2023, (d) Accretion land based on produced map.

Figure 4 and Table 5, respectively, demonstrate the extent of mangrove damage in the study area. Approximately 11% of the existing mangroves on the coast of Bekasi Regency are classified as damaged, while the remaining 89% are classified as good with moderate criteria. The majority of the existing mangrove forests in Pantai Bahagia Village are still dominated by good with medium canopy cover, with a low percentage of damaged mangroves. However, dense mangroves were not observed in the study area. Based on these findings, it is recommended that stakeholders conduct an assessment of the mapping results to inform mangrove rehabilitation programs in the study area.

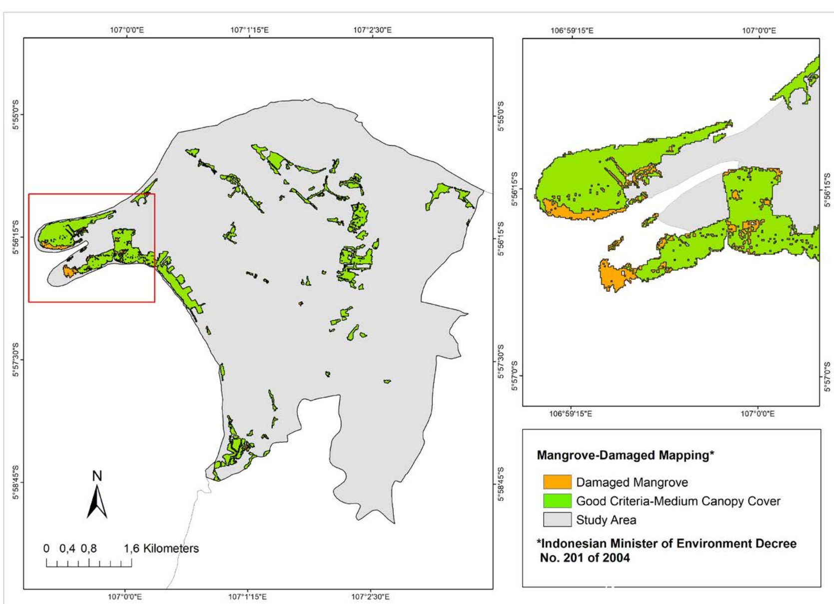

Figure 4. Map of mangrove damage in study area.

Table 5. Percentage of mangrove damage based on the Ministry of Environment Decree.

Criteria	Canopy cover	Areal extent (ha)	Percentage
Damaged mangrove	0-50 %	28.43	11%
Good–medium canopy cover	>50 %	222.11	89%
Good–dense canopy cover	>75 %	0	0%

3.6. Directions for rehabilitation of existing mangrove forests

According to the data obtained from overlay forest area status, a substantial portion of damaged mangroves are situated within the protected forest area, totaling 14.01 ha, and on accretion land, amounting to 10.91 ha. The remaining 2.03 ha of damaged mangroves are located in non-forest areas, and approximately 1.48 ha are found in permanent production forests (Table 6). The recommended planting directions for rehabilitation include 1) intensive planting, 2) enrichment planting, and 3) mangrove protection adapted to the forest area function. Intensive planting is carried out in mangrove areas with damaged status, species enrichment planting is carried out in mangroves with Good–medium canopy cover, whereas mangrove protection is recommended for mangroves with Good–dense canopy cover.

It is necessary to intensively plant the 14.01 hectares of protected forest classified as damaged with no-forest area functions inside, particularly ponds. Pantai Bahagia Village is classified as having numerous ponds and former ponds, and these are located inside protected forest area. Additionally, 205.02 hectares of protected forest, classified as having good mangroves with medium canopy cover, must be enriched through planting. Enrichment planting is an activity that increases diversity by optimally utilizing growing space by planting trees (as stated in Governmental Regulation 76/2008 on Forest Rehabilitation and Reclamation). Planting in areas with good criteria can be achieved by adding mangrove species or enriching the types of mangroves present in the region.

Table 6. Mangrove forest damage categories based on forest area status.

Damaged Category*	Non-forest area (ha)	Protected-forest (ha)	Permanent-producing forests (ha)	Accretion land* (ha)	Total (ha)
Damaged (CC<50%)	2.03	14.01	1.48	10.91	**28.43**
Good–medium canopy cover (50%<CC<75%)	5.89	205.02	10.59	0.60	**222.11**
Total (ha)	**7.92**	**219.03**	**12.07**	**11.52**	**250.54**

*) Minister of Environment Decree No. 201 of 2004

**) additional area of mangroves from accretion that is not included in the forest area status category.

The concept of permanent production forest areas refers to forested regions that primarily produce forest products while being maintained as permanent forests (Governmental Regulation 23/2021 on Forest Management). These areas are utilized for a variety of purposes, such as community, industrial, and export needs. In Pantai Bahagia Village, mangroves are often utilized by the local community to process food products, such as dodol (Palm Sugar Glutinous Rice Sweet), syrup, and chips (Dasman et al. 2024). Therefore, it is essential to continue intensive planting in production forest areas to fulfill community and industrial requirements and promote sustainable mangrove management. Additionally, approximately 10.59 ha of mangroves with good-moderate mangrove criteria necessitate enrichment planting and additional guidance on sylvofishery system in the pond area. Sylvofishery is a conventional aquaculture system that integrates fishing with mangrove planting, followed by the implementation of a management system that minimizes input and reduces environmental impacts (Paruntu et al. 2016). By employing the sylvofishery technique, the pond area can be utilized without disrupting the mangrove ecosystem.

Following the rehabilitation of the mangrove forest, it is recommended that 2.03 hectares of non-forest land, which is classified as damaged, undergo intensive planting. Additionally, if pond land is present, the sylvofishery technique is suggested. For the 5.89 hectares of mangroves with good criteria–medium canopy cover, enrichment planting with the addition of a sylvofishery system in the pond area is suggested. For the 10.91 hectares of accretion land classified as damaged, intensive mangrove planting is necessary to protect the land. Furthermore, 0.6 hectares of mangrove with good criteria–medium canopy cover should be enriched through planting.

4. CONCLUSION

Mapping mangrove damage using a spatial model between canopy cover and NDMI vegetation index is the recommended method based on this research findings. Apart from statistically having good performance, the mapping results also show that the modeling results are very good in distinguishing ponds in mangrove areas as damaged mangrove categories. About 11% or 28,43 ha of existing mangroves are classified as damaged. Good criteria with medium canopy cover is around 222,11 ha (89%), while good criteria with dense canopy cover were not found.

The majority of mangroves classified as damaged were located in protected forest areas, accretion land, and non-forest areas, with a few situated in permanent production forest areas. It was important to maintain areas classified as being in good condition. Additionally, mangrove area classified as damaged necessitated rehabilitation in accordance with planting directions and forest area function. Intensive and enrichment plantings were recommended for mangrove with damaged and good criteria (moderate canopy cover), respectively.

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CORRESPONDENCE TO

Luisa Febrina Amalo
PPLH IPB Building, IPB University Darmaga Campus, Dramaga District, Bogor Regency, West Java 16680, Bogor, Indonesia
e-mail: luisafebrinaluisa@apps.ipb.ac.id

AUTHORS' CONTRIBUTIONS

Luisa Febrina Amalo: Formal analysis (Lead), Investigation (Lead), Methodology (Lead), Validation (Lead), Visualization (Lead), Writing - original draft (Lead).
Yudi Setiawan: Conceptualization (Equal), Data curation (Equal), Methodology (Equal), Supervision (Equal), Writing - review & editing (Equal).
Cecep Kusmana: Conceptualization (Equal), Data curation (Equal), Methodology (Equal), Supervision (Equal), Writing - review & editing (Equal).

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