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SPATIOTEMPORAL ANALYSIS OF MANGROVE DENSITY DYNAMICS USING SENTINEL-2 IMAGERY AND CLOUD COMPUTING BASED MACHINE LEARNING ALGORITHMS (CASE STUDY: DEMAK REGENCY)

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ABSTRACT

Mangrove forests are vital coastal ecosystems that protect shorelines and help maintain coastal environmental balance. Mangrove forests undergo changes every year due to degradation or restoration, so monitoring needs to be carried out. This study analyzes the spatiotemporal dynamics of mangrove density in Demak Regency from 2020 to 2025 using Sentinel-2 imagery and the CART (Classification and Regression Tree) algorithm processed through the Google Earth Engine (GEE) platform. Six spectral indices were used as classification inputs, namely NDVI, NDWI, MVI, MI, AMMI, and CMRI. AMMI is the best index in identifying mangroves as a whole, both in narrow and large areas. Based on classification, the mangrove cover area has been restored or significantly increased from 1594.97 ha in 2020 to 1781.18 ha in 2025. The largest increase occurred in the high canopy density class of 400.02 ha. Meanwhile, the medium and low canopy density classes showed a decrease in area. Accuracy assessment showed an overall accuracy value of 99% for 2020 and 99% for 2025, with kappa coefficient above 97% in both years. These results show that the classification method with cloud computing support can be relied on in spatiotemporal monitoring of mangrove changes efficiently and accurately.

Keywords: Classification and Regression Tree, Cloud Computing, Machine Learning, Mangrove, Sentinel-2

1. INTRODUCTION

Mangrove forests are vital coastal ecosystems that grow along shorelines (Harefa et al., 2023) with a height of about 0.9 meters (Ellison et al., 2022) and covering approximately 2% of the planet's surface (Kinasih & Purnaweni, 2019). They play a critical role in sustaining coastal ecosystems such as preventing abrasion and storm surges, improving water quality, reducing sedimentation, and providing habitat for diverse marine species (Agduma et al., 2024). However, these ecosystems are increasingly threatened by factors such as aquaculture expansion and coastal urbanization, which contribute to widespread degradation (Wei et al., 2025). The area of mangrove forests has currently experienced an annual degradation of around 3.4%, especially in Southeast Asian (Bunting et al., 2022). Indonesia possesses one of the world's largest mangrove areas, covering about 3.489.140,68 ha or about 23% of the total global mangrove extent. Around 1.671.140,75 ha (47.89%) are in good condition and 1.817.999,93 ha (52.10%) have been degraded (Sentoso et al., 2021). An important indicator for assessing mangrove condition is from the level of vegetation density (Maurya et al., 2021). Although field surveys can accurately monitor mangrove density, their spatial and temporal scope is restricted and require substantial costs and labor. Another solution can be used with a remote sensing based approach that leverages satellite imagery for efficient and effective results in extensive and continuous monitoring (Lu & Wang, 2022).

Demak Regency, located on the northern coast of Central Java, Indonesia, has undergone significant mangrove loss over the last two decades (Irsadi et al., 2019). This loss is compounded by land subsidence, which reduces suitable areas for mangrove growth (Widjonarko et al., 2025) The degradation of mangrove forest ecosystems in Demak Regency causes several serious problems, including coastal abrasion of up to 41 m/year and changes in the average coastline of up to 25 m/year (Muskananfola et al., 2020). In addition, the coastal area of Demak is under pressure from land subsidence, but spatial and temporal-based monitoring approaches are still limited (Widodo et al., 2024). Advances in remote sensing technology and cloud-based processing systems, it is possible to see variations in mangrove changes dynamically (Amalia et al., 2024).

This research uses Sentinel-2 satellite imagery and the Classification and Regression Tree (CART) machine learning algorithm to classify mangrove distribution in Demak Regency. The CART algorithm has been shown to be effective in identifying mangrove cover patterns (Mahdavifard et al., 2023). Sentinel-2 is selected because it has high spatial and spectral resolution for detecting mangroves (Jaelani et al., 2025). The classification process is further enhanced by incorporating six spectral indices, including Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974), Normalized Difference Water Index (NDWI) (Gao, 1996), Mangrove Vegetation Index (MVI) (Baloloy et al., 2020), Mangrove Index (MI) (Purwanto et al., 2014), Automatic Mangrove Map and Index (AMMI) (Suyarso & Avianto, 2022), dan Combined Mangrove Recognition Index (CMRI) (Gupta et al., 2018).

The main objective of this research is to analyze the spatiotemporal dynamics of mangrove density in Demak Regency between 2020 and 2025 using the best accurate index. Changes in density and structural distribution serve as key indicators of mangrove ecosystem health. To achieve this, Google Earth Engine (GEE) platform is used to enable efficient and scalable cloud-based processing.

2. DATA AND METHODS

2.1 Study Area

This research was carried out in a mangrove ecosystem located along the coastal zone of Demak Regency, Central Java. The study site lies between the coordinates 6º 43' 26" to 7º 09' 43" S and 110º 27' 58" to 110º 48' 47" E, as illustrated in Figure 1.

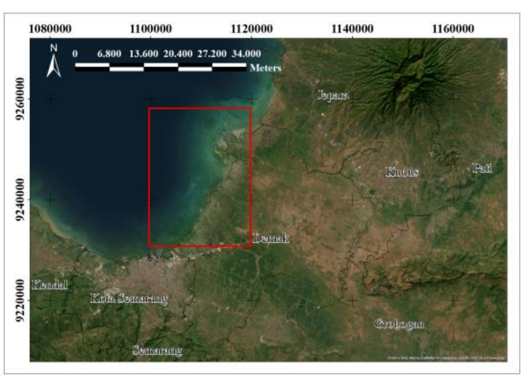


Figure 1. Study area

2.2 Data

The analysis used Sentinel-2 Level-2A satellite imagery, which has undergone atmospheric correction to produce surface reflectance data. The spectral bands used include B2, B3, B4, B5, B6, B7, B8, B9, B10, B11, and B12 with a spatial resolution of 10 meters. Sentinel-2 images from the year 2020 as t_0 and 2025 as t_1, were selected to evaluate spatial and temporal changes in mangrove distribution over a five-year interval.

2.3 Data Processing

Data processing was conducted systematically to extract information regarding mangrove distribution and density changes. The complete workflow is shown in Figure 2.

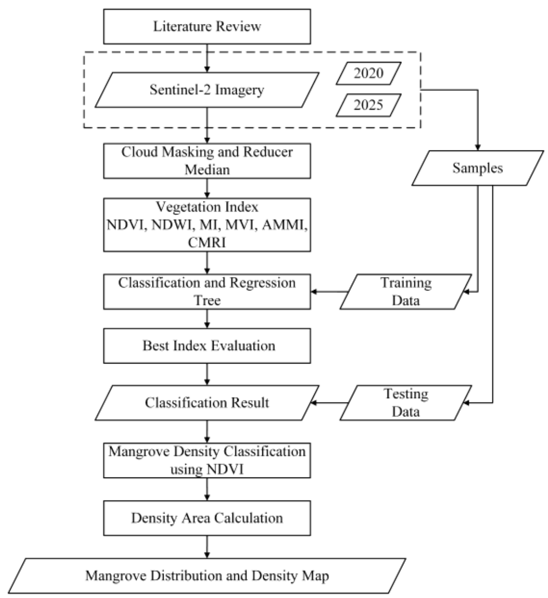


Figure 2. Flowchart

2.3.1 Pre-processing

Pre-processing of data is carried out on the Google Earth Engine (GEE) platform, a cloud computing tool designed for remote sensing data processing. The initial stage starts from collecting Sentinel-2 imagery data within a predetermined time frame and using the median reducer feature. Next, a cloud masking process was carried out to remove cloud cover and cirrus using the Scene Classification Layer (SCL) and Quality Assessment band methods(QA60) (Pertiwi et al., 2021), creation of areas of interest and sampling, in which the sample data were divided into a 70:30 ratio, consisting of 70% for training and 30% for accuracy assessment

(Muraina, 2022). The training data for distinguishing mangrove and non-mangrove classes were obtained through manual digitization based on high-resolution Sentinel-2 imagery.

2.3.2 Mangrove Classification

Mangrove distribution was classified using the Classification and Regression Tree (CART). CART is a very popular decision tree method in remote sensing and was introduced by Leo Breiman in 1984. CART builds a decision tree using the GINI index to select the best separator attributes based on data impurity (Abedinia & Seydi, 2024). CART works by dividing the data into increasingly homogeneous groups through binary branching that is automatically determined by the training data (Li et al., 2023).

One of the main advantages of CART is its ease of interpretation and model visualization. Each classification decision can be traced through tree nodes that define the threshold values of the input features (Abdelsamie et al., 2024). CART has also proven to be effective in handling high complexity data such as multitemporal imagery. This algorithm is able to adapt the model to dynamic environment variables (Sang et al., 2019).

In addition to utilizing the Classification and Regression Tree (CART) algorithm, the input variables consisted of spectral reflectance values from the Sentinel-2 bands and several spectral indices are used as input data to identification of mangrove and non-mangrove.

Table 1. Spectral variations of the index used

No	Index	Equation	Reference
1.	NDVI	$NDVI = \frac{NIR - RED}{NIR + RED}$	(Rouse *et al*., 1974)
2.	NDWI	$NDWI = \frac{RED - SWIR}{RED + SWIR}$	(Gao, 1996)
3.	MVI	$MVI = \frac{NIR - Green}{SWIR - Green}$	(Baloloy *et al*., 2020)
4.	MI	$MI = \frac{NIR - SWIR}{NIR \times SWIR} \times 10000$	(Purwanto *et al*., 2014)
5.	AMMI	$AMMI = \frac{(NIR - RED)}{(NIR + RED)} \times \frac{(NIR - SWIR)}{(SWIR - 0.65 \times RED)}$	(Suyarso & Avianto, 2022)
6.	CMRI	$CMRI = NDVI - NDWI$	(Gupta *et al*., 2018)

NDVI is used to detect vegetation cover in general by comparing reflectance of near infrared and red bands. NDWI is used to highlight water content and moisture in vegetation, particularly useful for coastal mangrove so that it is suitable in mangrove identification by comparing the reflectance of red bands and SWIR. MVI is a special index for detecting mangrove vegetation by comparing the reflectance of the NIR and SWIR bands to the green bands and utilizing the unique spectral characteristics of mangroves growing in water saturated environments (Baloloy et al., 2020). MI is used for the presence of mangroves by calculating the ratio between the NIR and SWIR bands, and multiplying the result by 10000 to obtain a clear contrast of the difference (Winarso & Purwanto, 2017). MI is suitable for distinguishing mangroves from non-coastal vegetation. AMMI is an index that combines NDVI's sensitivity to vegetation and SWIR's sensitivity to moisture, resulting in automatic classification of mangroves. CMRI combines NDVI and NDWI to more accurately identify mangroves in transition areas between land and sea.

2.3.3 Density Calculation

The classification of mangrove density is calculated based on the NDVI index. NDVI values range from -1 to +1, which represents the conditions and density of vegetation in an area. To determine the interval of mangrove canopy density values using the results of NDVI calculations, the following calculation formula can be used (Purwanto et al., 2014):

$$KL = \frac{xt - xr}{k} \quad (1)$$

Where KL is the class interval, xt is the highest NDVI value, xr is the lowest NDVI value, and k is the number of desired classes. In this study, canopy density was categorized into three classes: low, medium, and high.

2.4 Accuracy Assessment

In a study that utilizes specific data and methods, an accuracy assessment is required to ensure the validity of the results. This is important because the level of accuracy obtained significantly affects the

users' confidence in both the data used and the analytical methods applied. The accuracy of the classification results was assessed using a confusion matrix with calculates producer's accuracy, user's accuracy, overall accuracy, and kappa coefficient (Congalton & Green, 2019).
The following equations were used for the accuracy assessment:

$$User's\ Accuracy = \frac{x11}{x+1} \times 100\% \quad (2)$$

$$Producer's\ Accuracy = \frac{x11}{x1+} \times 100\% \quad (3)$$

$$Overall\ Accuracy = \left(\frac{(\sum_{i=1}^{r} x_{ii}}{N}\right) \times 100\% \quad (4)$$

$$Kappa\ Coefficient = \left[\frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} x_{i+}x_{+i}}{N^2 - \sum_{i=1}^{r} x_{i+}x_{+i}}\right] \times 100\% \quad (5)$$

2.5 Cloud Computing

Cloud computing is a technology that enables data processing, storage, and access via the internet without relying on local physical infrastructure. (Mell & Grance, 2011). Cloud computing has many advantages such as users do not need to provide large capacity hardware as the entire processing, supports scalability, allows customization of computing capacity as needed without being limited by local device specifications, and facilitates collaboration and accessibility, where data and analysis results can be accessed in real-time from different locations and devices. One of the platforms that implements cloud computing methods is Google Earth Engine (GEE). GEE is a cloud-based computing platform launched by Google in 2010. Google Earth Engine utilizes Google's computing infrastructure and a wide range of openly accessible remote sensing datasets. It is one of the most popular platforms for large scale geospatial data and supporting scientific discovery by providing users with free access to various remote sensing datasets (Amelia & Darmansyah, 2023).

2.6 Temporal Analysis

Temporal analysis in this study was conducted to compare the distribution and density of mangroves between 2020 (t_0) and 2025 (t_1), in order to identify spatial and statistical changes over the five year period. Several analytical approaches were applied, including calculating the difference in mangrove distribution area, density canopy classes, and density statistics between 2020 and 2025. To determine the differences, the area of mangrove distribution and the area of each mangrove density class were measured, and the changes in mangrove density between 2020 and 2025 were calculated in hectares. The statistical changes in mangrove density are illustrated through graphs showing changes in density area from t_0 to t_1. Through area based analysis, class change detection, and statistical evaluation of density, The goal was to observe spatial and temporal patterns in mangrove ecosystem dynamics over the five-year period.

3. RESULTS AND DISCUSSION

3.1 Comparison of Classification Indices

Figure 4 illustrates the ability of different indices to identify mangrove areas based on spectral reflectance values. Table 2 presents the classification accuracy and calculated mangrove area for each index in 2025.

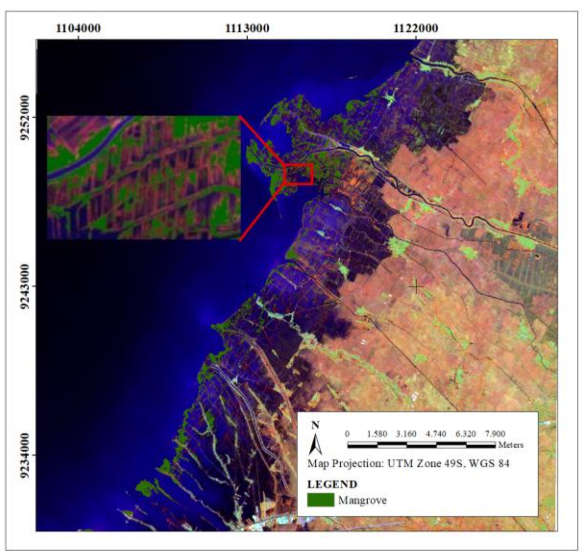


Figure 3. Mangrove distribution using bands of Sentinel-2

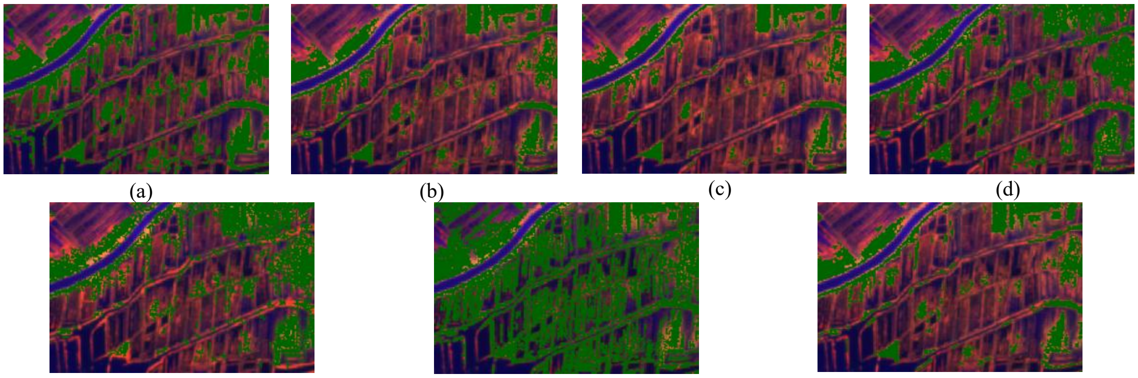


Figure 4. Comparison of classification indices (a) Sentinel-2, (b) NDVI, (c) NDWI, (d) MVI, (e) MI, (f) AMMI, (g) CMRI

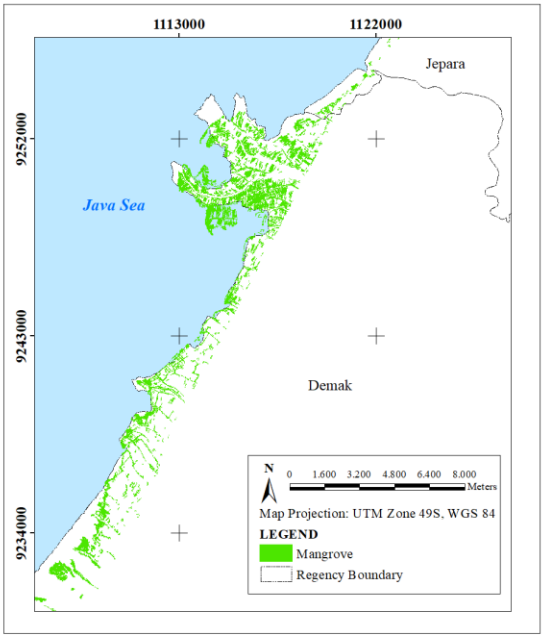
Table 2. Accuracy and area of the indices

No	Index	Overall Accuracy	Kappa Coefficient	Area (ha)
1.	Sentinel-2	0.99	0.99	1270.99
2.	NDVI	0.99	0.98	963.16
3.	NDWI	0.99	0.97	747.73
4.	MVI	0.99	0.97	1098.22
5.	MI	0.99	0.90	2019.22
6.	AMMI	0.99	0.97	1594.97
7.	CMRI	0.99	0.98	952.63

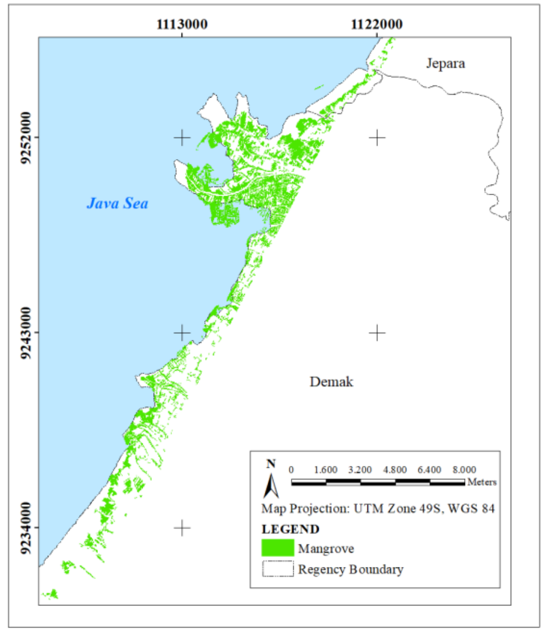
Among the tested indices (b) NDVI, (c) NDWI, and (g) CMRI are able to identify mangroves in areas with dense canopy coverage, but they are less effective in detecting mangroves in narrow or fragmented areas, as indicated by the total detected area being less than 1000 hectares. In contrast, image (a) Sentinel-2 and (d) MVI consistently detect mangrove presence in several locations that were not captured by other indices. Meanwhile, image (e) MI is less effective in identifying mangroves in sparse areas, yet it yields a significantly large total area of 2019.22 hectares with a kappa coefficient of 90%, which may indicate the presence of noise or misclassification in other land cover types. On the other hand, (f) AMMI successfully detects mangroves both in extensive and small fragmented areas, resulting in a total area of 1594.97 hectares. Overall, all tested indices demonstrated high classification accuracy, with overall accuracy values above 99% and kappa coefficient values exceeding 90%. Based on this comparison, AMMI is considered the most reliable index for mangrove identification and was chosen for application in this research. Consistency of AMMI in classification is also supported by previous studies, which have shown that AMMI achieves high accuracy in mapping mangroves under both sparse and dense canopy conditions, with a strong correlation (R^2 = 0.99) to NDWI/NDMI indices known for their effectiveness in detecting vegetation moisture and canopy structure. (Suyarso & Avianto, 2022). AMMI is more sensitive in distinguishing lower vegetation (such as nipa and shrubs) from the main mangrove canopy (Prayudha et al., 2024). In addition, in research on the accuracy of mangrove extraction using various threshold segmentation-based methods, AMMI is said to be a very promising method because it is able to reduce interference from non-mangrove objects and improve the detection of sparse mangrove areas (Zablan et al., 2023).

3.2 Mangrove Distribution

Based on the processing results using Sentinel-2 imagery in Demak Regency, the mangrove distribution is shown in Figure 4. The mangrove classification distribution was obtained using the CART algorithm. During the classification process, a total of 243478 training data pixels were used for the year 2020 and 188406 pixels for the year 2025. The classification results are represented in green.



(a)



(b)

Figure 4. Mangrove distribution in Demak Regency in (a) 2020 and (b) 2025

Based on the mangrove distribution area table on Table 3, there was a significant increase in mangrove area from 2020 to 2025. In 2020, the recorded mangrove area was 1594.97 ha, while in 2025 it increased to 1781.18 ha. This indicates an increase of 186.21 ha over the five-year period, equivalent to 11.67% compared to the initial area in 2020.

Table 3. Mangrove distribution area

2020 (ha)	2025 (ha)	Difference (ha)	Percentage (%)
1594.97	1781.18	186.21	11.67

The increase in mangrove area suggests that mangrove restoration occurred, possibly due to rehabilitation activities or natural mangrove growth. Based on the mangrove area data, changes in mangrove distribution can also be observed, in Figure 5 and Table 4. Between 2020 and 2025, there was an increase of 626.35 ha, a decrease of 431.18 ha, and an unchanged mangrove area of 878.85 ha.

Table 4. Changes in mangrove area

Year	Increase	Decrease	Unchanged mangrove
2020-2025	626.35	431.18	878.85

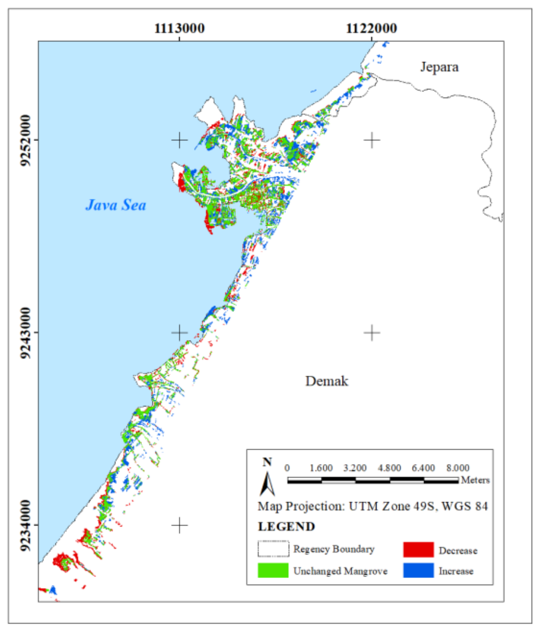


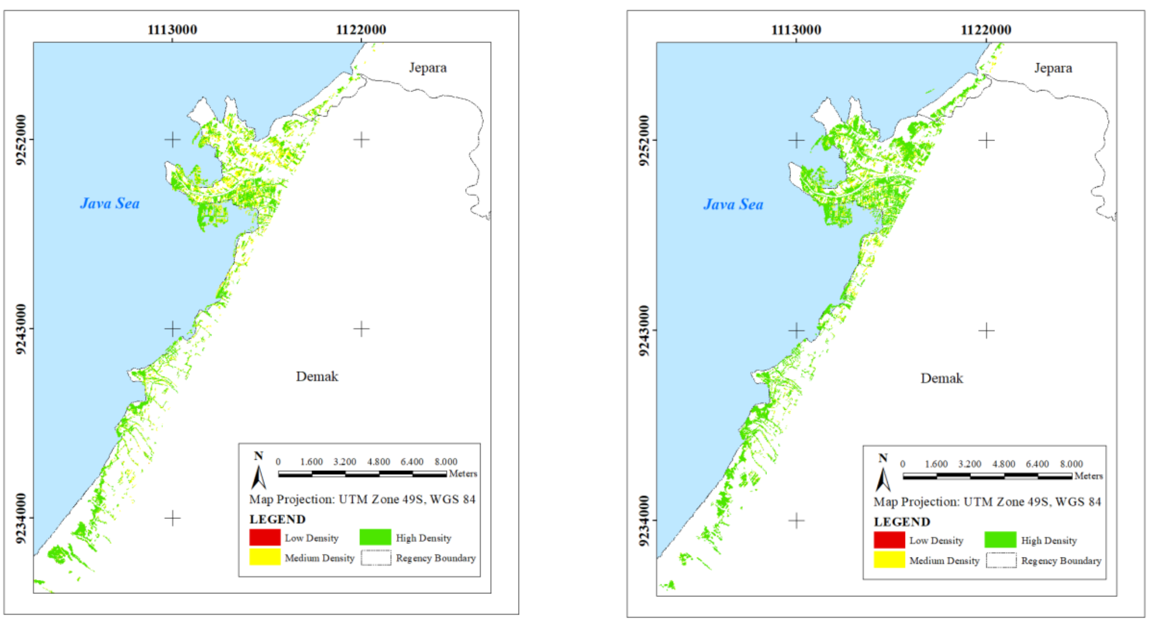
Figure 5. Changes in mangrove distribution

The extent of mangrove cover along the coastal zone of Demak Regency from 2020 to 2025 has increased significantly. The pattern of mangrove increase has also occurred in the previous year, namely from 2019 to 2020. The area of mangroves in 2019 was recorded to have an area of 1475.98 ha (Akbaruddin et al., 2020). This increase in area is also supported by mangrove rehabilitation and planting initiatives carried out in Demak Regency. In 2020, mangrove planting activities were undertaken as part of community service with a total of 500 plants in Bedono Village (Nugroho et al., 2020). Then in 2021, there were conservation program activities of 1000 mangrove trees by the Universitas PGRI Semarang and 3000 mangrove trees by the Faculty of Marine Sciences UNDIP Semarang and the Politeknik Ilmu Pelayaran Semarang around Glagahwangi beach, Demak Regency (Rohmawati et al., 2022). As well as 1 million mangrove trees were planted by the Demak Regency DPRD and the Demak Regency Forkopimda (DPRD Kabupaten Demak, 2021). In 2022 through the National Economic Recovery program, 12000 mangrove trees were planted on an area of 15 ha and the planting will continue until the following years (Wulandari et al., 2024). And in 2024, 2000 mangrove trees were planted across 2 hectares in Surodadi Village, Sayung District, Demak Regency (DLHK Provinsi Jawa Tengah, 2024). With the increase in mangrove area in 2025, it indicates the success of the rehabilitation program that has been implemented.

The spatial analysis shows that the largest mangrove expansion between 2020 and 2025 occurred along the northern coast of Demak, especially around Sayung, Bedono, and Timbulsloko villages areas that have been the focus of rehabilitation and community planting programs. This overlap suggests that the observed increase in mangrove cover is closely related to ongoing restoration activities, indicating that local and community-based efforts have played a direct role in mangrove recovery across the region.

3.3 Mangrove Density

Mangrove density is divided into three levels, low, medium, and high canopy, as visualized in Figure 5. The class intervals were determined by subtracting the lowest NDVI value from the highest NDVI value and dividing the result by three. The mangrove density is visualized in three classes. Areas with low mangrove density are represented in red, areas with medium density in yellow, and areas with high mangrove density are represented in green.



(a) (b)

Figure 6. Mangrove density classification (a) 2020 (b) 2025

Table 5. Comparison of areas in 2020 and 2025

No	Density class	Area (2020)	Area (2025)	Difference (ha)	Percentage (%)		Description
					Increase	Decrease	
1.	Low	5.58	2.89	0.95		50.53	The area of low density in 2025 decreased by 0.95 ha (50.53%) compared to 2020.
2.	Medium	511.95	301.09	210.85		41.19	The area of medium density in 2025 decreased by 210.85 ha (41.19%) compared to 2020.
3.	High	1077.17	1477.19	400.02	37.14		The area of high density in 2025 increased by 400.02 ha (37.14%) compared to 2020.
	Total	1594.97	1781.18	189.21			

Table 5 and Figure 6 present information on the changes in mangrove canopy density classes between 2020 and 2025. In the low-density class, the area decreased from 2.472 ha in 2020 to 1.821 ha in 2025, reflecting a reduction of 0.651 ha. In the medium-density class, the area declined from 471.674 ha to 398.679 ha, marking a decrease of 72.995 ha. Conversely, the high-density canopy class experienced a substantial increase, expanding from 1169.865 ha in 2020 to 2130.022 ha in 2025, a gain of 960.157 ha. The area of mangrove distribution in 2020 and 2025 is dominated high density class. The increase in mangrove area from 2020 to 2025 shows the restoration of mangrove ecosystems in a period of 5 years.

3.3 Accuracy Assessment

Presented below are the outcomes of the validation test using a confusion matrix for the classification of mangrove distribution in 2020 and 2025.

Table 6. Confusion matrix of 2020

	Non-Mangrove	Mangrove	Total	*User's accuracy*
Non-Mangrove	102813	46	102859	99%
Mangrove	28	1956	1984	97%
Total	102841	2002	104843	
Producer's accuracy	99%	98%		
Overall accuracy				0.99
Kappa coefficient				0.98

Table 7. Confusion matrix of 2025

	Non-Mangrove	Mangrove	Total	*User's accuracy*
Non-Mangrove	79115	39	79154	99%
Mangrove	28	1364	1392	97%
Total	79143	1403	80546	
Producer's accuracy	99%	97%		
Overall accuracy				0.99
Kappa coefficient				0.97

The confusion matrix calculation was performed in GEE using a total of 104843 sample pixels. Table 6 shows an overall accuracy value of 0.99 or 99%, and a kappa coefficient value of 0.98 or 98%. Meanwhile, in 2025, the confusion matrix was calculated using a total of 80546 sample pixels. Table 7 shows an overall accuracy of 0.99 or 99% and a kappa coefficient of 0.97 or 97%. Based on the confusion matrix results for both 2020 and 2025, the classification performance can be considered excellent, as both overall accuracy and kappa coefficient exceed 80%.

The high overall and kappa coefficient values obtained in this study are largely due to the validation process being conducted within the Google Earth Engine (GEE) environment using the testing samples derived from the same dataset as the training samples. The validation did not utilize direct field reference data, but relied on random sample splitting (70% for training and 30% for testing) performed in GEE. This method evaluates internal model consistency rather than true ground-truth accuracy, which can lead to slightly overestimated accuracy values. Therefore, the reported results should be interpreted as indicative of the model's strong internal performance, not necessarily its external field accuracy.

4. CONCLUSIONS AND SUGGESTIONS

From the result and analysis, it can be concluded that among the six spectral indices tested using the CART algorithm, the Automatic Mangrove Map and Index (AMMI) was the most effective for identifying mangrove cover. The classification results showed a significant increase in mangrove area from 1594.97 ha in 2020 to 1781.18 ha in 2025 indicating a gain of 886.511 hectares. The high-density canopy class increased by 400.02 ha, while the medium and low-density classes decreased by 210.85 ha and 0.95 ha, respectively. Validation using confusion matrices demonstrated high classification accuracy, with both overall and kappa coefficient values exceeding 97% in 2020 and 2025. The results demonstrate that among the six spectral indices tested using the CART algorithm, the Automatic Mangrove Map and Index (AMMI) provided the most consistent and reliable performance in identifying mangrove areas. AMMI showed strong sensitivity to both dense and sparse mangrove canopies, making it effective for detecting complex coastal vegetation structures. However, the NDVI-based density classification method used in this study has certain limitations, as it can be influenced by soil background, mixed pixels, and seasonal changes in vegetation moisture. These factors may cause uncertainty in distinguishing canopy density levels. Therefore, while the integration of Sentinel-2 imagery, the CART algorithm, and the AMMI index proved highly effective for spatiotemporal mangrove monitoring, future studies are recommended to incorporate additional field validation and multi-temporal datasets to improve the robustness of density estimation..

REFERENCES

Abdelsamie, E. A., Mustafa, A. rahman A., El-Sorogy, A. S., Maswada, H. F., Almadani, S. A., Shokr, M. S., El-Desoky, A. I., & Meroño de Larriva, J. E. (2024). *Current and Potential Land Use/Land Cover (LULC) Scenarios in Dry Lands Using a CA-Markov Simulation Model and the Classification and Regression Tree (CART) Method: A Cloud-Based Google Earth Engine (GEE) Approach*. *Sustainability (Switzerland)*, *16*(24). https://doi.org/10.3390/su162411130

Abedinia, A., & Seydi, V. (2024). B*uilding semi-supervised decision trees with semi-cart algorithm. International Journal of Machine Learning and Cybernetics*, *15*(10), 4493–4510. https://doi.org/10.1007/s13042-024-02161-z

Agduma, A. R., Tanalgo, K. C., Millondaga, A. M., Respicio, J. M. V., Dela Cruz, K. C., Lidasan, A. K., Terante, R. J., & Cao, K. F. (2024). *Knowledge shortfalls and research priorities for Philippine mangroves in the fast-changing world. Ocean and Coastal Management*, *255*(June), 107211. https://doi.org/10.1016/j.ocecoaman.2024.107211

Amalia, A. V., Fariz, T. R., Lutfiananda, F., Ihsan, H. M., Atunnisa, R., & Jabbar, A. (2024). *Comparison of Swat-Based Ecohydrological Modeling in the Rawa Pening Catchment Area, Indonesia. Jurnal Pendidikan IPA Indonesia*, *13*(1), 1–11. https://doi.org/10.15294/jpii.v13i1.45277

Amelia, R., & Darmansyah. (2023). *Potensi Google Earth Engine untuk Identifikasi Objek Wilayah Perairan pada Citra Satelit Sentinel-2. EQUIVA JOURNAL Journal of Mathematics & Information Technology*, *01*, 19–24.

Baloloy, A. B., Blanco, A. C., Rhommel, R. R. C. R., & Nadaoka, K. (2020). *Development and application of a new mangrove vegetation index (MVI) for rapid and accurate mangrove mapping*. *ISPRS Journal of Photogrammetry and Remote Sensing*, *166*, 95–117.

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: Global Mangrove. Remote Sensing*, *14*(3657), 1–32.

Congalton, R. G., & Green, K. (2019). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. In Mapping Science Series (3rd ed.)*. CRC Press. https://doi.org/https://doi.org/10.1201/9780429052729

Ellison, J. C., Buffington, K. J., Thorne, K. M., Gesch, D., Irwin, J., & Danielson, J. (2022). *Elevations of mangrove forests of Pohnpei, Micronesia. Estuarine, Coastal and Shelf Science*, *268*, 107780. https://doi.org/https://doi.org/10.1016/j.ecss.2022.107780

Gao, B. C. (1996). *NDWI - A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water From Space. In FDA Regulatory Affairs:* (3rd ed.). FDA Regulatory Affairs: https://doi.org/10.1201/b16471-3

Gupta, K., Mukhopadhyay, A., Giri, S., Chanda, A., Datta Majumdar, S., Samanta, S., Mitra, D., Samal, R. N., Pattnaik, A. K., & Hazra, S. (2018). *An index for discrimination of mangroves from non-mangroves using LANDSAT 8 OLI imagery. MethodsX*, *5*(September), 1129–1139. https://doi.org/10.1016/j.mex.2018.09.011

Harefa, M. S., Pasaribu, P., Alfatha, R. R., Benny, X., & Irfani, Y. (2023). *Identifikasi Pemanfaatan Hutan Mangrove Oleh Masyarakat Studi Kasus Kecamatan Teluk Mengkudu Kabupaten Serdang Bedagai*. *Journal of Laguna Geography*, *02*(pemanfaatan hutan mangrove), 1–7.

Irsadi, A., Anggoro, S., Soeprobowati, T. R., Helmi, M., & Khair, A. S. E. (2019). *Shoreline and mangrove analysis along semarang-demak, Indonesia for sustainable environmental management. Jurnal Pendidikan IPA Indonesia*, *8*(1), 1–11. https://doi.org/10.15294/jpii.v8i1.17892

Jaelani, L. M., Safitri, D. S., Kristian, N. E., Alina, A. N., Syariz, M. A., Sanjaya, H., & Rasam, A. R. A. (2025). *Mapping Mangrove Species Distribution and Density Using Sentinel-2 Satellite Imagery and Spectral Analysis. Journal of Human, Earth, and Future*, *6*(1), 1–11. https://doi.org/10.28991/HEF-2025-06-01-01

Kinasih, P. I., & Purnaweni, H. (2019). *Pemanfaatan mangrove untuk pemberdayaan masyarakat pesisir. Jurnal Collaborative Governance Dalam Pengembangan Pariwisata Di Indonesia Rekreasi*, *1*(1), 71–78.

Li, C., Cai, R., Tian, W., Yuan, J., & Mi, X. (2023). *Land Cover Classification by Gaofen Satellite Images Based on CART Algorithm in Yuli County, Xinjiang, China. Sustainability (Switzerland)*, *15*(3). https://doi.org/10.3390/su15032535

Lu, Y., & Wang, L. (2022). *The current status, potential and challenges of remote sensing for large-scale mangrove studies. International Journal of Remote Sensing*, *43*(18), 6824–6855. https://doi.org/10.1080/01431161.2022.2145584

Mahdavifard, M., Ahangar, S. K., Feizizadeh, B., Kamran, K. V., & Karimzadeh, S. (2023). *Spatio-Temporal monitoring of Qeshm mangrove forests through machine learning classification of SAR and optical images on Google Earth Engine. International Journal of Engineering and Geosciences*, *8*(3), 239–250. https://doi.org/10.26833/ijeg.1118542

Maurya, K., Mahajan, S., & Chaube, N. (2021). *Remote sensing techniques: mapping and monitoring of mangrove ecosystem—a review. Complex and Intelligent Systems*, *7*(6), 2797–2818. https://doi.org/10.1007/s40747-021-00457-z

Mell, P., & Grance, T. (2011). *The NIST Definition of Cloud Computing. National Institute of Standards and Technology*.

Muraina, I. O. (2022). *Ideal Dataset Splitting Ratios in Machine Learning Algorithms: General Concerns for Data Scientists and Data Analysts. 7th INTERNATIONAL MARDIN ARTUKLU SCIENTIFIC RESEARCHES CONFERENCE*, *February*, 496–504. https://www.researchgate.net/publication/358284895

Muskananfola, M. R., Supriharyono, & Febrianto, S. (2020). *Spatio-temporal analysis of shoreline change along the coast of Sayung Demak, Indonesia using Digital Shoreline Analysis System. Regional Studies in Marine Science*, *34*, 101060. https://doi.org/10.1016/j.rsma.2020.101060

Pertiwi, A. P., Lee, C. B., & Traganos, D. (2021). *Cloud-Native Coastal Turbid Zone Detection Using Multi-Temporal Sentinel-2 Data on Google Earth Engine. Frontiers in Marine Science*, *8*(September). https://doi.org/10.3389/fmars.2021.699055

Purwanto, A. D., Asriningrum, W., Winarso, G., & Parwati, E. (2014). *Analisis Sebaran dan Kerapatan Mangrove Menggunakan Citra Landsat 8 di Segara Anakan, Cilacap. Seminar Nasional Penginderaan Jauh 2014*, *21 April 2*, 232–241.

Rouse, J. W., Haas, R., Schell, J., & Deering, D. (1974). *Monitoring vegetation systems in the Great Plains with ERTS.* In *NASA Special Publication* (Vol. 351). NASA.

Sang, X., Guo, Q., Wu, X., Fu, Y., Xie, T., He, C., & Zang, J. (2019). *Intensity and Stationarity Analysis of Land Use Change Based on CART Algorithm*. *Scientific Reports*, *9*(1), 1–12. https://doi.org/10.1038/s41598-019-48586-3

Sentoso, M. S., Ardi, A. C., Rahmasari, N. A., Millenia, R. A., Bangun, J. A. C., Puspitasari, A. D., Budi, N. P. N., Putra, R. W., Jovenski, T. W., Dampi, A., & Kristianto, I. I. (2021). *Pemanfaatan Buah Mangrove menjadi Olahan Makanan/Minuman di Desa Jangkaran, Kulon Progo. Jurnal Atma Inovasia*, *1*(1), 20–25. https://doi.org/10.24002/jai.v1i1.3926

Suyarso, & Avianto, P. (2022). *AMMI Automatic Mangrove Map and Index: Novelty for Efficiently Monitoring Mangrove Changes with the Case Study in Musi Delta, South Sumatra, Indonesia. International Journal of Forestry Research*, *2022*. https://doi.org/10.1155/2022/8103242

Wei, S., Zhang, H., & Ling, J. (2025). *A review of mangrove degradation assessment using remote sensing: advances, challenges, and opportunities. GIScience and Remote Sensing*, *62*(1).

https://doi.org/10.1080/15481603.2025.2491920

Widjonarko, Purnaweni, H., & Maryono. (2025). *Spatio-Temporal pattern of coastal flooding due to microclimate change and mangrove deforestation in Semarang and Demak Coastal Area. E3S Web of Conferences*, *605*. https://doi.org/10.1051/e3sconf/202560503012

Widodo, J., Trihatmoko, E., Khomarudin, M. R., Ardha, M., Nugroho, U. C., Setyaningrum, N., Dinanta, G. P., Arief, R., Setiyoko, A., Novresiandi, D. A., Handika, R., Priyatna, M., Sobue, S., Sarah, D., & Hermawan, W. (2024). *Dynamic Geo-Visualization of Urban Land Subsidence and Land Cover Data Using PS-InSAR and Google Earth Engine (GEE) for Spatial Planning Assessment. Urban Science*, *8*(4). https://doi.org/10.3390/urbansci8040234

Winarso, G., & Purwanto, A. D. (2017). *Evaluation of Mangrove Damage Level Based on Landsat 8 Image. International Journal of Remote Sensing and Earth Sciences (IJReSES)*, *11*(2), 105. https://doi.org/10.30536/j.ijreses.2014.v11.a2608