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Machine Learning-Based Mapping of Mangrove Forest Changes from Sentinel-2 in Balikpapan Bay, East Kalimantan

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Abstract

Balikpapan Bay contains extensive mangrove forests which play an important role as habitat for a range of species and in providing a range of ecosystem services. In recent years, the mangrove forests around Balikpapan Bay are increasingly being lost and degraded due to development pressures. Thus, change detection in mangrove ecosystem has become highly relevant, as it can provide essential information to support the conservation practices and coastal management. This study aims to map mangrove forest change in Balikpapan Bay, East Kalimantan over a five-year period from Sentinel-2 using machine learning. Five machine learning algorithms (Random Forest (RF), Support Vector Machine (SVM), Classification and Regression Tree (CART), K-Nearest Neighbors (KNN), and Minimum Distance), implemented on the Google Earth Engine platform, were evaluated to determine the most suitable method. The evaluation results indicate that RF, SVM, and CART yielded mangrove mapping accuracies of 80% or higher. Notably, the CART algorithm surpassed the other tested models, demonstrating the highest overall accuracy of 84% and a Kappa coefficient of 0.78. Mapping using the selected CART model shows that, between 2020 and 2025, mangrove areas in Balikpapan Bay decreased by 21% (2,906.17 ha). Approximately 97% (2,834.49 ha) of this loss is concentrated in the North Penajam Paser, which has a high rate of land conversion to built-up areas.

Keywords: machine learning, google earth engine, mangrove, Sentinel-2, Balikpapan Bay

1. Introduction

Mangrove forests represent a type of coastal vegetation ecosystem commonly found in tropical and subtropical regions. This plant community consists of diverse mangrove tree species that can survive in the intertidal area, which is the muddy coastal zone routinely influenced by tidal activity (Warsidi and Endayani, 2017). This ecosystem serves a dual function: it plays a crucial role in maintaining environmental stability while also offering essential resources for life. In addition to providing economic benefits such as timber and acting as important habitats for fish and crabs, mangrove forests also serve as a significant natural defence. They are effective at dampening wave energy and preventing seawater intrusion deep onto the mainland (Takarendehang et al., 2018).

Despite their importance, mangrove forests in many coastal regions are facing widespread damage. Take, for example, Balikpapan Bay in East Kalimantan, which is home to a substantial mangrove area. Unfortunately, this region recorded significant mangrove destruction in 2018, totalling 1,092.41 hectares (Anwar et al., 2021). This damage was triggered by several main factors, including land conversion for industrial and port expansion, as well as mining and smelting activities. These pressures have led to severe environmental consequences, such as increased sedimentation, coastal erosion, and a drastic decline in biodiversity. Key endangered species include proboscis monkeys, dolphins, sea turtles, and dugongs (Anwar et al., 2021). Therefore, accurate and timely mapping of mangrove forests at a regional scale is an urgent need to effectively monitor the dynamics of deforestation.

The use of remote sensing, especially medium-resolution satellite data like Sentinel-2, has significantly improved the ability to monitor mangrove forests over large areas and with greater frequency. Sentinel-2's combination of suitable spatial resolution (10m, 20m, 60m) and spectral bands makes it an excellent tool for classifying coastal land cover, allowing researchers to successfully identify mangroves that were previously hard to differentiate from other vegetation using lower-resolution data. In fact, many studies utilizing Sentinel-2 for mangrove mapping have achieved high accuracies, often exceeding 80% (Saputra et al., 2021).

Mapping mangroves using multiple images with conventional methods often demands repetitive processing, requires large storage capacity, and consumes a significant amount of time, especially when applied to vast areas. Addressing these constraints, the emergence of cloud-based geo-big data processing platforms, specifically Google Earth Engine (GEE), offers a compelling solution (Kamal et al., 2020). GEE is a free, cloud-based platform that enables large-scale geospatial analysis utilizing Google's cloud infrastructure (Gorelick et al., 2017). This platform provides a very comprehensive catalogue of satellite and remote sensing products, in addition to features supporting advanced image processing and machine learning algorithms.

While mangrove mapping using the Google Earth Engine (GEE) platform has been widely conducted, many studies tend to rely on Landsat 8 satellite imagery (Fariz et al., 2021a; Husnayaen et al., 2023). Conversely, the utilization of medium-resolution Sentinel-2 imagery for mangrove mapping via GEE remains largely underexplored, particularly at a regional level such as Balikpapan Bay. Therefore, this study attempts to map mangrove forest changes in Balikpapan Bay, East Kalimantan. Furthermore, this assessment also includes the evaluation of various classification methods for mangrove mapping using Sentinel-2 imagery in the study area.

2. Methodology

2.1. Study Area and Data

This research area is in Balikpapan Bay (**Figure 1**). Administratively, Balikpapan Bay is located within the East Kalimantan Province and is geographically situated between Balikpapan City, North Penajam Paser Regency, and a small part of Kutai Kartanegara Regency. The mangrove species found at this research location are *Avicennia marina*, *Avicennia alba,* and *Rhizophora apiculate* (Pratama et al., 2025).

Figure 1. Map of Research Location for the Coastal Area and Balikpapan Bay. Covering the Administrative Regions of Penajam Paser Utara Regency and Balikpapan City, East Kalimantan.

Data used in this study is Sentinel-2 satellite imagery sourced from the ESA Copernicus Harmonized Sentinel-2 MSI: Multi Spectral Instrument, Level-2A (SR) dataset. This image has been pre-processed, already undergone orthorectification and reflectance calibration. The Sentinel-2 satellite imagery used in this study consists of scenes from 2020 and 2025, covering the period from January to May. This time range was selected since the GEE provides cloud removal and median composite algorithms, ensuring that the images are cloud-free and representative of the specified period (Fariz and Nurhidayati, 2020). The analysis utilized Sentinel-2 spectral bands 2, 3, 4, 5, and 8. Bands 1, 6, and 7 were excluded due to their susceptibility to atmospheric interference, which may adversely affect classification accuracy (Shelestov et al., 2017). To focus the study the images were subsequently cropped to the specific research area.

2.2. Data Processing

Data collection and processing were carried out on the Google Earth Engine (GEE) platform using its JavaScript API at earthengine.google.com. This work was developed and executed within the GEE's web-based Code Editor (an Integrated Development Environment), which is designed for creating and running geospatial analysis scripts (Google Earth Engine, 2021). Separately, QGIS software was utilized for essential tasks such as filtering data, manipulating attribute tables, and creating the final map layouts.

Mangroves were identified through a land cover classification process that separated the area into four categories: mangrove, water bodies, built-up areas, and non-mangrove land cover (which included all other vegetation and bare land). To train the classification model, 309 training samples were chosen using a purposive random sampling method, informed by visual inspection of high-resolution Google Earth images. This sample quantity meets the required statistical standards, which recommend a minimum of 50 samples per class (Congalton, 2001; Story and Congalton, 1986).

This study utilized machine learning (ML) techniques, implemented within the Google Earth Engine (GEE) platform, for the classification process. ML is highly effective for analysing the high-dimensional data found in satellite imagery, enabling the efficient categorization of complex land features (Maxwell et al., 2018). Although GEE supports several ML algorithms (Farda, 2017; Shelestov et al., 2017), this research specifically compares the performance of five well-established classifiers available in the platform: Classification and Regression Tree (CART), Random Forest (RF), Minimum Distance (MD), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) (Gorelick, 2021). These specific algorithms were chosen because they have consistently achieved classification accuracies greater than 80% in multi-temporal mapping. The classification itself was executed using a pixel-based (multispectral) approach (Farda, 2017).

Every machine learning classifier utilized has unique benefits and drawbacks. The CART algorithm is known for its interpretable and easy-to-visualize results, but it risks overfitting the training data (Neetu and Ray, 2019). The related Random Forest (RF) classifier improves upon CART using ensemble methods for better performance, though this also increases its complexity. The K-Nearest Neighbors (KNN) is versatile for multi-class problems and handles various distance measurements, but it can suffer from slow prediction times on large datasets because it must calculate the distance to every training example. Finally, the Support Vector Machine (SVM) is a powerful and popular classifier for both classification and regression. However, its main limitation is the need for careful, complex, and computationally demanding tuning of its hyperparameters (like C, gamma, and the kernel).

The Minimum Distance (MD) classifier is valued for its simplicity and speed, as it classifies instances based solely on the Euclidean distance to the closest class centroid. Because it requires no complex training or parameter tuning, MD is ideal for quick implementation, especially in image processing. However, its significant drawback is that it only considers the class mean, completely ignoring class variance and covariance. This omission makes it prone to misclassification when class distributions overlap or have different spreads.

2.3. Accuracy Assessment

To determine how well the machine learning algorithms performed in classifying the land cover, an accuracy assessment was carried out using a separate, independent dataset. This test dataset consisted of 120 samples—30 for each of the four categories: mangrove, water bodies, built-up areas, and non-mangrove land cover. These samples were chosen through purposive random sampling.

The evaluation was conducted using a confusion matrix to determine both the Overall Accuracy (OA) and the Kappa Coefficient. Overall Accuracy is defined as the proportion of correctly classified samples across all land cover classes relative to the total number of test samples. The Kappa Coefficient provides a statistical measure of agreement between the classified data and the reference data, adjusted for the agreement that could occur by chance (Hendrawan et al, 2018). The OA and Kappa measures are formulated as follows (Congalton and Green 1999; Congalton and Green 2009):

$$OA = \frac{\sum_{i=1}^{k} x_{ii}}{N} x \; 100\% \tag{1}$$

$$\kappa = \frac{N \sum_{i=1}^{k} x_{ii} - \sum_{i=1}^{k} (x_{i+} x_{+i})}{N^2 - \sum_{i=1}^{k} (x_{i+} x_{+i})} \tag{2}$$

where x_{ii} is the number of correctly classified samples for class i, x_{i+} represents the total number of samples in row i (reference class totals), and x_{+i} denotes the total number of samples in column i (predicted class totals), k is the total number of classes, and N is the total number of test samples.

3. Results and Discussion

3.1. Land Cover Classification Results Using Machine Learning

The land cover classification results of Sentinel-2 satellite imagery in Balikpapan Bay using machine learning are shown in **Figure 2 (a)** to **(e)** for the year 2025 and **Figure 2 (f)** to (j) for the year 2020. The classification methods applied sequentially for each satellite image year are RF, SVM, CART, KNN, and MD, respectively. The accuracy assessment results using testing data are shown in **Table 1**. From a visual perspective, classification using machine learning on the 2025 image (**Figure 2a-2d**) yields similar outcomes for the building class but differs for the mangrove and non-mangrove classes. Specifically, certain classifiers frequently misclassified mangrove regions as general vegetation and vice versa. These errors are likely attributable to the spectral similarities in digital number values and tonal characteristics between mangrove forests and other vegetation types.

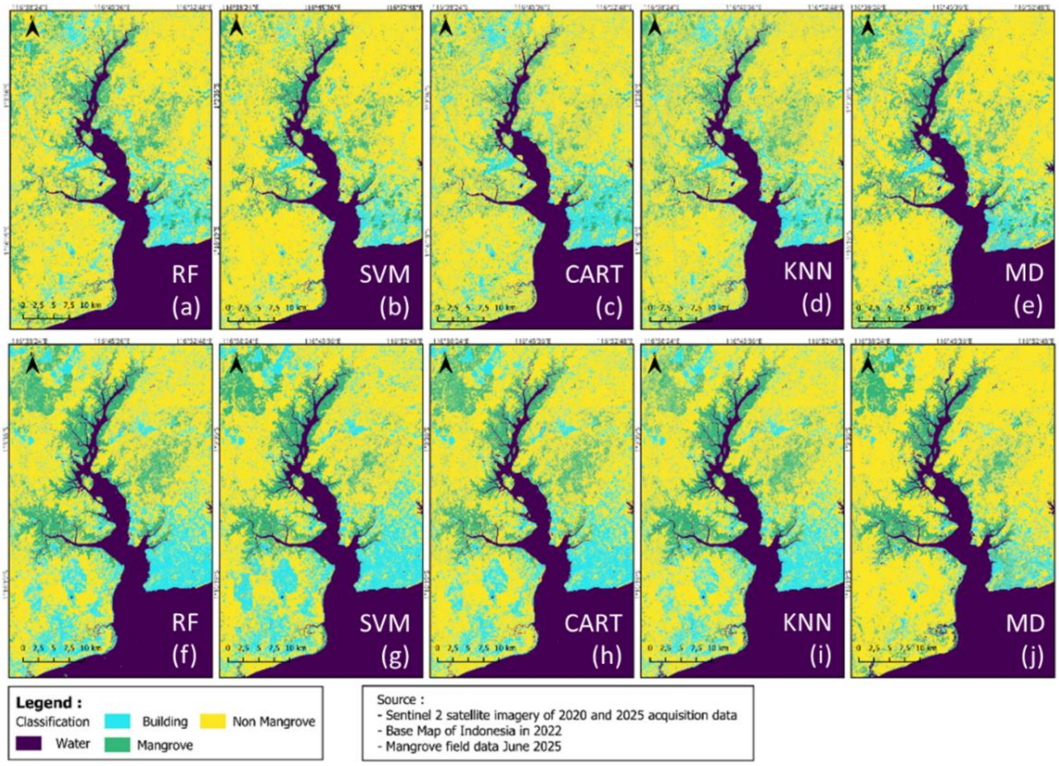

Figure 2. Classification results from Sentinel-2 imagery using machine learning algorithms for 2025 (upper row): (a) Random Forest, (b) Support Vector Machine, (c) CART, (d) K-Nearest Neighbors, (e) Minimum Distance; and for 2020 (lower row): (f) Random Forest, (g) Support Vector Machine, (h) CART, (i) K-Nearest Neighbors, (j) Minimum Distance.

The classification results for 2020 (**Figure 2f–2j**) show greater variability compared to other years. This variation is most apparent in the output generated by the Mahalanobis Distance (MD) method (**Figure 2k**), especially when classifying non-mangrove areas. The MD method tends to overestimate the size of non-mangrove regions when compared to the results from the other classifiers (**Figure 2f–2i**). This is likely due to the high spectral variation and diversity within the non-mangrove class. Since the MD algorithm considers only the class mean and ignores both variance and covariance, it may inadequately reflect the true spectral complexity of that class.

In terms of accuracy assessment, MD obtained the lowest overall accuracy and kappa coefficient values compared to the others (**Table 1**). In contrast, the other three classifiers, i.e. RF, SVM, and CART, yielded an overall accuracy of 80% or higher (**Table 1**). This implies that at least 80% of the total pixels tested were correctly classified by the three classifier models. Furthermore, the kappa coefficients of the three classifiers (**Table 1**) showed a high (significant) level of agreement between classification results and the reference data. This suggests that their performance was significantly better than merely guessing randomly; in other words, their accuracy was not due to coincidence.

Table 1. Accuracy assessment results of Sentinel-2 satellite classifications against reference data from 2025 in Balikpapan Bay. The best-performing results were obtained using the CART machine learning model, as shown in bold.

Machine Learning	Accuracy of Sentinel 2025 Satellite	
	Overall Accuracy (OA) (%)	Kappa Coefficient
Random Forest	80%	0.74
Support Vector Machine	81%	0.75
CART	**84%**	**0.78**
KNN	79%	0.73
Minimum Distance	76%	0.68

However, of all the models tested, the CART algorithm demonstrated superior performance (**Table 1**). This superiority is primarily due to CART's ability to handle complex spectral data and non-linear interactions between features without assuming data distribution (Breiman et al., 1984; Pal and Mather, 2003). CART automatically selects important features from Sentinel-2 bands and builds efficient decision tree-based classification rules. The tree pruning process also reduces overfitting, which improves model generalization (Lillesand et al., 2015).

The CART classifier's high accuracy is supported by various Indonesian studies. For instance, in Kubu Raya, Kalimantan, Fariz et al. (2021a) found that CART was superior to RF, GMO Max Entropy, and SVM for classifying mangroves and water bodies. Similarly, a mangrove mapping project in Bali by Husnayaen et al. (2023) using CART achieved excellent results (OA of 95.7% and kappa of 0.91). Furthermore, CART delivered the highest accuracy for land use mapping in the Sagara Anakan Lagoon (Farda, 2017) and for land cover in the Kreo Sub-Watershed (Fariz et al., 2021b), even when utilizing lower-resolution Landsat imagery. Given this track record of consistent success, CART was chosen for mapping mangrove changes in Balikpapan Bay.

3.2. Mangrove Area Changes

Given the superior classification accuracy, CART was employed to map mangrove areas in Balikpapan Bay in 2020 (**Figure 3a**) and 2025 (**Figure 3b**) for change detection. The change in mangrove areas subtracted from 2020 to 2025 is shown in **Table 2**, which is divided into two parts: the eastern (Balikpapan City) and the western (North Penajam Paser) parts of Balikpapan Bay.

Based on visual interpretation, it is evident that the mangrove class showed a marked change between 2020 and 2025, as indicated by a noticeable reduction in green coverage (**Figure 3**). Predictive analysis using the CART model estimated a total decrease in mangrove area within Balikpapan Bay of approximately 2,906.17 hectares, representing around 21% of the total area. From the Balikpapan Bay mangrove area, the most substantial reduction was observed in the western region, which is part of Penajam Paser Utara, accounting for approximately 97% of the total area change (**Table 2**).

The considerable loss of mangrove area can be attributed to a range of factors, both natural and human activities. Among the natural causes, excessive sedimentation is a key driver, often leading to the burial of mangrove aerial roots and subsequent forest degradation.

According to Anwar et al. (2021), dieback symptoms were observed along the Tritip coastline in East Balikpapan, where the seaward mangrove zones have deteriorated. The sediment responsible for this originates from upstream rivers discharging into the coastal zone of Balikpapan City. This process predominantly affects mangroves situated on gently sloping shores, where sediment can accumulate more easily and impair root function.

However, compared to natural factors, human activities such as oil spills, waste disposal, and land conversion are believed to have a more substantial impact. Balikpapan City is recognized as the largest centre of oil extraction in Indonesia, with drilling operations conducted in both coastal and offshore areas (Anwar et al., 2021). Moreover, Balikpapan Bay, particularly the North Penajam Paser region, is situated close to the site of the Ibu Kota Negara (IKN) construction, which began in July 2022. This has led to extensive land conversion, including the replacement of mangrove forests with built-up areas.

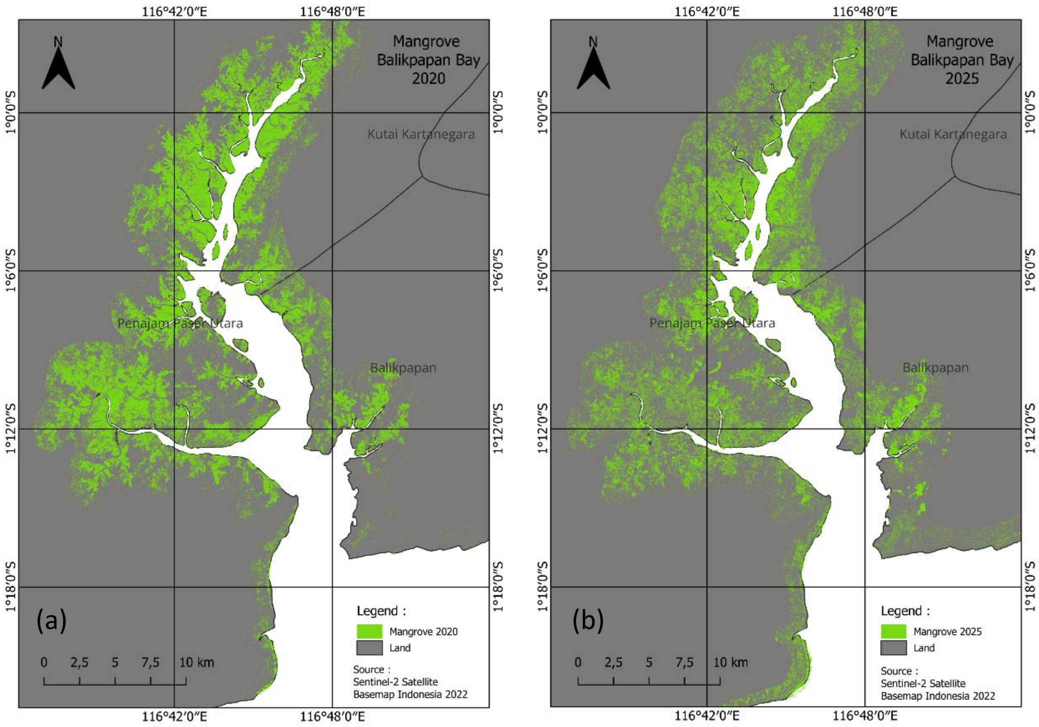

Figure 3. Change in mangroves from Sentinel-2 satellite imagery: (a) mangroves in 2020 and (b) mangroves in 2025.

Table 2. Changes in Mangrove Area (ha) between 2020 and 2025 for North Penajam Paser Utara and Balikpapan.

City/Regency	Mangrove Area (Ha)		Δ (Ha)
	2020	2025	
North Penajam Paser	13,956.95	11,122.46	**2,834.49**
Balikpapan	2,169.22	2,097.54	**71.68**

Previous research conducted by Afifah et al. (2024) used Sentinel-2 satellite imagery from 2016 and 2023 in Balikpapan Bay. Afifah et al. (2024) showed different results from this study, reporting a consecutive decline in mangrove forest area of 20,192.72 hectares and 16,173.53 hectares, with a total decline of 4,019.19 hectares. The differing research results regarding the decline in mangrove area may be due to the simultaneous timing of the studies, during which the construction of the National Capital City (IKN) begun.

In contrast, previous research on mangrove changes using satellite imagery in another region of Indonesia, the Belitung Archipelago, recorded an increase of 49.03 hectares between 2000 and 2020 (Cipta et al., 2021). This improvement was attributed to mangrove restoration efforts through replanting activities carried out in the early 2000s. The restoration success in Belitung Archipelago may serve as a reference for future mangrove rehabilitation initiatives in Balikpapan Bay.

4. Conclusions

This study produced a map of mangrove areas in Balikpapan with a spatial resolution of 10 meters from Sentinel-2 imagery using machine learning techniques implemented through the Google Earth Engine platform. Among the five classification algorithms evaluated, three (Random Forest, Support Vector Machine, and CART) demonstrated strong performance in mangrove mapping, each achieving overall accuracies of 80% or higher and Kappa coefficients above 0.74, indicating a high level of agreement between classification results and reference data. Of these, the CART algorithm showed the best performance, with an overall accuracy of 84% and a Kappa coefficient of 0.78 and was therefore selected to map mangrove forest changes. Using the CART model, the analysis revealed that mangrove areas in Balikpapan Bay decreased by 21% (2,906.17 hectares) between 2020 and 2025. Approximately 97% (2,834.49 hectares) of this loss occurred in North Penajam Paser, an area experiencing a high level of land conversion to built-up areas.

Conflicts of Interest

The author declares that there are no conflicts of interest in this study.

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AI Writing Statement

During the preparation of this work, the author(s) used Chat GPT to help paraphrase paragraph and translaste in English. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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