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Cloud Computing and Machine Learning Approach for Mangrove Mapping in Marine Protected Area (MPAs) of Banggai, Sulawesi Island Archipelago, Indonesia

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Abstract: Mangroves are coastal forest ecosystems that serve multiple functions for coastal communities. Their ecological role as essential habitats for coastal and estuarine fauna, combined with their economic function as areas for fish production, makes mangrove ecosystems crucial for coastal and marine management. Unfortunately, within the context of sustainable fisheries, mangrove areas in Sulawesi remain underexplored, especially using satellite-based approaches. Therefore, this study focuses on quantifying the extent of mangroves within the Marine Protected Areas (MPAs) of Banggai – Banggai Kepulauan – Baggai Laut, Sulawesi Seascape. Utilizing a combination of Landsat-8 and Landsat-9 satellites through the Google Earth Engine (GEE) cloud computing platform, the mangrove mapping process incorporated machine learning techniques. In the MPAs of Banggai-Bangkep-Balut, mangroves were mapped covering an area of 5,323 hectares, approximately 0.62% of the total designated protected area. Mangrove detection using the two Landsat satellites achieved high accuracy levels, with an overall accuracy of 0.91 and a kappa statistic of 0.83. The error matrix indicated 6 misclassifications out of 73 validation points. These findings confirm the reliability of mangrove data within the Banggai MPAs management framework, supporting its use as blue carbon data to strengthen national emission reduction policies. In addition, cloud computing has proven to be excellent in extracting mangrove data in MPA areas and is highly recommended in future monitoring to create sustainable MPA governance.

Keyword: Machine learning, mangrove, marine protected area, Banggai

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INTRODUCTION

Mangroves represent a complex and essential ecosystem, distributed within tidal marine environments, and function as a vital link between terrestrial and marine systems (Yang *et al.* 2021; Bindiya *et al.* 2023; Chanda 2024; Nagarajan *et al.* 2025). Their coastal distribution plays a critical role in regulating ocean currents that threaten coastal lands and in reducing the risk of damage from tsunami events (Karminarsih 2007; Yanagisawa *et al.* 2010; Babu *et al.* 2025). Mangroves provide crucial benefits across multiple dimensions, including economic contributions as fishing grounds that serve as income sources for coastal communities, and ecological functions in mitigating atmospheric carbon dioxide burdens (Arifanti *et al.* 2022). Globally, mangroves covered an area of 145,068 km² in 2020, positioning Indonesia as the country with the largest mangrove extent (Jia *et al.* 2023). According to data from the Ministry of Forestry, Indonesia's mangroves cover an area of 3.2 million hectares, distributed across the big islands (Kusmana and Sukristijiono 2016). Within the total national mangrove area, only about 22% is legally protected under Indonesia's forest conservation framework, while the remainder is threatened by anthropogenic activities (Sidik *et al.* 2018). In terms of species diversity, Indonesian mangroves comprise 157 species, including 52 tree species, 21 shrub species, 13 liana species, 7 palm species, 14 grass species, 8 herb species, 3 parasitic species, 36 epiphyte species, and 3 fern species (Kusmana and Sukristijiono 2016).

Currently, mangrove mapping utilizes remote sensing technology, which efficiently reveals mangrove information at regional and global scales (Green *et al.* 1998; Kuenzer *et al.* 2011; Heumann *et al.* 2011; Pastor-Guzman 2018; Wang *et al.* 2019). Advances have followed this in remote sensing technology, which increasingly provide high-resolution, open-source imagery of the Earth's surface (Jayakumar 2019; Mancheño *et al.* 2021; Viquez *et al.* 2025). For instance, the Landsat satellites operated by USGS-NASA have supplied Earth observation data continuously since 1972 (Williams *et al.* 2006; Goward *et al.* 2006; Wulder *et al.* 2016; Wulder *et al.* 2022). Most recently, Landsat launched its ninth-generation satellite, Landsat-9, on September 27, 2021, which possesses capabilities similar to those of Landsat-8, featuring the OLI/TIRS sensor instruments (Masek *et al.* 2020; Lulla *et al.* 2021; Aeon *et al.* 2024). In practice, satellite and remote sensing technologies have been widely applied in diverse research contexts, including land cover monitoring (Phiri and Morgenroth 2017; You *et al.* 2020; Chaves *et al.* 2020), environmental change detection (Roy *et al.* 2014; Kennedy *et al.* 2014), natural disaster impact assessment (Zhang *et al.* 2013; Sivanpillai *et al.* 2020), and biodiversity studies (Leimgruber *et al.* 2005; Madonsela *et al.* 2017; Kacic and Kuenzer 2022; Valero-Jorge *et al.* 2024). In Indonesia, mangrove monitoring using Landsat multispectral imagery has been conducted in several studies, such as Marfi *et al.* (2025) in Aceh Tamiang, Jhonnerie *et al.* (2015) in Riau, and Jamaluddin *et al.* (2022) in East Luwu.

High capabilities in mangrove detection using open-source remote sensing technology provide significant opportunities for quantifying environmental impacts, preventing damage, and improving the effectiveness of climate adaptation in mangrove ecosystems (Hu *et al.* 2017; Pham *et al.* 2019; Sunkur *et al.* 2024). This is especially true in protected fisheries areas that have mangrove distributions, which play a crucial role as a source of nutrients and habitat for fish diversity. Unfortunately, information on mangroves in the Banggai region is still very limited, which is considered one of the factors hindering the sustainable management of marine protected areas. Therefore, this study was conducted to quantify the distribution of mangroves in the Banggai seascape that is included in the designation of marine protected areas (MPAs).

METHODOLOGY

Study Area

The study area is located within the Marine Protected Areas (MPAs) and OECMs of the Banggai Region, which encompasses three administrative regencies: Banggai Regency, Banggai Kepulauan Regency, and Banggai Laut Regency. The MPAs-OECMs of Banggai cover an area of 856,649.13 ha, which was established based on national regulations on protecting water zones for sustainable fish production (Fig. 1). This is outlined in the national policy launched by the Ministry of Marine Affairs and Fisheries as stated in the Decree of the Minister of Marine Affairs and Fisheries No. 53 of 2019 (SK-KKP-53-2019). The Banggai MPAs-OECMs area is divided into 13 regions, with most of them located in the Banggai Laut Regency.

Data Source

This study utilized remote sensing data derived from Landsat-8 OLI/TIRS and Landsat-9

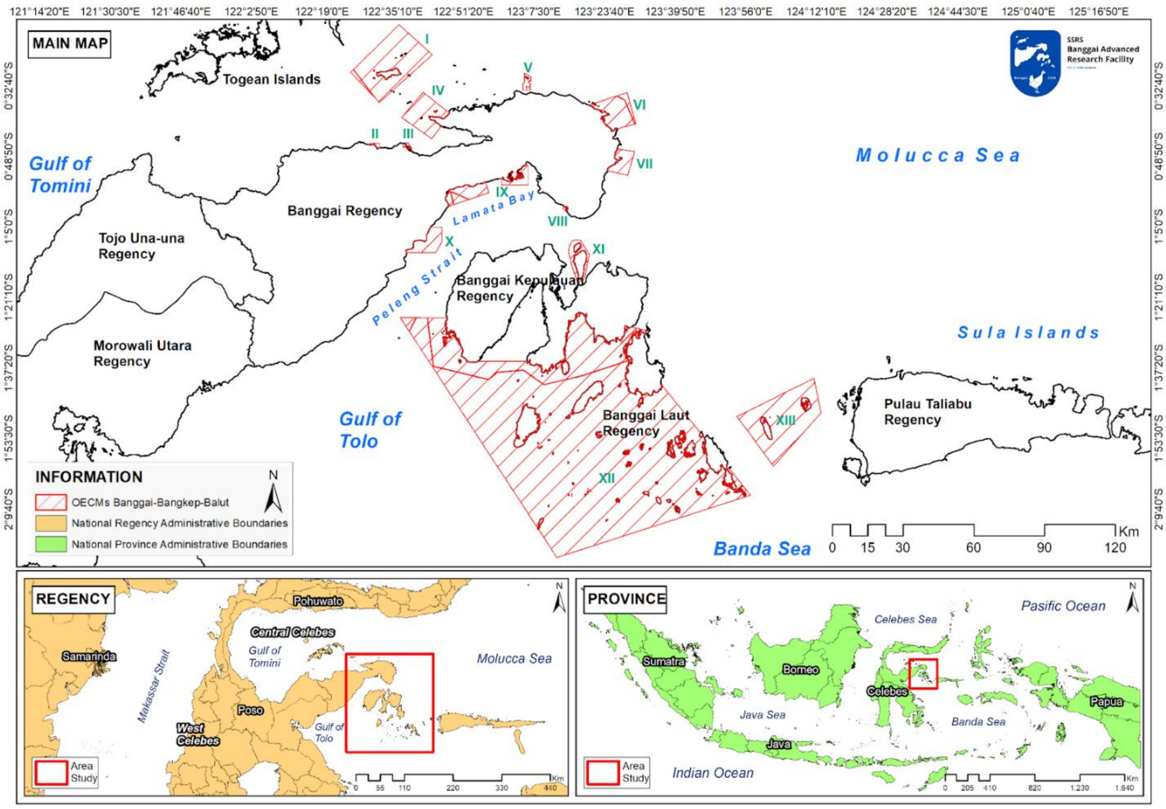

Figure 1. Study area in MPAs-OECMs Banggai, Banggai Kepulauan, and Banggai Laut

OLI2/TIRS2 satellite imagery. These satellites offer a medium spatial resolution of up to 10 meters and a temporal resolution of 16 days (Hansen and Loveland 2012). Spectrally, the sensors encompass 11 bands, comprising Coastal Aerosol (430–450 nm), Blue (450–510 nm), Green (530–590 nm), Red (640–670 nm), Near Infrared (850–880 nm), SWIR 1 (1570–1650 nm), SWIR 2 (2110–2290 nm), Panchromatic (500–680 nm), Cirrus (1360–1380 nm), and two thermal bands (10600–12510 nm). Imagery was accessed from the USGS archives within the Earth Engine Data Catalog using the Google Earth Engine functions ee.ImageCollection("LANDSAT/LC08/C02/T1_2") and ee.ImageCollection ("LANDSAT/LC09/C02/T1 _L2").

Remote Sensing Analysis and Machine Learning

Mangrove mapping was conducted using Landsat-8 and Landsat-9 remote sensing data within a machine learning framework. The geospatial analyses were performed on the Google Earth Engine (GEE), a cloud-based computing platform that significantly enhances the efficiency of large-scale spatial analysis of the Earth's surface (Gorelick *et al.* 2017; Wang *et al.* 2020). The classification employed the Random Forest (RF) algorithm, with hyperparameters optimized to 100 trees (ntree), implemented through the ee.Classifier.smileRandomForest() function. A total of 517 training samples were utilized, incorporating multiple predictor variables derived from Landsat-8 OLI/TIRS and Landsat-9 OLI2/TIRS2 spectral bands known to be sensitive to mangrove presence, following the recommendations of Asy'Ari *et al.* (2022). These predictors comprised three categories of spectral indices: vegetation indices (NDVI, SAVI, EVI, SLAVI, ARVI, RVI, and GDNVI), water indices (NDWI, ANDWI, and LSWI), and built-up indices (IBI and NDBI). The mathematical formulations of these indices are presented in Equations (01 – 12).

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad \text{.....(Eq. 01)}$$

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad \text{.....(Eq. 02)}$$

$$SAVI = \frac{(NIR - Red)(1 + 0.5)}{NIR + Red + 0.5} \quad \text{.....(Eq. 03)}$$

$$EVI = G \times \frac{NIR - Red}{NIR + C1 \times Red - C2 \times Blue + L} \quad \text{.....(Eq. 04)}$$

$$IBI = \frac{NIR}{NIR + Red} \times \frac{Green}{Green + SWIR1} \quad \text{.....(Eq. 05)}$$

RVI = Ratio Vegetation Index

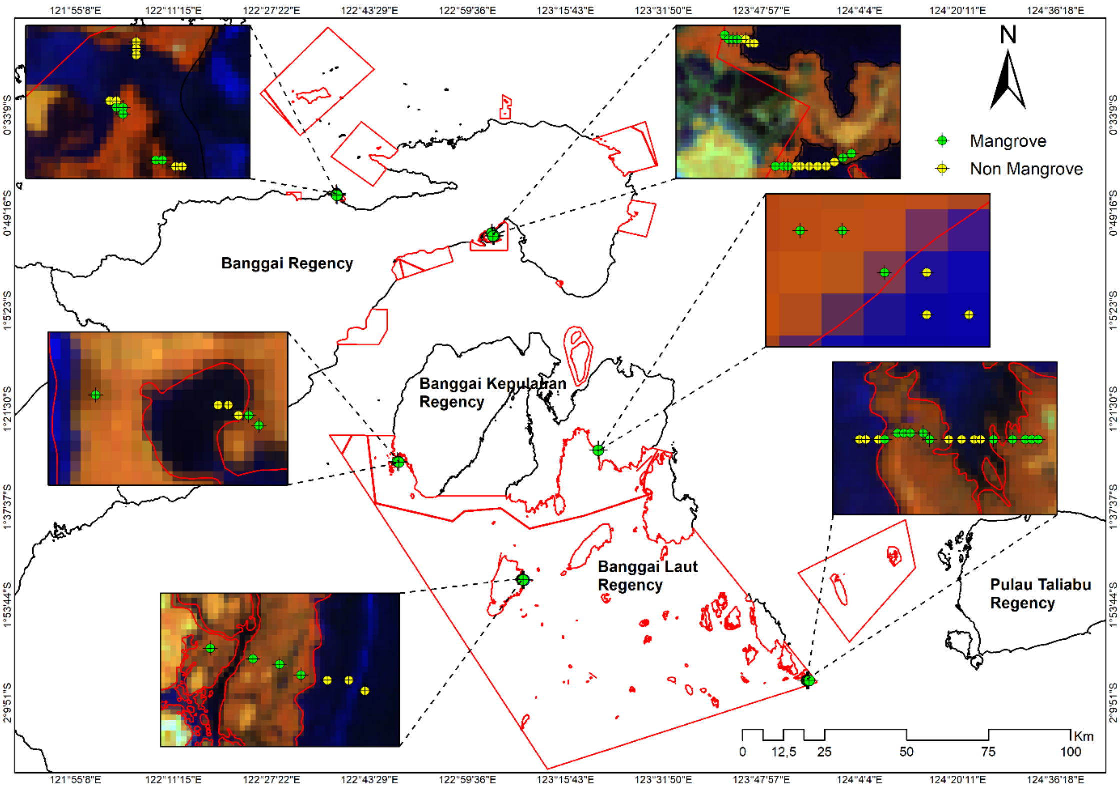

Figure 2. Spatial distribution of validation data

$$ARVI = \frac{NIR - (Red - (1 \times (Red - Blue)))}{NIR + (Red - (1 \times (Red - Blue))} \quad \text{.....(Eq. 06)}$$

$$SLAVI = \frac{NIR}{Red + SWIR1} \quad \text{.....(Eq. 07)}$$

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \quad \text{.....(Eq. 08)}$$

$$ANDWI = \frac{Blue + Green + Red - NIR - SWIR1 - SWIR2}{Blue + Green + Red - NIR - SWIR1 + SWIR2} \quad \text{.....(Eq. 09)}$$

$$GNDVI = \frac{NIR - Green}{NIR + Green} \quad \text{.....(Eq. 10)}$$

$$RVI = \frac{NIR}{Red} \quad \text{.....(Eq. 11)}$$

$$LSWI = \frac{NIR - SWIR}{NIR - SWIR} \quad \text{.....(Eq. 12)}$$

Information :
NDVI = Normalized Difference Vegetation Index
NDWI = Normalized Difference Water Index
SAVI = Soil Adjusted Vegetation Index
EVI = Enhanced Vegetation Index
IBI = Index-Based Built-up Index
ARVI = Atmospherically Resistant Vegetation Index
SLAVI = Specific Leaf Area Vegetation Index
NDBI = Normalized Difference Built-up Index
ANDWI = Augmented Normalized Difference Water Index
GNDVI = Green Normalized Difference Vegetation Index
LSWI = Land Surface Water Index
Blue = Blue band
Green = Green band
Red = Red band
NIR = Near-infrared band
SWIR = Shortwave-infrared band
L = Calibration factor of canopy and soil effects (value : 1.0)
C1 = Aerosol coefficients (value : 6.0)
C2 = Aerosol coefficients (value : 7.5)
G = Gain factor (value : 2.5)

Accuracy Assessment

Accuracy assessment was conducted on the machine learning classification outputs to evaluate algorithm accuracy. The test employed 73 validation points representing mangrove and non-mangrove classes, distributed across each district in a line transect formation extending along the boundary between classes, thereby capturing the broad spatial variability of mangrove areas (Fig. 2). The validation data were determined based on actual conditions observed in the NIR-SWIR-Red composite imagery, which reflects the existing state on the GEE platform. These validation data were tested within the GEE environment using the errorMatrix function and four statistical measures, namely Overall Accuracy (OA), Kappa Statistics (KS), User Accuracy (UA), and Producer Accuracy (PA) (Eq. 13–16). OA provides a general overview of classification performance (Kramarczyk dan Hejmanowska 2025), KS accounts for the possibility of correct predictions occurring by chance (Foody 2020), UA quantifies commission error and reflects the reliability of classification results from the user's perspective (Nicolau *et al.* 2023), while PA measures omission error and indicates the probability of correct classification from the producer's perspective (Farhadpour *et al.* 2024). The combined use of these four metrics offers a comprehensive evaluation of classification accuracy by integrating overall performance with class-specific error diagnostics.

$$UA = \frac{X_{ii}}{X_{i+}} \text{.....(Eq. 13)}$$

$$PA = \frac{X_{ii}}{X_{+i}} \text{.....(Eq. 14)}$$

$$OA = \frac{1}{N}\sum_{i=1}^{r} X_{ii} \times 100\% \text{.....(Eq. 15)}$$

$$KS = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{ii}(X_{i+} \times X_{+i})}{N^2 \sum_{i=1}^{r} X_{ii}(X_{i+} \times X_{+i})} \text{.....(Eq. 16)}$$

Information :

UA = User's Accuracy
PA = Producer's Accuracy
OA = Overall Accuracy
KS = Kappa Statistic
X_{ii} = Number of corrected classified samples of class i
X_{i+} = Total number of samples classified as class i (row total)
X_{+i} = Total number of reference samples of class i (column total)

RESULTS AND DISCUSSION

Mangrove Distribution

The Random Forest machine learning algorithm successfully mapped the mangrove forest extent within the Banggai-Bangkep-Balut Marine Protected Areas (MPAs) through efficient hyperparameter tuning on the GEE platform. The mapping results indicate a total mangrove area of 5,323 hectares. Located within the designated Banggai-Bangkep-Balut MPAs, this mangrove area constitutes 0.62% of the total MPA area (856,649.13 ha) (Fig. 3).

The highest concentration of mangrove distribution was found in Area XII (679,544.06 ha), covering a total area of 3,805.82 ha (Table 1). These mangroves are partially located on Paleng Island within the Banggai Kepulauan Regency (northern part of Area

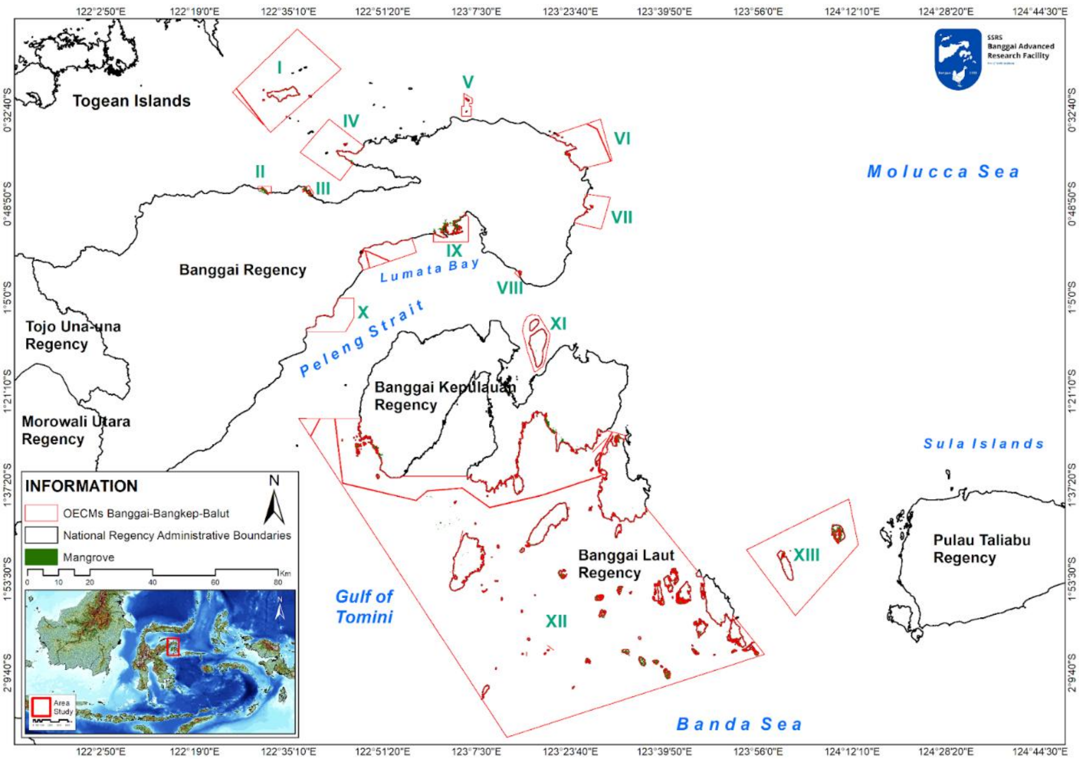

Figure 3. Mangrove spatial distribution in MPAs Banggai – Banggai Kepulauan - Banggai Laut

XII), with the remainder distributed across several islands (both large and small) in the Banggai Laut Regency (Fig. 5). The substantial extent of the remaining mangrove ecosystem in this area indicates a superior capacity for blue carbon sequestration compared to other regions (Choudhary *et al.* 2024). According to previous findings, the mangrove species inhabiting the study location include *Bruguiera gymnorrhiza, Lumnitzera littorea, Bruguiera cylindrica,* and *Rhizophora mucronata* (Babo *et al.* 2020).

The area with the most minor mangrove extent (0.324 ha) was identified in Area X (9,283.06 ha). As clearly shown in Figure 4, the classification results reveal an almost complete absence of mangrove distribution in this zone. In contrast, areas with the highest proportion of mangrove cover include Area II (24.80%) and Area III (16.36%), which exhibit distinct distribution patterns: coastal mangroves in Area II and estuarine mangroves in Area III (Fig. 4). This coastal mangrove pattern is also prevalent in other zones, which are predominantly characterized by extensive mangrove forests. In contrast, estuarine mangroves are found in Area VIII, Area IX, and specific sections of Area XII (sub-areas F, I, J, M) (Fig. 5).

Mangroves distributed across areas A, E, F, and H (Fig. 4) are located adjacent to coconut plantation zones, a primary local commodity in Banggai Regency (Neeke *et al.* 2015). This adjacency constitutes a critical consideration for these areas, as potential future expansion of coconut plantations could lead to mangrove conversion and subsequent degradation. A similar pattern of mangrove loss driven by plantation expansion has been documented, for instance, in the Air Telang Protected Forest (ATPF) of South Sumatra (Eddy *et al.* 2021). Consequently, management policies should not rely solely on a government-led approach

Table 1. Mangrove distribution in MPA Banggai-Bangkep-Balut by area based on national policy of SK-KKP-53-2019

MPA Area	MPA Area (ha)	Mangrove (ha)
I - Puah Island	51,289.40	45.07
II - Lobu Area	540.08	133.96
III - Pagimana Area	554.29	90.71
IV - Pagimana Area	18,922.83	145.48
V - Bualemo Area	1,696.71	0.812
VI - North Balantak Area	16,895.20	37.36
VII - Balantak Area	7,566.49	2.16
VIII - Mantoh Area	221.08	13.67
IX - East Luwuk Area	5,462.58	513.77
X - Kintom, Nambo Area	9,283.06	0.324
XI - Tinangkung, Bangkalan Island	5,733.60	15.35
XII - Paleng Island, Banggai Island, Bangkulu Island, Melilis Island, Labobo Island	679,544.06	3,805.82
XIII - Masoni Island and Timpaus Island	61,632.28	518.47
Total	**856,649.13**	**5,322.96**

Table 2. Mangrove distribution in MPAs Banggai-Bangkep-Balut, by regencies data

Regency	MPA Area (ha)	Mangrove (ha)
Banggai Regency	74,204.94	983.32
Banggai Kepulauan Regency	367,327.06	2,001.83
Banggai Laut Regency	415,117.13	2,337.81

but must incorporate integrated community-based conservation efforts to ensure more effective MPA outcomes (Estradivari *et al.* 2022; Berdej and Armitage 2016; Williams *et al.* 2018). In contrast, other designated areas (D, I, J, L, M, and N) comprise small, uninhabited islands where mangrove ecosystems are less potential for degradation due to anthropogenic activities (Akram *et al.* 2023).

The distribution of the mangrove ecosystem within the MPAs of the Banggai-Bangkep-Balut area exhibits distinct spatial variations across regencies (Table 2). The most considerable mangrove extent was found in Banggai Laut Regency (2,337.81 ha); however, the highest percentage of mangrove cover relative to the MPA area was recorded in Banggai Regency (1.32%). This finding is due to the fact that the designated MPA boundary in Banggai Laut Regency is predominantly

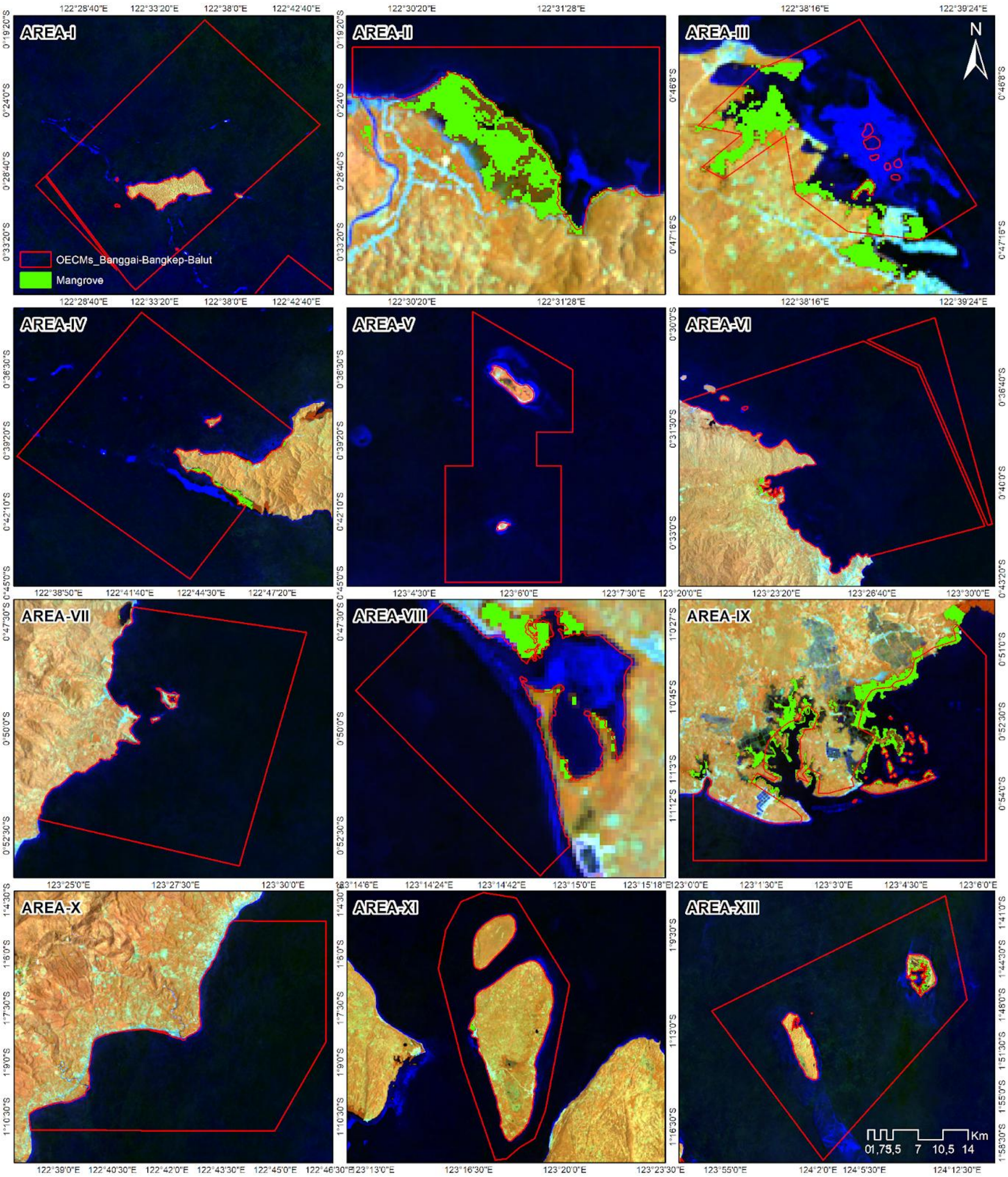

Figure 4. Mangrove spatial distribution in Area-I to Area-XI, and Area-XIII

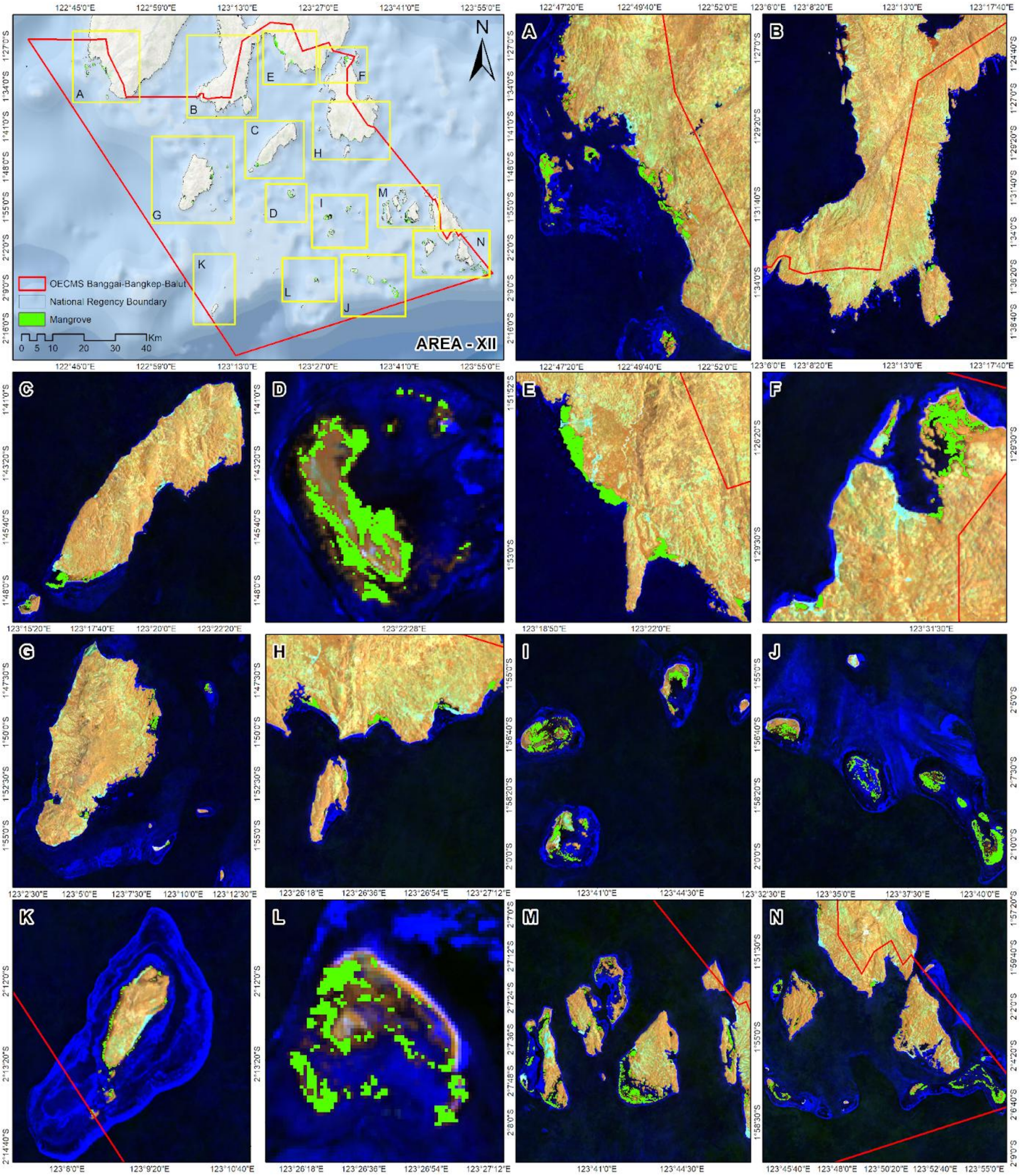

Figure 5. Mangrove spatial distribution in Area-XII

comprised of open water. In contrast, in other regencies, the proportion between coastal land and water bodies is more balanced (Fig. 3).

Machine Learning Performance

Analysis of mangrove mapping capability using the variable importance approach provided clear insights into the contribution of each index in accurately distinguishing between classes (Fig. 6). The results indicated that the NDBI (VI = 19.36) played the most significant role compared to other indices. This signifies a non-negligible contribution from NDBI in the classification process, particularly in identifying non-mangrove areas (built-up land) (Zha *et al.* 2003). Conversely, studies conducted by Santoso *et al.* (2025) and Tran *et al.* (2024) highlighted the dominance of water indices, reporting that the highest variable importance was attributed to the MNDWI and NDWI, respectively. Meanwhile, among vegetation indices, the highest value was yielded by SLAVI (VI = 11.82),

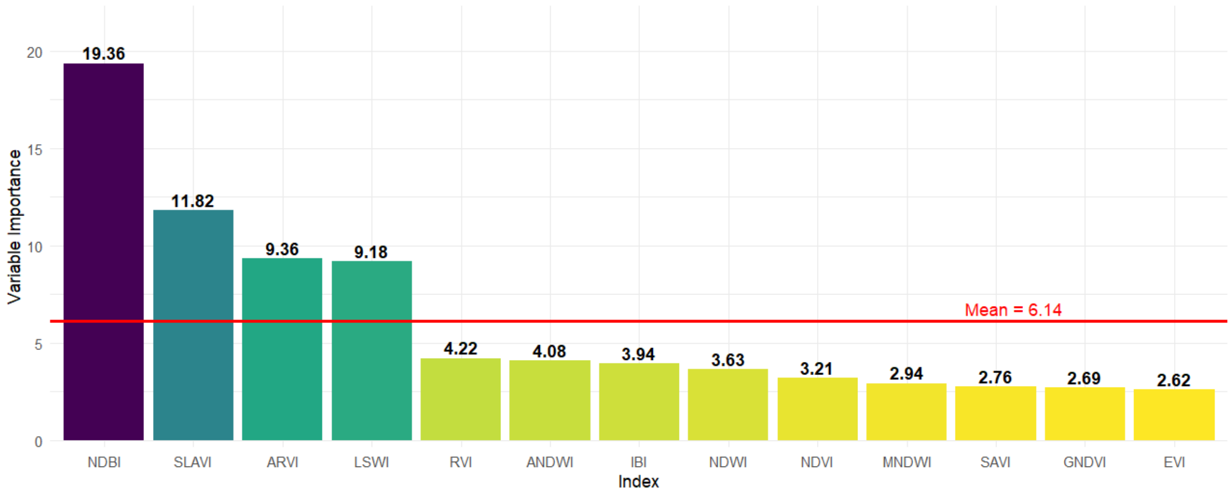

Figure 6. Variable importance of machine learning mapping

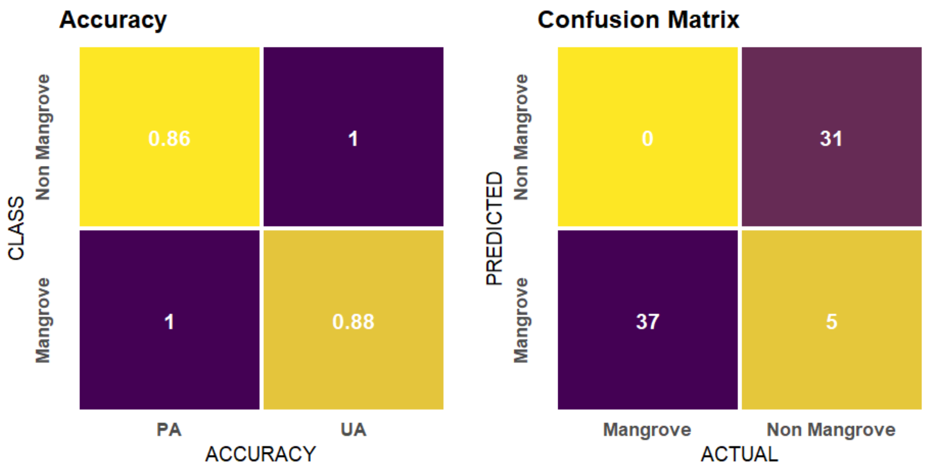

Figure 7. Matrix error and accuracy

followed by ARVI (VI = 9.36) and LSWI (VI = 9.18), all of which remained above the mean line (Mean VI = 6.14). SLAVI demonstrates superior capability in discriminating vegetation as it is less susceptible to cloud shadows (Triet *et al.* 2018) and capable of mitigating soil reflectance effects (Lymburner *et al.* 2000), thereby better characterizing the structural and biochemical conditions of mangroves (Novanda *et al.* 2025). The remaining indices fell below the mean line, with RVI (VI = 4.22) being the highest among them, and EVI (VI = 2.62) showing the lowest contribution. The finding regarding the low contribution of EVI to the performance of the RF algorithm in classification aligns with Santoso *et al.* (2025) in a case study of mangrove mapping in Subang, West Java.

Machine Learning Accuracy

The Random Forest algorithm successfully classified mangrove distribution optimally, as evidenced by the robust values in the confusion matrix (Fig. 7). A False Negative (FN) = 0 indicates that all mangrove areas designated as validation data were perfectly identified; however, for the non-dominant non-mangrove class in the training data, prediction errors were found in 5 samples (False Positive). OA value of 93% achieved for this classification has exceeded the minimum confidence level threshold of 85% (Anderson *et al.* 1976). This OA value is higher than those reported by Marfi *et al.* (2025), Santoso *et al.* (2025), and Asy'ari *et al.* (2022), which only reached 79%, 84%, and 82%, respectively, for mangrove areas in Sumatra (2023), West Java (2025), and Banten, Jakarta, and West Java (2021) using the same algorithm. However, this OA value is lower than that reported by Wiarta *et al.* (2025), who successfully mapped mangroves in Kalimantan (OA = 95%). The obtained Kappa Statistic (KS) value reached 0.86, classified as almost perfect according to Landis and Koch (1977). This value is also higher than those reported by Marfi *et al.* (2025), Santoso *et al.* (2025), and Asy'ari *et al.* (2022), with kappa values of only 0.73 (2023), 0.77 (2025), and 0.70 (2021), respectively. However, this KS value (0.86) is lower compared to those reported by Wiarta *et al.* (2025) and Dzulfigar *et al.* (2024), with KS values of 0.90 and 0.87, respectively. Both metrics (OA and KS), each showing high values, demonstrate excellent classification performance with consistency significantly better than random chance (Zafar *et al.* 2024; Gülci *et al.* 2025; Wu *et al.* 2025).

Due to the characteristic of binary classification, which can potentially lead to less accurate evaluations based on previous metrics, this study incorporated user accuracy and producer accuracy to ensure a more objective performance assessment (He and Garcia 2009; Maxwell *et al.* 2018). The Producer Accuracy (PA) for the mangrove class (1) was assessed based on the correct mapping of all mangrove class validation samples (100%), with no omission errors. However, this differs from the machine's classification precision in identifying mangroves compared to actual conditions, which achieved a value of only 0.88. This means that when a user views the mapping results, only 88% truly represent mangroves, while the remaining 12% constitute a commission error, involving the misclassification of non-mangrove objects.

The perfect PA value for the mangrove class only applies within the context of the validation sample distribution. Therefore, there remains a possibility of detection uncertainty in areas that are actually mangroves, as shown in Figure 5, which clearly illustrates the limitations of this study. These limitations are evident in areas D and L, where some existing mangrove areas, represented by a pale dark orange color in the NIR-SWIR-Red composite, were not classified as mangroves (Zhang *et al.* 2023). This could be attributed to limited discriminative capability for degraded mangroves (Wei *et al.* 2025), spectral confusion between mangrove and similar non-mangrove classes (e.g., lowland forests) (Be *et al.* 2025), and an insufficient number of validation samples to represent the overall heterogeneity of the biophysical characteristics of mangrove areas within the study site (Kamal and Phinn 2011).

Recommendation

Management of MPAs is crucial for maintaining fishery resources and rare to endemic biodiversity (Weigel *et al.* 2014; Lopes *et al.* 2015; Marshall *et al.* 2019). Ecosystem-level protection is crucial for maintaining habitats and ensuring the sustainability of fishery resources (Done and Reichelt 1998; Baran and Hambrey 1999; Stal *et al.* 2008; Barbier *et al.* 2011; Fenner 2012; Woodhead *et al.* 2019). The Banggai MPAs have 5,323 ha of mangroves covering three regency administrative areas, requiring multi-stakeholder collaboration to strengthen monitoring of fishery resource sustainability. The Fishery Agency and Environmental Agency of each regency administrative area are the prominent leaders in strengthening the management policy of the Banggai MPAs. Multi-stakeholder partnerships can also be established with local universities (in the Banggai-Bangkep-Balut region) and national universities, which can serve as knowledge transfer agents for science-based governance. Rashid *et al.* (2013) in their study of a fisherman group in Malaysia found that knowledge transfer from universities can be realized through social innovation, knowledge innovation, and technological innovation in coastal communities. NGOs and CSOs can be utilized as partners in monitoring and intensive assistance at the fisherman group level, thereby increasing the role of grassroots organizations in their impact on the community. In addition, the optimization of fishery business groups is essential to boost the economic cycle of villages that utilize fishery resources, thereby creating a blue economy (Grafeld *et al.* 2017). This has the potential to support national policies on the blue economy and regional policies of Central Sulawesi Province in implementing the blue economy in the Tolo Bay area.

Regional mangrove protection policies are essential, especially for coastal mangrove areas that are integrated with coral reefs and seagrass beds, which form blue carbon potential. Mangrove destruction in these areas poses a serious threat to coral reefs, as it increases the likelihood of sedimentation from erosion carried by runoff from land (McLaughlin *et al.* 2003; Weber *et al.* 2012; Hairsine 2017; Rogers and Ramos-Scharrón 2022). Therefore, policies that can intervene in the activities of coastal communities are urgently needed, especially those involving the participation of fishermen as key actors who utilize fishery resources. Sustainable governance can also be strengthened through transparency in the supply chain of fishery products from fishing groups. In addition, a traceability system for fishery products has the potential to connect distributors, restaurants, and fish exporters. The traceability system enables consumers of fishery products to monitor the environmental impact of destructive fishing activities (Parreño-Marchante *et al.* 2014; Oliveira *et al.* 2021; Rahman *et al.* 2021; Patro et al. 2022).

Conclusion

Mangroves play a crucial role in providing habitat for fish species within the Marine Protected Areas (MPAs) of Banggai – Banggai Kepulauan – Banggai Laut, encompassing the Banggai Kepulauan Regency, Banggai Laut Regency, and Banggai Regency. The mapping of mangroves in the Banggai MPAs, utilizing Landsat-8 OLI/TIRS and Landsat-9 OLI2/TIRS2 data via a cloud computing platform, revealed a mangrove spatial distribution covering 5,322.96 hectares. This area represents approximately 0.62% of the total MPA expanse of 856,649.13 hectares. The mapping achieved an OA of 0.93 and a kappa statistic of 0.86. This accuracy is derived from error analysis, yielding a user accuracy of 0.88 for the mangrove class and 1.00 for the non-mangrove class, alongside a producer accuracy of 1.00 for the mangrove class and 0.86 for the non-mangrove class. The high accuracy level of this mangrove cloud computing mapping substantiates the data's suitability as a foundation for the sustainable management of the Banggai MPAs. Furthermore, these findings can serve as a foundational database for blue carbon calculations, supporting national carbon emission reduction policies such as the FOLU (Forestry and Other Land Use) Net Sink 2030 program.

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