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Mapping mangrove forest distribution on Banten, Jakarta, and West Java Ecotone Zone from Sentinel-2-derived indices using cloud computing based Random Forest

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Abstract*. Mangrove ecosystem is a very potential area, generally located in ecotone areas (a combination of intertidal and supratidal areas), where there is an interaction between waters (sea, brackish water, and rivers) with land areas. Indonesia, especially the Banten and West Java Regions, have vast mangrove areas and are currently under threat of land conversion. Moreover, mapping the distribution of mangrove forests using the Google Earth Engine platform based on Cloud Computing is less published. Therefore, this research was conducted by introducing the distribution of mangrove forests which involved the Random Forest (RF) classification algorithm method and looking for the best modification of the index. The combination test was carried out by involving the NDVI, EVI, ARVI, SLAVI, IRECI, RVI, DVI, SAVI, IBI, GNDVI, NDWI, MNDWI, and LSWI indexes. There is a distribution of mangroves in three provinces (West Java, Banten, and Jakarta) which are 933.54 ha (8.37%), 1 537.89 ha (18.23%), and 8 184.82 ha (73.397%). Of the 70 combination tests, the LSWI index (K13, Type-A) is the combination with the lowest accuracy rate of 58.45% (overal accuracy) and 39.59 (Kappa statistic), and the combination of K23 (SAVI-MNDWI-IBI) is a combination the best are 96.48% and 92.79. The results and recommendations in this study are expected to be used as a reference in determining policies for the protection of mangrove areas and a reference for further research.*

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INTRODUCTION

Mangroves are coastal forests on the banks of rivers that thrive at the confluence of land and sea (ecotone areas) in tropical and subtropical regions. Currently, there are about 14 to 15 million hectares of mangrove forests spread across 124 countries, the most extensive in developing countries in Asia (Giri *et al*., 2011). Putra and Gumilang (2019) reported that mangroves in Indonesia have a quite large area, but their area has decreased by 40% in the last 3 decades. Mangroves provide many ecosystem services, such as pollution control, nutrient storage and recycling, biomass production (Sannigrahi *et al*., 2020), carbon sequestration and storage (Bouillon *et al*., 2008; Donato *et al*., 2011; Duarte *et al*., 2005), coastal protection and coastal water quality management (Danielsen *et al*., 2005; Benfield *et al*., 2005) including the potential to protect and stabilize coastlines, thereby reducing erosion and protecting natural and artificial communities at higher elevations (Barbier *et al*., 2011). Mangroves are increasingly being considered as a potential solution to current and emerging environmental problems (Chow, 2018). However, human activities make it unable to last long. Urban development and population growth require space in the form of strategic land so that it is possible to erode mangrove lines along the coast (Zhu *et al*., 2017).

Generally, remote sensing is used for mapping and quantifying mangrove areas (Blasco *et al*., 1998; Berlanga-Robles and Ruiz-Luna, 2020). Advances in remote sensing enable rapid mapping of mangroves with limited ground-based observation datasets, complex classifiers, skill-dependent classification techniques, cost-effective, efficient, and can be used in physically inaccessible areas (Baloloy *et al*., 2020; Muhd-Ekhzarizal *et al*., 2018). Remote sensing methods for mangrove mapping, with approaches ranging from aerial photography to multispectral satellite imagery and hyperspectral and radar data (Vo *et al*., 2013). As in the research of Navarro *et al*. (2019) which uses a combination of UAV imagery, Sentinel-1 radar data, and MSI Sentinel-2 imagery to monitor Aboveground Biomass (AGB) of mangrove vegetation in the Sine Saloum and Casamance deltas, Senegal. Wang *et al*. (2018) used Sentinel-2, Landsat 8, and Pléiades-1 satellite imagery to monitor the development of mangrove forests on Hainan Island, China. And Aprilianti *et al*. (2021) used sentinel-2 to identify and classify LU (land use) based on the index. Others, Asy'ari and Putra (2021) used Sentinel-2 imagery to map mangrove density as a reference for planning the mangrove-Proboscis monkey-peatland ecotourism area through the Google Earth Engine (GEE) platform based on cloud computing in West Kalimantan Province, Indonesia.

Monitoring of mangrove vegetation is important, as a benchmark in determining the protection and management of the coastal area. As stated by Cao *et al*. (2018), Berlanga-Robles and Ruiz-Luna (2020), that mapping the distribution of mangrove species is important to do as a consideration for policymaking in protecting and conserving mangroves. However, Wang *et al*. (2018) reveal that accurate mapping of the extent and species of mangroves is still a challenge in remote sensing, especially the accessibility of these mangroves. Large-scale and detailed mapping requires a long process and of course, requires considerable resources. Nowadays, since the birth of the GEE platform based on cloud computing, it has had a good impact on the world of cartography (Gorelick *et al*., 2017). GEE is a web-based platform that has resources in the form of large storage, data access to various satellites, and it can process data quickly. Several studies have revealed that the combination of GEE based on cloud computing is capable of mapping using the Random Forest (RF) Algorithm classification (Yancho *et al*., 2020).

All forms of the earth's surface will emit different spectral values including mangrove vegetation and then be recorded by satellite (Han *et al*., 2021). Each satellite packs a specific range of spectral values and divides them into several bands according to their function (Perich *et al*., 2021). Generally, these spectral values can be used to identify the distribution of vegetation through the help of a vegetation index (Lyon *et al*., 1998). Rees (1999) states that the vegetation index is a mathematical operation performed on reflections measured in two or more spectral bands of optical near-infrared images, therefore producing parameters that are correlated with the amount of vegetation present in these pixels. Currently, there have been many developments of vegetation indexes dedicated to identifying specific types of vegetation. For example, the NDVI index uses two wavelength channels from optical satellite imagery, namely red infrared and near-infrared (NIR) to distinguish vegetation from other land cover types (Muhd-Ekhzarizal *et al*., 2018). These vegetation and non-vegetation indices can be combined to identify specific vegetation, but until now in Indonesia, especially in the Java region, there are still few studies that focus on this. In addition, there is a lack of detailed mapping of the mangrove cover area inside and outside government agencies. This is the reason why this research was conducted, to find out the area of mangrove cover on a detailed scale with a combination of indices and through the help of the Random Forest algorithm using the GEE cloud computing platform.

METHODS

Study Area

Administratively, the research locations cover three provinces including West Java, Banten, and Jakarta. Meanwhile, geographically, the research location is at the western end of Java Island with details on the north of the location bordering the Java Sea, in the south bordering the Indian Ocean, and in the west bordering the Sunda Strait (Figure 1). Within the research location, there is an urban area which is one of the important mega cities in Indonesia. These cities are connected and form a regional node known as the Jabodetabek metropolitan city (Jakarta-Bogor-Depok-Tangerang-Bekasi). It is different from the surrounding area which is a buffer zone for food and shelter. Many of these areas are used as residential areas to accommodate the needs of urban communities.

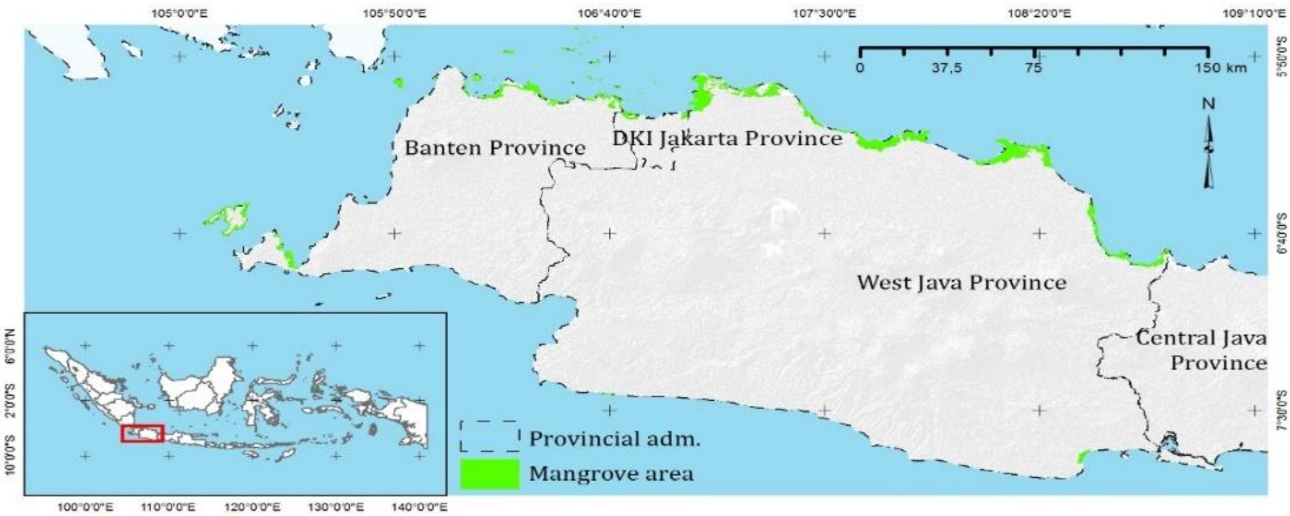

Figure 1 Location research map

Data and GIS Processing

Initially, this research was carried out by collecting data on mangrove vegetation at the study site. Data retrieval is done by collecting training data first. Training data collection is a very important step in producing higher classification quality, especially when classifying with a higher spatial resolution. The training data was taken with several test variables in the form of mangrove area (210) and non-mangrove (416) with a total data of 656. GIS processing is carried out using Sentinel-2 satellite imagery of MSI (Multispectral Instrument) type with 12 bands. Other data involved in the GIS process are the Indonesian Topographical Map (Rupa Bumi Indonesia Map), and the Shuttle Radar Topography Mission Digital Elevation Model (DEM-SRTM). The data process is carried out first through the Random Forest classification with the help of a combination of 13 indices as a formula to identify mangroves. The data processing is carried out using the GEE platform based on cloud computing so that it does not require large storage resources. Processed by GEE and then the mangrove area will be mapped with the help of ArcMap 10.2 software.

Random Forest Algorithm for Mangrove Classification

Land use classification has been completed before getting the distribution of mangroves and this process uses the RF algorithm. The Random Forest classification method is a collection of regression trees and is a product of the Machine Learning algorithm (Collins *et al*., 2020; Rodriguez-aliano *et al*., 2012; Zhou *et al*., 2020). This data process involves GEE based on cloud computing because the land use classification process is accurate and fast due to a large amount of data and involves many indices (Yancho *et al*., 2020). The use of classification methods with algorithms aims to improve the quality of the desired results. Several types of land use will be classified, including mangrove areas, forests (not mangroves), water bodies, built-up areas, barren land, and agriculture.

The formation of the RF formula involves several analytical indices including NDVI (Normalized Difference Vegetation Index), EVI (Normalized difference water index), SAVI (Soil Adjusted Vegetation Index), SLAVI (Specific Leaf Area Vegetation Index), DVI (Difference Vegetation Index), ARVI (Atmospherically Resistant Vegetation Index), RVI (Ratio Vegetation Index), GNDVI (Green Normalized Difference Vegetation Index), IRECI (Inverted Red-Edge Chlorophyll Index), NDWI (Normalized difference water index), MNDWI (Modified Normalized Difference Water Index), LSWI (Land Surface Water Index), and IBI (Index-Based Built-up Index) and combined with several additional bands consisting of Band-2, Band-3, Band-4, Band-5, Band-8, and Band-9.

Index Combination Test

The process of identifying land use in the form of mangroves has serious challenges because objects are classified as the same type of vegetation by separating mangrove vegetation from other vegetation. However, mangrove vegetation, which has different physiography from other vegetation types, certainly has different characteristics when viewed from a spatial perspective. Currently, many studies have focused on mapping mangrove vegetation by creating new index formulas or combining existing indices. We created index combinations and tested them from 13 indices with Sentinel-2 image sources. Of the 13 indices used, we divided the group of index combination test variables into six test groups, namely noncombination (index only), combination of vegetation index, combination of water index, combination of 3 types of index, combination of indices considering threshold values, and all index.

Accuracy Measurement

Classification of land use, especially mangroves, often produces data that is not in accordance with actual conditions. Therefore, it is important to have an accuracy calculation based on a comparison between predictive data and validation data. This accuracy calculation involves a Confusion matrix table with an assessment of the accuracy level of the classification using Overall Accuracy (OA) and Kappa Statistic (Formula 1, 2, 3, and 4).

$$Kappa\ Statistic\ = \frac{N\ \sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{i+}X_{+1}}{N\ \sum_{i=1}^{r} X_{i+}X_{+i}}$$

$$User's\ Accuracy = \frac{X_{ii}}{X_{+i}} \times 100\%$$

$$Producer's\ Accuracy = \frac{X_{ii}}{X_{i}} \times 100\%$$

$$Overall\ Accuracy = \frac{\sum_{i=1}^{r} X_{ii}}{N} \times 100\%$$

According to Scepan (1999), the value of OA has a set limit, namely a minimum level of confidence of 85%. In addition to OA, Kappa Statistics (KA) values have interpretation classes, namely Poor (<0.0), Slight (0.00-0.20), Fair (0.21-0.40), Moderate (0.41-0.60), Substantial (0.61-0.80), Almost perfect (0.81-1.00)

(Landis and Koch, 1977). Several studies explain that the error matrix and Kappa analysis are often used to assess accuracy in the land use change detection process. Google Earth Pro software which is equipped with high-resolution imagery is the media for taking 506 validation data in this study.

RESULT AND DISCUSSION

Mangrove's Distribution in Location Research

The research study locations are in three different locations, namely, West Java Province 3 537 776 ha (BPS Statistic of West Java Province, 2021), Banten 966 292 ha (BPS Statistic of Banten Province, 2021), and Jakarta 66 401 ha (BPS Statistic of Jakarta Province, 2021). Geographically, the study area is located between the Java Sea to the north and the Indian Ocean to the south and in the west, bordering the Sunda Strait which of course has a beach as the land and sea boundary (Figure 1). The northern coast of Java Island has a quite sloping topography, compared to the southern coast. Dsikowitzky *et al*. (2019) stated that the corals along the coast in the southern part of the island of Java are very narrow and also have basins with a depth of more than 7 000 meters close to the shoreline. This affects the distribution of mangrove vegetation and it is known that coastal areas with sloping topography have a large area of mangrove growth. Kustanti (2011) suggests that the zoning that occurs in mangrove forests is influenced by several factors, including the frequency of inundation, salinity, the dominance of plant species, tides, and openness of mangrove forest locations to wind and waves, as well as plant distance from the shoreline. Given the condition of the South Coast which is directly facing the open sea (Indian Ocean) the influence of the strength of the waves is a factor inhibiting the growth of mangroves with very large wave conditions. On the other hand, the north coast is bordered by the Java Sea where the waves are relatively small. This causes the physiographic appearance and physiognomy of mangrove vegetation in the two areas to be different (Sutarno and Lymbery, 2000).

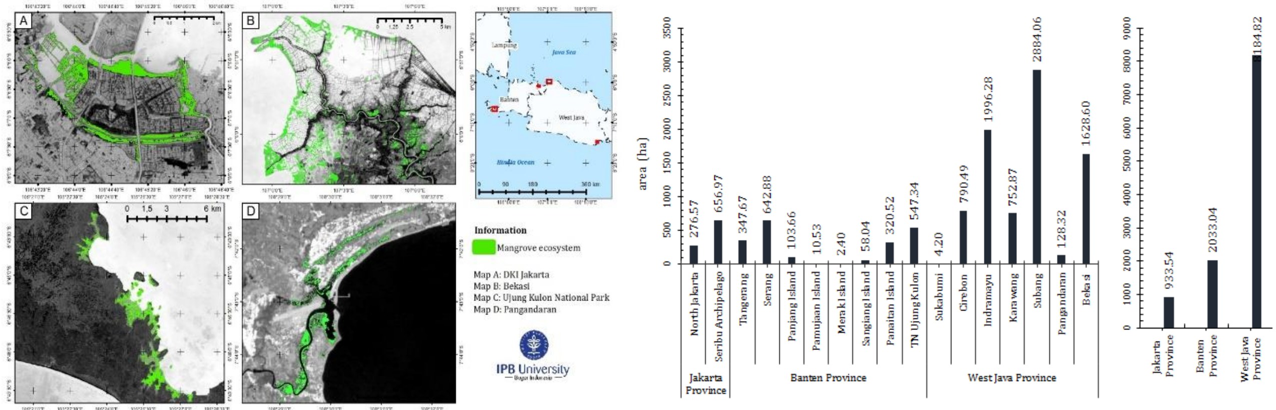

Figure 2 Spatial and statistically for mangrove forest ecosystem distribution

Sentinel-2 satellite image analysis has identified 16 mangrove ecosystem sites with a total area of 11 151.40 ha spread across the province of West Java. Jakarta and Banten (Table 1). The results show that the coast in the northern part of the study area has the largest mangrove area, which is 9 319.42 ha or equivalent to 83.57% of the total mangrove area of the study area. Compared to the southern coast, it only has 132.52 ha, or equal to 1.19%. The northern coastal area also has other land uses, namely agriculture and silvofishery, thus fragmenting the forest area (including mangroves) along the coast (Figure 2: Map B). It is known, overexploitation and reclamation of mangroves can lead to degradation and loss of mangroves (Kusmana, 2013).

Ambinari *et al*. (2015) explained that in 1949 the Indonesian government purchased a land area of 9 311 ha in the coastal area of the Bekasi area intending to control forest damage on the coast and downstream of the Citarum River as well as other ecological impacts. Currently, almost all areas along the northern coast of the study area have mangrove expanses, although the extent is still relatively low. Compared to the west coast of Java Island which only has a stretch of mangrove that is included in the Ujung Kulon National Park, Pandeglang Regency, Banten and covers an area of 547.34 ha or about 4.91% of the total mangrove area of the study area, And also, Natharani (2007) and DKP Tangerang Regency (2013) reported that the mangrove ecosystem in Banten Province has a degraded mangrove ecosystem, in 2007 it had an area of 487.5 ha to an area of 222.9 ha in 2013. The distribution of mangroves in the area is widely spread over the islands, namely Sangiang Island, Panjang Island, Pamujaan Besar Island, and Panaitan Island.

Table 1 Mangrove area per regency

No	Mangrove Ecosystem Area (per regency)	Area (ha)	*Percentage (%)
	Jakarta province (933.54 ha, 8.37%)		
1	North Jakarta mangrove ecosystem	276.57	2.48
2	Seribu Archipelago mangrove ecosystem	656.97	5.89
	Banten province (1 537.89 ha, 18.23%)		
3	Tangerang mangrove ecosystem	347.67	3.12
4	Serang mangrove ecosystem	642.88	5.77
5	Ujung Kulon National Park mangrove ecosystem	547.34	4.91
6	Sangiang Island mangrove ecosystem	58.04	0.52
7	Panjang Island mangrove ecosystem	103.66	0.93
8	Pamujaan Besar Island mangrove ecosystem	10.53	0.09
9	Panaitan Island mangrove ecosystem	320.52	2.87
	West Java province (8 184.82 ha, 73.39%)		
10	Sukabumi mangrove ecosystem	4.20	0.04
11	Cirebon mangrove ecosystem	790.49	7.09
12	Indramayu mangrove ecosystem	1 996.28	17.90
13	Karawang mangrove ecosystem	752.87	6.75
14	Subang mangrove ecosystem	2 884.06	25.86
15	Pangandaran mangrove ecosystem	128.32	1.15
16	Bekasi mangrove ecosystem	1 628.60	14.60
	Total	11 151.40	100

Note: *Percentage of mangrove area to the total area

Including the Province of Jakarta, which has the lowest mangrove ecosystem location from other areas (West Java Province and Banten Province) with a total area of 933.54 ha spread over the Thousand Archipelago National Park (656.97 ha) and North Jakarta (276.57 ha) (Including Angke Kapuk Nature Tourism Park and PIK Mangrove Ecotourism) (Table 1, Figure 2: Map A, Figure 3). The area of mangroves in DKI Jakarta is increasing because the mapping coincides with the area of the PIK ecotourism area (Figure 3: Map B). According to research by Yanuartanti *et al.* (2015), the mangrove area of TWA Angke Kapuk is about 264.65 ha, generally damaged by the construction of residential areas, toll roads, power generation facilities, airport infrastructure, and ponds. However, land use in the form of ponds (silvofishery) can be combined with mangrove rehabilitation activities and can have an economic impact on local communities.

Handayani's (2006) research reports that the mangroves in Angke Kapuk Nature Tourism Park are only left and are dominated by *Avicennia marina* and *Rhizophora mucronata* species which have the potential to reduce heavy metal overflow. In addition, Mahardhika *et al.* (2018) explained that the mangrove ecosystem in Muara Angke has an area of approximately 964.98 ha where this area is divided into three zonings, which consist of Muara Angke Wildlife Sanctuary, Muara Angke Fish Landing Base, and Angke Kapuk Nature Tourism Park, and other, Rahmawati and Asy'ari (2022) detected 267.86 urban mangroves forest areas in DKI Jakarta City.

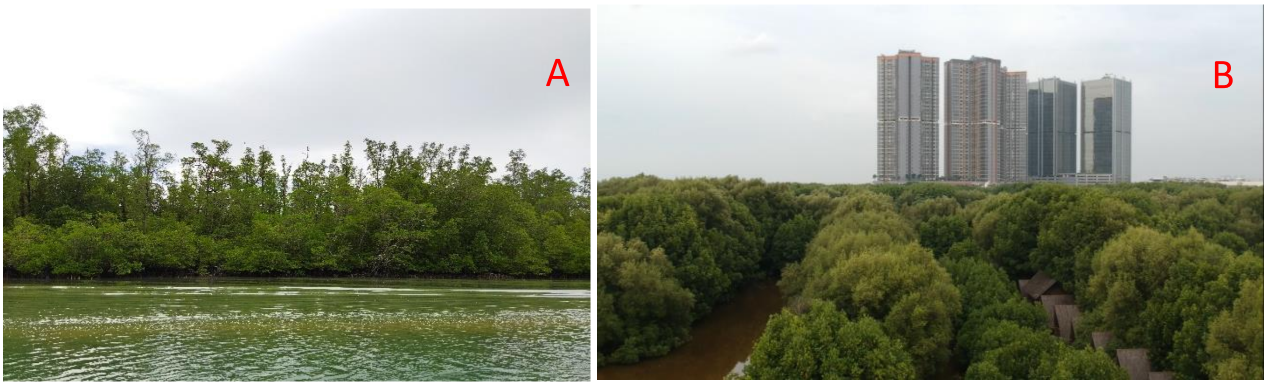

Figure 3 Mangroves forest in Ujung Kulon National Park (A) and mangrove urban in TWA Angke Kapuk (B)

West Java Province is a province located in a location with the largest mangrove area, which is 8 184.82 ha or equivalent to 73.40% (Figure 2) which consists of seven mangrove ecosystem areas (Table 1). In this province, there is also the largest mangrove ecosystem area, namely Subang Regency which covers an area of 2 884.06 ha (25.86%). Subang Regency has a mangrove ecosystem that is affiliated with silvofishery activities as well as extensive rice farming. It is different to the mangrove ecosystem of the West Java Province in the southern coast, which has mangrove expanses, only two locations are located, namely Pangandaran Regency (4.20 ha or equivalent to 0.04%) and Sukabumi Regency (128.32 ha or equivalent to 1.15%). However, Hikmah (2017) reports that the mangrove ecosystem in Sukabumi Regency has a mangrove forest area on Ciletuh Beach with an area of about 7.9 ha. Known types of mangroves in this area include *Rhizophora mucronata*, *Avicennia marina*, *Avicennia alba*, *Bruguiera gymnorrhiza*, *Sonneratia alba*, *Ceriops tagal*, *Calophyllum inophyllum*, *Nypa fruticans*, and *Barringtonia asiatica*.

Threshold Values and Index Spatial Characteristics for Mangroves

Based on the index assessment obtained, there is a threshold value of mangrove vegetation in each index. The threshold values obtained from each index are NDVI 0.39 – 0.61, ARVI 0.16 – 0.43, DVI 0.25 – 0.39, EVI (-0.01)-(-0.005), GNDVI 0.25-0.48, IRECI 0.49-0.73, NDWI (-0.48)-(-0.25), MNDWI 0.321-0.60, and LSWI 0.60-0.79. This is in accordance with previous research records which reported that the NDVI index on mangrove vegetation had a threshold value of >0.2 (Nguyen *et al*., 2020). In addition, there are indices that have almost the same threshold value and some are different. For example, the threshold value of the SAVI index (0.200.41) and DVI (0.25-0.38) is within the ARVI index threshold (0.16-0.42). It is the same with the threshold value of the IBI index which is on the LSWI index and also the DVI index which is still at the GNDVI threshold value. Meanwhile, the threshold values for other indices overlap (Figure 4). This threshold value is an alternative for assessing mangrove vegetated land. This can help the classification algorithm in identifying mangroves which are generally very difficult to distinguish from non-mangrove vegetation.

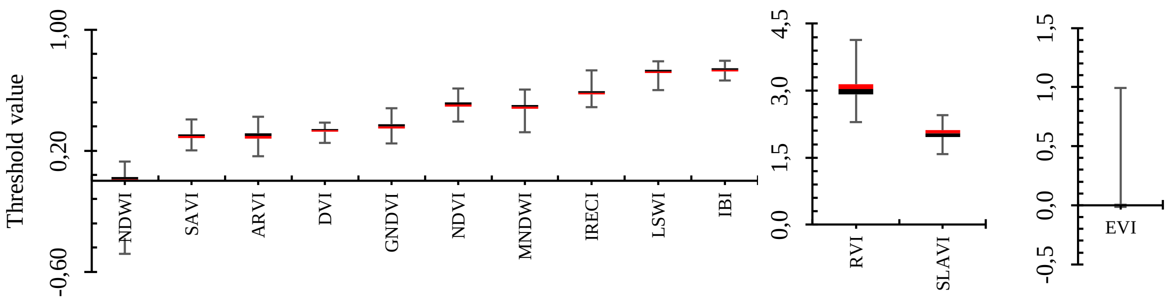

Figure 4 Distribution of threshold values of mangrove vegetation

When viewed from the spatial characteristics of the index, the location of the mangrove threshold value is different. Figure 5 shows the spatial characteristics of the distribution of threshold values in the mangrove area. In the overall index, there are three types of distribution of mangrove threshold values, namely those at the lowest value (EVI-IBI-NDWI), in the middle (MNDWI), and those at the highest (NDVI-ARVI-SLAVI-IRECI-DVI-RVI-SAVI-GNDVI-LSWI). When viewed from the ability to identify mangroves visually, the MNDWI index can distinguish mangroves from non-mangrove vegetation (Figure 5). However, for the other indices, it is almost impossible to distinguish between mangrove and non-mangrove vegetation, while the index has a vegetation identification function. Several previous studies have revealed that the MNDWI index can also be used as a detector of non-water land cover types. Meanwhile, the LSWI index cannot distinguish between water and vegetation (including mangroves). Therefore, the LSWI index is not recommended to be involved in classifying vegetation, especially mangroves, and requires further detailed research.

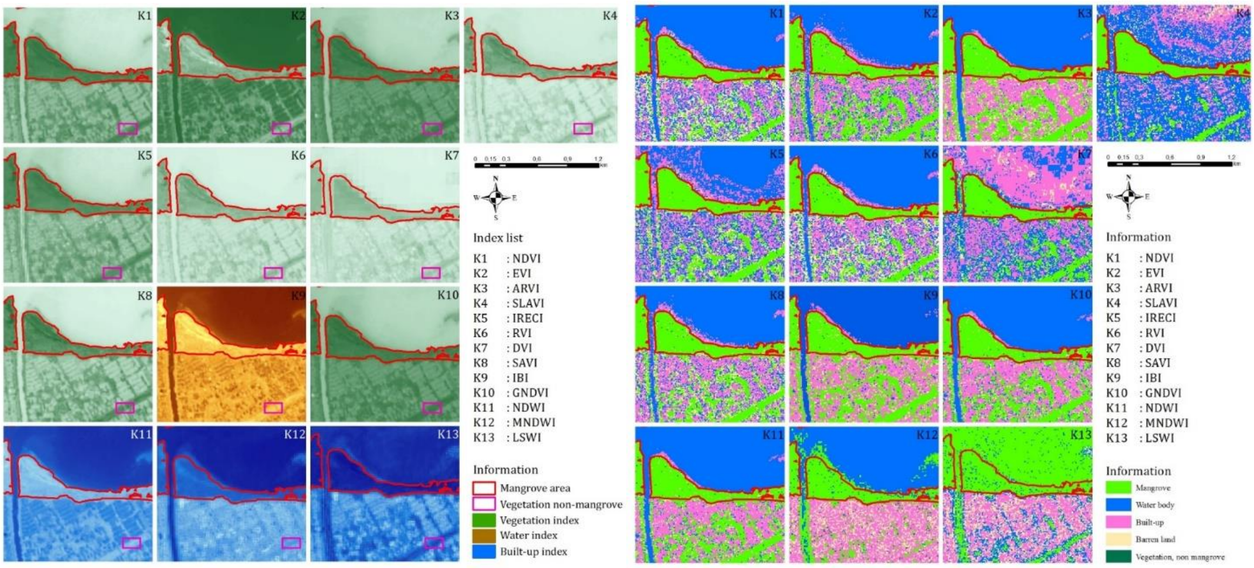

Figure 5 Spatial characteristics for index and mangrove classification using an index without combination

Combination of Indexes in Identifying Mangrove Distribution

Each index has different strengths and abilities in identifying vegetation. Moreover, mangrove vegetation has an appearance that is almost similar to other types of vegetation. However, if viewed from a physiographic point of view, this vegetation has a habitat that is always and usually submerged by water. So that this vegetation can be identified and distinguished through the help of water-related indexes. The results of the variable test with a case study of the Angke Kapuk Nature Tourism Park mangrove ecosystem showed that almost all of the index combinations identified mangroves, but could not distinguish between mangroves and other vegetation. Then if corrected, approximately 35.18-79.49% of the mangrove area from the classification results is included in the actual mangrove area.

The test results for non-combination (index only) (Type-A) show that the LSWI index is the highest (832.17 ha, or 641.50 ha with actual area correction) and the SLAVI index (476.74 ha, or 294.98 ha) is the lowest in classifying mangrove areas. Identification by involving one index resulted in an average mangrove area of 668.58 ha (312.78 ha). An index with limited capabilities cannot provide more benefits than its role. It may be due to the special functions and reasons for launching these indices that are not in accordance with the mangrove ecosystem. These effects require a combination of algorithms in the form of collaboration with other indices that have the ability to translate the affected wavelengths and are sensitive to the physical properties of the mangroves. These indices in this case are sensitive to the influence of soil brightness (SAVI index) and the presence of water on the ground surface (NDWI, MNDWI, and LSWI). When viewed from the detection error, Figure 6 shows that the NDWI index has a greater detection error than the MNDWI and LSWI indices.

However, in Figure 3, where the description shows the LSWI index detects mangroves which should be water bodies, and is much wider for error detection when compared to other indices. According to the calculation of the detection error which is the result of the correction of the mangrove area boundary, it shows that the ARVI index has the highest error detection with a land area of 502 ha and the lowest on the SLAVI index is 182 ha (Figure 6).

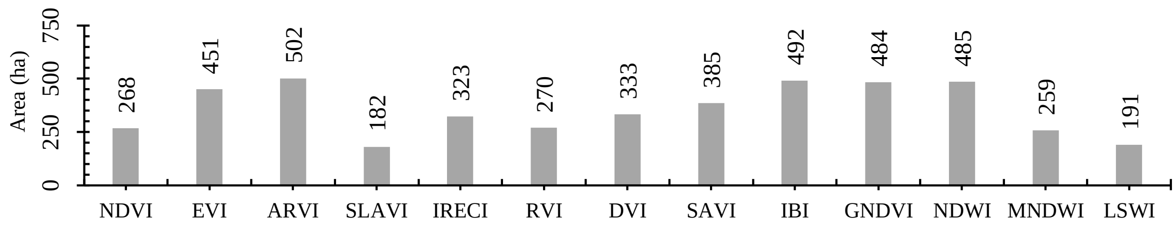

Figure 6 Mangrove detection error for each index

In contrast to the combination with the same type of index, for example, the combination of vegetation index (Type-B) and water index (Type-C) shows 440.67 ha (282.84 ha) and 378. 76 (274.72 ha) respectively, which are lower than the average results of each index. This shows a slight difference when compared to the minimum and maximum results of the previous combination. Combinations involving only one index have shortcomings in identifying mangroves. The physiographical nature of mangroves that are always submerged in water has a major influence on the classification process carried out.

Next, Type-D is a combination of indexes with test variables of each type of vegetation, water, and building index. The combination resulted in the distribution of mangroves with an average area of 500.80 ha (283.27 ha with correction) with a minimum-maximum area of 394.41 ha-805.09 ha (265.20 ha-301.00 ha). The average land area of the correction results has a value that is almost the same as the tests carried out on the Type-B combination or the combination coded K14 (Figure 8).

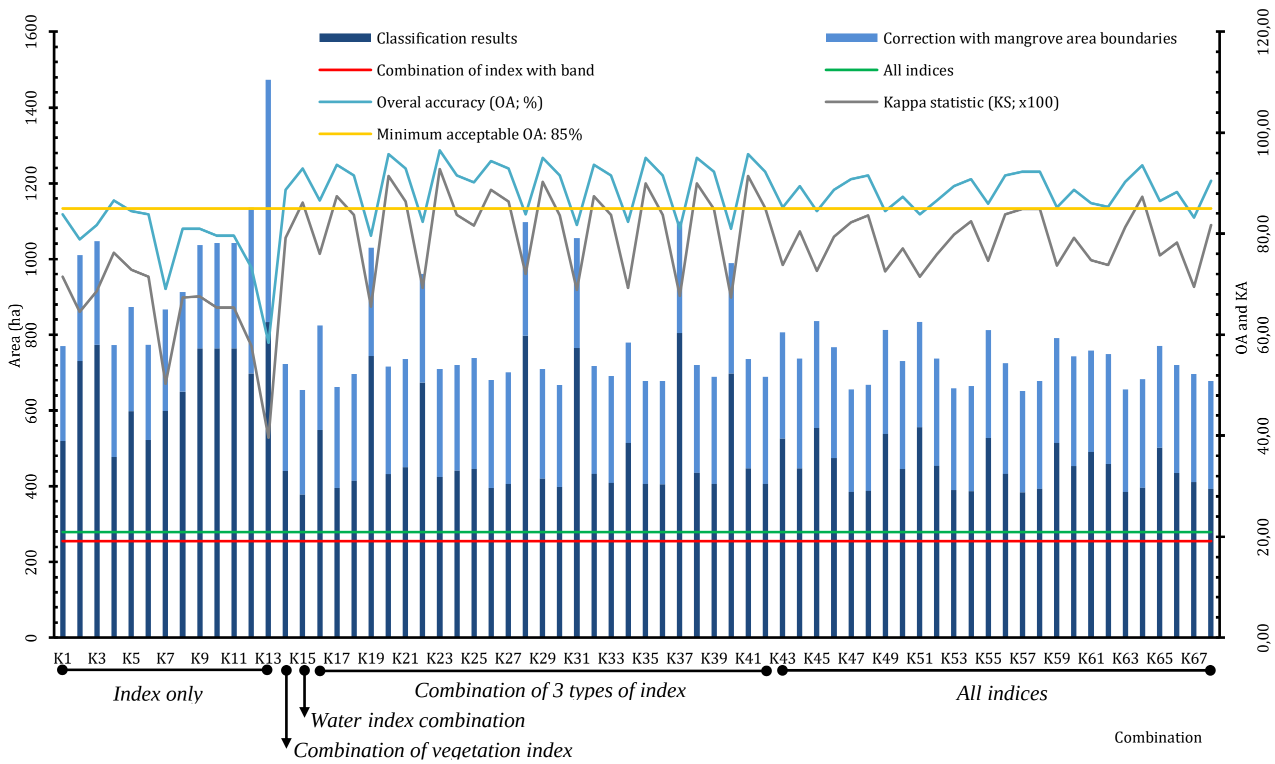

Figure 7 Muara Angke mangrove area through index combination test, case study in the mangrove area of Angke Kapuk and PIK

In this type of combination test, it produces a movement pattern from the identification of mangroves. The combination is coded K16-K42, where the NDWI index has a large influence and produces a larger mangrove distribution area than the combination involving the MNDWI and LSWI indices, and when compared with the Type-E combination, where the involvement of the variables considers the threshold value of each index and produces an average area of 450.81 ha (280.44 ha). However, testing on this index combination entirely involves the NDWI index, so the influential indices are IBI and RVI. It is known that these two indices have a large influence, which results in a larger mangrove area than the combination involving other indices. On the other hand, the index combination involving all indices (Type-F) and also the index combination with the Sentinel-2 band (Type-G) resulted in a land distribution of 399.69 ha (278.44 ha) and 320.99 ha (255.14 ha), respectively (Figure 7).

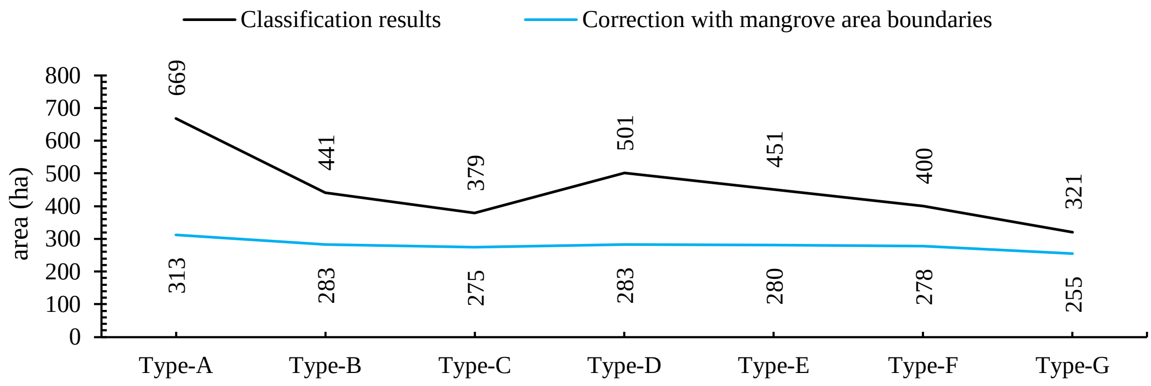

Figure 8 The difference and the moving average area of each type of index combination

The 70 index combinations resulted in different areas of mangrove land, as well as in the corrected results. In Figure 8, it is explained that there is a movement of the average land area of each type of index combination. In addition, the figure shows the difference between the classification results and the corrections made to the classification results. Based on the results of nonparametric statistical analysis using the Kruskal-Wallis method, it was shown that there was a significant difference (p-value 0.000, α= 5%) between the types of index combinations. In contrast to the tests carried out on the corrected classification results, where there is no significant difference between the types of index combinations (p-value 0.251).

Accuracy Assessment

Accuracy Assessment on Classification Mangrove in the Study Area

In the practice of remote sensing, especially in land use mapping and the resulting error detection (Foody, 2002). In this case, we tested the level of accuracy of the mangrove classification that has been carried out and is presented in Table 2. According to the calculation results obtained, the OA value is 82.41% with the Kappa statistics value of 0.70. Based on the notes developed by previous researchers, where a good level of accuracy is in accordance with the spatial concept and can be shown by the OA value with a minimum percentage of accuracy of 85% (Scepan, 1999). This of course makes the accuracy we get smaller than the minimum that has been set. When viewed from the value of kappa statistics, the classification results show a high level of accuracy with a substantial class of 0.61-0.80 (Rwanga and Ndambuki, 2017). In addition, this calculation shows that the percentage of User's accuracy and Producer's accuracy in mangroves is 87.38% and 75.10%, respectively, while for non-mangroves are 78.77% and 89.49%. The value of User's accuracy in mangroves is greater than in the non-mangrove class, and the percentage of Producer's accuracy has a greater value in the non-mangrove class compared to the mangrove class.

The high percentage of User's accuracy and Producer's accuracy is based on the error detection table. In our calculations, there were 62 mangrove detection errors, and 27 non-mangrove detection errors (Table 2). The resulting errors of detection are one of the evaluations of this study on the involvement of the index and classification methods that have been used (Fitzgerald and Lees, 1994; Story and Congalton, 1986). In addition, the type of image used is one of the important factors in producing a quality land classification map (Bazzi *et al.*, 2019). This requires further research on land use classification testing using several classification methods, index algorithms, different types of images, and concepts. The amount of accuracy obtained is one way to describe the feasibility of the map that we produce and is recommended to users. As mentioned in previous studies, it is explained that the accuracy of the classification that produces maps determines the quality and feasibility of using maps (Aronoff, 1985).

Table 2 Confusion matrix and accuracy measures for mangrove classification

	Class	Reference Data		Sum
		Mangrove	Non-mangrove	
Classified data	Mangrove	187	27	214
	Non-mangrove	62	230	292
	Sum	249	257	506
	User's Accuracy (%)		Producer's Accuracy (%)	
Mangrove	87.38		75.10	
Non-mangrove	78.77		89.49	
Overall accuracy (OA)	: 82.41%			
Kappa statistic	: 0.70			

Assessment of Accuracy for Combination Test Results

The index combination test that was carried out resulted in different mangrove areas and of course had different levels of accuracy. From the results we get, there are differences in the accuracy values of the percentage of OA and Kappa statistics. Figure 7 shows that there is an accuracy distribution pattern in the combination of Type D and Type E. While in Type A with testing without a combination or only involving one index per test, where there is no pattern of accuracy distribution formed. This distribution of accuracy, depends on the resulting classification results and the index involved in the test.

In this accuracy calculation, there are 47 out of 70 total combinations that meet the assumption of the minimum OA value (Figure 7). The 47 combinations are spread over each type of index combination, namely Type-A-B-C-F-G (one combination each), Type D (20 combinations), and Type E (22 combinations). When viewed from the value of Kappa statistics, all combinations are spread across four accuracy interpretation classes, namely fair class (one combination), moderate (two combinations), substantial (35 combinations), and almost perfect (32 combinations). From all combinations, the test with only one variable, namely LSWI (K13) had the lowest percentage of OA and Kappa statistics, which was around 58.45% and 39.59, respectively. This proves the descriptive analysis carried out in Figure 5 and at the same time downloading the visualization of Figure 6, that the LSWI index has a higher error rate than other indices.

This could result from the involvement of bands in the index algorithm. It is different from the K23 combination with the SAVI-MNDWI-IBI index combination, which has the highest accuracy values of 96.48% (OA) and 92.79 (Kappa statistics). The three indices involved in the K23 combination have a level of sensitivity and sensitivity to mangrove vegetation, especially watery soil surfaces. The MNDWI index has the ability to distinguish mangrove and non-mangrove vegetation (Figure 5). The SAVI index has a sensitivity level to soil brightness, and of course, it can distinguish soil texture in mangrove and non-mangrove vegetation. While the IBI index helps the SAVI index in increasing the sensitivity to soil brightness through the NIR and SWIR bands involved in the index algorithm.

CONCLUSION

Mangrove mapping using Sentinel-2 imagery with the study areas of West Java, Banten, and Jakarta resulted in a mangrove area of 933.54 ha (8.372%), 1 537.89 ha (18.231%), and 8 184.82 ha (73.397%, respectively). While overall the results were obtained with a mangrove area of 11 151.40 ha. Mangrove ecosystems are more widely distributed along the north coast than the south coast in the study area. The mangrove ecosystem obtained from the mapping is divided into 13 namely North Jakarta, Seribu Archipelago, Tangerang, Serang, Ujung Kulon National Park, Sangiang Island, Panjang Island, Pamujaan Besar Island, Panaitan Island, Sukabumi, Cirebon, Indramayu, Karawang, Subang, Pangandaran, and Bekasi. One area, namely North Jakarta, is one of the case studies that was tested for a combination of indices and produced extraordinary findings. Index combination testing with 70 combinations was carried out and classified into seven classes/types, namely Type A (index only), Type B (Combination of vegetation index), Type C (water index combination), Type D (Combination of 3 types of index). Type E (the index combination considers the threshold value), Type F (all index), and Type G (combination of index with band). From the whole test, the LSWI index (K13, Type A) resulted in a mangrove area of 424.48 ha and had the lowest accuracy rates of 58.45% (OA) and 39.59 (Kappa statistics).

The best combination that was found was the K23 combination with the SAVI-MNDWI-IBI index combination, which had the highest accuracy values of 96.48% and 92.79. The discovery of classification results and good accuracy from testing 70 indexes provides recommendations for the use of the SAVI-MNDWI-IBI index combination on Sentinel-2 images and involves the RF algorithm through the GEE platform. In addition, these results have shown the weakness of indices in helping the classification process and also requires detailed research on the differences in classification algorithms and different types of imagery, so as to measure the ability of the index in various conditions. It is hoped that this research can be useful for future studies, and especially the mangrove distribution data is important to be taken into consideration in determining mangrove area protection policies in three provinces (Jakarta, West Java, and Banten).

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