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Spatiotemporal Analysis of Mangrove in Subang Regency using Sentinel-2 Timeseries Data

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Abstract: The mangrove forest ecosystem is one of the types of ecosystems that grow in the tidal areas of the ocean and play an essential role in addressing global issues such as climate change. Remote sensing technology can be used to monitor mangrove areas accurately and efficiently. This study aims to detect the spatiotemporal distribution of mangroves from 2017 to 2022 using remote sensing techniques, identify the spectral characteristics and threshold values of the indices involved in mangrove area detection, and determine the accuracy of mangrove area detection in Subang Regency, West Java. Mangrove area detection is carried out using Land Use Land Cover (LULC) classification involving several vegetation, water, and built-up indices to obtain the mangrove area from 2017 to 2022. The research results showed that the mangrove area was 1972.98 ha and distributed in areas A, B, C, and D. Area D showed an increase in mangrove area due to natural succession or planting.The spectral vegetation index tends to increase while the water index and built-up index tend to decrease. MNDWI has the ability to distinguish between mangrove and non-mangrove vegetation. The research results show that there are examples of mangrove succession points (area D) which can be used as a consideration for policy-making to optimize the role and function of mangroves as a natural barrier.

Keyword: Mangrove, Sentinel-2, Spatiotemporal

INTRODUCTION

Mangrove ecosystem is one of the forest ecosystems that grows in the area of tidal seawater with high salinity on its growing substrate. The vegetation that grows in the mangrove forest is divided into several zones following its salt content. The foremost zone is the mangrove that is more resistant to high salinity, such as api-api (*Avicennia* sp.), and as it moves towards the land, the mangrove trees characteristic are less resistant to high salinity (Siburian and Haba 2016). Mangrove forest ecosystem directly or indirectly affects the lives of coastal communities such as providing natural resources and the environment to meet their needs (Purwowibowo 2016). The mangrove area has physical, biological, and economic benefits. The physical benefits include protecting the coastline, holding back strong winds, and preventing seawater intrusion (Raharjo *et al.* 2016). The biological benefit is a place for the growth and development of mangrove biota, such as fish and crabs, as a source of germplasm (Jalaluddin *et al.* 2020). Meanwhile, the economic benefits include producing firewood, raw materials for industry, fish seedlings, medicinal resources, and ecotourism (Fidyansari & Hastuty 2016).

The condition of the mangrove ecosystem can be detected using remote sensing. Remote sensing is the application of GIS that facilitates users in analyzing spatial data on land cover or land use. The use of remote sensing in mangrove ecosystem analysis can detect the location of mangrove vegetation, the distribution of mangrove vegetation, and the physical condition, such as vegetation density (Irawan *et al.* 2016). Detection of mangrove areas is carried out by separating pixels based on spectral values with the same spectral values in pixels that have been grouped into one class. Analysis of mangrove area density is carried out using the NDVI algorithm using red and infrared bands on satellite images (Latifah *et al.* 2018). The application of remote sensing in mangrove areas can also detect the spatiotemporal condition of the mangrove ecosystem regarding the addition and reduction of mangrove areas (Utami *et al.* 2016).

Mangrove monitoring needs to be done to determine the condition of the mangrove area for consideration in mangrove management decision-making. One method for approaching the monitoring of mangrove areas is through remote sensing. Remote sensing can detect mangrove areas by translating the reflectance on mangroves and distinguishing them from other land covers based on their spectral characteristics. The reflectance of mangroves in the NIR band is quite high, so mangrove areas can be distinguished using an index that is built with the NIR band (Tran *et al.* 2022). Remote sensing can also indicate submerged and non-submerged mangroves using an index algorithm involving red and SWIR bands (Jia *et al.* 2019). Remote sensing detects mangrove areas using the random forest algorithm method by involving several vegetation, water, and built-up indices and can produce an accuracy of more than 90% (Yancho *et al.* 2020). The use of various indices can also explain multiple mangrove characteristics. Using regression models, remote sensing can detect aboveground mangrove biomass

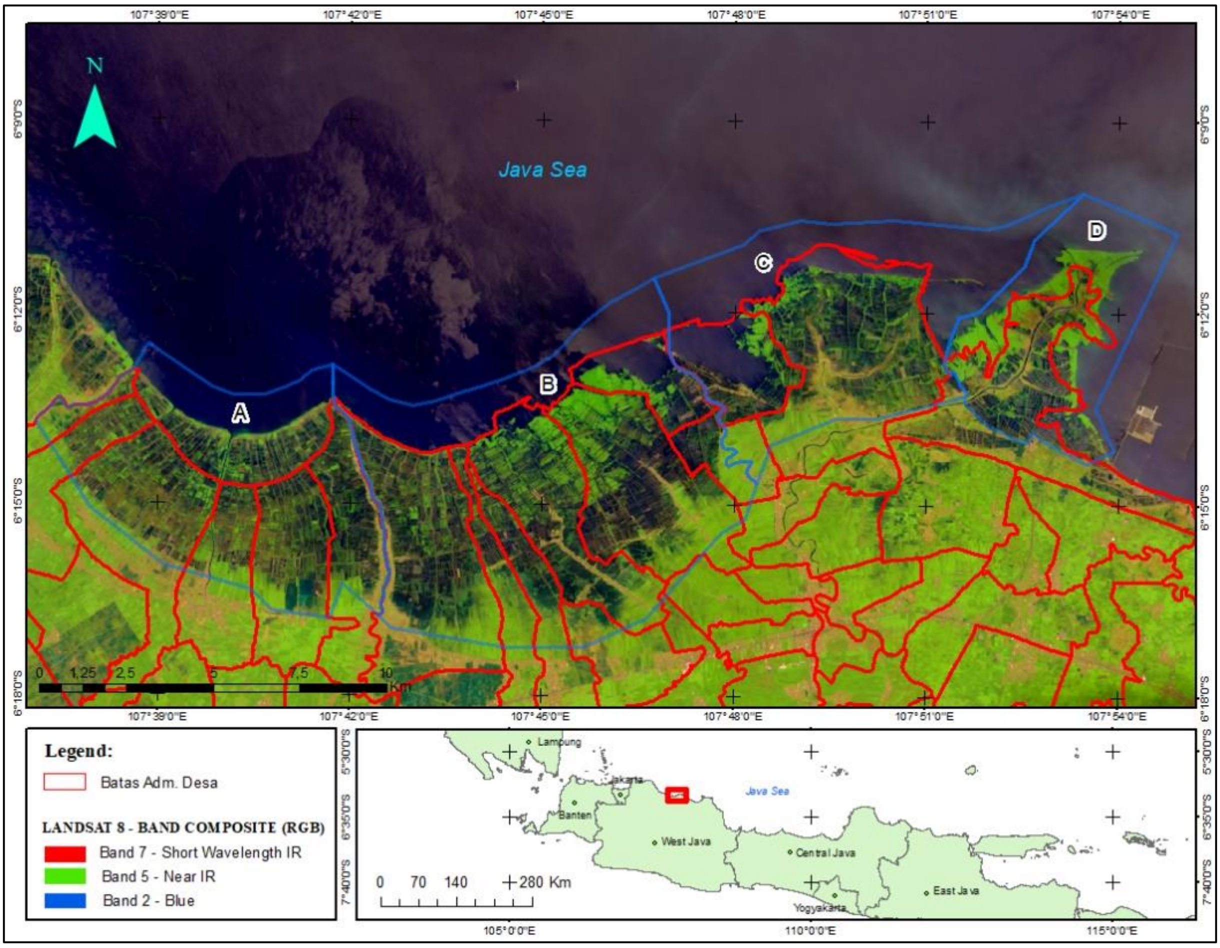

Figure 1. Research location

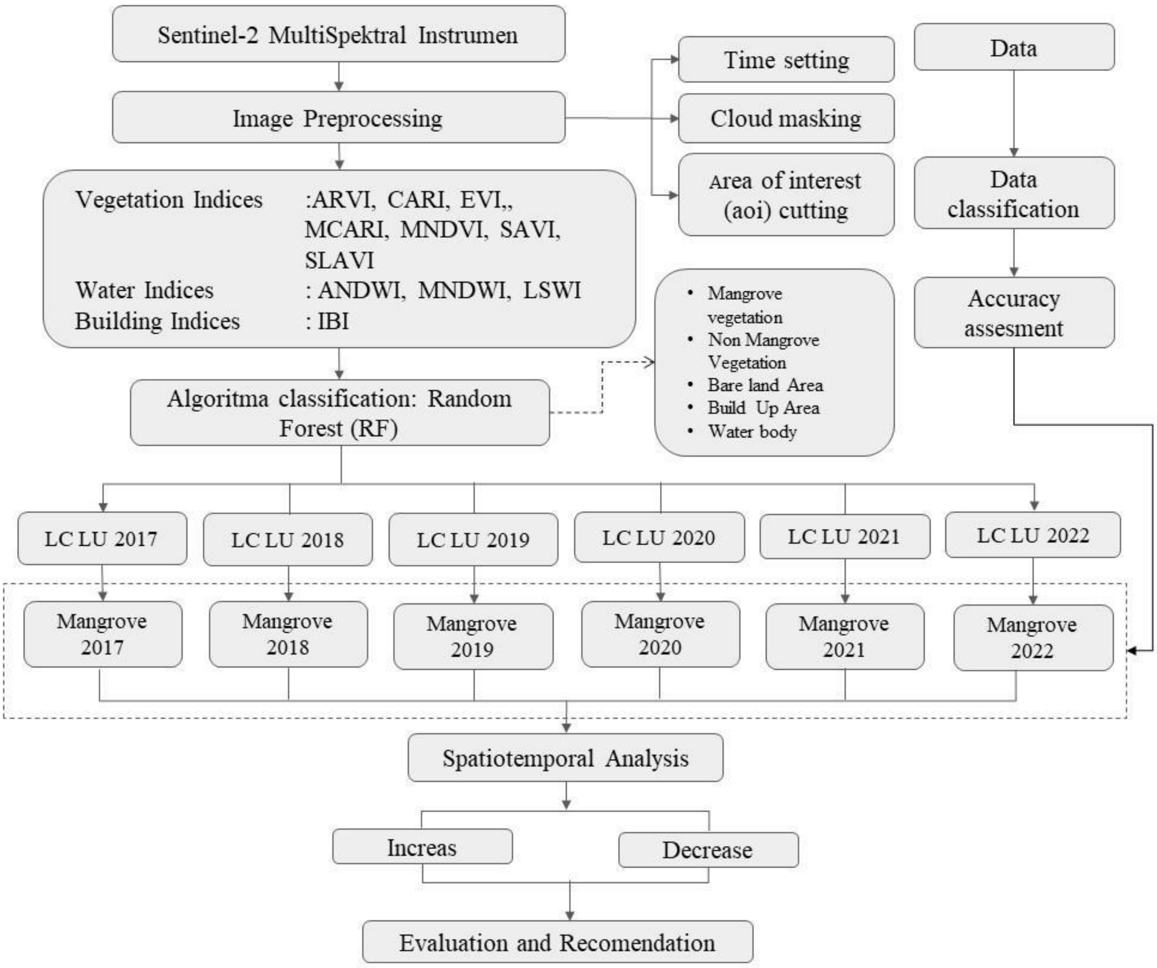

Figure 2. Research flow chart

(Muhsoni *et al.* 2017). The use of multivariate analysis on several indices can improve the accuracy of biomass estimation (Baloloy *et al.* 2018). The presence of mangroves can be detected by a new index algorithm that uses green, NIR, and SWIR bands (Baloloy *et al.* 2020). Therefore, this study aims to detect the spatiotemporal distribution of mangroves from 2017-2022 using remote sensing techniques to understand the spectral characteristics and threshold values of the indices involved in the detection of mangrove areas and to determine the accuracy level of detecting mangrove areas in Subang Regency, West Java.

METHODOLOGY

Study Area

The study location is administratively located in Subang Regency, West Java. Subang Regency is located at coordinates 6.18 - 6.81 S and 107.81 - 107.92 E. The mangrove area is located on the north coast of Subang Regency, which borders the Java Sea. Subang Regency consists of thirty districts, and the research location involves four districts located on the north coast of Java Island, namely Blanakan, Sukasari, Legon Kulon, and Pusakanagara. A map of the research location is shown in Figure 1.

Data Sources and Reseach Flow

The data used in this research consists of Sentinel-2 satellite data, Indonesia's Land Cover Map, and ground check data to determine the condition of mangroves from a biophysical and socio-cultural perspective. The Sentinel-2 images were taken from 2017 to 2022 and were launched by the European Space Agency (ESA) to monitor the condition of the Earth (Kushardono *et al.* 2017). Sentinel-2 is a multispectral image with 13 bands with spatial resolution ranging from 10 to 60 meters (Mandanicii and Biteli 2016). The bands available on Sentinel-2 are shown in Table 2. Sentinel-2 is good enough in land use and land cover classification, especially in monitoring agricultural areas, forests, built-up areas, and water bodies, with an accuracy of more than 80% (Phiri *et al.* 2020). Ground data was collected at two points: mangrove successional and degraded mangrove areas. Biophysical data collected were the distribution, density, and dominance of mangroves. Socio-cultural data collected were land-use change, pond management, and the role of the community in the mangrove succession process. The research flowchart is shown in Figure 2.

Classification in detecting mangrove areas using the Random Forest (RF) algorithm based on spectral characteristics involved in the index. The RF algorithm is a development of the decision tree (DT) algorithm, which uses many decision trees to obtain optimal classification results (Maxwell *et al.* 2018). Training data is created for each land cover to obtain spectral characteristic data for each land cover. A machine learning system then uses this training data to determine the land cover type in the study area. The training data consists of mangrove vegetation, non-mangrove vegetation, bare land area, built-up area, and agriculture. The land cover classification results are used to analyze the spatiotemporal mangrove area from 2017 to 2022.

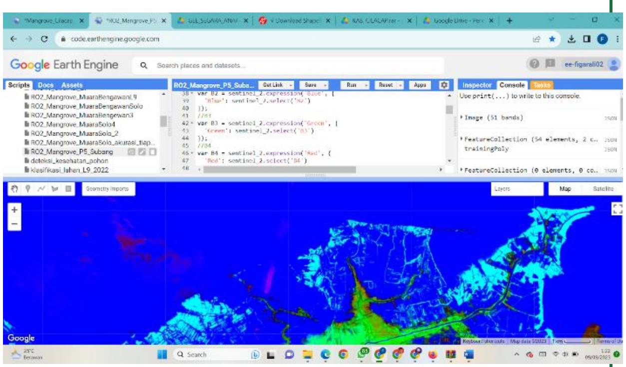

Figure 3. Google Earth Engine (GEE) platform

Google Earth Engine Platform: Classification

Data processing was done on the Google Earth Engine (GEE) platform. Land classification for mangrove area detection was carried out following a pre-built script. The script was built and connected with the satellite image resource Sentinel-2 available on GEE. GEE is a cloud computing platform designed to store and process large-sized data. GEE resources archive all data collections and connect to open-access cloud computing machines. The data archive includes satellite-based Geographic Information System (GIS) data, demographics, weather, Digital Elevation Model (DEM), and climate data. GEE can be applied to vegetation mapping, land cover mapping, agriculture, and natural disasters (Mutanga and Kumar 2019).

Vegetation Index

Vegetation index is a remote sensing algorithm obtained from the range of spectral values reflected by vegetation canopy. The vegetation index can explain quantitative or qualitative variables of vegetation through allometric calculations (Bannari *et al.* 2009). The vegetation indices used in the classification process are ARVI, EVI, MCARI, MNDVI, SAVI, and SLAVI (Table 1). MNDVI is a modification of NDVI used to improve linearity with specific variables at high leaf area index (LAI) to increase accuracy in modeling variables (Dong *et al.* 2015). Additionally, NDVI is highly sensitive to atmospheric and substrate effects, so ARVI was developed to reduce atmospheric effects and SAVI to reduce substrate effects. EVI was created to improve atmospheric and soil effects using multiplication factors, thereby better explaining vegetation parameters (Xue and Su 2017). ARVI can provide good information on seasonal and temporal variations (Somvanshi and Kumari 2020). SLAVI has a high correlation with vegetation canopy density, thus explaining vegetation density well (Trier *et al.* 2018). CARI and MCARI are more commonly used to describe physiological responses in specific vegetation (Cui *et al.* 2019).

Built-up Index

The built-up index is one of the index algorithms used to detect built-up areas as an indication of urbanization (Kaur and Pandey 2022). The built-up index can map the presence of the urban regions through land classification processing involving vegetation indices (Zha *et al.* 2003). The building type index used in mangrove mapping is IBI indices (Table 1).

Water Index

The water index is generally used to detect the presence of water content in a land. The water index can be widely used to detect the dynamics of water bodies such as lakes, rivers, etc. The water index uses NIR and SWIR bands that relate to information on the characteristics of the presence of water content, such as

Table 1. List of Indices involved in this study

No	Index	Formula	References
1	Atmospherically Resistant Vegetation Index (ARVI)	ARVI = (NIR – (2 Red) + Blue) / (NIR + (2 x Red) + Blue)	Kaufan et al. 1992
2	Chlorophyll Absoption Ratio Index (CARI)	CARI = ((RE – Red) – 0,2 x (RE – Green)) x (RE – Red)	
3	Enhanced Vegetation Index (EVI)	EVI = 2.5 x ((NIR – Red) / ((NIR) + (C1 x Red) – (C2 x Blue) + L))	Huete et al. 2002
4	Modified Chlorophyll Absorbtion Ratio Index (MCARI)	MCARI = ((NIR – Red) – 0,2 x (NIR – Green)) x (NIR – Red)	
5	MNDVI (Modified Normalized Vegetation Index)	MNDVI = (NIR – RED)/(NIR+RED)	
6	Soil Adjusted Vegetation Index (SAVI)	SAVI = ((NIR – Red) / (NIR + Red + L)) x (1 + L) L = 0.5	Huete 1988
7	Specific Leaf Area Vegetation Index (SLAVI)	SLAVI = NIR / Red + MIR	Lymburner et al.2019
8	Index-Based Built-up Index (IBI)	IBI = NDBI − ((SAVI + MNDWI) / 2) / NDBI + ((SAVI + MNDWI) / 2)	Xu 2008
9	Augmented Normalized Difference Water Indeks (ANDWI)	ANDWI = (Blue + Green + Red + NIR – SWIR1 – SWIR2) / (Blue + Green + Red + NIR + SWIR1 + SWIR2)	
10	Land Surface Water Index (LSWI)	LSWI = NIR − SWIR1 / NIR + SWIR1	Xiao et al. 2002
11	Modified Normalized Difference Water Index (MNDWI)	MNDWI = Green - SWIR / Green + SWIR	Xu 2006

Information: Blue : blue band; Green: green band; Red: red band, RE: red-edge; NIR: near-infrared band; SWI: shortwave-infrared band; C1 C2: the aerosol coefficients were 6.0 and 7.5, respectively, G: gain factor (value 2.5); S2: Sentinel 2 MSI

depth and humidity. In addition, the water index can also detect urbanization (Yang and Chen 2017).

Accuracy Assesment

One of the most important processes in land classification research is accuracy assessment. Accuracy assessment is conducted to test the level of accuracy in the land classification process. The level of accuracy in classification is estimated by the overall accuracy percentage and kappa statistic values presented in the confusion matrix. Accuracy assessment involves 426 validation pixels consisting of each land cover (mangrove vegetation, non-mangrove vegetation, bare land area, build-up area, water bodies, and agriculture). The validation data is tested and compared with the land classification results to obtain the overall accuracy and kappa statistic values.

RESULTS AND DISCUSSION

Mangrove Ecosystem Condition

Mangrove forest is a type of forest that grows in areas with tidal waters, such as along the coast, lagoons, or river mouths. The mangrove ecosystem consists of biotic components (animals and plants) that interact with environmental factors and each other in a mangrove habitat (Ashari *et al.* 2018). The functions of the mangrove ecosystem are divided into two categories: ecological and economic. Ecological functions are related to protecting the coastline and serving as habitats for various plants and animals. Economic functions are related to providing raw materials for household, industrial, and breeding purposes (Warpur 2016). In the study location, the

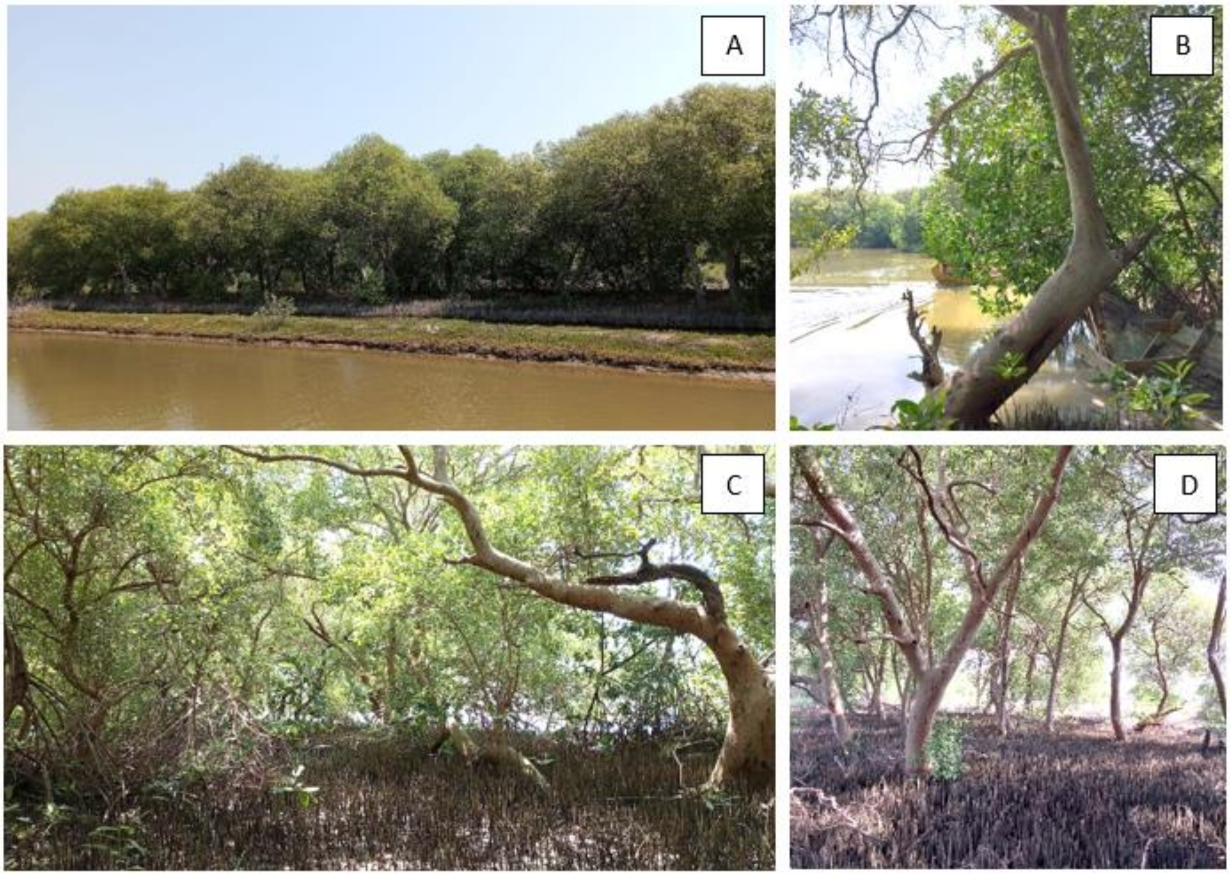

Figure 4. Condition of the mangrove forest ecosystem at the study location. (a) coastal barrier mangrove, (b) River estuary mangrove, (c) Dense mangrove stands, (d) Sparse mangrove stands

mangrove forest is located in the area of a fish pond and a river mouth, as shown in Figure 4.

The field observation results show several differences between succession and degradation of mangrove areas. The pond area in mangrove succession does not carry out production activities because it is often flooded. This also causes mangrove succession to occur. Active ponds have traditional water gates. In addition to natural succession, artificial succession also occurs through planting. Access to the mangrove succession area is quite difficult, so it is unsuitable for tourism activities. Rikardi *et al.* (2021) reported that mangrove vegetation in the Patimban area (succession area) has a high level of environmental sensitivity, making it very vulnerable to pollution and can cause economic, ecological, and social losses.

Something different happens in the degraded mangrove area. The degraded mangrove area is located in Legonkulon District. The road access to the degraded mangrove area is in the form of a mining area. In this area, we found a silvofishery system, an integrated cultivation of ponds with mangrove vegetation, specifically Rhizophora apiculata (figure 5). In this area, we also found traces of cutting of *Avicennia* sp.

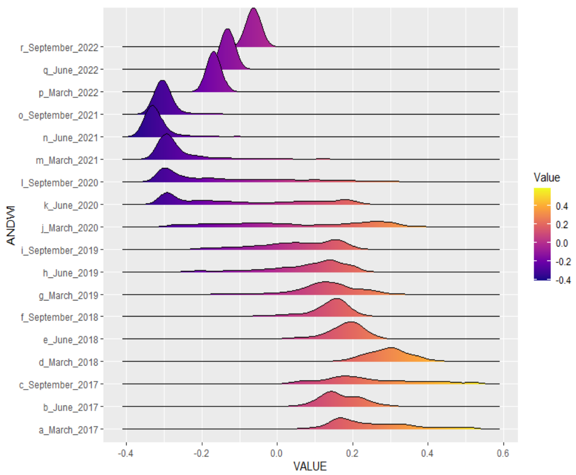

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Figure 5. The silvofishery system in the mangrove area is degraded

mangrove species to be replaced with *Rhizophora apiculata*. Mangrove degradation occurs in this area. We found many deaths of *Avicennia* sp. and the conversion of mangrove ecosystems into mining areas. Mangrove damage in Subang Regency is caused by natural factors, namely abrasion, and human factors, namely excessive land use (Narendra *et al.* 2018). Many algae were found in the pond waters in this area, making the water green in color, and the water gates are still operated manually. The abundance of phytoplankton in silvofishery ponds in this area is higher compared to conventional ponds, making it possible to have natural feed in the pond area. Furthermore, the presence of phytoplankton is an essential factor in the pond's fertility (Sahidin *et al.* 2019). The crab population in the mangrove waters of Legonkulon District has a diverse age range and a high exploitation rate, even though it has yet to reach the maximum sustainable point. However, controlling the catch of young crabs is necessary to maintain the sustainability of coastal resources (Syam *et al.* 2017).

Mangroves are a type of ecosystem that has unique flora and fauna. Mangrove flora has its own characteristics, while mangrove fauna consists of marine, terrestrial and transitional fauna (Kustanti 2011). The land fauna that can be found can be primate species such as proboscis monkeys which have the potential to provide attractions for the use of environmental services in the form of ecotourism (Asy'Ari & Putra 2021). Based on field observations in degraded mangroves, several species have been found, namely *Avicennia marina*, *Rhizophora mucronata*. Meanwhile, in the succession area, *Avicennia alba*, *Rhizophora apiculata*, *Rhizophora mucronata*, and *Sonneratia alba* were found.

Mangrove Detection

The identification of species and mapping of mangrove areas is important data to be used as a reference in mangrove forest management because the characteristics of each species are related to the geomorphic and environmental conditions and changes. Mapping of land and identifying mangrove forest species using remote sensing technology has been widely used in various disciplines, including monitoring mangroves. Remote sensing can display mapping data of mangrove biophysical and structural parameters, including biomass and carbon stock, with better effectiveness and efficiency than field measurements (Pham TD *et al.* 2019).

Mangrove vegetation has been detected in several places, such as river mouths and shrimp farm areas as shown in the picture. Most of the mangrove vegetation is distributed at the river mouth, which is site D. Mangrove vegetation is distributed in the shrimp farm area at sites A and B. Meanwhile, at site C, a coastal area experiences erosion.

The result of mangrove distribution detection shows that the area of mangrove vegetation is 1972.98 hectares. This result is based on classification involving

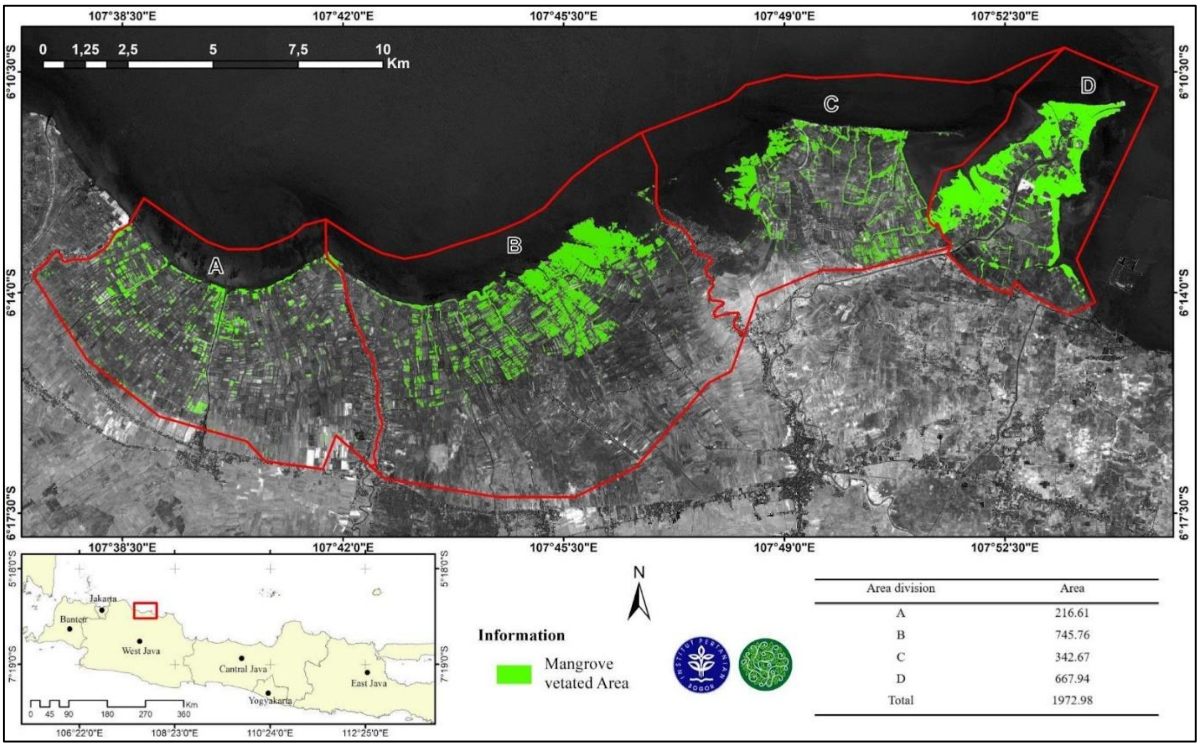

Figure 6. Mangrove distribution in site study

11 indices consisting of vegetation index, water index, and built-up index. The classification process was done using the GEE platform with the random forest algorithm. The classification using the GEE platform allows for a more straightforward method and more accurate detection. GEE can process images by setting datasets at certain periods of time, thereby reducing classification bias caused by seasonal land cover changes (Phan *et al.* 2020).

The detection of mangrove vegetation areas involves several indices displayed in a table. The use of spectral indices is highly potential in mangrove ecosystem management such as mapping distribution, biomass estimation, and detection of mangrove ecosystem changes. NDVI and EVI are commonly used indices in mangrove research because of their high accuracy in distinguishing and explaining mangrove vegetation characteristics (Tran *et al.* 2022). The results of mangrove area detection are presented in the form of geographic information or GIS. In this case, GIS works by processing and integrating mangrove distribution data (analyzed using remote sensing) and landforms to visualize them in the form of a map (Figure 6).

Spatiotemporal for Mangrove Distribution

The spatial dynamics of mangroves at the Site show a decreasing trend from 2017 to 2022 and are presented as a spatio-temporal map in Figure 7 - 10. Mangroves are distributed in the aquaculture area. Site A is located in Blanakan District. The mangrove area in Blanakan District has several benefits, including physical benefits (abrasion resistance), biological benefits (providing fish food), ecotourism, and optional benefits (biodiversity) with an economic valuation of more than three trillion per year (Indrayanti *et al*, 2016). The decrease in mangrove area in Blanakan District is caused by the conversion of mangroves into aquaculture. The pond area tends to increase, accompanied by a reduction in the mangrove area, so there is a correlation between the increase in the pond area and the decrease in the mangrove area. An increase in pond area causes 83% of the reduction in mangrove ecosystem area, and the remaining 17% is caused by logging, flooding, and other factors (Soraya *et al.* 2012). The ability of the Blanakan District mangrove ecosystem to recover (resilience) is influenced by the knowledge of the community regarding the function of the mangrove ecosystem, which is quite good, so there is a need for socialization efforts to the community for the restoration of degraded mangrove ecosystems (Yulianti *et al.* 2013).

Unlike the mangroves in site A, the mangroves in site D have expanded in area (Figure 9). Site D is located in Pusakanagara District, where sedimentation has occurred in the river estuary area between 1998 and 2016. This sedimentation has transformed the seagrass and coral reef areas into mangrove land. The mangrove area is an estuarine ecosystem that serves many ecological functions, such as wave attenuation, flood control, absorption of pollutants, erosion protection, breeding ground for various biota, tourism, and others (Handiani *et al.* 2017). This mangrove area has the potential to be a blue carbon site, with the highest carbon reserves found in the Rhizophora sp. species, with carbon absorption equivalent to 342.87% (Nurruhwati *et al.* 2017).

Spectral Pattern on Mangrove Succession

Several vegetation, water, and built-up indices play a crucial role in detecting mangrove land cover sites. Mangrove succession in site D forms a spectral pattern on each index due to changes in spectral values with mangrove succession (Figure 11). Most vegetation indices experience an increase in value with the growth of the mangrove ecosystem. The spectral values of ARVI, MCARI, MNDVI, SAVI, and SLAVI increased rapidly starting from 2020. Based on exponential regression analysis, the ARVI spectral value has a positive correlation with mangrove stand biomass, so it has the potential to provide a good model for estimating mangrove biomass and carbon storage (Sidiq *et al.* 2020). Lemenkova and Debeir (2023) reported that the distribution of ARVI spectral values in healthy mangroves has a positive trend, and changes in mangrove land cover (degradation) cause the distribution of ARVI values to spread and have many negative residuals. MCARI is an index algorithm that can indicate the relative chlorophyll content of vegetation. MCARI also has the ability to detect mangrove vegetation health through chlorophyll leaf damage and water content in vegetation (Hati *et al.* 2020). The increase in MNDVI value with the growth of mangrove vegetation is caused by the increasing Leaf Area Index (LAI). MNDVI is able to explain and estimate LAI quite well, with a coefficient of determination reaching 0.72 and an error of 13% (Cheng *et al.* 2019). Similarly to MNDVI, SLAVI also has a strong correlation with LAI. SLAVI is a vegetation index designed to estimate vegetation's LAI value and positively correlates with vegetation height and density (Trier *et al.* 2018). Meanwhile, SAVI can detect the presence of mangrove vegetation well. SAVI can minimize sensitivity to soil using correction factors. The best correction factor, according to Rhima *et al.* (2020) is 0.75 to differentiate mangrove land cover. In contrast to other vegetation indices, EVI decreases with the growth of the mangrove ecosystem. EVI is a vegetation index built with correction factors for atmospheric and canopy background sensitivity effects and can explain mangrove biophysical properties at high density (Tran *et al.* 2022). EVI can explain annual mangrove phenology well and can predict mangrove growth. Moreover, EVI positively correlates with rainfall

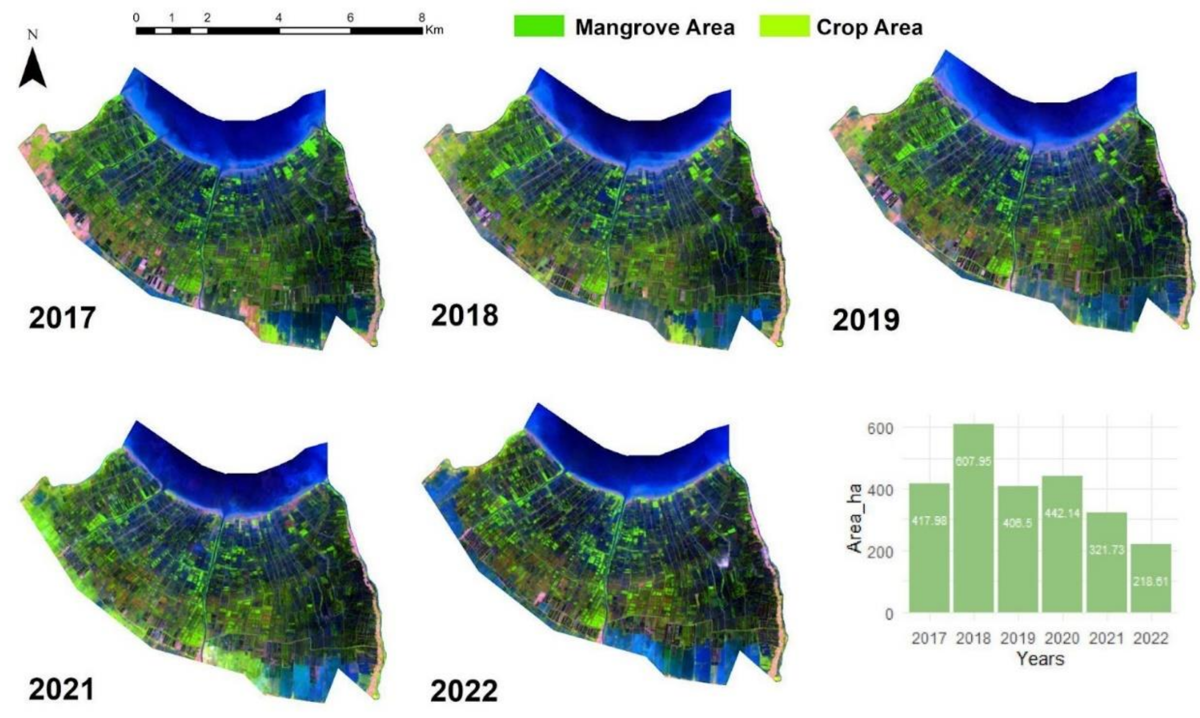

Figure 7. Spatial distribution in site A

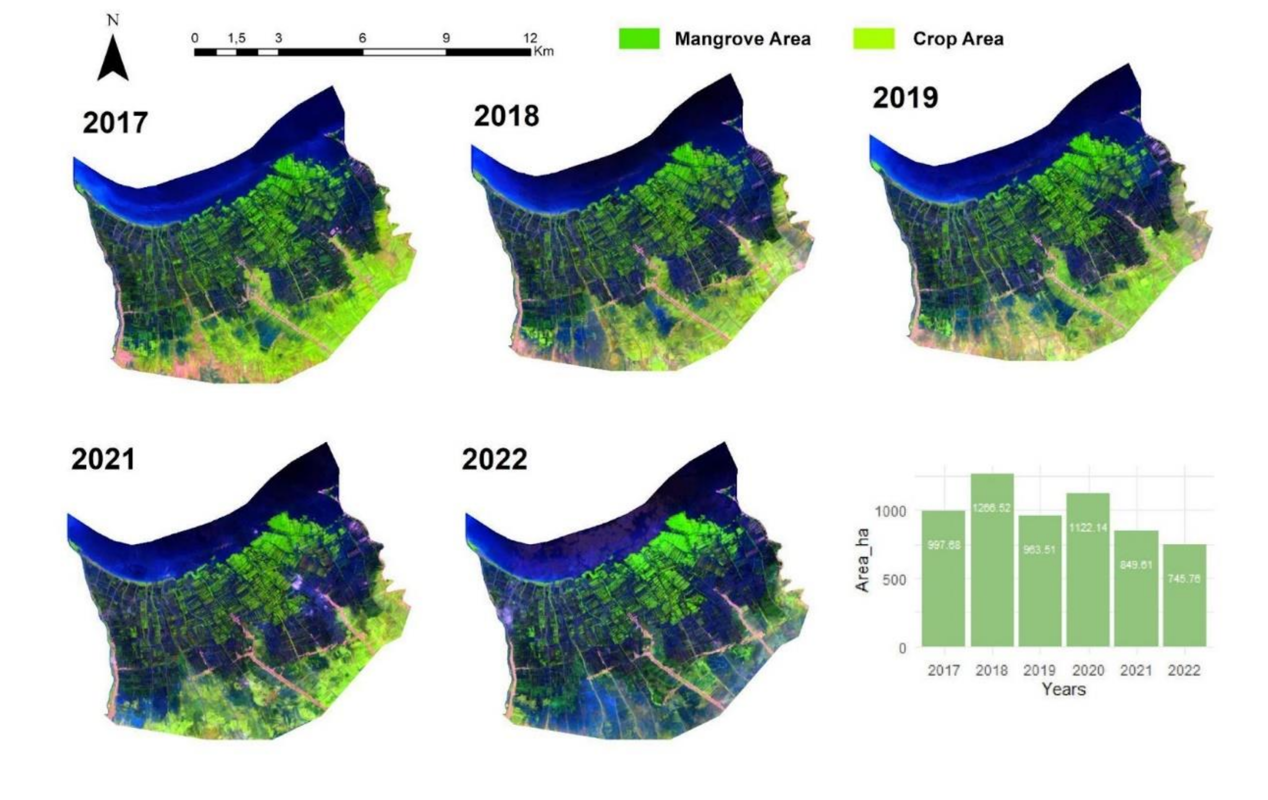

Figure 8. Spatial distribution in site B

(Songsom *et al.* 2019). This can cause the EVI value to tend to increase in March (the wet month).

In contrast to the vegetation index, the water index and built-up index have a tendency to decrease in spectral value as mangroves grow. The spectral value of MNDWI does not show much difference in values so that MNDWI has a low level of sensitivity to mangrove succession. The ANDWI spectral value decreases along with mangrove growth, so it can be interpreted that the denser the mangrove vegetation, the ANDWI value decreases. Meanwhile, LSWI had a rapid increase in 2020 when mangroves began to grow rapidly. MNDWI is able to distinguish well between mangrove and non-mangrove vegetation and can differentiate between watery and non-watery land cover (Asy'ari *et al.* 2022). MNDWI has a high correlation with the presence of water features so that the involvement of MNDWI in detecting mangrove areas can increase accuracy because mengroves themselves have watery or wet land substrates (Guo *et al.* 2021). Meanwhile, the built-up index used, namely IBI, shows a decrease when mangrove density increases. This shows that IBI is quite sensitive to the presence of mangroves. The same results were reported by Asy'ari *et al.* (2022) which shows that IBI is sensitive to the presence of mangroves, especially on watery surfaces.

Indices Threshold

The mangrove threshold value shows the range of spectral values of mangroves on several indices involved, including vegetation, water and built-up indices (Figure 12). The highest threshold value for the vegetation index is SLAVI which has a threshold value of 1.36 to 1.55, while the smallest threshold value is EVI which has a value range of -0.013 to -0.011. Rahmawati *et al.* (2022) reported that the SLAVI threshold value in mangrove areas is in the range of 1.7 to 2.7 and EVI has a range of -0.2 to 0.2. Apart from that, Asy'Ari *et al.* (2022) reported that the SLAVI threshold value is in the range of 1.5 to 3 and EVI is in the range of -0.01 to -0.005. SLAVI is an index designed to estimate leaf canopy cover and has good ability to explain vegetation in heterogeneous forests (Cavada *et al.* 2017). In wetlands, SLAVI is able to explain dry leaf biomass well and has a positive correlation with dry biomass with R-square 0.67 and RMSE 0.034 (Ali *et al.* 2019). EVI is an index that is able to better explain the biophysical condition of mangroves in high density forests compared to other vegetation indices (Tran *et al.* 2022). however, EVI still tends to be sensitive to annual climate variability and is specific to certain mangrove areas (Cavanaugh *et al.* 2017). EVI is also able to predict the health of mangrove tree canopies because it has a positive correlation with mangrove canopy density (Nepita-Villanueva *et al.* 2019). Based on the report by Zhu *et al.* (2021), EVI has good capabilities in analyzing spatiotemporal changes in mangroves with a mangrove area threshold value of 0 to 0.74. in this case, the mangrove area is very heterogeneous so it has a high range in the EVI index. This is why EVI can detect changes in mangrove land cover.

Other vegetation indices have almost the same range of values. The threshold value for the vegetation index for each vegetation index is ARVI (0.30 to 0.36);

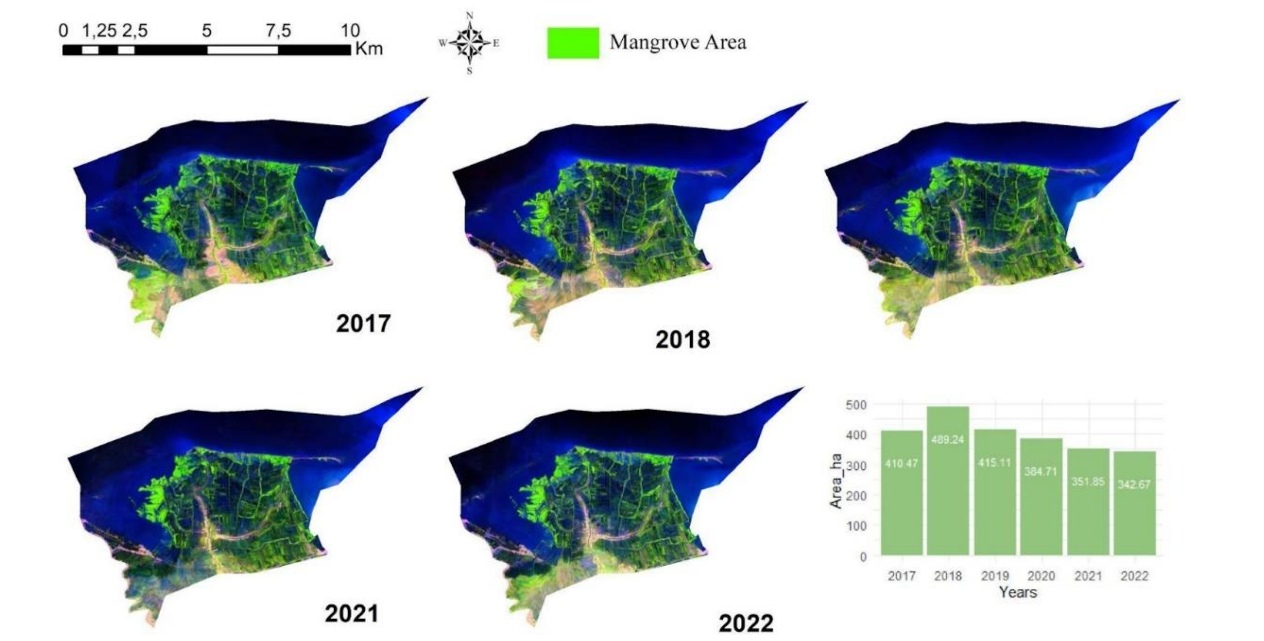

Figure 9. Spatial distribution in site C

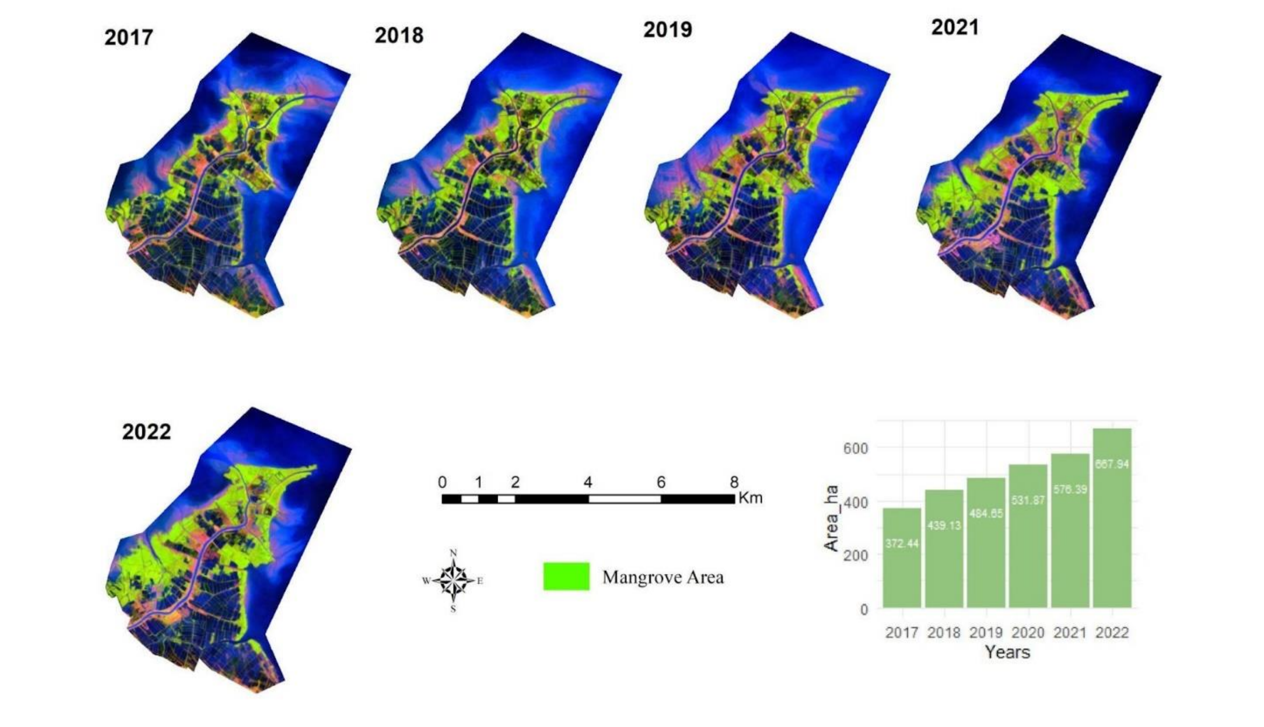

Figure 10. Spatial distribution in site D

MNDVI (0.27 to 0.30); SAVI (0.34 to 0.39); MCARI (0.04 to 0.05); SEARCH (0.04 to 0.05). The research results of Simarmata *et al.* (2021) shows that ARVI has a range of values as low as -0.70 and as high as 0.74 in 2010, 2015 and 2020 and a combination of several vegetation indices has the ability to differentiate mangrove density levels with an accuracy of 84.38%. The ARVI threshold value in wetlands ranges from -0.60 to 0.77 and is able to explain vegetation biomass (Dos Santos *et al.* 2019). MNDVI is an update of NDVI which has a higher ability to explain plant conditions and can show the condition of mangrove damage (Jurgens 1997). The research results of Xia *et al.* (2020) shows that mangroves with low density have a value range of around -0.2 to 0, while mangroves with high density have a value range of around 0.5 to 0.7 and have high sensitivity to tides because they use the NIR band which is widely absorbed. water. MCARI is an index that can explain the abundance of chlorophyll in vegetation. The mangrove study area has an average MCARI value of 0.58 and is higher than the research results of Baloloy *et al.* (2021) which reported that the average MCARI was 0.003 in mangroves and 0.002 in degraded mangroves. The results of classifying the health level of the mangrove ecosystem using the decision tree algorithm showed that mangroves with high health had MCARI values above 0.086, medium health (0.039 to 0.086) and low health below 0.039 (Kumar *et al.* 2020).

The Built Index and water index have threshold values: ANDWI (-0.15 to -0.11); LSWI (0.51 to 0.56), MNDWI (0.22 to 0.25); IBI (0.56 to 0.60). The water index is an index designed to detect the presence of water features on land, reducing sensitivity to vegetation in distinguishing watery land cover using the NIR and SWIR bands which have quite low reflectance in water bodies (Rad *et al.* 2021). MNDWI has the ability to reduce sensitivity to vegetation and soil and is able to

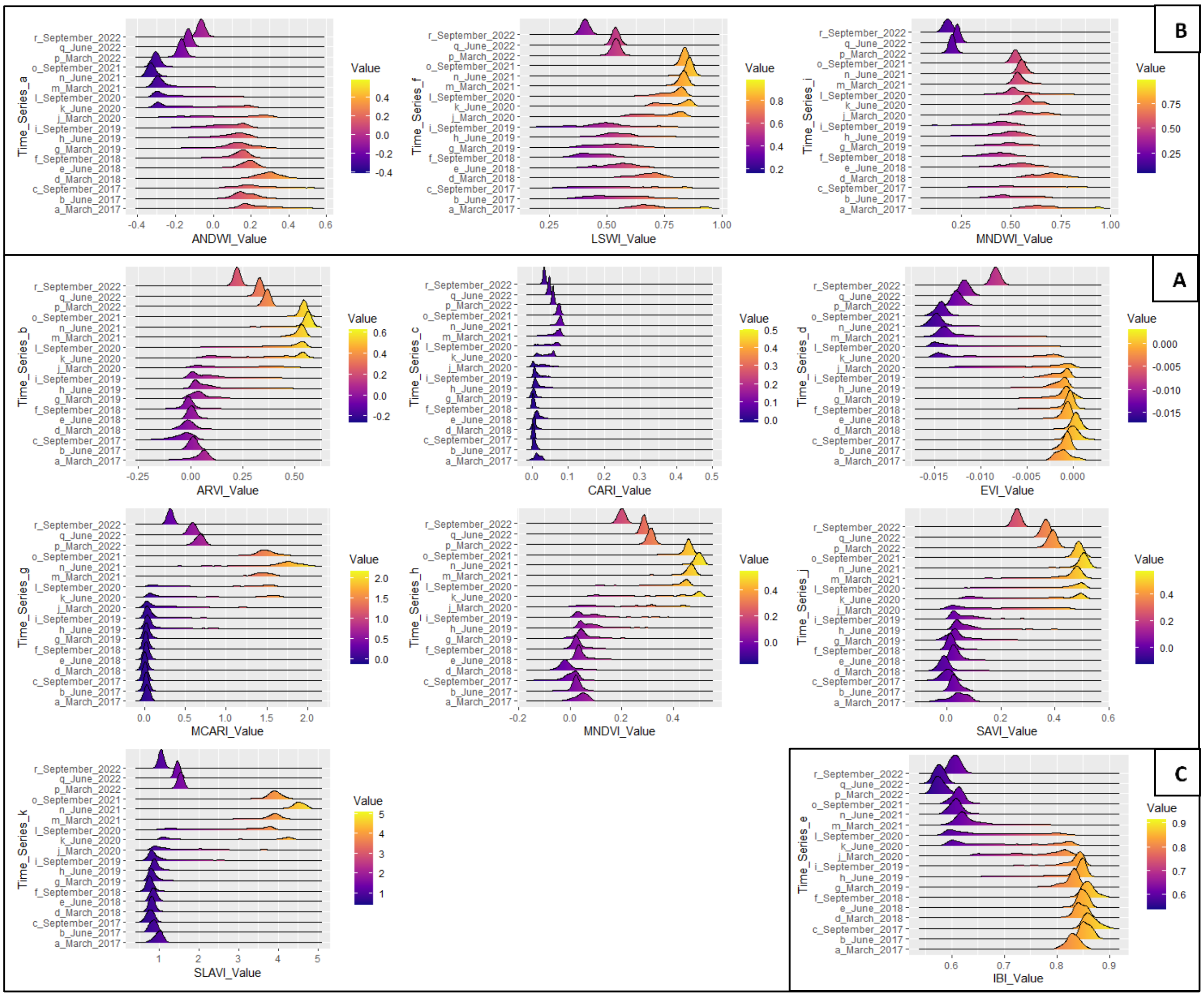

Figure 11. Spectral pattern of mangrove succession, (A) Vegetation index, (B) Water index (C) Built-up index

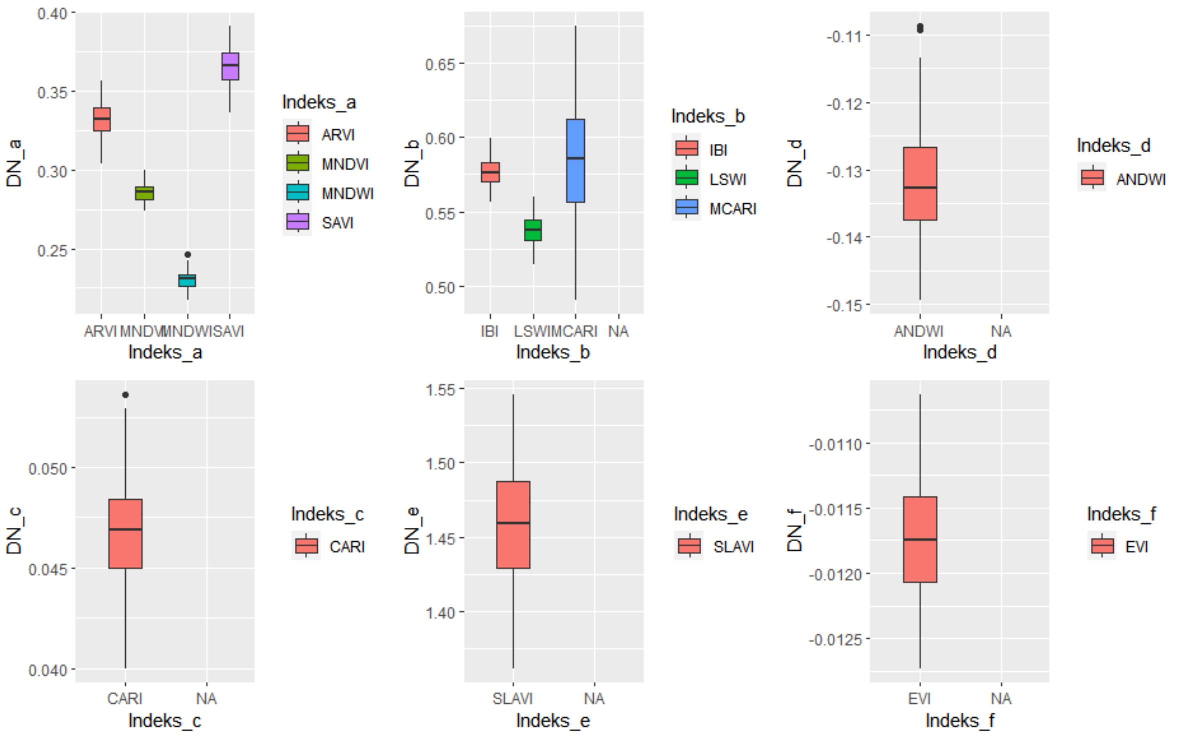

Figure 12. Threshold values for mangrove land cover on several indices involved

differentiate between submerged mangroves and water bodies. Submerged mangroves have a range of -0.25 to 0.75, while water bodies have a narrower range of values, namely around 1 (Jia *et al.* 2019). Hickey and Radford (2022) reported that the range of MNDWI values for mangroves is in the range of 0.1 to 0.125 and is an important index in detecting the presence of mangroves because it shows a correlation with the presence of mangroves in the random forest classification algorithm. LSWI is the most important indicator in distinguishing wetlands and dry lands and has a value range for mangrove cover of around 0.4 to 0.6 (Fan *et al.* 2023). The research results of Rahmawati *et al.* (2022) shows that IBI is an index that has a weak level of accuracy in classifying mangroves individually and has a value range of around 0 to 0.2.

Indices Abbility for mangrove classification

The mangrove ecosystem has several object features that can be received by remote sensing sensors, namely vegetation and water, so that the spectral index value has the potential to be in the range of values for water bodies and non-mangrove vegetation. Figure 13 shows the index threshold values for land cover of mangrove vegetation, non-mangrove vegetation and water bodies. The threshold values for the three land covers in the water index show the order of the highest spectral values, namely water bodies, mangroves and non-mangrove vegetation. Similar results were reported by Sahadevan *et al.* (2021) that the MNDWI value in mangroves has a range of values below water bodies and above non-mangrove edge vegetation that still overlaps with the range of values for non-mangrove vegetation so that this index is able to differentiate well between mangrove vegetation and water bodies. In contrast to other water indices, LSWI for mangroves has a slightly smaller middle value than for non-mangrove vegetation even though non-mangrove vegetation has a value that extends downwards. When used simultaneously with the LSWI vegetation index, it is able to differentiate types of water bodies from wetlands (Dong *et al.* 2014). Vegetation indices such as CARI MCARI and SAVI in mangroves have the highest spectral index values compared to non-mangrove vegetation and water bodies, while EVI has the lowest spectral values compared to other land covers. The SAVI formula uses a multiplier factor in producing an index algorithm and the value of the multiplier factor can be optimal in several circumstances according to the type of land cover being classified (Rhima *et al.* 2020).

Each index has the ability to detect mangroves in the study area. The ability of a single index to differentiate mangrove and non-mangrove vegetation is shown in Figure 14. This figure shows that MNDWI and MCARI are able to differentiate well between mangrove and non-mangrove vegetation. Based on the report by Rahmawati *et al.* (2022), MNDWI is able to distinguish two types of vegetation, namely mangrove and non-mangrove vegetation, which other spectral indices do not. Basically, MCARI is an index used to estimate tree health, including nutrient deficiencies such as nitrogen and has no correlation with the presence of land cover such as water bodies (Perry and Robert 2008). MCARI has a large correlation with the relative amount of chlorophyll in leaves and has low values in water bodies (Gillani *et al.* 2023).

Sentinel-2 Indices Time Series of Mangrove

Time series tracking results of NDVI values from April 2016 to October 2023 show that starting January 2020, NDVI values increased rapidly (figure 15). This is also shown in Figure 10 that the vegetation index has a tendency to increase in value as mangrove succession progresses. An increase in NDVI values indicates mangrove succession both naturally and as a result of planting at certain locations, especially site D. Site D is located at a river estuary which is prone to sedimentation. Mangrove vegetation has the ability to trap sediment. Mangrove roots, especially the Rhizophora sp type, have a good ability to trap sediment (Erlangga *et al.* 2022). Trapped sediment stimulates mangrove succession which leads to land accretion (Salim *et al.* 2016). The results of the regression analysis show that NDVI has a linear correlation with mangrove density with an R square value of 81.66% (Umarhadi and Syarif 2017). Apart

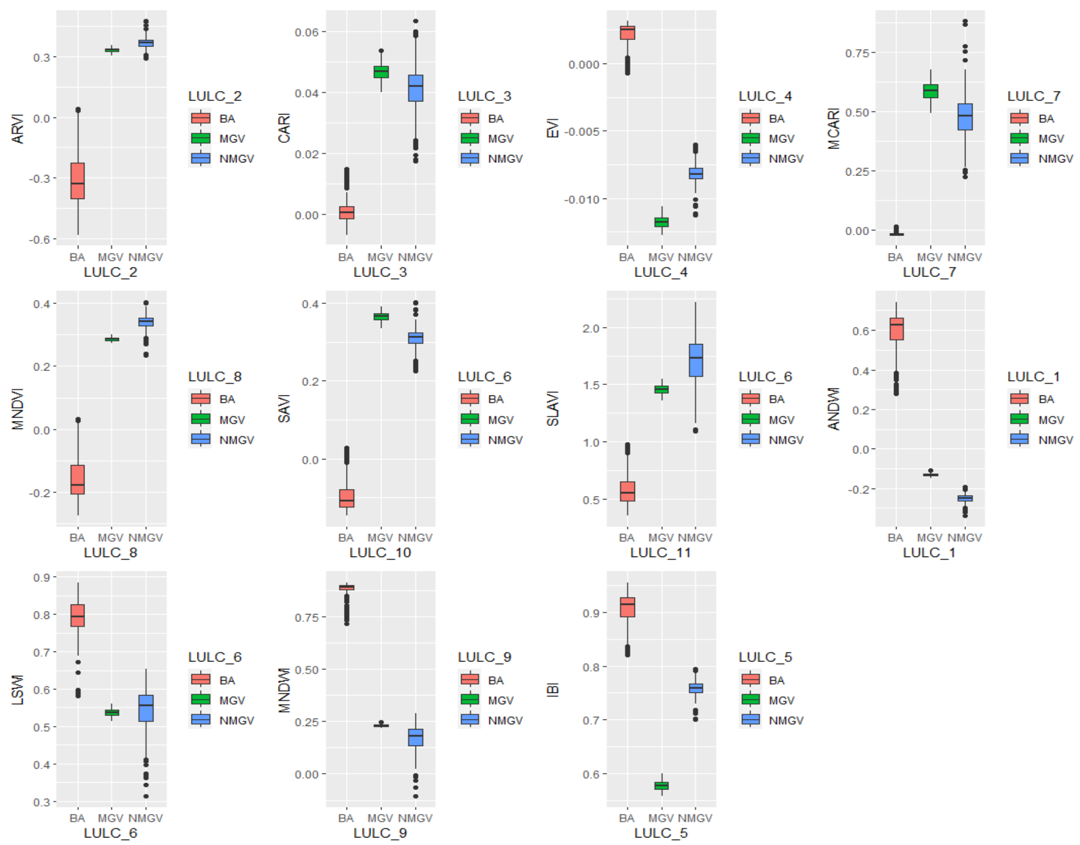

Figure 13. Differences in index threshold values for mangrove land cover, non-mangrove vegetation and water bodies

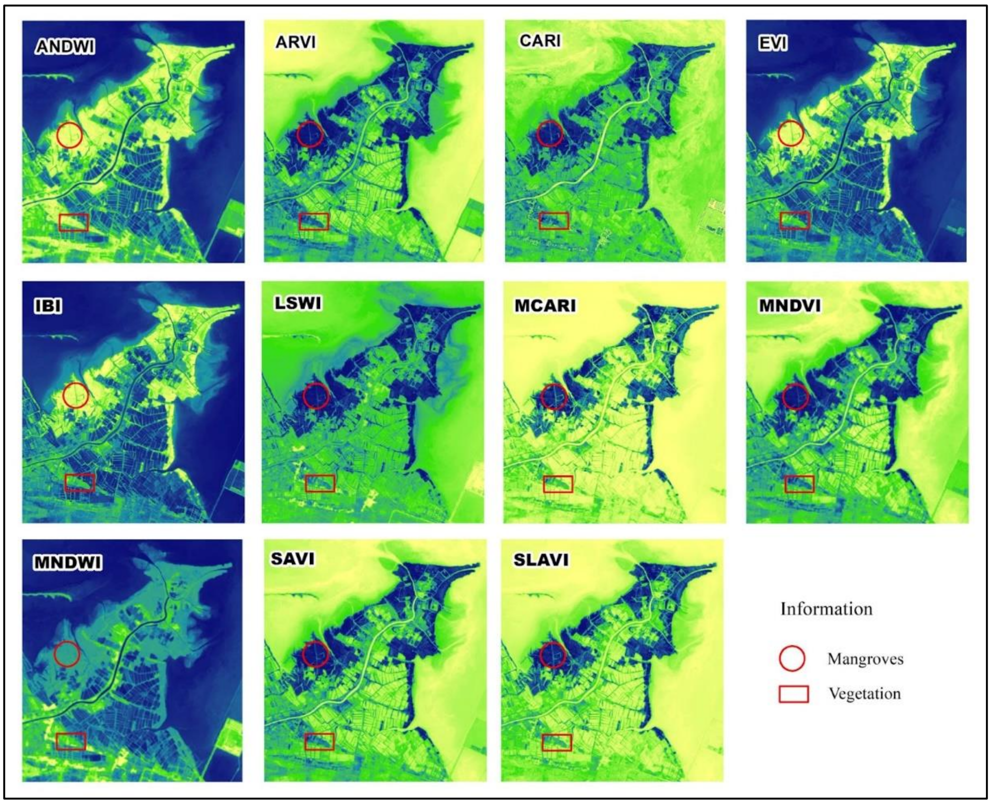

Figure 14. The ability of the index to visually differentiate mangrove and non-mangrove vegetation

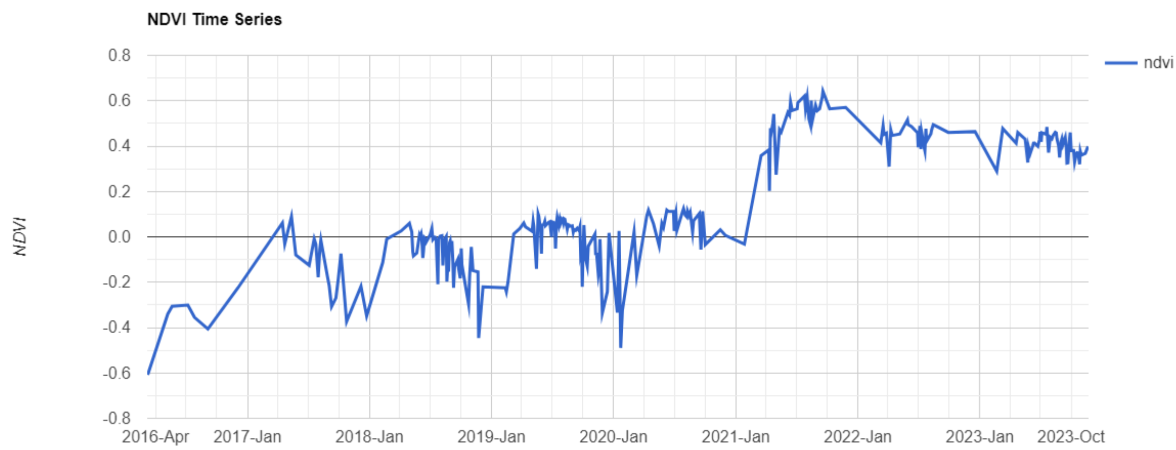

Figure 15. Sentinel-2 Time Series of mangrove

from that, NDVI can also estimate mangrove biomass through linear regression modeling (Muhd-Ekhzarizal *et al.* 2018). Fluctuations in NDVI values occurred during this period. NDVI spectral values tend to fall in January. This decrease is indicated by a wet month and flooding during that month, which affects the reflectance emitted by mangroves. NDVI spectral values tend to be low in water bodies and are able to detect areas affected by waterlogging (Amarnath 2013).

Accuracy Assesment

The accuracy assessment aims to determine the performance of the machine learning system that was built in carrying out land classification. The results of the accuracy analysis are displayed in the confusion matrix (Table 2). The results of the accuracy assessment show that the overall accuracy in detecting LULC is 90.38% with a kappa statistic of 86.66%. Mangrove producer accuracy is quite high at 98.44% and this means the system is capable of detecting mangrove areas well. As a comparison to the research results of Jhonnerie et al. (2015) showed that the overall accuracy of mangrove detection using the random forest algorithm was 81.1% involving the NDVI, NDWI and NDBI indices. The number of land cover detected was 8 types so it had high heterogeneity in land cover. Rahmawati & Asy'Ari (2021) reported that the use of several water and built vegetation indices in detecting mangrove areas gave an overall accurate value of 96.5% with kappa statistics of 0.93. The use of several indices with a random forest algorithm is also able to detect heterogeneous land cover of 10 types of land cover and produces an overall accuracy of 80.08% (Asy'Ari *et al.* 2023). Meanwhile, the research results of Purwanto *et al.* (2023) shows an overall accuracy value for mangrove area classification of 97.79 with the land cover involved, namely mangrove, non-mangrove and water bodies. This shows the need for the involvement of several indices to detect LULC to increase accuracy. The random forest algorithm also has the ability to detect the spatial distribution of mangrove species. The use of several spectral indices in Sentinel-2 can detect the spatial distribution of mangrove species with an overall accuracy of 74% (Bahera *et al.* 2021).

Approach limitation and Spatial Future Work

This research aims to reveal the spatial distribution of mangroves on the coast of Subang Regency, West Java using remote sensing technology and the spectral characteristics of the indices involved. The research results only show the presence of mangroves displayed in GIS. Ecosystem assessments such as carbon storage and uptake, ability to withstand tidal waves and wind, and their benefits as food need to be carried out to find out how much actual value the mangrove ecosystem has in providing ecosystem services as a consideration for local government policy making. In the future, spatial analysis involving several indices needs to be assessed for its ability to model economic valuations such as stored carbon reserves, temperature reduction capabilities, and abrasion resistance capabilities with time series data.

Policy Recommendation and Mangrove Social Action

Table 2. Confusion matrix and accuracy measures

Land use	Data validasi						Sum (User's)
	MGV	Non-MGV	Bare Land area	Build-up area	Water body	Agriculture	
MGV	190	0	3	0	0	0	193
Non-MGV	0	32	0	0	0	1	33
Bare Land area	0	0	20	5	0	2	27
Build-up area	0	0	17	22	0	0	39
Water body	7	0	0	0	55	0	62
Agriculture	4	0	2	0	0	66	72
Sum (Producer's)	201	32	42	27	55	69	426

	User's accuracy (%)	Producer's accuracy (%)
MGV	98,44	94,53
Non-MGV	96,97	100,00
Bare Land area	74,07	47,61
Build-up area	56,41	81,48
Water body	88,71	100,00
Agriculture	91,66	95,65

Overall accuracy (OA)	: 90,38%
Kappa statistics	: 86,67%

Restoring the mangrove ecosystem is the latest solution now to contribute to suppressing rapid climate change. This paper has provided information on mangrove areas that are degraded, but in some places still have a good future. Mangroves in the eastern river delta area of the Subang Regency area make it possible to become an example of a mangrove ecosystem restoration area. Even in this landscape, it was found that some residential areas had been submerged and this was followed by concern for planting mangrove species in the surrounding areas. In this area, some mangroves grow abundantly and experience natural succession in the pond area, especially for the Rhizophora Sp species. This opportunity is a natural barrier to protect coastal residential areas that were previously threatened by tidal floods. Land use needs to be controlled, especially use in the form of fish farming. This has been a threat for years to the existence and ecological function of mangroves in protecting the coast.

CONCLUSIONS

GIS remote sensing technology involving several indices shows its ability to detect mangrove distribution. The results of mangrove distribution detection show that mangrove vegetation is distributed at sites A, B, C and D with a total area of 1972.98 ha. Spatio temporal analysis shows that only site D experienced an increase in the area of mangrove vegetated sites due to natural succession and planting. Several indices involved have their own characteristics in modeling mangrove succession. The vegetation indices except EVI showed a fairly rapid increase in 2020, which indicates mangrove planting, while the water and built indexes have a downward trend due to mangrove succession. The index threshold values for mangrove land cover from the highest median to the lowest in sequence are SLAVI, CARI, IBI, LSWI, SAVI, ARVI, MNDVI, MNDWI, CARI, EVI, and ANDWI. Meanwhile, the spectral values of several indices are not overlaid with the other indices ANDWI, CARI, SLAVI, and EVI. The water spectral index value in mangroves is lower than water bodies and higher than non-mangrove vegetation. MNDWI has good abilities in distinguishing mangrove and non-mangrove vegetation. The results of the accuracy assessment show that the overall accuracy value for the LULC classification is 90.38% and the kappa statistic is 86.67%.

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