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Research Article

Vegetation-Water-Built Up Index Combined: Algorithm Indices Combination for Characterization and Distribution of Mangrove Forest through Google Earth Engine

Vegetation-Water-Built Up Index Combined: Kombinasi Algoritma Indeks untuk Karakterisasi dan Distribusi Hutan Mangrove Melalui Google Earth Engine

Azelia Dwi Rahmawati[1,2*], Rahmat Asy'Ari[1,2], Muhammad Aqbal Fathonah[1,2], Priyanto[3], Neviaty P. Zamani[4,5], Rahmat Pramulya[6,7], Yudi Setiawan[7,8]

[1] Undergraduate Student, Department of Forest Management, Faculty of Forestry and Environment, IPB University, Bogor, 16680, West Java, Indonesia

[2] IPB Sustainable Science Research Students Association (IPB SSRS Association), IPB University, Bogor, 16680, West Java, Indonesia

[3] Department of Forest Management, Faculty of Forestry and Environment, IPB University, Bogor, 16680, West Java, Indonesia

[4] Department of Marine Science and Technology, Faculty of Fisheries and Marine Sciences, IPB University

[5] Center for Transdisciplinary and Sustainability Sciences, IPB University

[6] Faculty of Agriculture, University of Teuku Umar, Meulaboh, 23681, Aceh, Indonesia

[7] Department of Forest Resources Conservation and Ecotourism, Faculty of Forestry and Environment, IPB University, Bogor, 16680, West Java, Indonesia

[8] Center for Environmental Science, IPB University

Abstract: Mangroves that live in ecotone areas have a fairly significant role in the economy and ecology. This strategic role requires spatial data to facilitate the management and development of mangrove areas. The mangrove mapping process usually uses a manual method, namely through software, and has shortcomings and limitations in image management that require massive data storage. Cloud computing-based Google Earth Engine (GEE) mapping platform can manage images with an extensive scope and spatiotemporal data processing. However, this platform requires index formulas or combinations to help classify and increase accuracy in mapping the earth's surface. The innovation with the combined VWB-IC (Vegetation-Water-Built-up Index Combined) formula is projected to classify the characteristics of mangrove areas in Jakarta Bay. The combination consists of three types of indices, namely vegetation index (NDVI, GNDVI, ARVI, EVI, SLAVI, and SAVI), water (NDWI, MNDWI, and LSWI), and buildings (IBI and NDBI). This combination is used to translate the classification of mangroves using the Random Forest (RF) machine learning algorithm method with the Sentinel-2 MSI (Multispectral Instrument) satellite image source and through the GEE platform. This platform generates raster data for land use classification (including mangroves), and then the analysis is continued using ArcMap software. The obtained mangrove area is 220.43 ha, located in Jakarta Bay and divided into the Angke Kapuk Nature Tourism Park and the Pantai Indah Kapuk Mangrove Ecotourism Area. The data from this research is expected to provide a recommendation for a combination index formula for mapping mangrove areas in urban areas. The spatial distribution area can be used as an evaluation material in mangrove areas in Jakarta Bay.

Keywords: Index, Machine learning, Mangrove Forest, Random Forest, Sentinel-2 MSI.

Abstrak: Mangrove merupakan vegetasi yang hidup di wilayah ekotone dan memiliki peranan yang cukup besar diantaranya sebagai sumber ekonomi (silvofishery dan ekowisata) dan ekologi (mitigasi bencana, biofilter air, dan habitat satwa liar). Peran strategis tersebut membutuhkan data distribusi berbasis spasial untuk memudahkan pengelolaan dan pengembangan kawasan mangrove terutama di Teluk Jakarta. Proses identifikasi ataupun estimasi secara temporal pada kawasan mangrove biasanya memakai citra satelit dengan proses data melalui software pemetaan yang memiliki keterbatasan dalam pengolahan citra dengan penyimpanan data yang cukup besar. Kehadiran platform pemetaan Google Earth Engine berbasis cloud computing memiliki kemampuan dalam pengelolaan citra besar dengan cakupan sangat luas, maupun pemprosesan data berbasis

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spatiotemporal. Akan tetapi, platform ini membutuhkan formula indeks maupun kombinasinya yang dapat membantu klasifikasi dan meningkatkan akurasi dalam memetakan permukaan bumi. Inovasi dengan formula indeks kombinasi VWB-IC (*Vegetation-Water-Built up Index Combined*) diproyeksikan dapat memberikan klasifikasi yang sesuai dengan karakteristik kawasan mangrove di wilayah studi. Kombinasi tersebut terdiri dari tiga jenis indeks yaitu indeks vegetasi (NDVI, GNDVI, ARVI, EVI, SLAVI, dan SAVI), air (NDWI, MNDWI, dan LSWI) dan bangunan (IBI dan NDBI). Kombinasi tersebut digunakan untuk menerjemahkan klasifikasi mangrove dengan metode klasifikasi machine learning algoritma Random Forest (RF) dan menggunakan citra satelit Sentinel-2 MSI (MultiSpectral Instrument) melalui platform pemetaan Google Earth Engine. Dari hasil analisis tersebut, dihasilkan data raster klasifikasi land use (termasuk mangrove) dan analisisnya menggunakan software ArcMap. Kawasan mangrove yang didapatkan seluas 220,43 ha yang berada di Teluk Jakarta dan terbagi atas dua kawasan yaitu Taman Wisata Alam Angke Kapuk dan Kawasan Ekowisata Mangrove Pantai Indah Kapuk. Data hasil riset ini diharapkan dapat memberikan rekomendasi formula kombinasi indeks untuk pemetaan kawasan mangrove di wilayah urban dan luas distribusi spasial dapat dijadikan bahan evaluasi dalam pengelolaan kawasan mangrove di Teluk Jakarta.

Kata kunci: Indeks, Machine learning, Mangrove, Random Forest, Sentinel-2 MSI

*email:
azeliadrazelia@apps.ipb.ac.id

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INTRODUCTION

Mangroves are a group of plants that live in coastal or ecotone areas whose lives are influenced by tidal activity (Reis-Filho et al. 2016; Yao & Liu 2017). Its location on the coast makes this vegetation group have a strategic role both in terms of ecology and economy. Mangroves were discovered in 325 BC and scientifically published by Bowman (1917) for the first time, hiding their uniqueness and diverse functions. It is known that this vegetation plays a role in socio-economic terms in the form of physical use (firewood, silvofishery, and others) and ecologically (ecotourism) (Sandilyan & Kathiresan 2012; Lee et al. 2014). In addition, there are other important roles, namely as a protector of coastal areas (Giri et al. 2008) and climate change disaster mitigation (Ghosh et al. 2020; Pham et al. 2019A). Flores-Cardenas et al. (2018) revealed that mangroves are essential components of coastal ecosystems, including regulating nutrient filtration, as well as providing habitat and nursery areas for various terrestrial and marine species. However, this role is currently being used continuously without considering vegetation regeneration which requires a long process (Pham et al., 2019B; Liu et al., 2018). As a result, overexploitation occurs in various areas with mangrove distribution and is in contact with the community, making the area's status critical (Goldberg et al., 2020; Ghosh et al., 2020; Huxham et al., 2017).

Vaiphasa et al. (2006) and Goldberg et al. (2020) reported that the global decline in tropical mangrove forests is one of the world's most severe problems for coastal ecosystems. The worst impact of this problem is the loss of carbon stocks in mangrove areas as climate change disaster mitigation (Ghosh et al., 2020; Twilley et al., 2017). The follow-up to this problem prompted researchers to respond by identifying the spatial distribution of mangroves to assist decision-makers in protecting and rehabilitating the area (Terchunian et al., 1986; Sandilyan & Kathiresan, 2012). Remote sensing with object-based methods with various advantages has been used since 1986 to identify the earth's surface vegetated with mangroves (Conchedda et al., 2008). This is in line with the discovery of indices since the 19th century, which are intended to help identify the earth's surface, such as the vegetation index (Rouse jr et al. 1974) and the water index (McFeeters 1996), as well as following the building index in the 20th century (Zha et al. 2003; Xu 2008).

Various studies have used a single index and a modification in the identification of mangroves by translating the spectral reflected by mangrove vegetation and received by satellite (Rees 1998; Curran et al. 1990; Jackson & Huete 1991). For example, the NDVI index (Normalized Difference Vegetation Index) has long been used in monitoring mangroves. Valderrama-Landeros et al. (2014) used an index to map mangroves in Mexico and involved four image sources, namely Landsat-8, SPOT-5, Sentinel-2, and WorldView-2. And other indices, such as Berlanga-Robles & Ruiz-Luna (2020), use the EVI index, while Maryantika & Lin (2017) use a combination index (NDVI-GNDVI-SAVI) to explore changes in mangrove cover in Sidoarjo. In addition, using the Google Earth Engine (GEE) platform for mangrove detection is one of the breakthroughs/alternatives provided by Google in managing geospatial data globally (Gorelick et al., 2017; Mutanga & Kumar, 2019). The platform can access various satellite imagery (Kumar & Mutanga, 2018), so it is often used in monitoring mangrove vegetation (Chen et al., 2017; Liu et al., 2021).

It is necessary to have maximum conservation and protection based on the condition of mangroves in Jakarta, which are essential and threatened (Dsikowitzky et al. 2016). Furthermore, the Jakarta area is located in a river delta prone to natural disasters (Dsikowitzky et al., 2019); this makes the mangrove area a vital role on the coast. Therefore, mapping that combines various indices to detect the distribution of mangroves is one form of support in fulfilling an accurate database. The same thing was expressed by Terchunian et al. (1986) and Ghorbanian et al. (2021) that it is crucial to have mapping products to help protect, preserve, and plan reforestation in mangrove areas.

This study uses Sentinel-2 imagery with a spatial resolution of 10 to 60 meters (Phiri et al., 2020) and through the classification process of the Random Forest (RF) algorithm on the GEE mapping platform. Kamal et al. (2014) stated that the optimal pixel size of the image helps support practical mapping activities in the mangrove environment. Therefore, the detailed scale mapping is hoped to provide recommendations for determining policies. In addition, the results of this paper can be used as reference material for further research on the combination of indices and their involvement in identifying mangroves.

MATERIALS AND METHODS

Research Location and Time

This research was conducted in the mangrove area of Angke Kapuk Nature Tourism Park and Pantai Indah Kapuk ecotourism, North Jakarta City, DKI Jakarta Province (Figure 1). This research took place in August - September 2021 using remote sensing media and various spatial data.

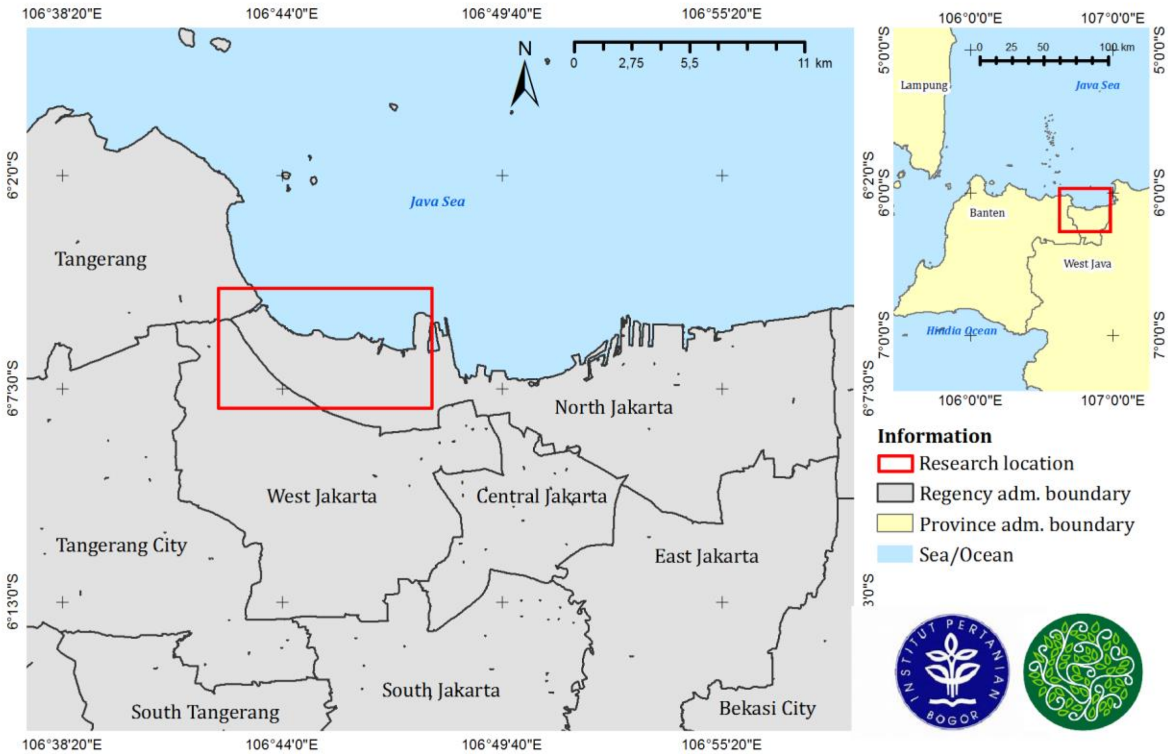


Figure 1. Study location

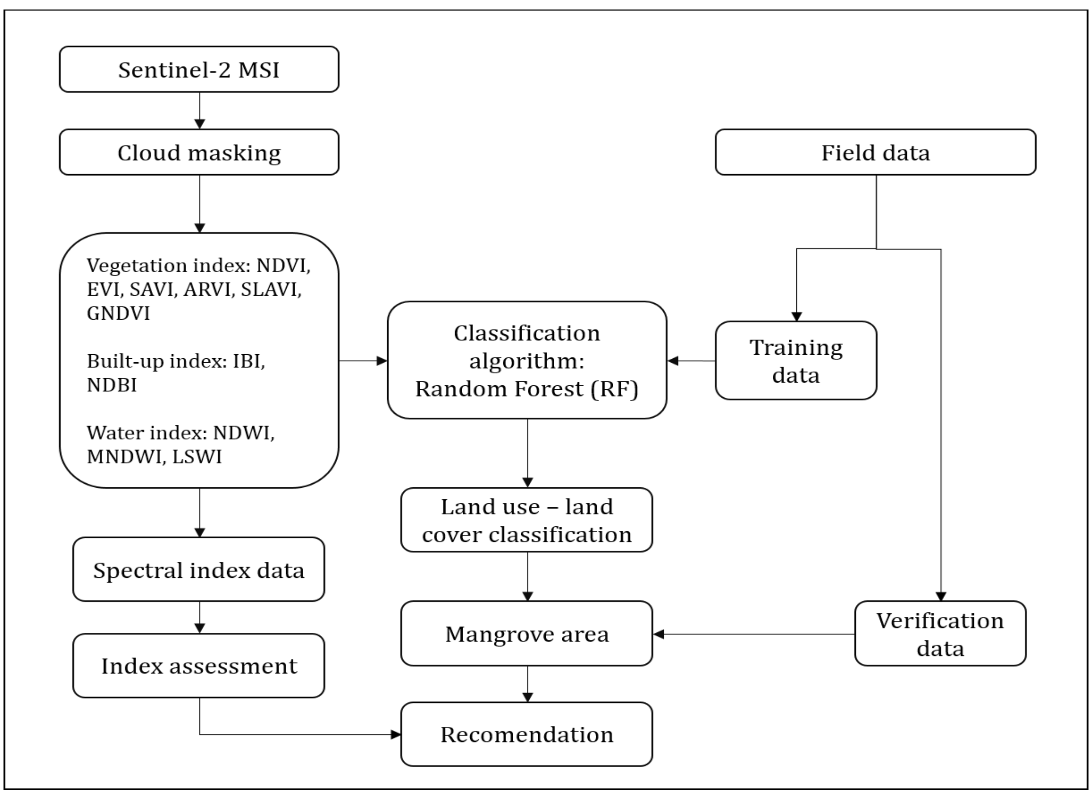


Figure 2. The methodological framework of this study

Data Sources and Research Flow

This study uses data sources, including Sentinel-2 MSI (Multispectral Instrument) satellite imagery, SRTM (Shuttle Radar Topography Mission) data, and RBI (Indonesian Rupa Bumi) maps. Sentinel-2 image data processing through various land use classification analyses using the Random Forest (RF) algorithm by considering the modified index through the Google Earth Engine (GEE) platform, then proceeding with the separation of mangroves from other land uses using ArcMap software. The resulting image then overlapped with the elevation from the SRTM and RBI data to find the administrative location of the mangrove distribution. The flow of scientific thinking is presented in a flow chart (Figure 2).

Table 1. Sentinel-2 MSI bands

Band	Band	Wavelength (nm)	Bandwidth (nm)	Resolution (m)
B1	Coastal aerosol	433 – 453	20	60
B2	Blue	458 – 523	65	10
B3	Green	543 – 578	35	10
B4	Red	650 – 680	30	10
B5	Red-edge 1 (RE1)	698 – 713	15	20
B6	Red-edge 2 (RE2)	733 – 748	15	20
B7	Red-edge	773 – 793	20	20
B8	Near infrared (NIR)	785 – 900	115	10
B8a	Near infrared narrow (NIRn)	855 – 875	20	20
B9	Water vapour	935 – 955	20	60
B10	Shortwave infrared/Cirrus	1360 – 1390	30	60
B11	Shortwave infrared 1 (SWIR1)	1565 – 1655	90	20
B12	Shortwave infrared 2 (SWIR2)	2100 – 2280	180	20

Spectral Analysis with Vegetation, Water, and Building Index Algorithms

Several indices have been included in this study to assist the process of identifying mangrove vegetation in the study area. The index can translate the spectral reflected by the earth's surface, especially mangroves (Rees, 1999). Several indices were involved and selected based on their specific function and purpose according to the characteristics of the water-affected mangroves. The build-up index is involved because the mangrove area is located in an urban area with ecotourism-supporting buildings (Slamet et al., 2020). The indices used are presented in this table.

Table 2. List of indexes involved in this study

No	Method	Formula	Reference
1	Normalized Difference Vegetation Index (NDVI)	NDVI = (NIR - Red) / (NIR + Red)	Rouse jr. (1974)
2	Normalized Difference Water Index (NDWI)	NDWI = (Green - NIR) / (Green + NIR)	McFeeters (1996)
3	Enhanced Vegetation Index (EVI)	EVI = G ((NIR - Red) / (NIR + C1 x Red - C2 x Blue + L))	Huete et al., (2002)

No	Method	Formula	Reference
4	Soil Adjusted Vegetation Index (SAVI)	SAVI = 1.5 (NIR - Red)/ (NIR + Red + 0.5)	Rouse jr. (1974)
5	Atmospherically Resistant Vegetation Index (ARVI)	ARVI = (NIR - (Red - (Blue - Red))) / NIR + (Red - (Blue -Red)))	Kauffman & Tanre (1992)
6	Specific Leaf Area Vegetation Index (SLAVI)	SLAVI = NIR / (Red + SWIR)	Lymburner et al. (2000)
7	Index- Based Built- up Index (IBI)	IBI = ((NIR)/NIR + Red)) + ((Green)/Green + SWIR1))	Xu (2008)
8	Green Normalized Difference Vegetation Index (GNDVI)	GNDVI = (NIR - Green) / (NIR + Green)	Gitelson et al. (1996)
9	Normalized Difference Built-up Index (NDBI)	NDBI = (SWIR - NIR) / (SWIR + NIR)	Zha et al. (2003)
10	Modified Normalized Difference Water Index (MNDWI)	MNDWI = (Green - SWIR1) / (Green - SWIR1)	Xu (2006)
11	Land Surface Water Index (LSWI)	LSWI = (NIR - SWIR) / (NIR + SWIR)	Xiao et al. (2002)

Information:

Blue	: Blue Band (Band-2)
Green	: Green Band (Band-3)
Red	: Red Band (Band-4)
NIR	: Near-Infrared Band (Band-8)
NIRn	: Near-Infrared narrow Band (Band-9)
SWIR	: Shortwave-Infrared Band (Band-11)
L	: Canopy calibration factor and soil brightness effect (value 1)
C1 C2	: Aerosol coeffisient, 6.0 and 7.5
G	: Value 2.5

Random Forest (RF) Algorithm Classification

Land use classification is carried out to separate land use in mangroves from other land uses. Previously known, the Random Forest (RF) algorithm is one of the machine learning products (Maxwell et al., 2018). This product is often applied in several studies regarding the detection of LULC (land use & land cover) and using Sentinel-2 imagery, for example, in the research of Thanh Noi & Kappas (2018). This classification method was launched in 2001 by Breiman (Breiman, 2001) and employed decision tree-based capabilities with accurate data classification (Qi, 2012; Maxwell et al., 2018; Sheykhmousa et al., 2020).

This RF classification process takes place on the Google Earth Engine platform based on a JavaScript programming script. In addition, this method requires training as a desire to determine the type of land use. Therefore, the training data was taken using a random sampling method based on the distribution of land use types, namely mangroves (55), water bodies (43), settlements (50), non-mangrove vegetation (16), and open land (44). The training data collection took place in the Google Earth pro software, with the image source taken in June 2021. This training data was inputted into the GEE platform as RF reference material for classifying mangroves at the study site. The classification process used the RF algorithm with 10 trees.

Accuracy Analysis

Accuracy analysis is the final step in the research process. This is needed to know how accurate our research is (Story & Congalton, 1986). In remote sensing studies, validation data is essential for precise analysis to present accurate results (Lewis & Brown, 2001; Hu & Wang, 2013). This accuracy calculation involves a Confusion matrix table with an assessment of the classification accuracy using Overall Accuracy (OA) and Kappa Statistics. Berberoglu & Akin (2009) explain that the error matrix and Kappa analysis are often used to assess land use change detection accuracy. The accuracy calculation in this research is based on validation data obtained from the Google Earth software equipped with high-resolution images in June 2021 data of 82 data. Then, the equations used in the accuracy method are presented in the following equation.

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

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

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

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

RESULTS AND DISCUSSION

Study Location Mangrove Condition

Slamet et al. (2020) explained that the mangroves in Jakarta are one of the remaining urban mangrove areas in DKI Jakarta Province; the rest are in the Seribu Archipelago (Seribu Archipelago National Park). This mangrove area is also one of the mangrove ecosystems on the south coast with specific characteristics. The mangrove area in the study area has various potentials that can be utilized by the local community (Wardhani, 2011; Bibin & Ardian, 2020). For example, local people use the area for silvofishery activities (Wijaya et al., 2019). On the other hand, the Ministry of Environment and Forestry (KLHK) and The Provincial Environment Service have made this area a natural tourism centre of mangroves (Putra, 2014). This is also supported by the determination of the status of the area as a natural tourism park (TWA) and wildlife reserve (SM) by the central government (Yusrini, 2018).

The existence of mangrove areas in the study area has many good impacts from an economic and ecological perspective that can be obtained by the local community (Zainuri et al., 2017). Its location in Jakarta Bay makes this area very strategic and essential in mitigating natural disasters. However, population growth followed by urban development requires land to construct settlements, public facilities, and supporting infrastructure. As a result, the mangrove area on the north coast of DKI Jakarta Province often experiences the threat of reclamation, which causes prolonged land degradation (Slamet et al., 2020). In addition, unsustainable use also frequently occurs in this area, disrupting the ecology of the mangrove area. Diaz & Blackburn (2003) explain that the mangrove ecosystem is very fragile and sensitive to fluctuations in environmental changes caused by high soil salinity, tides, and storms. This also impacts the flora and fauna biodiversity level (Table 3). Therefore, protection and rehabilitation of the area are necessary, involving many parties ranging from government, local communities, and private companies operating in the surrounding area.

Table 3. Mangrove composition

No	Local Name	Scientific Name	Location				Source
			MA	AK	HL	EM	
1	Pidada merah	*Sonneratia caseolaris*	1	1	1	0	Ba; Mu
2	Pidada putih	*Sonneratia alba*	0	0	0	1	Mu
3	Bakau	*Rhizophora apiculata*	0	1	1	0	Mu
4	Bakau	*Rhizophora stylosa*	0	1	1	0	Ba; Mu
5	Bakau	*Rhizophora mucronata*	1	1	1	0	Mu
6	Bakau	*Rhizophora mangle*	0	0	0	1	Mu
7	Api-api	*Avicennia marina*	1	1	1	0	Mu
8	Api-api	*Avicennia alba*	0	1	0	0	Mu
9	Api-api	*Avicennia officinalis*	0	0	1	0	Mu
10	Putut	*Bruguiera gymnorrhiza*	0	1	1	0	Mu
11	Berus	*Bruguiera cylindrical*	0	0	0	1	Mu
12	Nyiri	*Xylocarpus moluccensis*	1	0	1	0	Mu
13	Nyiri	*Xylocarpus granatum*	0	1	0	1	Mu
14	Bintaro	*Cerbera manghas*	0	0	1	0	Mu
15	Nipah	*Nypa fruticans*	1	0	0	1	Mu
16	Madengan	*Excoecaria agallocha*	1	0	0	0	Mu
17	Ketapang	*Terminalia catappa*	1	0	0	0	Mu
18	Waru	*Hibiscus tiliaceus*	1	0	0	0	Mu

Note: MA:Muara Angke, AK:Angke Kapuk, Ba: Baihaqi et al. (2017), Mu: Mulyaningsih et al. (2018)

Landuse and Mangrove Classification

Classification of land use types produces a mangrove area of 220.43 ha. The result from a classification process supported by 11 indices and the Random Forest (RF) classification was carried out through the Google Earth Engine platform. The analysis results show that the mangrove distribution is primarily focused on Jakarta Bay or the mangrove area of TWA Angke Kapuk (Angke Kapuk Nature Tourism Park; Figure 3). In contrast, the other mangroves are scattered in the Pantai Indah Kapuk Mangrove Nature Tourism area (PIK). A reclamation island squeezes the mangrove area in the study area from the north. The surrounding area is also a housing complex for urban communities in Jakarta. This followed the statement of Slamet et al. (2020), which explains that reclamation activities on an artificial island threaten the mangroves in the study area.

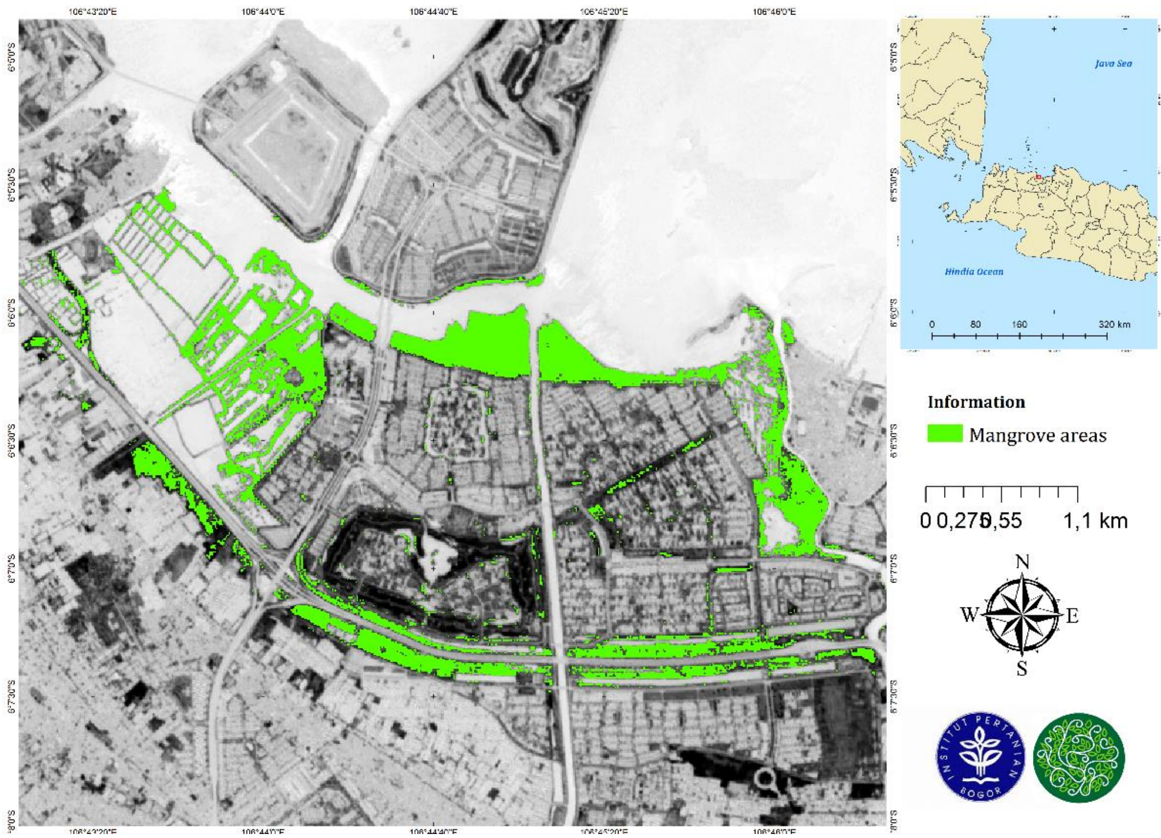


Figure 3. Spatial distribution of mangroves at the study site

Indices Characteristics

Each index has different characteristics in translating the earth's surface. This can be seen from the threshold value read on mangrove vegetation through each index (Figure 4). The threshold values obtained have differences and similarities between the threshold interval between the index. For example, the index ARVI (0.0803 - 0.5632), GNDVI (0.1750 - 0.5946), and SAVI (0.1477 - 0.5303) have the same threshold interval, and other indices such as the NDWI and NDBI indices. However, other indices (*i.e.,* SLAVI and EVI) have significant interval differences. This matter is the advantage of the spectral index after translating the characteristic wavelength of an object on the earth's surface that is reflected and received by satellite sensors.

If we look at the frequency distribution characteristic of the threshold value, the index has the same shape as the index spectral frequency curve (Figures 5, 6, and 7). However, each index has a different distribution frequency. Spatially, these indices have differences in showing the color pattern of land vegetated with mangroves, as well as the type of use. For example, the NDVI, ARVI, and GNDVI indexes have a sharpness that differs from the EVI, SLAVI, and SAVI indexes describing color sharpness only on vegetated land.

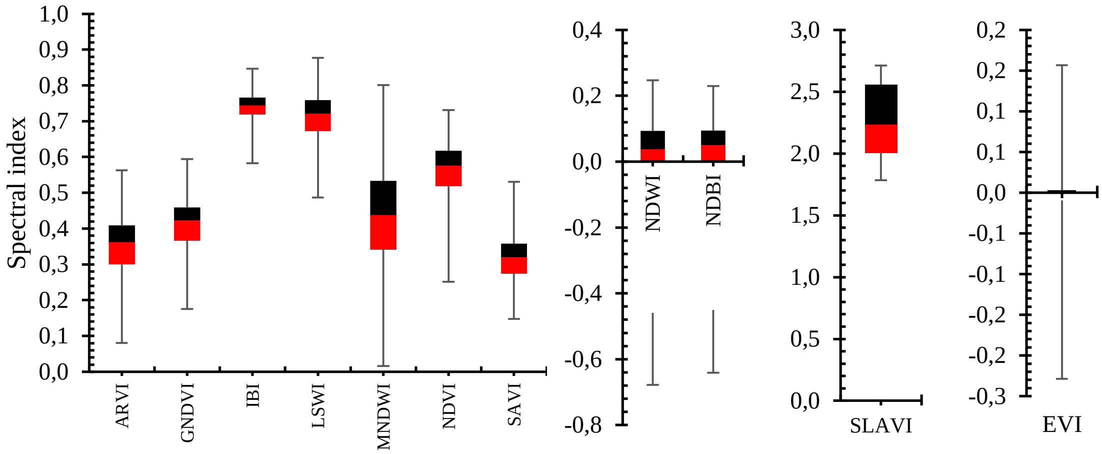
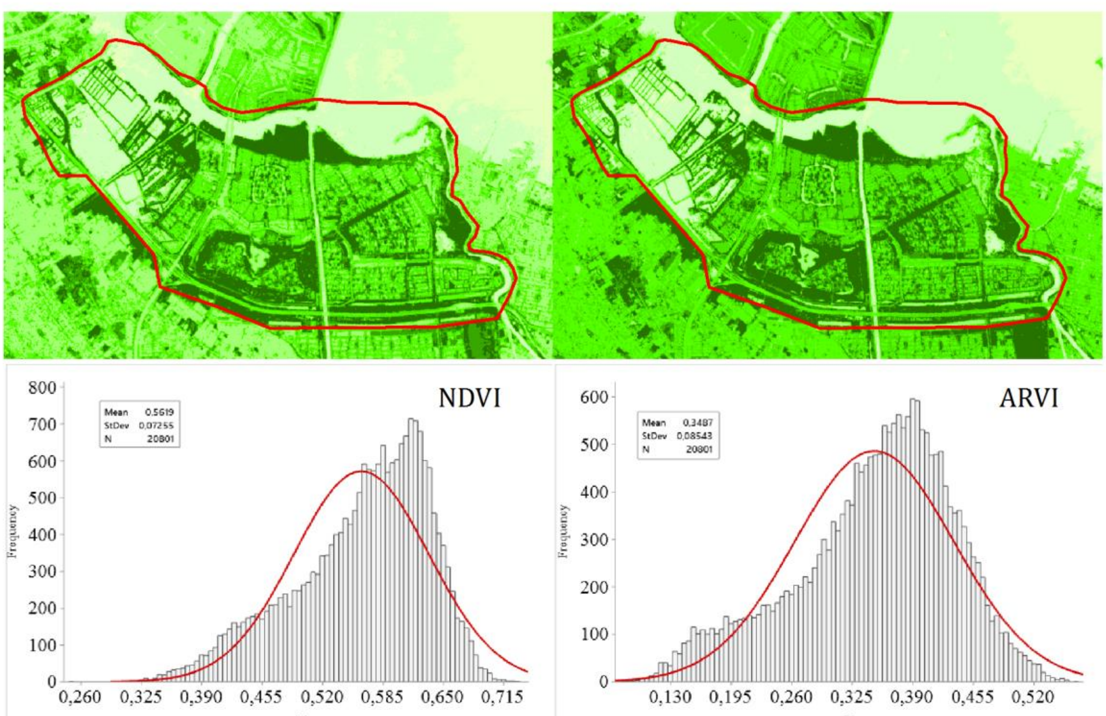


Figure 4. The threshold values specified for each index

In the SAVI index, the soil and building brightness impact is visible in the effects of the wavelength and can be read by the index. SAVI Spectral showed a more striking difference in non-vegetated land, as indicated by the spectral index's low value compared to vegetated land. In contrast, the SLAVI index was specially developed to monitor vegetated objects with a sensitivity level of leaf area. Lymburner et al. (2000) explained that the specific leaf area (SLA) is an essential ecological variable in identifying vegetation based on the length of reflected waves because it relates to plant ecophysiology and leaf biochemistry.



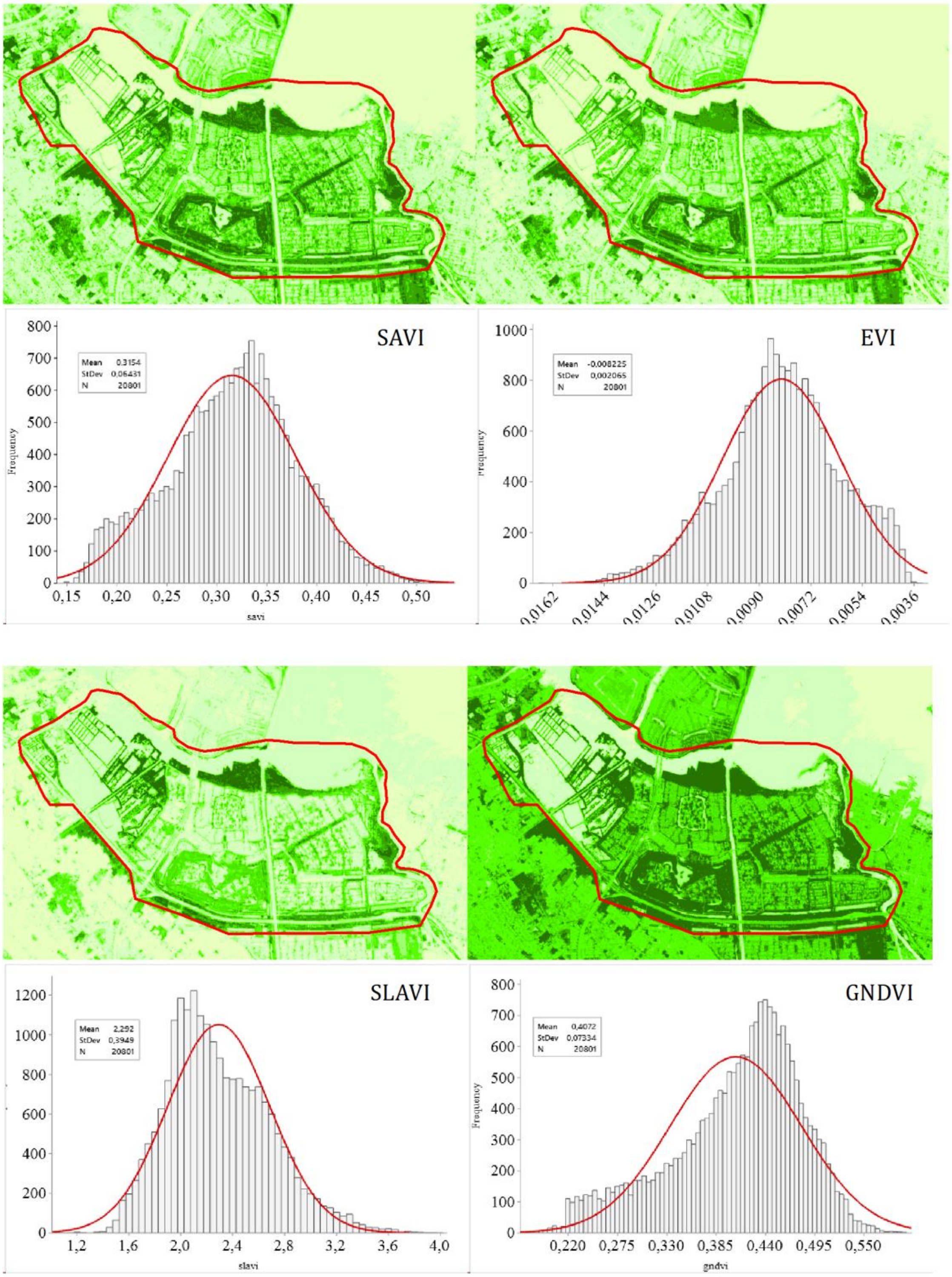


Figure 5. Characteristics of each vegetation index

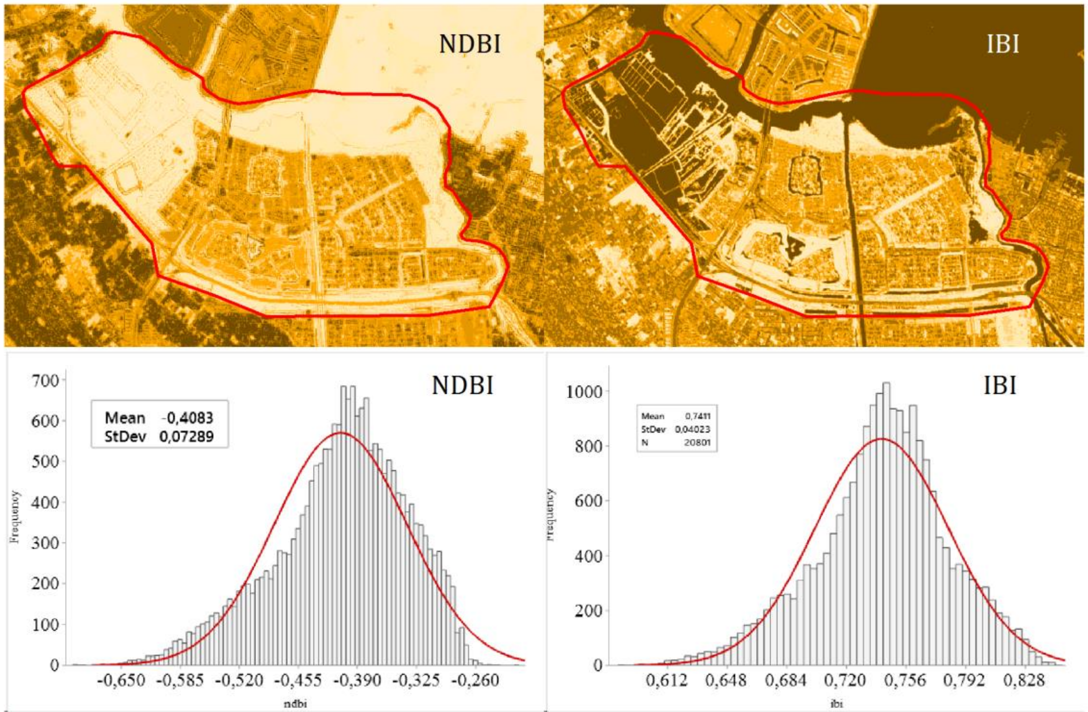


Figure 6. Characteristics of each build-up index

Water and building indices were included in this study considering the two effects are visible at the study site. For example, using a build-up area index, the study area has been developed as an ecotourism area, and infrastructure development occurs to support facilities. On the other hand, the water index involved in monitoring this mangrove also considers the physical condition of the vegetation mangroves affected by the tidal effects of seawater. This index shows the fundamental differences in vegetation identification of mangroves based on the index of both types. In the NDWI, LSWI, and MNDWI indexes, for example, there are differences in successfully decoded spectral placement (Figure 7). NDWI puts the spectral area of mangrove objects at the lowest spectral vulnerability, MNDWI at mid-spectral, and LSWI at high spectral. In contrast, the index functioned to identify buildings that place mangrove spectra with the lowest spectral range (Figure 6).

Several indices have exhibited readable spectral characteristics in Figures 5, 6, and 7. The spectral read in each index has affected bands' involvement in formulating the index algorithm. For example, the vegetation index used to detect vegetated land includes the NIR band in the formula (Rouse jr et al. 1974; Lymburner et al. 2000; Kaufman & Tanre, 1992; Huete et al. 2002; Huete 1988). More like a water index involving the SWIR band in identifying the effect of grade on the surface soil (McFeeters, 1996; Xu, 2006; Xiao et al., 2002).

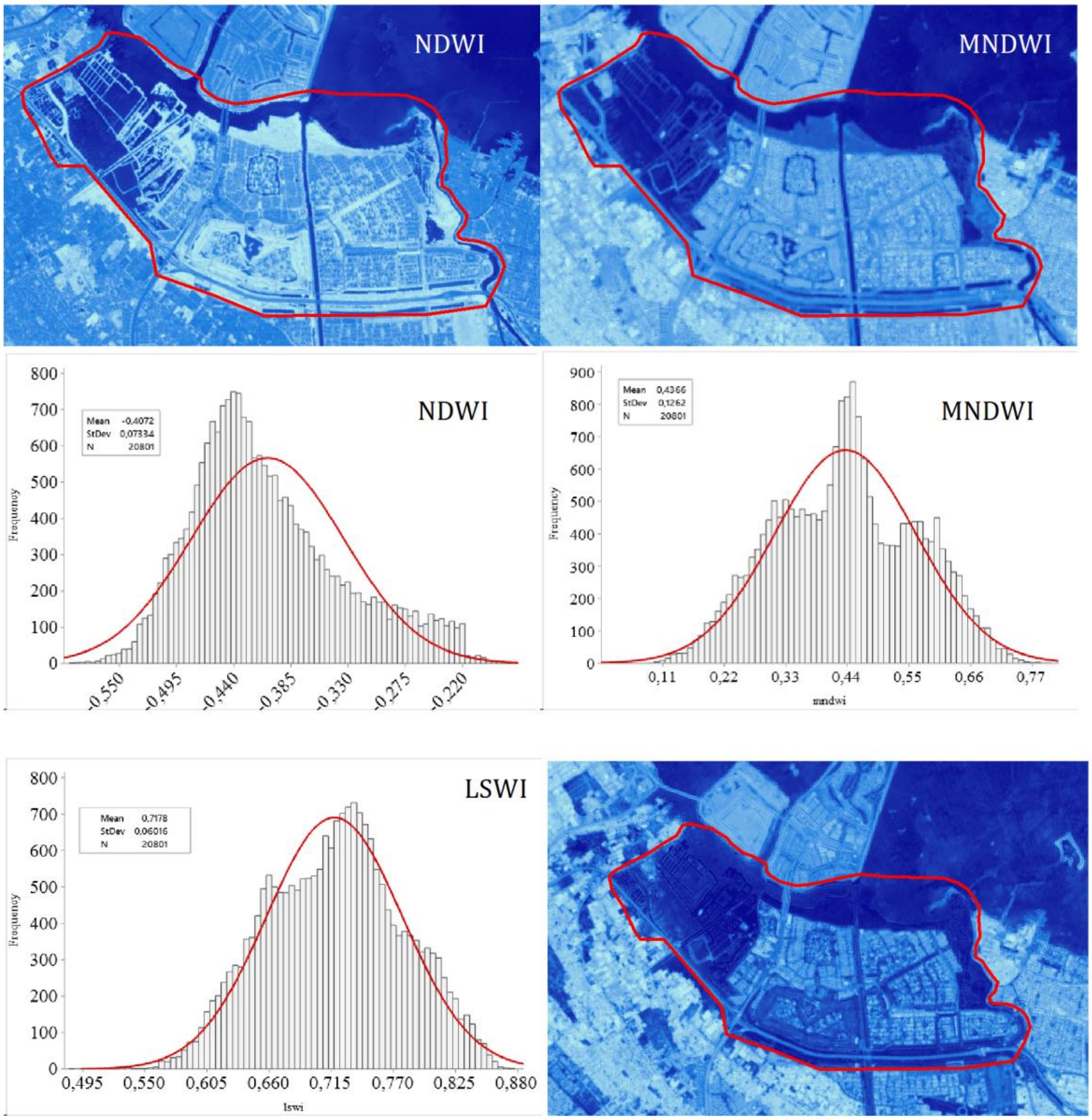


Figure 7. Characteristics of each water index

Index Ability

The index was developed with the intent of certain functions and purposes in identifying the earth's surface. The results of the analysis of each index illustrate that there are differences in each index that detects mangroves. The involvement of the vegetation index considered the mangrove vegetation as a research object. However, all of the included vegetation indices did not provide a clear picture of the mangrove vegetation. However, the vegetation's characteristics of the vegetation in the mangrove area are very different, where water inundates the roots of mangrove trees (Jia et al., 2019). This is because of the ability of a vegetation index that cannot translate the spectral affected by water. Previously, since the late 19th century, the research of Jensen et al. (1991) used 14 indices, including the vegetation index, in monitoring mangroves in Southwest Florida with SPOT MS imagery.

Figure 8 shows that almost all indices (except the MNDWI index) cannot distinguish between mangrove and ordinary non-mangrove vegetation. It differs from the MNDWI index, which can determine the two vegetation types. This can be seen from the box-shaped shape that shows the vegetation's ordinary and round shape indicating mangrove vegetation. Similar to Guo et al. (2021) report, the NDWI index in identifying vegetation pays attention to the effect of water on the soil surface. The result found that the MNDWI index differed from the NDWI index, which showed that vegetation has the lowest wavelength value. While on the MNDWI index, vegetated land, including mangroves, was in the middle wavelength between the water spectral and the building. LSWI has the same characteristics as the MNDWI index and showed no difference between mangrove and non-mangrove vegetation. This could also be observed in the type of building index, which had differences in characterizing the earth's surface.

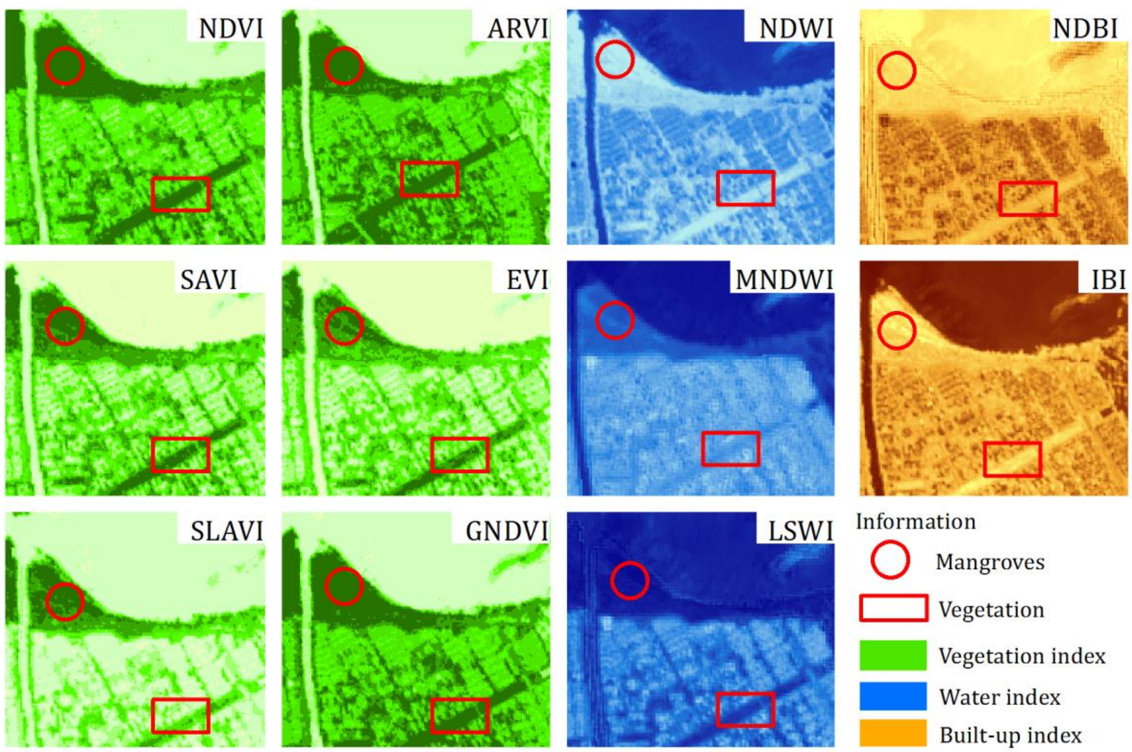


Figure 8. Comparison of the index's ability to detect mangroves

When viewed from its ability, the MNDWI index is an index that is formulated from water-sensitive SWIR and Green bands (Xu 2006; Chen et al. 2017). Hence, these indices were often combined in mangrove monitoring or vegetation that influences water through satellite imagery (Jia et al. 2019; Wang et al. 2018; Chen et al. 2017; Chamberlain et al. 2021), aerial portrait of both UAVs and a combination of the two (Wang et al. 2019). In contrast to the NDWI index, which has low sensitivity to the spectral characteristics reflected by vegetation under the influence of water (Dennison et al. 2005).

The ability of different indexes also certainly affects the identification of mangroves by producing different land areas. Figure 9 shows that each index has different identification results. Compared to the index combination results, there are differences in the mangrove area identified by each index. Some indexes have less than or more area land than the combined index area. For example, NDVI, ARVI, SLAVI, SAVI, EVI, GNDVI, and NDWI have fewer mangrove areas than the index combination, while the index MNDWI, LSWI, IBI, and NDBI had more mangrove areas. This is due to the presence of SWIR bands in the index formula, which is sensitive to water occurrence.

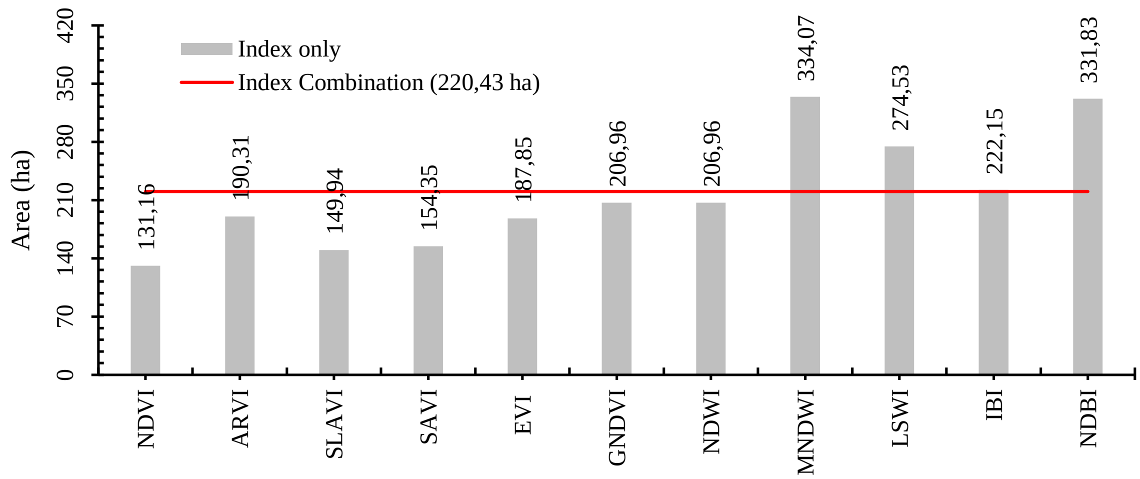


Figure 9. Comparison of mangrove area on each index and index combination

Mangrove Spectral Fluctuation Detection: MNDWI and NDVI

Tidal water often submerges roots or soil surfaces in the mangrove-vegetated area. Therefore, this condition will affect the threshold value of the index. The MNDWI index is used to identify fluctuations spectrally because this index is sensitive to the effect of water on the soil surface (Xu, 2006). In addition, another index, NDVI, was also involved in this detection to compare the ability to detect differences in soil surface conditions in mangroves area during the period 2017 to 2021. These two indices show how the soil surface's situation in the mangrove area in the study area is affected by tides (Figure 10). The results showed a significant spectral change striking from June to September; this condition recursively occurs yearly.

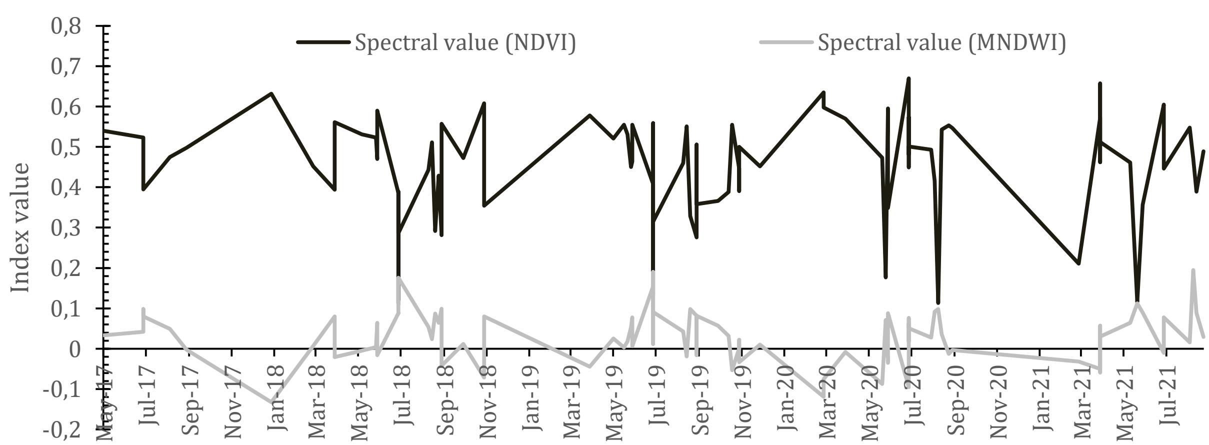


Figure 10. The fluctuation of the NDVI and MNDWI index spectral value over several months with the 2017-2021 period

Accuracy Assessment: Land Use and Mangrove Classification

The classification process often produces data that does not match the actual conditions and many identification errors. Therefore, it is crucial to compare the predicted classes with validation data as a form of assessment of the level of accuracy (Fitzgerald & Lees 1994). Story & Congalton (1986) explained the calculation by data classified sampling, showed by an error matrix in the form of a confusion matrix or contingency table (Table 4). In this case, we test this analysis and get the Overall accuracy (OA) value of 76.83%, with a value of Kappa statistics is 0.71. According to Table 4, the User's and Producer's accuracies showed that the classification of water bodies and settlements could achieve up to 100% accuracy.

Table 4. Confusion matrix and calculation of accuracy with a combination of indices

	Validation data					
Land use	**Water body**	**Mangroves**	**Built-up**	**Bare land**	**Vegetation**	**Sum (*User's*)**
Water body	**16**	0	0	0	0	16
Mangroves	2	**19**	0	0	3	24
Built-up	2	4	**16**	1	0	23
Bare land	0	0	0	**10**	5	15
Vegetation	0	1	16	12	**2**	4
Sum (*Producer's*)	20	19	16	12	10	**82**

	User's accuracy (UA, %)	**Producer's accuracy (PA, %)**
Water body	100,00	80,00
Mangroves	79,17	79,17
Built-up area	69,57	100,00
Bare land	66,67	83,33
Vegetation non mangrove	50,00	20,00
Overall accuracy (OA, %)	: 76,83 %	
Kappa statistics (KA)	: 0,71	

The low-high accuracy results are influenced by the training data built into the classification process and the classification method used (Zekoll et al., 2021; Fitzgerald & Lees, 1994; Story & Congalton, 1986). Bazzi et al. (2019) explained that in the identification of watery vegetation, the type of image is essential to affect the accuracy of the classification. In addition, the involvement of several indices in the datasets improved classification results. That matter can be seen from the accuracy test on the classification results which only involve the single index. The results obtained from these tests are different and lower the level of accuracy is compared with the classification using a combination of indices. Including the IBI index which has relatively the same mangrove area, but has a lower level of accuracy compared to the classification results. This shows that the index's capabilities are relatively diverse and often do not the classification process. A similar result was also revealed by Ramdani et al. (2018), that conventional index such as the index NDVI in its application is still superior to the mangrove special index because it has a high degree of accuracy. In addition, there is a water effect that can affect the object of observation and cannot be translated by an index of the number of misclassifications that occur. This is one of the drawbacks of monitoring mangroves in remote sensing imagery (Guo et al., 2021).

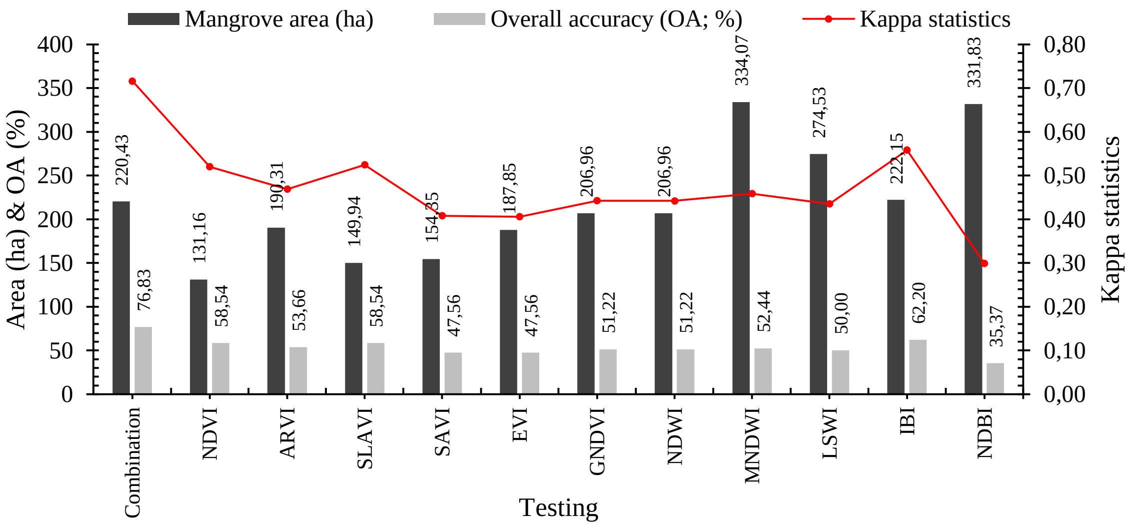


Figure 11. Comparison of the level of accuracy obtained from the classification

CONCLUSIONS

Mangroves are a group of plants that live in ecotone areas that have a strategic role both from an ecological and economic point of view. The role requires area protection, conservation, and rehabilitation that involves various stakeholders and is supported by a detailed database. For this reason, mangrove mapping is one of the contributions to efforts and that goal. Mangrove identification using cloud-based remote sensing computing provides many benefits and access to limited areas, as well as following the current conditions with the Covid-19 pandemic. Eleven indices were involved in the mangrove identification process in helping the classification process Random Forest (RF) algorithm via the Google Earth Engine (GEE) platform. Results showed that 220.43 ha of mangrove vegetation spread over two areas, Angke Kapuk Nature Tourism Park and Pantai Indah Nature Tourism Kapok. Classification of land use types and mangroves results in the level of accuracy of 76.83% (Overall accuracy) and 0.71 (Kappa statistics). On the other hand, there are differences in the identification results from testing the use of a single index and a low level of accuracy compared to the use of a combination index.

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