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Mapping Mangrove Distribution in Muara Jenggalu, Bengkulu City Using Sentinel 2A-Imagery and OBIA

Syafa Aisyah Putri*, Ayub Sugara, Zamdial
Department of Marine Science, Faculty of Agriculture, University of Bengkulu, Bengkulu, 38371, Indonesia
*Corresponding Author: syafa.aisyah.p@gmail.com

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ABSTRACT

Mangroves are coastal ecosystems that play a vital role in maintaining coastal stability, providing habitat for diverse biota, and reducing the impacts of climate change. However, these ecosystems continue to face threats, including in Muara Jenggalu, Bengkulu City. This study aims to map the spatial distribution of mangroves using Sentinel-2A imagery with the Object-Based Image Analysis (OBIA) method, which employs SVM (Support Vector Machine) as a statistical technique for prediction and classification, while also examining the relationship between the vegetation index (NDVI) and mangrove canopy cover. The results indicate that the segmentation scale influences classification accuracy, with scale 3 achieving a high accuracy of 97.17% and a mangrove area of 41.01 ha. The classification segments the study area into four main classes: mangroves, non-mangrove vegetation, water bodies, and non-vegetation. NDVI values ranged from 0.12 to >0.35, with mangrove areas primarily in the medium to high vegetation category. Simple regression analysis revealed a significant positive relationship between canopy cover percentage and NDVI values. The information acquired from this research can be used as a basis for planning the conservation and sustainable management of coastal ecosystems.

Keyword: Mangrove, Muara Jenggalu, NDVI, OBIA, Sentinel-2A

1. Introduction

The importance of mangroves in relation to the environment in undeniable because mangroves can maintain the stability of the coastline [1], withstand strong winds from the sea [2], resist the abrasion process [3], and preserve buffer zones [4], filtering seawater into freshwater at [5], processing toxic waste [6], producing oxygen [7], and absorbing carbon dioxide [8]. Therefore, preserving mangroves is crucial for the balance of ecosystems and life on Earth. However, mangroves also face threats from climate change, development, and degradation, which have led to a decline in the area and quality of mangroves in various parts of the world, such as the Muara Jenggalu Mangrove in Bengkulu City, Indonesia.

The Muara Jenggalu mangrove area is located in Bengkulu, Indonesia[9]. The area is situated at 3°50'29.5" South latitude and 102°17'30.4" East longitude, within the Gading Cempaka District of Bengkulu City, covering a water area of approximately 247 hectares with gentle topography. The area is bounded by a Pantai Panjang Nature Reserve (Indonesian term: *Taman Wisata Alam*/TWA) to the north, Sumber Jaya District to the south, Muara Dua District to the east, and the Indian Ocean to the west [10] This mangrove forest location is susceptible to rapid erosion or sedimentation [11].

Based on Sentinel-2A satellite imagery analysis, the total mangrove area in Bengkulu City is 242.35 ha, distributed across Muara Jenggalu, Kandang, Pulau Baai, Sumber Jaya, Teluk Sepang, and Padang Serai [12]. Agustini et al. (2023)[9] reported that the mangrove community at Muara Jenggalu tends to lack a single dominant mangrove species. The mangrove vegetation at Muara Jenggalu, Bengkulu, comprises nine species: *Avicennia alba*, *Avicennia marina*, *Bruguiera gymnorrhiza*, *Lumnitzera littorea*, *Rhizophora apiculata*, *Sonneratia alba*, *Sonneratia caseolaris*, *Nypa fruticans*, and *Xylocarpus granatum*. Additionally, there are two mangrove-associated species: *Hibiscus tiliaceus* L. and *Pandanus tectorius*. The most frequently observed mangrove species at Muara Jenggalu, Bengkulu, are *Rhizophora apiculata* and *Sonneratia alba*. This mangrove forest is categorized as having low stand density, as the density value is ≤ 1,000 ind.ha-1.

The mangroves in Muara Jenggalu are ecologically important because they support biodiversity conservation. Mangrove forests provide habitat and breeding grounds for various species of fish, crustaceans, and marine organisms, maintaining the biodiversity of coastal ecosystems [13]. In addition, mangroves act as a natural barrier against coastal erosion and storm waves, protecting the coastline and surrounding communities, and preventing habitat loss [14]. Mangroves are also the largest suppliers of nutrients for marine organisms, supporting food webs in coastal areas. Furthermore, mangroves play an important role in carbon sequestration and climate change mitigation [15]. Therefore, mangrove conservation efforts are important. One such effort is the use of satellite imaging technology.

Satellite imaging technology plays an important role in mangrove mapping, providing a comprehensive picture of the distribution and density of mangroves in an area[16]. Techniques such as the Normalized Difference Vegetation Index (NDVI) are used to determine the distribution and density of mangroves. Among many mangrove-density-related researches, NDVI is proven effective to map the vegetation density [17] [18]. Although the NDVI composite is sensitive to detect the light-wave of chlorophyl which contained in green leaves of various plant canopy the ground sample spots acquired from field data collection is used to determine and eliminate vegetation areas that are not mangroves. Conversely, traditional mangrove mapping methods involve field surveys and direct observation of the whole area [19]. These methods often consider various factors, such as salinity, tidal influence, growth zones, and soil type [20]. Although these traditional methods provide valuable data, they can be time-consuming, labor-intensive, and costly. Therefore, integrating satellite imagery technology and traditional methods can offer a more efficient and accurate approach to mangrove mapping.

In this study, the satellite image analysis process involves creating "objects" by grouping uniform pixels according to specific criteria through image segmentation. This method is known as Object-Based Image Analysis (OBIA), which presents a new approach to remote sensing image analysis. Research on mangrove mapping using Sentinel-2A satellite imagery with the OBIA method has been widely conducted in Indonesia. Among them are the studies that used Sentinel-2 to map mangrove forests around Java Island [21], [22]. However, similar studies have not been widely conducted in Bengkulu City, especially in the Muara Jenggalu area of Bengkulu City. Muara Jenggalu is an area with mangrove potential that has not been fully identified, but it has already experienced pressure from human activities, including fishing, agriculture, and industry. Mangrove forest data maps should be updated at least every 5 years to meet the needs of policymakers [23]. Several considerations for this time frame include changes in waterways, logging, and damage to mangrove forests due to natural activities. Therefore, this research aims to map mangroves in Muara Jenggalu, Bengkulu City, using Sentinel-2A satellite imagery with the OBIA method, measure the spatial distribution of mangroves, test the accuracy of the mapping results, and compare NDVI and canopy cover percentages from hemispherical photography.

2. Method

The method carried out in this research involved field data collection and remote sensing analysis. This involves several steps: imagery pre-processing, calculation of classification accuracy using OBIA across 5 segmentation scales, analysis of NDVI values for mangrove extent in Muara Jenggalu, and determination of the correlation between canopy coverage percentage and NDVI values.

2.1. Study Area

This research is divided into two stages: field data collection and data analysis. The first stage of data collection (in situ) was conducted in September 2022 at the Muara Jenggalu mangrove forest in Bengkulu City, within 3°50'29.5" south latitude and 102°17'30.4" east longitude. (Figure 1). Data collection points were located in two subdistricts, namely 10 points in Lempuing Subdistrict, Ratu Agung District, and 43 points in Muara Dua Subdistrict, Kampung Melayu District.

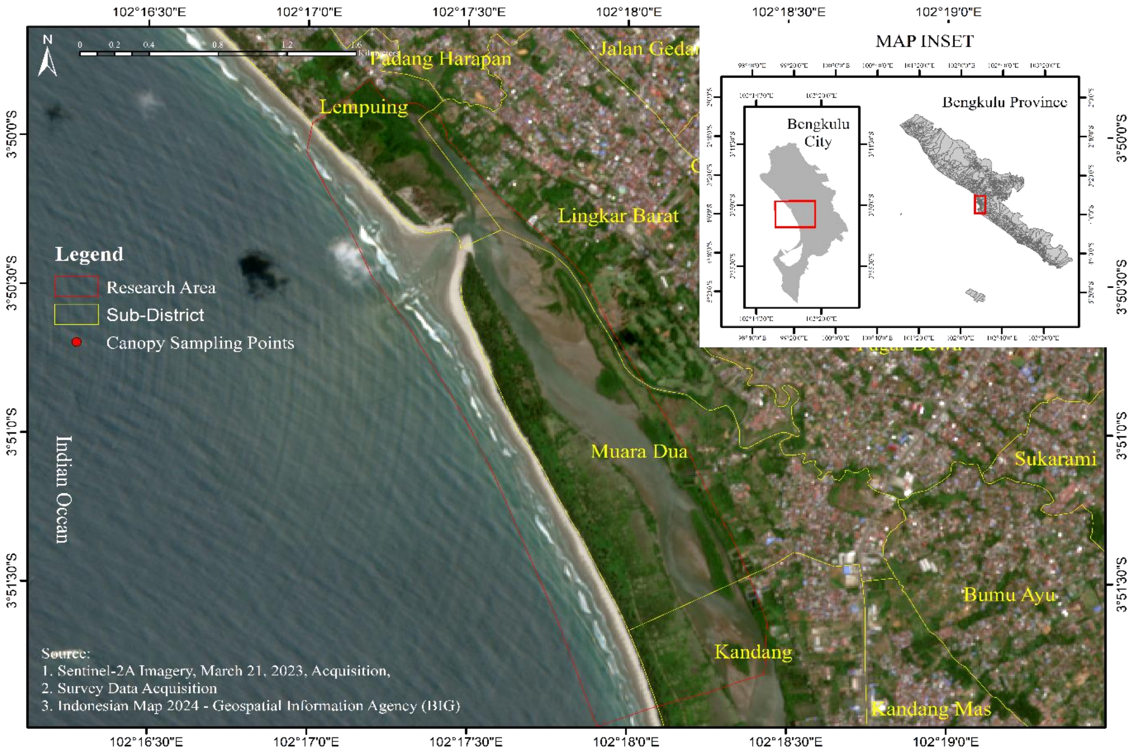

Figure 1. Study area

2.2. Data and Tools

This study required equipment for data collection in the field and data analysis. The field research equipment is listed in Table 1 and the research materials is listed in Table 2.

Table 1. Research equipment

No	Name	Purpose
1.	Office Supplies	Recording data in the field
2.	ArcMap 10.8	Creating maps and processing image data
3.	*Boots*	Protecting feet
4.	eCognition 9.0.1	Processing Support Vector Machine (SVM) data
5.	Garmin 78s GPS	Determining the coordinates of field data locations
6.	ImageJ 1.54d	Processing canopy cover data
7.	Microsoft Excel	Calculating data for correlation and regression analysis
8.	Camera	Documenting mangrove canopy density
9.	Roll Meter	Measuring the distance between sampling points
10.	Raffia rope	Creating a 10 × 10 m transect
11.	*Wide Angle Lens*	Produces *hemispherical photography* images

Table 2. Research materials

No	Material Name	Function
1.	Sentinel-2A satellite imagery	This is image material that will be processed, acquired on March 21, 2023, from the website https://dataspace.copernicus.eu/, already with atmospheric correction [24] and with only 4.4% cloud cover
2.	Survey plan map	Used to determine the research location

2.3. Canopy Coverage Data Acquisition and Analysis

This study employed purposive sampling, selecting 53 field survey locations (on site) that best represent the various conditions of mangrove canopy cover, namely dense, moderate, and sparse. The canopy in the locations will then be photographed using hemispherical photography. Hemispherical photography is a technique for collecting mangrove canopy photo data in a single plot by pointing the camera perpendicular to the sky. The plot of a 10 m by 10 m square transect, along with the proper camera position, is shown in Figure 2 [25]. From the photos, the binary pixel analysis using ImageJ will separate the canopy pixel from the sky. ImageJ will show mangrove pixel value as 255 and sky as 0.

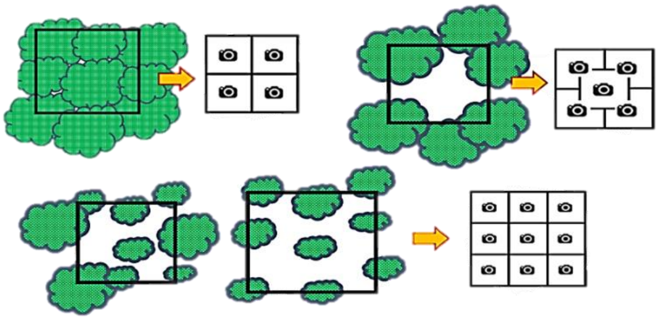

Figure 2. Hemishpherical photography technique [26]

The result of hemispherical photography is calculated using MS. Excel using formula (1):

$$\% \text{ Mangrove pixel} = \frac{P255}{\Sigma P} \times 100\% \tag{1}$$

Explanation:
P255 = pixel value 255
ΣP = Total number of pixels.

The analysis of mangrove canopy density and cover percentage are used to describe the status of mangrove forests in accordance with the Decree of the Minister of Environment No. 201 of 2004 (Table 3).

Table 3. Standart criteria for mangrove damage

No	Criteria		Coverage (%)
1.	Good	Dense	>75%
2.		Moderate	50 - 75%
3.	Damaged	Sparse	<50%

2.4. Imagery Pre-Processing

The next step is to combine several relevant Sentinel-2 image bands through the Composite Band technique for further analysis. This aims to improve visualization and spectral information in the identification and classification of mangroves, utilizing the high spatial resolution of Sentinel-2 images [27]. The following (Table 4) contains the list of relevant bands that are used to craft the proper imagery for OBIA and NDVI analysis.

Table 4. Relevant Bands for Imagery Pre-Processing

No	Band	Description	Spatial Resolution
1.	Band 2	*Blue*	10 m
2.	Band 3	*Green*	10 m
3.	Band 4	*Red*	10 m
4.	Band 8	*Near Infrared (NIR)*	10 m
5.	Band 11	*Short Wave Infrared (SWIR)*	20 m

A combination of Band 4-3-2 produces True Color Composite (TCC), visualized in Figure 1 helps to interpret the overall scenery in its actual colors. Another combination, Band 8-11-4, produces a False Color Composite that visually helps separate vegetation from the rest of the scenery. However, Band 11 should be resampled first using ArcMap to make it compatible with the 10 m resolution of the other bands. Bands 4 and 8 are also used to visualize and calculate the NDVI value. Finally, all these bands, combined, will be integrated in eCognition for use in OBIA. After the necessary combination is complete, the imagery will be clipped to focus only on the area around the research site.

2.5. Analysis of Mangrove NDVI Values

The NDVI algorithm is calculated using the following formula:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \quad (2)$$

Explanation:
NDVI = Normalized Difference Vegetation Index
NIR = Spectral reflectance value in the NIR band
R = Spectral reflectance values in the Red band

NDVI values range from -1 to 1. Values close to 1 indicate high vegetation density. Values close to 0 indicate low vegetation density. Negative values indicate areas without vegetation, such as water or bare land. Table 5 contains mangrove density categories that refer to Ministry of Forestry Directorate General of Land Rehabilitation and Social Forestry(2005) [24].

Table 5. NDVI Value

No	Criteria	Minimum	Maximum
1	Rare	-1	0.32
2	Moderate	0.32	0.42
3	Dense	0.42	1

The total mangrove area is then obtained from the total of all pixels classified as mangrove.

2.6. NDVI and Canopy Coverage Correlation

Correlation analysis was performed by calculating the Pearson correlation coefficient (r) to assess the strength of the linear relationship between two variables (NDVI values and Canopy Cover), as well as determining the p-value to evaluate the significance of the relationship. Next, a linear regression model was constructed to analyze the relationship between canopy cover percentage (x) and NDVI (y). This process included calculating the R^2 value to determine how much of the variation in NDVI was explained by canopy cover percentage, as well as calculating the regression coefficient values (a and b) to understand the effect of changes in canopy cover percentage on NDVI[29].

2.7. Segmentation

This study employs a multiresolution segmentation algorithm [17], which groups or separates images into polygons based on similar spectral and spatial values [30]. Threshold setting, which involves determining shape, scale, and compactness, is achieved through a trial and error approach. Scale parameters of 3, 9, 15, 21, 27, and 33 were selected to compare the segmentation results. The other parameters, shape and compactness, use default values of 0.5 and 0.1, respectively, in the software.

2.8. Object Classification

This algorithm operates according to a ruleset in a process tree. The process tree comprises three main rule sets: the segmentation, the shapefile as a thematic layer of ground sampling data, and the application of Support Vector Machine (SVM), which utilizes a classifier algorithm. SVM is a statistical technique used for prediction in classification. The SVM classifier algorithm has been proven to provide high accuracy compared to other machine learning methods, such as decision trees, random trees, and k-nearest neighbors. This process classifies two or more classes by finding the maximum hyperplane that utilizes the data at the separation points (support vectors) [31].

2.9. Accuracy Assessment of OBIA

Supervised classification of the satellite imagery was conducted using training samples representing four land-cover classes: mangroves (n = 26), water bodies (n = 28), non-vegetated areas (n = 26), and non-mangrove vegetation (n = 26). Classification accuracy was then assessed by comparing the classified image with independent reference points. The validation dataset consisted of 26 points for mangroves, 25 for water bodies, 28 for non-vegetated areas, and 27 for non-mangrove vegetation. The reference points were distributed using the equalized stratified sampling method to ensure an even representation of each land-cover class across the study area [32]. The accuracy assessment produced four evaluation metrics: overall accuracy, producer's accuracy, user's accuracy, and the kappa coefficient (Equation 3-6) [31].

$$\textit{Producer accuracy} = \frac{X_{\kappa\kappa}}{X_{\kappa+}} \times 100\% \tag{3}$$

$$\textit{User accuracy} = \frac{X_{\kappa\kappa}}{X_{+\kappa}} \times 100\% \tag{4}$$

$$\textit{Overall accuracy} = \frac{\sum X_{\kappa\kappa}}{N} \times 100\% \tag{5}$$

$$\textit{Kappa accuracy} = \frac{N \sum_k^r x_{kk} - \sum_k^r X_{k+} X_{+k}}{N^2 - \sum_k^r X_{k+} X_{+k}} \tag{6}$$

Description:

$X_{\kappa\kappa}$	= Correctly classified values
$X_{\kappa+}$	= Total value of each class column
$X_{+\kappa}$	= Total row values for each class
$\sum X_{\kappa\kappa}$	= Number of correctly classified values
N	= Total number of data obtained.
$\sum_k^r X_{k+} X_{+k}$	= each total number x number of columns

3 Result and Discussion

3.1. Research Location General Overview

Based on earlier research, the mangrove community in Muara Jenggalu tends not to have a dominant mangrove species [24]. Therefore, the process of identifying mangroves using satellite imagery requires higher-resolution imagery and more accurate classification techniques, one of which is Sentinel-2A. In Muara Jenggalu, Bengkulu, the mangrove vegetation consists of eight species: *Avicennia alba, Avicennia marina, Bruguiera gymnorrhiza, Lumnitzera littorea, Rhizophora apiculata, Sonneratia alba, Sonneratia caseolaris, and Xylocarpus granatum*. In addition, there are three species associated with mangroves, namely *Nypa fruticans*, *Hibiscus tiliaceus L,* and *Pandanus tectorius*. The most common mangroves in Muara Jenggalu, Bengkulu, are *Rhizophora apiculata* and *Sonneratia alba*. This mangrove forest is categorized as having low species density because its density value is ≤ 1,000 ind.ha^{-1}. Figure 3 shows an overview of the research location.

Figure 3. General overview of the research location in Muara Jenggalu, Bengkulu City

3.2. Canopy Coverage and NDVI Correlation

The canopy cover value in each transect varied from 63.79% in transect 11 to 96.14% in transect 9, with an average of around 87.6%. % (Figure 4). This value indicates that the mangrove ecosystem in Muara Jenggalu has a relatively dense canopy cover, based on the Mangrove Cover Criteria from the Ministry of Forestry and Environment, which exceeds 75%. This score was achieved mostly likely due to the fact that the very position of the mangrove ecosystem has nutrient rich soil, adequate biodiversity, and enough sunlight to keep it thriving. Table 6 shows the variety in canopy cover percentage of the 53 spots captured using hemispherical photography.

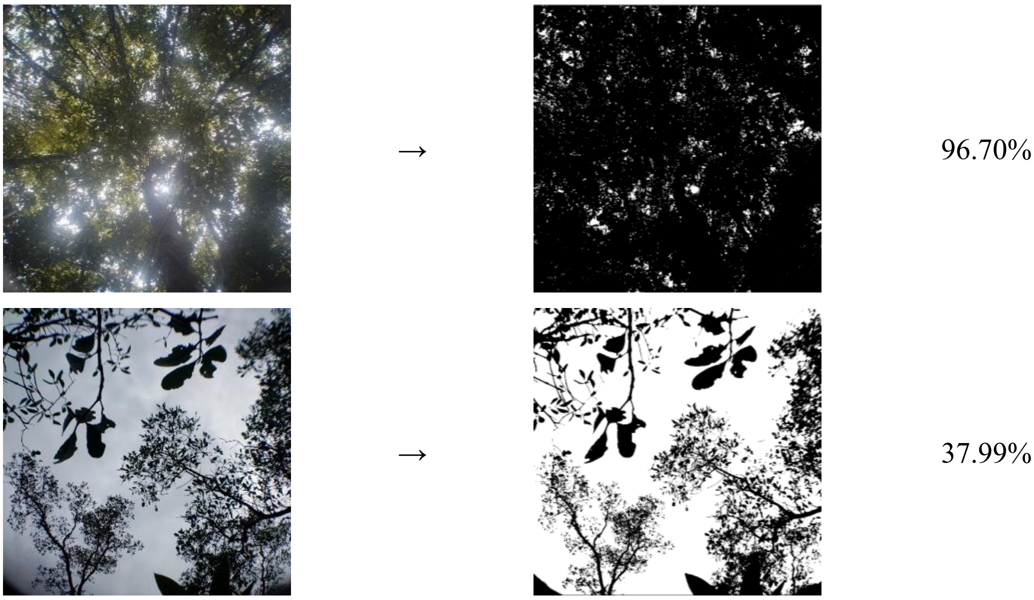

Figure 4. Image processing using Image

Table 6. Overall percentage of mangrove cover for each transect

No	Transect	Criteria (%)	Transect	Criteria (%)	Transect	Criteria (%)
1.	1	77.28	19	80.89	37	94.74
2.	2	85.7	20	87.85	38	91.68
3.	3	82.67	21	90.52	39	82.55
4.	4	90.57	22	89.54	40	85.26
5.	5	91.58	23	88.79	41	92.86
6.	6	91.40	24	87.81	42	91.42
7.	7	91.53	25	88.16	43	83.38
8.	8	94.27	26	87.74	44	84.32
9.	9	96.14	27	89.42	45	74.92
10.	10	95.93	28	86.83	46	85.71
11.	11	63.79	29	91.02	47	87.06
12.	12	87.86	30	94.68	48	90.72
13.	13	89.24	31	90.88	49	90.59
14.	14	90.05	32	85.05	50	83.35
15.	15	88.9	33	90.13	51	88.27
16.	16	89.88	34	86.51	52	89.65
17.	17	88.07	35	68.63	53	90.11
18.	18	86.65	36	94.2		

Undoubtedly, the NDVI values agree with the canopy coverage percentages. The results of Sentinel-2A image processing yielded a total NDVI value range at the study site, spanning from 0.1249 to 0.663834. Figure. 5 illustrates the mangrove area and NDVI Scale 3 that classify vegetation indices into three categories: rare, moderate, and dense (Table 7). Meanwhile, the processing of vegetation indices specifically for mangrove classes was carried out using the OBIA method with eCognition *software* to obtain the area of mangrove land based on vegetation levels.

Table 7. Comparison of mangrove coverage based on vegetation level

No	Category	NDVI
1.	Rare	0.12 – 0.32
2.	Moderate	0.33 – 0.42
3.	Dense	0.43 – 0.66

NDVI classification methods, such as this, have been widely used in mangrove vegetation mapping research. [33] demonstrates that the use of the NDVI index can effectively distinguish the density of mangrove vegetation in the coastal areas of Kalimantan. Similar research [34] also confirms that NDVI values above 0.5 indicate dense and healthy vegetation cover. Thus, this approach not only supports the mapping of mangrove spatial distribution, but also serves as an important tool in detecting changes in ecological conditions and planning sustainable coastal zone management.

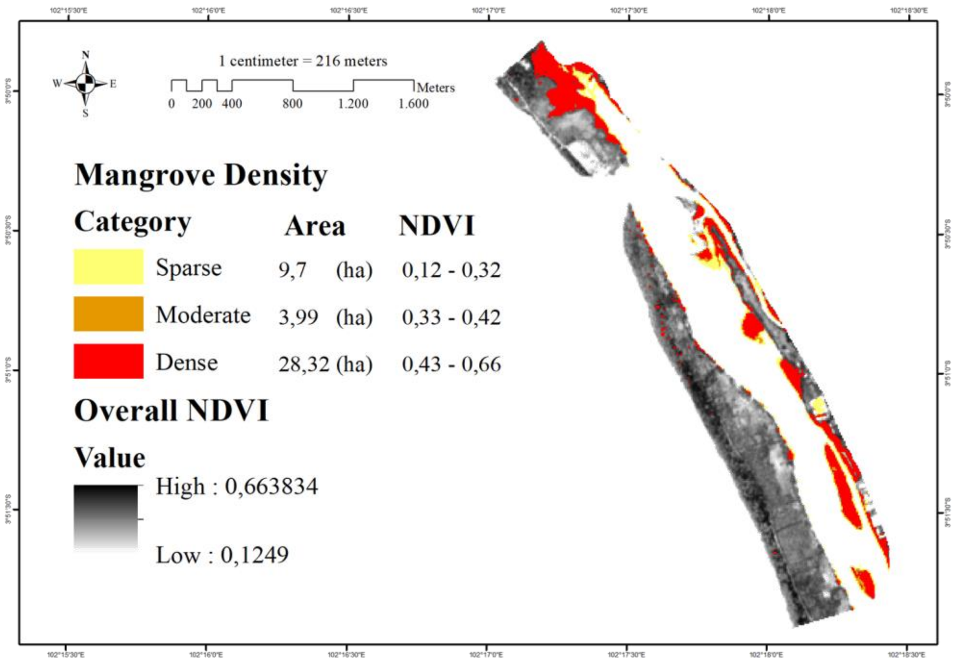

Figure 5. Mangrove area and NDVI Scale 3

The analysis results showed a strong correlation between NDVI and the percentage of mangrove canopy density, with a Pearson coefficient of 0.9278 (Figure 6). This positive correlation indicates that the higher the NDVI value, the higher the mangrove canopy density measured in the field. This finding aligns with the study [26], which reported a similar correlation between NDVI and mangrove canopy cover in East Bolaang Mongondow, with an r value of 0.9516. This reinforces that NDVI can be used as a representative indicator to describe the condition of mangrove vegetation density.

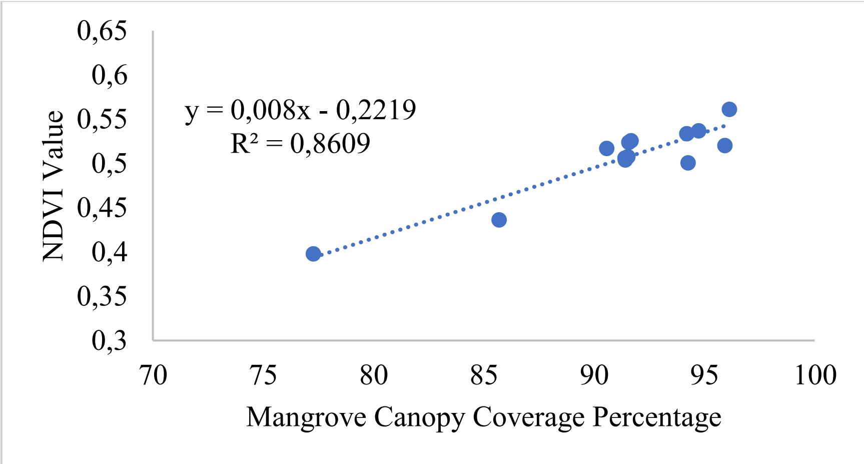

Figure 6. Relationship between NDVI values (y axis) and Mangrove Canopy (x axis)

Simple linear regression analysis shows that the model built has a high level of reliability. An R^2 value of 0.8609 indicates that NDVI can explain 86% of the variation in canopy density, while the remaining 14% is attributed to factors not accounted for in the model. A relatively high Adjusted R^2 value (0.8482) also confirms the model's stability. These results align with the study [35], which reported an accuracy of 83.33% for NDVI-based mangrove density classification. Thus, this study provides empirical support for the effectiveness of NDVI in quantitative analysis of mangrove vegetation density.

The model significance test yields an F-value of 4,87E-06, which is far below the significance threshold of 0.05. This indicates that the constructed regression model is statistically significant and that the relationship between NDVI and mangrove canopy density is not coincidental. These results align with [27], which utilized Sentinel-2 data to monitor changes in mangrove density, finding that NDVI is effective in describing the dynamics of vegetation density. The regression equation obtained is Canopy Percentage = 36.6748 + 108.0316 × NDVI. The interpretation of this equation is that a 0.01 increase in NDVI value will result in an estimated 1.08% increase in canopy density. The intercept value of 36.67% indicates a baseline density level even when NDVI values are low. These results are consistent with [36], which found that NDVI values ranging from 0.5 to 0.9 represent moderate to high mangrove density in PlanetScope imagery.

The results of this study are also supported by [37], which shows a positive correlation between multispectral camera data and Sentinel-2A in estimating mangrove density using NDVI. Although the accuracy obtained was lower, at 73–75%, the study still confirms that NDVI can be used as a quantitative proxy for mangrove vegetation density. This comparison indicates that the data have a higher level of reliability, possibly due to more suitable image conditions and field sampling. In general, the results of the correlation and regression analysis in this study are consistent with those of previous studies. NDVI has been proven to significantly explain the variation in mangrove canopy density and provide strong estimation results. Thus, NDVI can be positioned as a quantitative proxy that can be used in the spatial mapping of mangrove distribution and density.

However, the applicability of NDVI is not universal. Several studies have reported that NDVI may underestimate or overestimate canopy density due to background soil reflectance in sparse mangrove stands and saturation effects in dense canopies, which can reduce its predictive performance. Consequently, alternative vegetation indices such as the Soil-Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), and Modified Soil-Adjusted Vegetation Index (MSAVI) have been suggested to provide more accurate estimates under certain environmental conditions[38][39]. Therefore, while the findings of the present study support the use of NDVI as a reliable quantitative proxy for mangrove canopy density in the study area, its performance should be interpreted in the context of site characteristics, canopy structure, and image conditions, and the selection of vegetation indices should be adapted to the specific objectives and environmental conditions of each study.

3.3. OBIA's Accuracy and Mangrove Distribution

The scale optimization used in the Sentinel-2A satellite image is scale 3, 9, 15, 21, 27, and 33, with *shape* and *compactness* values of 0.1 and 0.5. This experiment yielded the following Overall Accuracy (OA) results:

97.17%, 82.08%, 77.36%, 70.75%, 67.92%, and 59.43% (Table 8). In the following table, it can be observed that the smaller the scale value, for example, scale 3, the smaller the segments will be with a greater number and a tendency to be heterogeneous, and vice versa with larger scales. This is inversely proportional to the accuracy value.

Table 8. OBIA's *r*esults

Class	Segmentation Scale						Notes
	3	9	15	21	27	33	
Mangrove	42.01	41.98	41.98	41.87	41.87	41.87	Class extent in hectares (ha)
Non-Mangrove Vegetation	132.58	130.22	130.22	136.73	130.22	57.84	
Mangroves Coverage Category							
Rare	9.70	9.69	9.69	9.56	9.56	9.56	Class extent in hectares (ha)
Moderate	3.99	3.98	3.98	3.97	3.96	3.96	
Dense	28.32	28.31	28.31	28.34	28.35	28.35	
Total Segments	39.338	13.687	5.064	2.847	1.462	1.040	
Accuracy (%)	97.17	82,08	77.36	70.75	67.92	59.43	

From these results, it can be concluded that smaller segmentation scales (scales 3 and 9) tend to produce higher classification accuracy because they create more segments that can better represent image details. Scale 3 achieved the highest accuracy of 97.1%, comprising a total of 39,338 segments. However, using too small a scale also increases processing complexity and the potential for over-segmentation. Conversely, larger segmentation scales (scales 27 and 33) produce fewer segments and lower accuracy, indicating that objects in the image tend to be overly combined, resulting in the loss of important details. This also occurred in research by [40], where the smallest scale, scale 5, produced the highest accuracy compared to scales 10, 20, 35, 50, and 70.

Over-segmentation occurs when the classification algorithm breaks down segments of an object that tend to have the same spectral value, causing an object that can be classified in one segment to be classified in several segments. This results in high accuracy but with a segmentation processing time that tends to be longer than scales with larger numbers. Conversely, under-segmentation occurs when the classification algorithm groups different objects into one segment. This results in decreased accuracy because some pixels are not classified correctly [41].

At scale 3, the accuracy reaches 97.17% with 39,338 segments, making it the most detailed and complex scale. As the scale increases, the number of segments decreases dramatically and accuracy also reduces, to the point where at scale 33 there are only 1,040 segments remaining with an accuracy of 59.43%. This confirms the inverse relationship between segmentation detail and classification accuracy. The area of mangroves showed relatively stable results, ranging from 41.87 ha to 42.01 ha. Scale 3, with the highest accuracy, detected 42.01 ha of mangrove land. Then scales 9 and 15 show the exact area figure, namely 41.98. Finally, scales 21, 27, and 33 show a stable area at 41.87. Non-mangrove vegetation is relatively stable at small scales, with an area of approximately 130 ha at scales 3 to 15. However, at scale 21, there is an increase to 136.73 ha, before falling sharply to only 57.84 ha at scale 33. This significant decrease indicates that, with low accuracy, the non-mangrove vegetation class loses its spatial consistency due to its mixing with mangroves and non-vegetation. In other words, the lower the accuracy, the greater the distortion in the estimation of non-mangrove vegetation area

These findings are in line with studies by [42], which state that object-based classification using SVM on Sentinel-2A imagery can produce an OA above 83% with optimal segmentation parameters. However, as shown by [43] , SVM performance is greatly influenced by the penalty and kernel parameters used. In fact, in some cases, the use of data fusion, such as Sentinel-1, Sentinel-2, and Landsat, has been shown to significantly improve OA, especially for classes with high complexity, such as mangroves [33].

Thus, it can be concluded that the segmentation scale plays an important role in determining the quality of OBIA classification results. The more detailed the segmentation, the higher the accuracy and the better the class distribution, even though the data becomes complex. Conversely, coarse segmentation reduces accuracy and produces unstable area estimates, especially for mangrove and non-mangrove vegetation classes. This confirms that the selection of the segmentation scale must consider the balance between accuracy and ease of data processing.

4 Conclusion

This study demonstrates that the Object-Based Image Analysis (OBIA) method, utilising Sentinel-2A imagery, is capable of producing highly accurate mangrove distribution maps in Muara Jenggalu, Bengkulu City. The segmentation scale was found to affect the classification quality, with scale 3 providing a high *overall accuracy* (97.17%) with a Kappa of 0.96. The classification results revealed that the mangrove area in the sparse category was 4.69 ha, in the moderate category was 3.99 ha, and in the dense category was 28.31 ha, totalling 41.01 ha. Simple regression analysis also revealed a significant positive relationship between NDVI values and canopy cover percentage, as indicated by an R^2 of 0.86 and r of 0.92, suggesting that NDVI can serve as an indicator of mangrove vegetation density. The results of this study confirm that integrating Sentinel-2A satellite imagery and the OBIA method can be an efficient approach for mapping mangrove ecosystems on a local scale. The information can be used as a basis for planning the conservation and sustainable management of coastal ecosystems.

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