

RESEARCH ARTICLE

Classification and Distribution Of Mangrove Genus Using Multispectral Unmanned Aerial Vehicle (UAV) In The Waters Of Lancang Island, Kepulauan Seribu, Indonesia

Armanda^{1*}, Syamsul Bahri Agus¹, Jonson Lumban Gaol¹

¹Department of Marine Science and Technology, Faculty of Fisheries and Marine Science, IPB University, Jl. Agatis, Babakan, Kec. Dramaga, Bogor Regency, West Java 16128 Indonesia .

*Corresponding author email: mandajrarmanda@apps.ipb.ac.id

Tel:+62-852-6257-9640; fax:+62-852-6257-9640

Received: May 24, 2024; Accepted: Jun 28, 2024.

DOI: 10.25299/jgeet.2024.9.2.17195

Abstract

Mapping of mangrove distribution is important as basic information in mangrove resource management. development of remote sensing technology with multispectral unmanned aerial vehicle (UAV) with high spatial resolution. This study aims to determine the classification and distribution of mangrove genera using a pixel-based classification method and calculate the accuracy level of mangrove genus classification using a multispectral unmanned aerial vehicle (UAV) in Lancang Island Waters, Kepulauan Seribu. This research was carried out in August 2023 by obtaining 481 mangrove genus observation points using the DJI Phantom 4 multispectral drone. Image classification was processed using a pixel-based classification method with two classification levels, including level 1 (mangrove), resulting in an area of 18.72 ha. Level 2 (mangrove genus) uses guided classifications such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest (RF). Based on the classification results, the best results were obtained using the RF algorithm with an accuracy of 89.78% and a kappa index of 0.51, followed by the SVM algorithm with an accuracy of 89.78% and a kappa index of 0.45, then using the KNN algorithm with an accuracy of 88.32% and a kappa index of 0.43.

Keywords: Lancang Island, Mangrove, UAV Multispectral

1. Introduction

1.1 Background

Mangroves are one of the ecosystems in the tropics and subtropics that connect land and ocean (Giri et al. 2011; Zhang dan Tian 2013; Begeen 2001) and is a plant whose life and life depend on high salinity (Hogarth 2007), tides (Tomlinson 1986), and support life activities and biological cycle balance in their environment (Sukmawati 2008). Ecologically, mangroves play a role in reducing coastal erosion (Thampanya et al. 2006), storm protection, and flood control. However, over the past century mangroves have experienced a very drastic and serious decline (Jones et al. 2016). Accurate mangrove distribution mapping is important as a basis for optimal and sustainable management. In addition to general mangrove distribution mapping, Accurate classification of mangrove genera is an important component in mangrove zoning inventory.

Mangrove mapping using remote sensing technology is rapidly evolving. Remote sensing technology in the marine sector, especially the classification and distribution of mangroves (Mastu et al. 2018). In previous studies, multispectral sensors on unpaired satellites such as

the Landsat Thematic Mapper (TM) or Enhanced Thematic Mapper Plus (ETM+) (Aslan 2016; Zhang et al. 2017) with an accuracy of 62.7% to 71.11% (Siregar et al. 2019; Mallinis et al. 2018) and Sentinel with an accuracy of 75% to 76.6% (Rosmasita et al. 2018; Alfani 2022; Zabrina 2023) has been done a lot in mangrove mapping. Satellites with small spatial and spectral resolution in the application of mangrove classification are rarely used. The development of spatial and high spectral resolution satellite sensors has been able to accurately determine mangrove classifications such as WorldView satellites (Kanekaputra 2018; Rida 2021; Nagarajan et al. 2022), SPOT (Oktorini, 2021), IKONOS and QuickBird (Osei Darko et al. 2021).

Obstacles that are often experienced in mapping with remote sensing using satellite imagery such as the cost of high-resolution imagery are relatively expensive and the high frequency of cloud cover (Nababan et al. 2021), The application of high spectral resolution and the development of sensor technology can be used on drones. Drones equipped with multispectral cameras can take spectral data in several channels so that more object information is obtained compared to ordinary cameras.

The use of multispectral drones for mangrove classification includes the development of optimal imaging methodologies, appropriate data processing, and validation and verification of classification results.

Multispectral image capture can be done using a drone that has a multispectral camera installed that can capture 5 channels of the colour spectrum, namely: Red, Green, Blue, Red-edge, and Near-infrared (NIR). The advantage of this camera is that it can capture images on 5 types of channels in one take. According to Lo in Laremba (2014), new applications of multispectral remote sensing have focused on estimating the amount and distribution of vegetation. The estimation is based on reflections from the vegetation canopy. The intensity of the reflection depends on the wavelength used and the three components of vegetation, namely leaves, substrate and shadow. Leaves reflect weakly at blue and red wavelengths, but reflect strongly at near infrared wavelengths. Leaves have a characteristic green colour, where chlorophyll absorbs the red and blue spectrum of radiation and reflects the green spectrum of radiation.

Several studies for the application of multispectral drones have been used in dryland monitoring (Mitchell et al. 2012; Hruska et al. 2012), Utilization of remote sensing for watershed reclamation and rehabilitation (Rahmandhana et al. 2022). Research using drones in the marine field such as research conducted by Oleksyn (2021) monitoring habits and habitats from stingrays, Hamad (2022) monitoring habitat characteristics from seaweed in tropical waters and Cao J. et al (2018) explaining the classification of object-based mangrove species using Hyperspectral UAV imagery with K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) algorithms of 76.12% (Kappa = 0.73) and 82.39% (Kappa = 0.801) respectively.

Heumann (2011) and Keunzer et al. (2011) stated that mangrove classification was carried out using pixel-based methods such as spectral angle mapper (SAM) (Su et al. 2020; Sanjoto et al. 2022). Pixel-based classification groups objects based on their pixel values where each pixel is classified into one category (Murmu and Biswas 2015). In the pixel-based classification method, there are commonly used algorithms, including maximum likelihood (MLH), support vector machine (SVM), random forest, and k-nearest neighbors. Based on the description above, this study aims to identify the distribution and classification of mangrove genera using multispectral unmanned aerial vehicle (UAV) in the waters of Lancang Island, Thousand Islands and analyze the accuracy produced by multispectral UAV images with support vector machine (SVM), k-nearest neighbor (KNN), and random forest (RF) algorithms for classification and distribution of mangrove genera.

2. Research Methodology

2.1 Research Location

Geographically, Lancang Island is located between 5.9284°S, 106.5857°E. Data processing in this study was carried out at the Remote Sensing Laboratory of Marine Science and Technology, Faculty of Fisheries and Marine Sciences, Bogor Agricultural Institute. (Fig. 1)

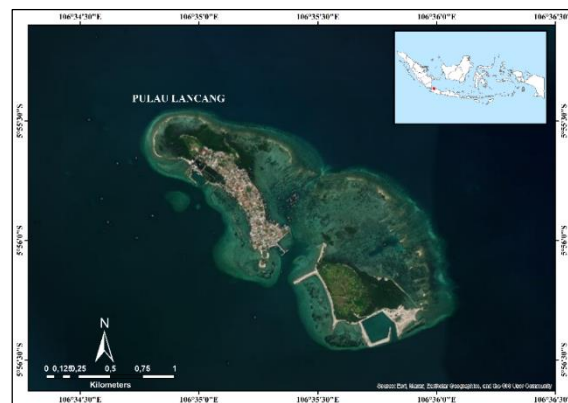


Fig. 1 Map of the Research Location

2.2 Research Framework

The process of classification and mangrove land cover change begins several stages (Figure 2) The research consists of 2 main stages, field data processing to obtain density data, mangrove canopy cover data and mangrove genus distribution data in the field that will be taken and multispectral Drone image data then the image will be processed data. Drone image data will produce a map of mangrove genus distribution. This map of mangrove genus distribution and classification will be tested for accuracy and compared using the Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest (RF) algorithms.

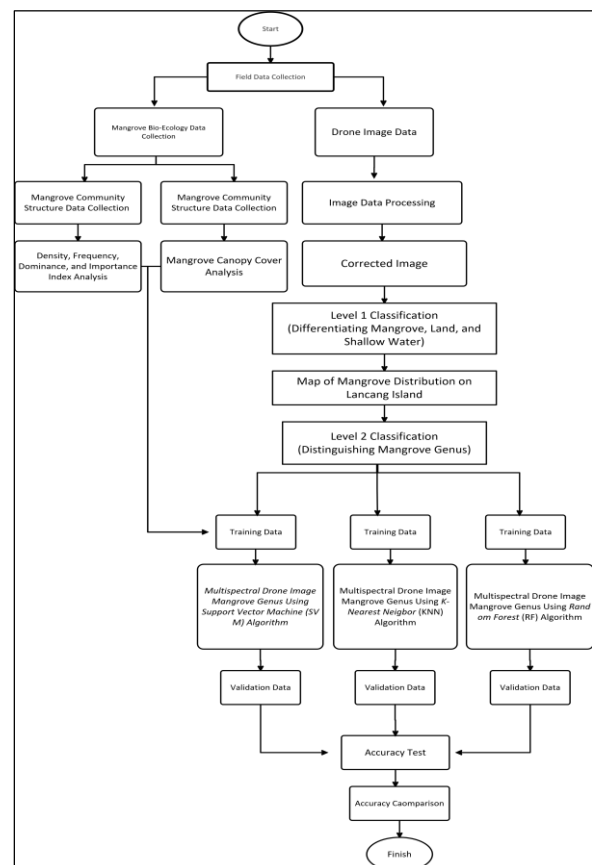


Figure 2. Flowchart of the Research Stages

2.3 Data Sources

Data collection of mangrove genera in the field was carried out by direct observation and data collection of

mangrove canopy density and cover was carried out using line transect and hemispherical photography methods. There are three transect points and three repetitions each. The square transect used is 10x10m² with a stratified random sampling data collection method. Benthic habitat data were taken as many as 481 observation points, as many as 337 points as training data and 144 for accuracy tests (Fig. 3).

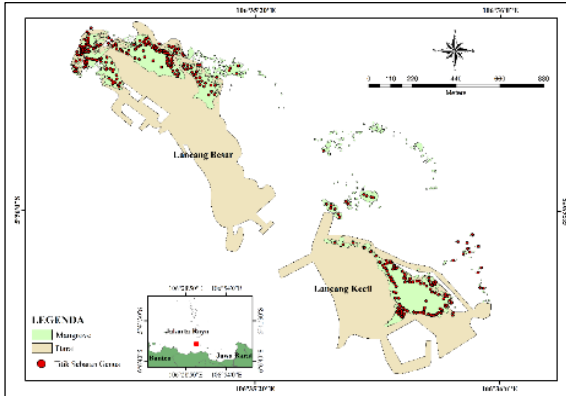


Figure 3. Map of the Distribution of Mangrove Genus Observation Points

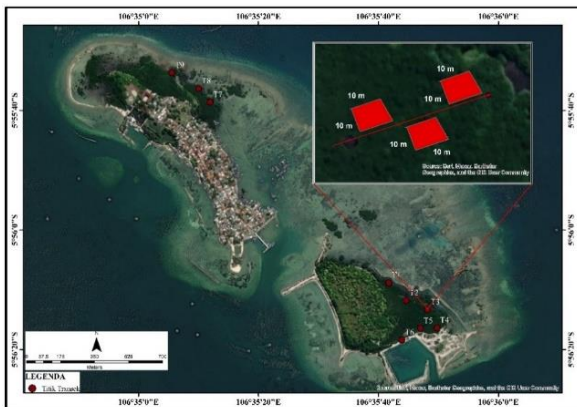


Fig 4. Transect Point Map

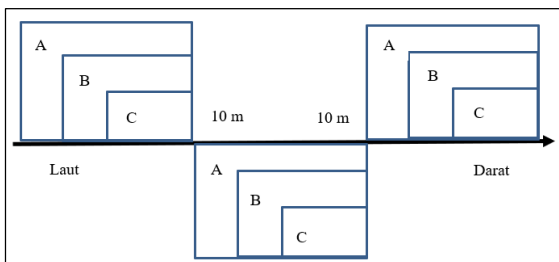


Fig 5. Transects and Plots of Mangrove Community Structure

2.4 Data Analysis

2.4.1 Mangrove Density Analysis

Data were collected on mangrove species, number of stands and tree diameter. The data collected were calculated to obtain values of density, frequency, closure, importance index (Bengen 2001).

a. Mangrove Density

Density gives an idea of the number of individuals in another sample plot (the number of trees that make up the stand). The value of the density is calculated using the following formula:

$$\text{Density (phn/Ha)} = \frac{\text{The Number of Individuals of a species}}{\text{Total Number of Plot}}$$

$$\text{Relative Density} = \frac{\text{Specific Density}}{\text{Density of all Species}} \times 100\%$$

b. Frequency

Frequency is the chance of finding vegetation on an observed plot or map. This value is obtained by counting the number of instance tiles that a type occupies and dividing by the sum of all existing instance tiles.

$$\text{Frequency} = \frac{\text{The Number of Plots Filled with a Species}}{\text{Total Number of Plot}}$$

$$\text{Relative Frequency} = \frac{\text{Specific Frekuensi}}{\text{Frekuensi of all species}} \times 100\%$$

c. Basal Area (Area of Base Field)

Basal area is the area or area covered by mangrove tree trunks at a height of 1.3 m or at a point at chest level.

$$\text{Basal Area} = \frac{\pi \text{ DBH}^2 \text{ Cm}^2}{4}$$

DBH = Diameter at Breast High (Diameter tree at 1.3 m height) CBH/phi (Cm²)

CBH = Circle Breast High

Π = 3.1428

d. Dominance

Dominance is a description of the degree of mastery of a type in an example plot.

$$\text{Dominance} = \frac{\text{Basal Area of a Species}}{\text{Area of the Entire Plot}}$$

$$\text{Relative Dominance} = \frac{\text{Dominansi Jenis}}{\text{Dominansi seluruh jenis}} \times 100\%$$

e. Important Values

From the calculation of the above formula, an important value (NP) will be obtained. Important values are used to calculate the percentage of mastery value of each type of vegetation in an area. Calculated by the formula:

$$\text{NP} = \text{FR} + \text{KR} + \text{DR}$$

Where : FR = Relative Frequency (%)

KR = Relative Possession (%)

DR = Relative Dominance (%)

2.4.2 Mangrove Cover Analysis

Hemisphere photograph taken using a fish eyes lens camera (180 degrees) (Jenning *et al.* 1999). Photos are taken in four quadrants within each plot. The cover percentage is calculated using image software. This application is used to separate sky pixels and mangrove canopy cover.

$$\% \text{Mangrove Cover} = \frac{P255}{\sum P} \times 100\%$$

Information:

P255 = Camera pixel value worth 255

∑ P = Total number of camera pixel values in the photo

2.4.3 Mangrove Genus Classification Analysis

The mangrove genus classification process is carried out using pixel-based classification by arranging and grouping various pixels into several classification classes based on the criteria of an object (Hendrawan *et al.* 2018). The classification carried out in determining the genus of mangroves is carried out with 2 levels where level 1 classification is to separate land and sea, level 2 classification is used to distinguish mangrove vegetation and non-mangrove vegetation, and level 3 classification is used to distinguish several mangrove genera found.

In this study, classification at level 1 uses digitization to distinguish land and sea while distinguishing mangroves and non-mangroves. Level 2 classification is using a classifier with the application of several classification algorithms such as SVM (*support vector machine*), KNN (*k-nearest neighbor*), and RT (*random forest*) with *thematic layer input* or training area from field data to classify mangrove genus classes. The concept of defining objects into specific class classes uses *rule sets* in the *process tree*. (Table 1)

Table 1. Machine Learning Algorithm

Name	Algoritma
Support Vector Machine (Tzotsos 2006)	$f(x) = \sum_{i \in S} \lambda_i y_i K(x_i x) + w_0$
K-Nearest Neighbor (Wei <i>et al</i> 2005).	$d(s - o) = \sqrt{\sum_f \left[\frac{v_f^{(s)} - v_f^{(o)}}{\sigma_f} \right]^2}$
Random Forest (Kulkarni and Sinha 2013)	$\{h(\mathbb{Q}, \mathbb{Q}^2), \mathbb{Q} = 1, 2, \dots, \mathbb{Q}\}$

2.4.4 Accuracy Test

Accuracy testing is carried out to determine the accuracy of the classification method used. In general, accuracy tests use an error matrix by measuring overlay accuracy (OA), which is the percentage of the appropriate number of objects from all classified objects and reference data, producer's accuracy (PA) reporting the probability of a particular mangrove genus in an area and user's accuracy (UA)

k,k	A	B	C	...	q	\sum
A	n_{AA}	n_{AB}	n_{AC}	...	n_{Aq}	n_{A+}
B	n_{BA}	n_{BB}	n_{BC}	...	n_{Bq}	n_{B+}
C	n_{CA}	n_{CB}	n_{CC}	...	n_{Cq}	n_{C+}
:	:	:	:	...	:	:
.
Q	n_{qA}	n_{qB}	n_{qC}	...	n_{qq}	n_{q+}
\sum	n_{+A}	n_{+B}	n_{+C}	...	n_{+q}	N

Table 4. Station 1 Mangrove Community Structure

Spesies	Σi	K (inc/ha)	KR	F	FR	BA	D	DR	NP(%)
Ra	71	788.89	31.56	0.56	35.71	2843.64	3.16	30.96	98.23
Rm	154	1711.11	68.44	1	64.29	6340.45	7.05	69.04	201.77
Total	225	2500	100	1.56	100	9184.087	10.21	100	300

Information

K : Kerapatan (Ind/Ha)

KR : Relative Density (%)

BA : Basal Area

D : Dominance (m²)

$$\text{Overall Accuracy}(\%) = \frac{\sum_{k=1}^q n_{kk}}{n} \times 100\%$$

$$\text{User's Accuracy}(\%) = \frac{n_{kk}}{n_{k+}} \times 100\%$$

$$\text{Producer's Accuracy}(\%) = \frac{n_{kk}}{n_{+k}} \times 100\%$$

The statistical calculation of the kappa coefficient is a coefficient used to measure the agreement of two data to be tested for accuracy (Table 2). This value indicates the condition of whether or not the accuracy of the suitability of the classification results from processed image data and conditions in the field (Candara *et al.* 2017)

$$K = \frac{n \sum_{i=1}^k n_{ii} - \sum_{i=1}^k n_i + n_{+i}}{n^2 - \sum_{i=1}^k n_i + n_{+i}}$$

Table 2. Kappa Value Accuracy Sustainability Category

Kappa Value(%)	Agreement
<0	Less than change agreement
0.01-0.20	Slight agreement
0.21-0.40	Fair agreement
0.41-0.60	Moderate agreement
0.61-0.80	Substantial agreement
0.81-0.99	Almost perfect agreement

3. Results and Discussion

Lancang Island has a naturally growing mangrove ecosystem that has diverse substrates, including sand, mud, and gravel. The condition of the waters around Lancang Island, located in the Java Sea, is influenced by seasonal changes, both eastern and western seasons.

Based on field observations, the types of mangroves found on Lancang Island based on field observations are quite diverse. Mangroves at the location have 5 species found at three station points, can be seen in Table 3.

Table 3. Mangrove Species Found on Lancang Island

No.	Species	ST 1	ST 2	ST 3
1.	<i>Avicennia alba</i>	-	-	+
2.	<i>Rhizophora apiculata</i>	+	+	+
3.	<i>Rhizophora mucronata</i>	+	+	+
4.	<i>Rhizophora stylosa</i>	...	+	-
5.	<i>Sonneratia ovata</i>	-	+	...

Information:

- : not found

+ : found

3.1 Mangrove Density Percentage

Observations of the structure of mangrove communities at station 1 obtained density values up to the important value index (INP). The results of the analysis of community structure can be seen in Table 4.

F : Frequency
 FR : Relative Frequency (%)
 Aa: *Rhizophora apiculata*

DR : Relative Dominance (%)
 INP : Important Value Index
 Rm : *Rhizophora mucronata*

Based on Table 4 there are 2 types of mangroves found, namely: *Rhizophora apiculata* and *Rhizophora mucronata*. Of the 2 types, *Rhizophora mucronata* has the highest density of 1711,11 Ind/Ha with an important percentage of 201,77%, while the lowest density value is *Rhizophora apiculata* with a density of 788,89 Ind/Ha and a percentage of importance of 98,23% The highest type

dominance found at Station 1 is *Rhizophora mucronata* amounted to 69,04 while the lowest value of the type of *Rhizophora apiculata* with a value of 30,96.

Observations of the structure of mangrove communities at station 2 obtained density values up to the important value index (INP). The results of the analysis of community structure can be seen in Table 5.

Table 5. Station 2 Mangrove Community Structure

Spesies	Σi	K (inc/ha)	KR	F	FR	BA	D	DR	NP(%)
Ra	48	533.33	19.05	0.44	25	1555.62	1.73	13.73	57.78
Rm	188	2088.89	74.60	1	56.25	8833.45	9.82	77.97	208.82
Rs	6	66.67	2.38	0.11	6.25	333.94	0.37	2.95	11.58
So	10	111.11	3.97	0.22	12.5	606.70	0.67	5.36	21.82
Total	252	2800	100	1.78	100	11329.71	12.59	100	300

Information

K : Kerapatan (Ind/Ha) BA : Basal Area
 KR : Relative Density (%) D : Dominance (m²)
 F : Frequency DR : Relative Dominance (%)
 FR : Relative Frequency (%) INP : Important Value Index
 Aa: *Rhizophora apiculata* Rm : *Rhizophora mucronate*
 Rs : *Rhizophora stylosa* So : *Sonneratia ovata*

Based on Table 5 there are 4 types of mangroves found, namely: *Rhizophora apiculata*, *Rhizophora mucronata*, *Rhizophora stylosa* and *Sonneratia ovata*. Of the 4 types, *Rhizophora mucronata* has the highest density level of 2088.89Ind/Ha with an important percentage of 208.80%, while the lowest density value is *Rhizophora stylosa* with a density of 66.67Ind/Ha and an

important percentage of 11.58% amounted to 9.82 while the lowest value of the type *Rhizophora stylosa* with a value of 0.37.

Observations of the structure of mangrove communities at station 3 obtained density values up to the important value index (INP). The results of the analysis of community structure can be seen in Table 6.

Table 6. Station 3 Mangrove Community Structure

Species	Σi	K (inc/ha)	KR	F	FR	BA	D	DR	NP(%)
Ra	75	833.33	35.89	0.44	26.67	4463.22	4.96	25.83	88.38
Rm	114	1266.67	54.55	0.89	53.33	11624.9	12.92	67.28	175.16
Aa	9	100	4.31	0.22	13.33	728.41	0.81	4.22	21.86
So	11	122.22	5.26	0.11	6.67	460.97	0.51	2.67	14.60
Total	209	2322.22	100	1.67	100	17277.5	19.20	100	300

Information

K : Kerapatan (Ind/Ha) BA : Basal Area
 KR : Relative Density (%) D : Dominance (m²)
 F : Frequency DR : Relative Dominance (%)
 FR : Relative Frequency (%) INP : Important Value Index
 Aa: *Rhizophora apiculata* Rm : *Rhizophora mucronate*
 Aa : *Avicennia alba* So : *Sonneratia ovata*

Based on Table 6 there are 4 types of mangroves found, namely: *Avicennia alba*, *Rhizophora apiculata*, *Rhizophora mucronata* and *Sonneratia ovata*. Of the 4 types, *Rhizophora mucronata* has the highest density of 1266.67Ind/Ha with an important percentage of 175.16%, while the lowest density values are *Avicennia alba* and *Sonneratia ovata* with densities of 100 Ind/Ha and 122.22Ind/Ha. The percentage of important values is 21.87% and 14.60%. The highest species dominance found by Station 2 was *Rhizophora mucronata* at 12,917 while the lowest values were from the types *Avicennia alba* and *Sonneratia ovata* with values of 0.81 and 0.51.

freshwater supply and salinity, nutrient supply, and substrate stability.

Based on the Decree of the Minister of Environment No. 201 of 2004 that the standard criteria for mangrove damage are said to be very good if the density is $\geq 1,500$ ind / ha, while the criteria are medium if the mangrove density is $\geq 1,000 \leq 1,500$ ind / ha and rare criteria if the mangrove density is < 1000 ind / ha. At station 1 the density condition of mangroves with a density of 2500 is relatively good. For station 2 the condition of mangrove density with a density of 2800 is classified as good and at station 3 the condition of mangrove forest density with a total density of 2322.22 is classified as good.

3.2 Percentage of Mangrove Canopy Cover

The density of mangroves at the field test site appeared different in each station sample, this was due to competition in the acquisition of nutrients and the sun. In addition, substrate and tidal factors of seawater exert a noticeable influence and difference. Dahuri (2003), stated that the growth rate of mangroves is influenced by

Measurement of the percentage of mangrove canopy cover was carried out using the hemispherical photography method based on the results of these field observations. A total of 3 observation stations with each

station having 3 transects and each transect having 3 observation plots. Taking photos of each plot is carried out 4 repetitions. Observation points were randomly drawn and scattered throughout the research area on Lancang Island, Thousand Islands. From these

measurements, various density values are obtained. Furthermore, for each plot, an analysis of 4 photos taken was carried out and the mangrove density value was calculated on average to obtain the percentage of canopy cover in each plot.

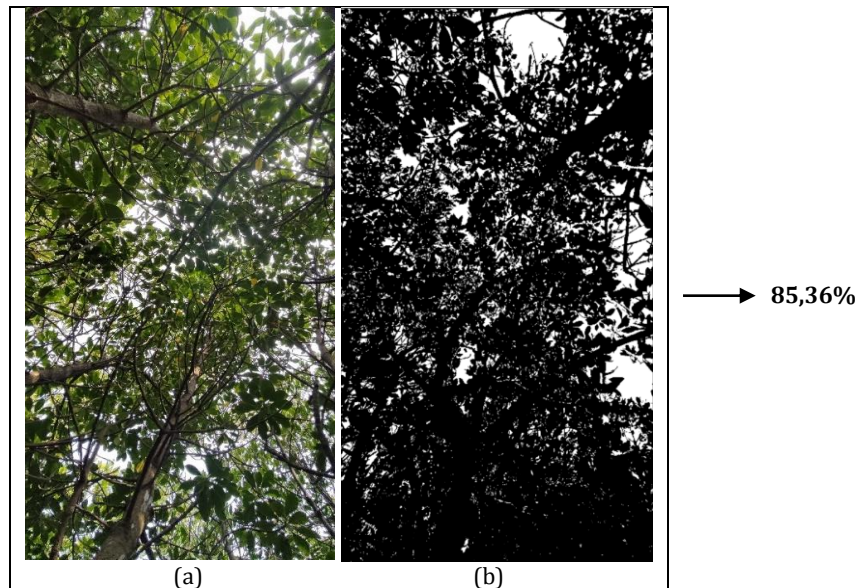


Fig 6. Example of the results of measuring mangrove canopy cover

The percentage results from each photo analysis using a wide angle camera in the entire plot. The results of the analysis of the percentage of mangrove canopy cover on Lancang Island, Thousand Islands can be found in Appendix 2. Field results showed that the highest

percentage of canopy cover recorded was 86,544% at Station 2 transect 4 plot 2. Meanwhile, the lowest percentage was recorded at 74,157% at Station 3 transect 7 plot 1. The average percentage of canopy cover generated from the field data is 82,773%.

Table 7. Percentage of Mangrove Canopy Cover

NO	P255 (Pixel)	ΣP (Pixel)	% Mangrove Cover
1	5219525	5992704	87.09
2	5185428	5992704	86.53
3	5154962	5992704	86.02
4	5185446	5992704	86.53
Average			86.54

Based on the Decree of the Minister of Environment No. 201 of 2004 that the standard criteria for the percentage of mangrove canopy cover are said to be very good if the density is >75%, while the criteria are medium if the mangrove density is 50-75% and the criteria are rare if the mangrove density is <50%. The highest percentage of land cover was found on Lancang Island at 86,544% classified as solid cover percentage, while the lowest percentage of land cover found at 74,157% was classified as medium cover percentage and the average percentage of canopy cover produced was 82,773% classified as solid cover percentage.

3.3 Classification scheme

Based on the results of observations at 481 observation points (Appendix 3), the constituent components of the mangrove genus were obtained at the research location as many as 2 classes of mangrove genus. The distribution of mangrove communities on Lancang Island is dominated by the genus *Rhizophora* sp. and *Sonneratia* sp. The determination of mangrove genus components is based on dominating mangroves obtained from direct observation in the field of visual transects.

Two classes of mangrove genera were produced, namely *Rhizophora* sp. (Rh) and *Sonneratia* sp. (So).

The frequency of the number of observation points obtained by each mangrove genus at 481 observation points for two classification classes can be seen in Figure 7 consisting of the genus class *Rhizophora* sp. (396) and *Sonneratia* sp. (85). The genus class of mangroves that has the highest frequency of presence is *Rhizophora* sp. a total of 396 observation points and followed by the genus class *Sonneratia* sp. A total of 85 observation points.

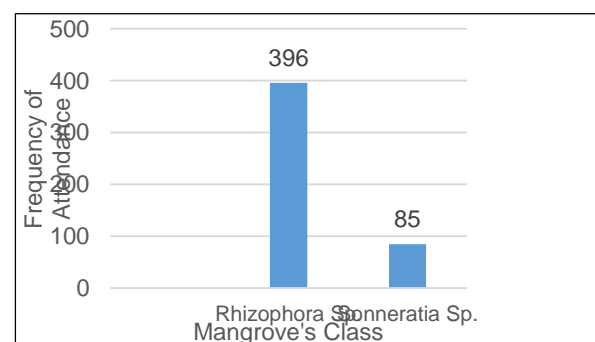


Fig 7. Frequency of Presence of Mangrove Genus

The determination of the mangrove genus classification scheme until now does not have standard provisions or standards, so that the naming of the mangrove genus class in this study is adjusted to the composition of the dominant mangrove genus constituents observed in the field. Several studies that have been conducted to determine the classification of mangrove genera are dependent on the dominance of genera found in certain locations, such as research conducted by Rosmasita et al. (2018) developed a classification scheme from the results of field observations consisting of 2 classes, namely *Xilocarpus granatum* and *Rhizophora apiculata* located in the Liong River, Bengkalis Regency, Riau Province. Aslan et al. (2016) developed a classification from observations consisting of 17 classes and among these 17 classes 4 of them are the dominant mangrove genus class, namely *Rhizophora sp.*, *Avicennia sp./Sonneratia sp.*, *Bruguiera sp.* and *Nypa Palm*. Romie (2015) developed a classification scheme from the results of field observations consisting of 2 classes, namely *Xilocarpus granatum* and *Rhizophora apiculata* located in the Bloating River, Bengkalis Regency, Riau Province. The classification scheme produced in this study consists of 2 levels of classification (Figure 8). The mangrove forest classification scheme (level 1) consists of 3 classes, namely land, mangrove and shallow water classes, while the mangrove genus classification scheme (level 2) consists of 2 mangrove genus classes in mangrove forest ecosystems. The classification scheme built in this research can be different from genus classification research in other locations, considering the complexity of mangrove ecosystems varies from region to region.

The mangrove genus classification scheme obtained from 481 observation points will then be divided into two, as many as 337 observation points will be used as training data to be juxtaposed with image data for mangrove genus classification and as many as 144 observation points will be used as accuracy test data from image classification.

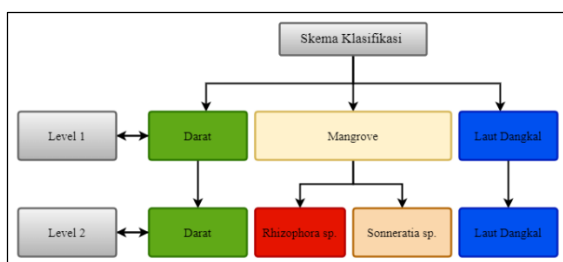


Fig 8. Results of Mangrove Genus Classification Scheme

3.4 Multispectral Drone Image Classification

Based on the results of field observations at 481 observation points, mangrove genus components were obtained at the study sites as many as two genus classes. The determination of the classification scheme is based on the dominant cover of components obtained from direct field observations on visually squared transects. The determination of mangrove genus components is based on mangroves that dominate obtained from direct field observations on visual transects. Two classes of mangrove genera were produced, namely *Rhizophora sp.* (Rh) and *Sonneratia sp.* (So). The level 1 classification used in this study resulted in 3 classes, namely land, mangroves, and shallow water (Figure 9). Several studies

in determining the level of classification determine the ROI limit (region of interest).

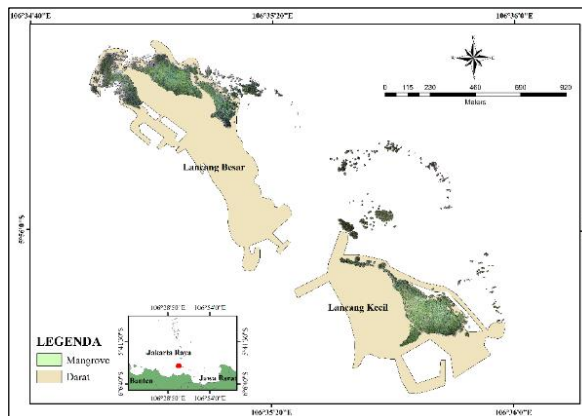


Fig 9. Level 1 Classification of Mangrove Genus

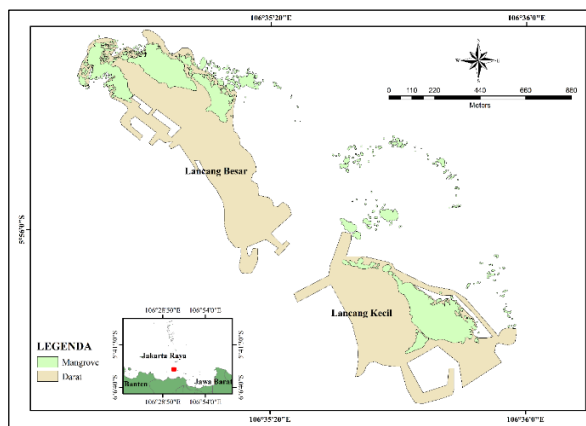


Fig 10. Level 1 Classification ROI Limit-Setting

The results of level 1 classification, especially in the shallow water class, are used as area limits in the mangrove genus classification process for level 2 classification. The results of level 1 classification can be known the total area of mangroves on Lancang Island, Thousand Islands amounting to 18.72 Ha. Average spectral reflectance from 2 mangrove genera was obtained from field training data. The general shape of the curves of this mangrove genus is very similar in that the wavelengths produced between the Blue, Green, Red, RedEdge and NIR bands differ from each other (Figure 11). This difference occurs due to differences in pigment content such as chlorophyll content and the internal structure of leaves.

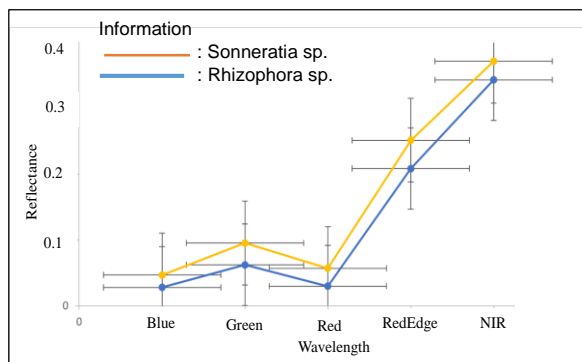


Fig 11. Spectral Reflectance Curve of Mangrove Genus

Map of mangrove genus classification using *support vector machine (SVM)*, *k-nearest neighbor (KNN)*, and

random forest (RF) algorithms is presented in Figure 12 to Figure 14

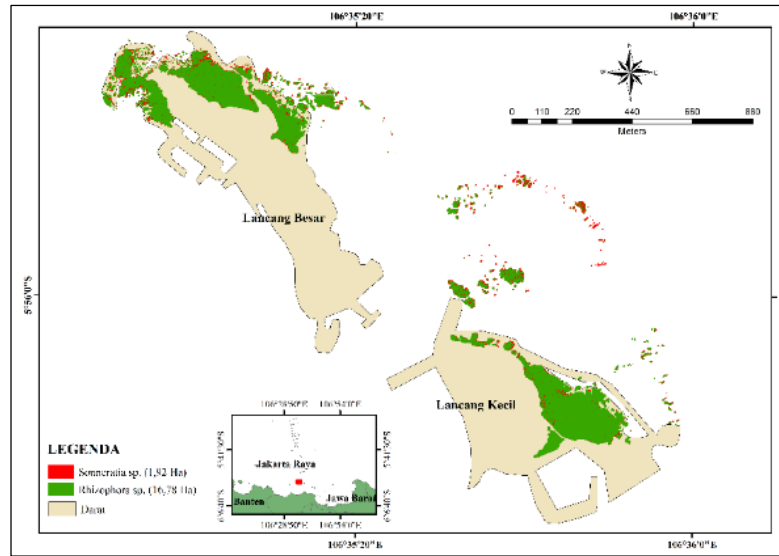


Figure 12. Distribution of mangrove genus using SVM algorithm

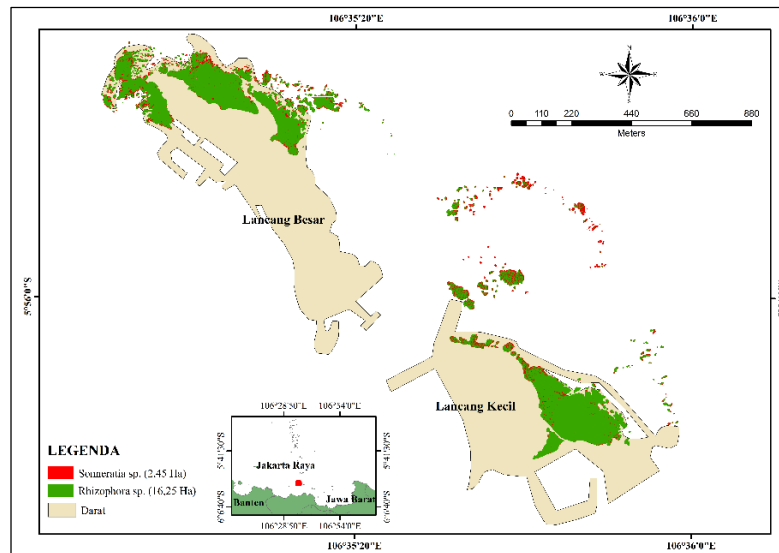


Figure 13. Distribution of mangrove genus using KNN algorithm

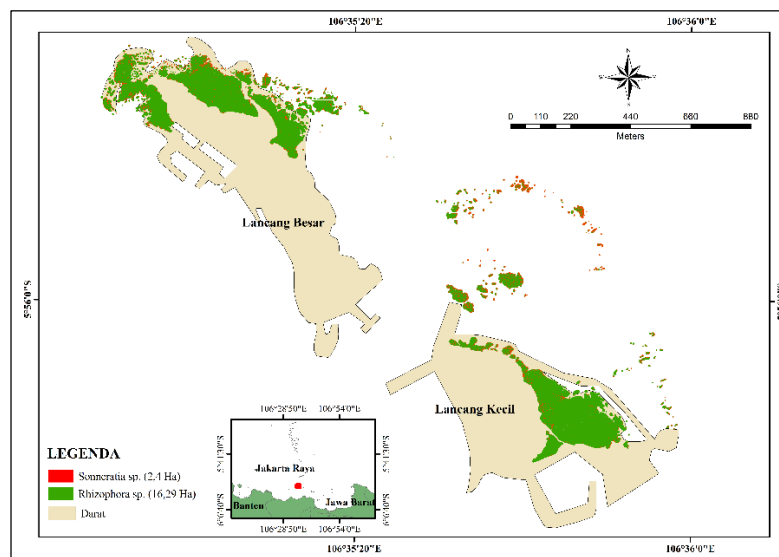


Figure 14. Distribution of Mangrove Genus Using RF algorithm

Based on the mangrove genus classification map (Figure 12 to Figure 14) using the SVM, KNN, RF algorithm shows that the most dominating genus is *Rhizophora sp.* about 87% of the total mangrove area on Lancang Island, Thousand Islands followed by the genus *Sonneratia sp.* amounting to 12.82% of the total area. Table 5 explains that the distribution of mangrove genera using the SVM algorithm obtained the area of *Rhizophora sp.* and *Sonneratia sp.* respectively 16.78 Ha and 1.92 Ha. The distribution of mangrove genera using the KNN algorithm

obtained the area of the genera *Rhizophora sp.* and *Sonneratia sp.* respectively 16.78 Ha and 2.45 Ha. The distribution of mangrove genera using the RF algorithm obtained the area of *Rhizophora sp.* and *Sonneratia sp.* respectively 16.29 Ha and 2.4 Ha. According to Alfani (2022), the most dominating mangrove on Lancang Island is *Rhizophora sp.* Christy (2024) explained that the mangrove that has the highest density on Lancang Island is the genus *Rhizophora sp.* (Table 8).

Table 8. Extent of the Mangrove Genus

No.	Class Code	Description	Area		
			SVM	KNN	RF
1	Rh	<i>Rhizophora sp.</i>	16.78	16.25	16.29
2	So	<i>Sonneratia sp.</i>	1.92	2.45	2.4
Total			18.7	18.7	18.69

3.5 Accuracy Test

The classification results using SVM, KNN and RF algorithms using 2 classes of mangrove genera were then tested for accuracy using an error matrix or *confusion matrix*. Test the accuracy of mangrove genus classification using 144 points for validation tests. The overall accuracy

scores between SVM, KNN, and RF algorithms were 89.78%, 88.32% and 89.78% respectively. The OA value obtained between the SVM and RF algorithms is the same, while the kappa accuracy used in the two algorithms is different, namely the SVM algorithm produces a kappa accuracy of 0.45 while the RF algorithm produces a kappa accuracy of 0.51 (Table 9-11).

Table 9. Accuracy test Using the SVM algorithm

Classification	<i>Rhizophora sp.</i>	<i>Sonneratia sp.</i>	Total	UA (%)
<i>Rhizophora sp.</i>	116	12	128	90,63%
<i>Sonneratia sp.</i>	2	7	9	77,78%
Total	118	19	137	
PA (%)	98,3%	36,84%		
OA (%)	89,78%	Kappa	0.45	

Table 10. Accuracy test Using the KNN algorithm

Classification	<i>Rhizophora sp.</i>	<i>Sonneratia sp.</i>	Total	UA (%)
<i>Rhizophora sp.</i>	113	11	124	91,13%
<i>Sonneratia sp.</i>	5	8	13	61,54%
Total	118	19	137	
PA (%)	95,76%	57,89%		
OA (%)	88,32%	Kappa	0.43	

Table 11. Accuracy test Using the RF algorithm

Classification	<i>Rhizophora sp.</i>	<i>Sonneratia sp.</i>	Total	UA (%)
<i>Rhizophora sp.</i>	114	10	124	91,94%
<i>Sonneratia sp.</i>	4	9	13	69,2%
Total	118	19	137	
PA (%)	96.61%	52,6%		
OA (%)	89,78%	Kappa	0.51	

Based on the results of mangrove genus classification using the SVM algorithm, the kappa index obtained is 0.45 which is included in the medium category (*Moderate agreement*) which means the level of compatibility between the classification model and reference data in the medium category is 45%. While the results of mangrove genus classification using the RF algorithm, the kappa index obtained was 0.51 which was included in the medium category (*Moderate agreement*) which means the level of compatibility between the classification model and reference data in the medium category is 51%. The kappa index produced by RF increased by 6% compared to the SVM algorithm. This is because RF is an algorithm that can overcome the instability of complex models with relatively small data sets (Tridawati, et al. 2020). This study aligns with (Kelley, et al. 2018) which states that RF

is a reliable algorithm in mapping land cover. According to Tridawati et al (2020). Stating that for land cover classification the best algorithm to use is the RF algorithm.

4. Conclusion

The distribution of mangrove genera can be mapped well using pixel-based classification methods with RF algorithms on multispectral drone imagery at the study site. The accuracy test results using RF are the best algorithm used compared to algorithms such as SVM and KNN with an overall accuracy value (OA) of mangrove genus classification of 89.78%. Based on the results of the kappa index test, a result of 0.51 was obtained where the RF algorithm was higher than other algorithms which

were included in the medium category (*Moderate agreement*).

5. Recommendations

Increasing spectral data of various leaves of the mangrove genus by taking data using spectroradiometers and considering mangrove zoning boundaries. Using Geodetic GPS so that mangrove distribution data produced in the field is more accurate.

References

- Alfani, F., Mangrove Mapping on Lancang Island Using Drones and Sentinel-2A with Object Based Image Analysis and Pixel Based Analysis Methods.
- Aslan, A., Rahman, A. F., Warren, M. W., & Robeson, S. M. (2016). Mapping spatial distribution and biomass of coastal wetland vegetation in Indonesian Papua by combining active and passive remotely sensed data. *Remote Sensing of Environment*, 183, 65–81.
- Bengen, D.G. 2001. Technical Guidelines for the Introduction and Management of Mangrove Ecosystems, Center for Coastal and Marine Resources Studies. Bogor Agricultural University. Bogor.
- Candra ID, Siregar VP, Agus SB. 2017. Geomorphological Zone and Benthic Habitat Mapping on Kotok Besar Island Using Object-Based Classification. *Journal of Fisheries Technology and Fisheries*. 8(2):209-219.
- Cao, J., Leng, W., Liu, K., Liu, L., He, Z., & Zhu, Y. (2018). Object-based mangrove species classification using unmanned aerial vehicle hyperspectral images and digital surface models. *Remote Sensing*, 10(1), 89.
- Giri C. Ochieng E. Tieszen LL. Zhu Z. Singh A. Loveland T. Masek J. Duke N. 2011. Status and distribution of mangrove forests of the world using earth observation satellite data. *Glob. Ecol. Biogeogr*. 20(1):154–159.
- Hamad IY, Staehr PAU, Rasmussen MB, Sheikh M. 2022. Drone-Based Characterization of Seagrass Habitats in the Tropical Waters of Zanzibar. *Remote Sensing*. 14,680.
- Hendrawan. 2018. Study of mangrove cover and density using satellite images on Sebatik Island, North Kalimantan [Thesis]. Bogor (ID): IPB Postgraduate Program.
- Heumann BW. 2011. An object-based classification of mangroves using a hybrid decision tree-support vector machine approach. *Remote Sens*. 3(11): 2440- 2460.
- Hogarth PJ. 2007. *The Biology of Mangroves and Seagrasses*. Third Edit. New York: Oxford University Press: Oxford. UK
- Hruska, Ryan; Mitchell, Jessica; Anderson, Matthew; Glenn, Nancy F. (2012). Radiometric and Geometric Analysis of Hyperspectral Imagery Acquired from an Unmanned Aerial Vehicle. *Remote Sensing*, 4(9), 2736–2752. doi:10.3390/rs4092736
- Jenning SB, Brown ND dan Sheil D. 1999. Assessing forest canopies and understorey illumination: canopy closure, canopy cover and other measures. *Forestry*. 72(1): 59–74.
- Jones TG. Glass L. Gandhi S. Ravaoarinarotsihoarana L. Carro A. Benson L. Ratsimba HR. Giri C. Randriamanatena D. Cripps G. 2016. Madagascar's mangroves: Quantifying nation-wide and ecosystem specific dynamics. and detailed contemporary mapping of distinct ecosystems. *Remote Sens*. 8(2).
- Kanekaputra, T. (2018). Mapping Of Mangrove Species *Avicennia Sp.* Based On Field Spectral Reflection And Worldview-2 Imagery (Doctoral Dissertation, Universitas Gadjah Mada).
- Kelley, L. C., Pitcher, L., & Bacon, C. (2018). Using Google Earth engine to map complex shade-grown coffee landscapes in Northern Nicaragua. R
- Kuenzer C. Bluemel A. Gebhardt S. Quoc TV. Dech S. 2011. Remote sensing of mangrove ecosystems: A review. *Remote Sens*. 3(5): 878-928.
- Mallinis, G., I. Mitsopoulos, & I. Chrysafi. 2018. Evaluating and comparing Sentinel 2A and Landsat-8 Operational Land Imager (OLI) spectral indices for estimating fire severity in a Mediterranean pine ecosystem of Greece. *GISci. Remote Sens.*, 55(1): 1–18. <https://doi.org/10.1080/15481603.2017.1354803>
- Mastu LOK, Nababan B, Panjaitan JP. 2018. Object-Based Benthic Habitat Mapping using Sentinel-2 Imagery in the Waters of Wangi-Wangi Island, Wakatobi Regency. *Journal of Tropical Marine Science and Technology*. 10(2):381-396
- Minister of the Environment. 2004. Decree of the Minister of Environment Number 201 of 2004 concerning Standard Criteria and Guidelines for Determining Mangrove Damage. Jakarta.
- Mitchell, Jessica J.; Glenn, Nancy F.; Anderson, Matthew O.; Hruska, Ryan C.; Halford, Anne; Baun, Charlie; Nydegger, Nick (2012). [IEEE 2012 4th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS) - Shanghai, China (2012.6.4-2012.6.7)] 2012 4th Workshop on Hyperspectral Image and Signal Processing (WHISPERS) - Unmanned aerial vehicle (UAV) hyperspectral remote sensing for dryland vegetation monitoring.
- Murmu S, Biswas S. 2015. Application of fuzzy logic and neural network in crop classification: a review. *Aquatic Pcedia*. 4(1):1203-1210.
- Nababan B, Mastu LOK, Idris NH, Panjaitan JP. 2021. Shallow-Water Benthic Habitat Mapping Using Drone with Object Based Image Analyses. *Remote sensing*. 13, 4452.
- Nagarajan, P., Rajendran, L., Pillai, N. D., & Lakshmanan, G. (2022). Comparison of machine learning algorithms for mangrove species identification in Malad creek, Mumbai using WorldView-2 and Google Earth images. *Journal of Coastal Conservation*, 26(5), 44.
- Oktorini, Y., Darlis, V. V., Wahidin, N., & Jhonnerie, R. (2021, March). The Use of SPOT 6 and RapidEye Imageries for Mangrove Mapping in the Kambung River, Bengkalis Island, Indonesia. In *IOP Conference Series: Earth and Environmental Science* (Vol. 695, No. 1, p. 012009). IOP Publishing.
- Oleksyn S, Tesetto L, Raoult V, Joyce KE, Williamson JE, 2021. Going Batty: The Challenges and Opportunities of Using Drones to Monitor the Behaviour and Habitat Use of Rays. *Drones*. 5,12.
- Osei Darko, Patrick, Margaret Kalacska, J. Pablo Arroyo-Mora, and Matthew E. Fagan. "Spectral complexity

- of hyperspectral images: a new approach for mangrove classification." *Remote Sensing* 13, no. 13 (2021): 2604. Ikonos quickbird
- Pretzsch H, Biber P, Uhl E, Dahlhausen J, Rotzer T, Caldentey J, Koike T, Con TV, Chavanne A, Seifert T, Toit BD, Farnden C, Pauleit S. 2015. Crown Size and Growing Space Requirement of Common Tree Species in Urban Centres, Parks, and Forests. *Urban Forestry & Urban Greening*. 14(3): 466-479.
- Rahmandhana, A.D., Aditama, M.H. And Mahendra, D., 2022. Utilization Of Gis Remote Sensing Technology For Pt Amman Mineral Nusa Tenggara's Watershed Reclamation And Rehabilitation Program. *Proceedings Of The Perhapi Annual Professional Meeting*, Pp.489-502.
- Ridha, S. M. (2021). Mapping Mangrove Species Using Worldview-2 Imagery And Object-Based Classification In Clungup Mangrove Conservation Malang, East Java (Doctoral Dissertation, Universitas Gadjah Mada).
- Rosmasita, R., Siregar, V. P., & Agus, S. B. Classification of Mangroves Based on Objects and Pixels Using Sentinel-2b Imagery in Liong River, Bengkalis, Riau Province. *Journal of Tropical Marine Science and Technology*, 10(3), 601-615.
- Sanjoto, T.B., Husna, V.N. and Sidiq, W.A.B.N., 2022. Spectral angle mapper algorithm for mangrove biodiversity mapping in Semarang, Indonesia.
- Siregar, V. P., Agus, S. B., & Jhonnerie, R. (2019, May). An object-based classification of mangrove land cover using Support Vector Machine Algorithm. In *IOP conference series: earth and environmental science* (Vol. 284, No. 1, p. 012024). IOP Publishing.
- Su, X., Wang, X., Song, D., Zhao, J., Fan, J., & Yang, Z. (2020, July). Improved Spectral Angle Mapper applications for mangrove classification using SPOT5 imagery. In *International Conference in Communications, Signal Processing, and Systems* (pp. 1232-1243). Singapore: Springer Singapore.
- Sukmawati, T. S. 2008. Detection of mangrove ecosystems in Cilacap, Central Java with Alos satellite imagery. Thesis. Marine Science and Technology Study Program, Faculty of Fisheries and Marine Sciences: Bogor Agricultural University.
- Thampanya U, Vermaat JE, Sinsakul S, Panapitukkul N. 2006. Coastal erosion and mangrove progradation of Southern Thailand. *Estuar Coast Shelf Sci*. 68(1):75-85
- Tomlinson BP. 1986. *The Botany of Mangroves* Second Edition. Cambridge University Press
- Tridawati, A., Wikantika, K., Susantoro, T. M., Harto, A. B., Darmawan, S., Yayusman, L. F., & Ghazali, M. F. (2020). Mapping the distribution of coffee plantations from multiresolution, multi-temporal, and multi-sensor data using a random forest algorithm. *Remote Sensing*, 12(23), 3933.
- ZABRINA, Waode Shifa. 2023. Analysis of Maximum Likelihood and Support Vector Machine Classification Methods on Mangrove Mapping.
- Zhang X. Tian Q. 2013. A mangrove recognition index for remote sensing of mangrove forest from space. *Curr. Sci*. 105(8):1149-1154
- Zhang X. Treitz PM. Chen D. Quan C. Shi L. Li X. 2017. Mapping mangrove forests using multi-tidal remotely-sensed data and a decision-tree-based procedure. *Int J Appl Earth Obs Geoinf*. 62(1):201-214.



© 2024 Journal of Geoscience, Engineering, Environment and Technology. All rights reserved. This is an open access article distributed under the terms of the CC BY-SA license (<http://creativecommons.org/licenses/by-sa/4.0/>).