COMPARISON OF THE MANGROVE FOREST MAPPING ALGORITHMS IN KELABAT BAY USING RANDOM FOREST AND SUPPORT VECTOR MACHINES

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Abstract. One of the tropical ecosystems is mangrove forests which thrive on protected coastlines such as bays, estuaries, lagoons, and rivers. These are usually found in the intertidal zone. Mangroves are a valuable natural resource because they can stabilize coastlines, prevent erosion, hold sediment and nutrients, protect from storms, regulate floods and currents, absorb carbon, maintain water quality, function as a breeding ground for fish and other marine biota, and provide food for plankton. Mangrove forests in Indonesia are among the largest in the world, covering around 18%–23% and covering around 59.8% of the total mangrove area on earth. This paper examines the uses of support vector machines (SVM) and random forests (RF) for mapping mangrove forests using the case study of Kelabat Bay in Bangka Regency Bangka Belitung Islands. 2022 Landsat-9 imagery taken via Google Earth Engine (GEE) is the data source used in this research. This research uses computer programming and accuracy testing on the GEE platform. As a result, RF detected mangrove forests covering an area of approximately 67 ha (OA: 0.932), while SVM detected mangrove forests covering an area of approximately 62 ha (OA: 0.912).

Keywords: *mangrove, mapping, remote sensing, machine learning, random forest, support vector machine, kelabat bay*

1 INTRODUCTION

One of the habitats that can be found in the tropics is the mangrove forest. Mangrove forests thrive in significantly distinct environmental conditions from other ecosystems, making them some of the planet's most productive and complex ecosystems (Woodroffe et al., 2016). Mangrove forests thrive on protected coastlines, including those in bays, estuaries, lagoons, and streams, and are typically found in the intertidal zone (Kuenzer et al., 2011). Mangroves are a valuable natural resource because they stabilize shorelines, prevent erosion, hold onto sediment and nutrients, protect against storms, regulate floods and currents, sequester carbon (Yusandi et al., 2018), and maintain water quality (Thakur et al., 2020), and generate income from a variety of forest (A. A. Md. A. P. Suardana et al., 2023). In addition, mangroves serve as a food source for plankton and fish breeding habitats for marine biota (Purwanto et al., 2023). Sadly, according to scientists' estimates, at least one-third of all mangrove forests have disappeared in recent years (Romañach et al., 2018).

According to (Purwanto et al., 2023), Mangrove forests in Indonesia are among the largest in the world, covering around 18%–23% and covering around 59.8% of the total mangrove area on earth. According to data from the (FAO, 2007), Indonesia's mangrove forests shrunk from 4.2 million ha to 2.9 million ha between 1980 and 2005. Human activities like transforming mangrove forest areas into fish or shrimp ponds and urban expansion are mostly to blame for losing mangrove regions (Richards & Friess, 2016). Due to its numerous advantages, mangrove forests must be continuously monitored through studies of the spatial-temporal dynamics of coastal land use/cover patterns.

Since the 1970s, mangrove forest zones have been mapped using remote sensing data (L. Wang et al., 2019). Several studies have used remote sensing data to monitor changes in mangrove ecosystems (A. Suardana et al., 2022). The NIR and SWIR bands are the best for identifying mangrove forests based on the spectral response of satellite imagery (Purwanto & Asriningrum, 2019), because the properties of mangrove vegetation reflect near-infrared (NIR) waves and absorb energy from SWIR waves, respectively (Winarso & Purwanto, 2014). Figure 1-1 shows the spectral characteristics of mangroves which are very clearly visible in the NIR and SWIR bands compared to other objects in Landsat imagery.

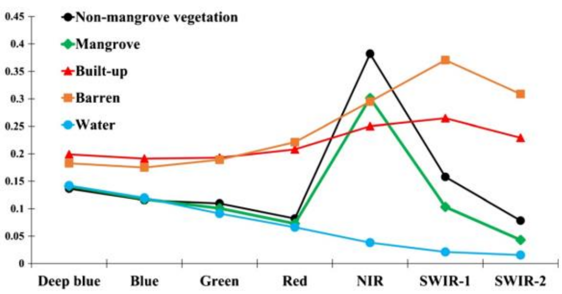

Figure 1-1: Spectral Characteristics of Mangroves Compared to Other Objects in Landsat Imagery (Ali & Nayyar, 2020)

In recent years, land cover classification techniques based on machine learning have become more popular, and Google Earth Engine (GEE) provides several algorithms (Avtar et al., 2020). (Diniz et al., 2019) used the random forest (RF) method on Landsat 5-8 data on the GEE platform to map Brazilian mangrove forests. The support vector machine (SVM) method is also widely used to map mangrove forests (Purwanto et al., 2023). To run classification algorithms on the GEE platform, one must have knowledge of computer programming, which is necessary to demonstrate this.

In this study, the mapping of mangrove forests using random forest (RF) and support vector machine (SVM) methods is compared using the example study of Kelabat Bay in the Bangka Regency and Bangka Belitung Islands. This location was chosen because according to media reports, the rampant tin mining around Kelabat Bay has contributed to the destruction of mangrove forests. This research uses the GEE platform and Landsat-9 imagery. By using Landsat imagery which has been used to monitor environmental conditions and natural resources since 1972, it is hoped that the resulting application can one day be used to further study the spatial-temporal dynamics of mangrove forests in Kelabat Bay several decades ago.

2 MATERIALS AND METHODOLOGY

2.1 Location and Data

The location of this study is Teluk Kelabat Dalam in the West Bangka Regency. Its precise coordinates are 1°36'48" to 1°51'35"S and 105°31'10" to 105°53'50"E. Figure 2-1 shows that this area is a closed sea body facing the South China Sea.

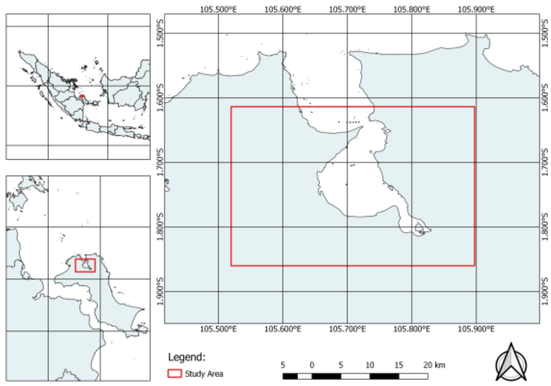

Figure 2-1: Research Location

This study used Landsat-9 imagery from January to December 2022 as the data source. The data was taken from the Google Earth Engine (GEE), starting with a cloud masking process, and then a mosaic was created for each band by taking the mean value across all bands.

2.2 Methods

Figure 2-2 schematically illustrates the details of the support vector machine (SVM) and random forest (RF) algorithm comparison approach for identifying mangrove forests in Kelabat Bay.

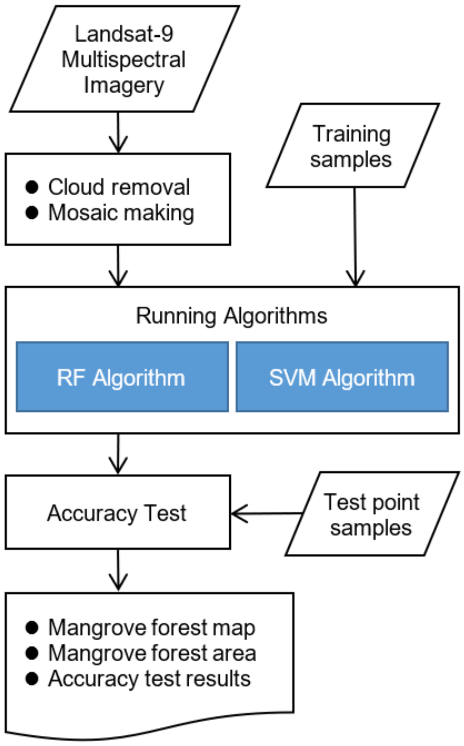

Figure 2-2: Study Flowchart

2.3 Taking Training Samples

In this stage, the history of high-resolution imagery stored in the Google Earth Pro application is searched for training samples. The collected samples are polygons that depict:

1. Samples of water bodies
2. Samples of mangrove forests
3. Non-mangrove samples (others), including populated areas, mining areas, paddy fields, terrestrial vegetation, and others.

2.4 Running the Algorithm

In this stage, the random forest (RF) and support vector machine (SVM) algorithms were tested on the Landsat-9 band 2-7 mosaic with training samples obtained from Google Earth Pro to create a mangrove forest map.

2.5 Sampling for Accuracy Test

In this stage, a search for the history of high-resolution imagery stored in the Google Earth Pro application is carried out to be used as an example of a test point. Test point sampling was carried out to evaluate the accuracy of the map produced using the random forest (RF) and support vector machine (SVM) methods. Based on (BSN, 2019), the minimum size of the test point is around 90 x 90 m (9 pixels of Landsat-9 images), and the samples needed in this research area are around 399 points consisting of water bodies, mangroves, and non-mangroves.

2.6 Accuracy Test

In this step, the map created with the support vector machine (SVM) and random forest (RF) algorithm is tested using test point examples taken from the Google Earth Pro program, and the result is a confusion matrix (BSN, 2019).

3 RESULTS AND DISCUSSION

3.1 Random Forests (RF)

Random Forest is a powerful and versatile ensemble learning method that combines a series of tree structure classifiers, making it suitable for a wide range of applications (Breiman, 2001). Random Forest classifiers have been widely used in remote sensing due to their ability to handle high data dimensions and multicollinearity (Triscowati et al., 2020), as well as their speed and insensitivity to over-fitting (Belgiu & Drăgu, 2016).

The Random Forest Classifier has been successfully applied to land cover classification from multi-sensor remote sensing imagery and achieved high overall accuracy. The use of Random Forests for multisource data classification has also been investigated, with promising results (Gislason et al., 2004). Compared to support vector machines, Random Forest classifiers were shown to perform equally well in terms of classification accuracy and training time, with fewer user-defined parameters (Pal, 2005).

3.2 Support Vector Machine (SVM)

Support vector machine (SVM) is a powerful machine learning method based on statistical learning theory, known for its excellent performance. It is widely used in classification applications because of its high accuracy (Zhang, 2012). The Support Vector Machine (SVM) algorithm was developed by Vapnik in 1965, and further advances were made in the 1970s and 1990s (Q. Wang, 2022).

This algorithm has been widely applied in various fields, including pattern recognition and natural language processing. Its effectiveness in classification tasks has been proven in studies using different data sets (Srivastava & Bhambhu, 2010). SVMs are of particular interest in the field of remote sensing due to their ability to generalize well with limited training samples, although parameter assignment problems can affect the results (Mountrakis et al., 2011).

3.3 Comparison and Evaluation

Figure 3-1 displays the classification results obtained using the random forest (RF) algorithm. Figure 3-1 shows that blue indicates waters, green indicates mangrove forests, and gray indicates non-mangroves.

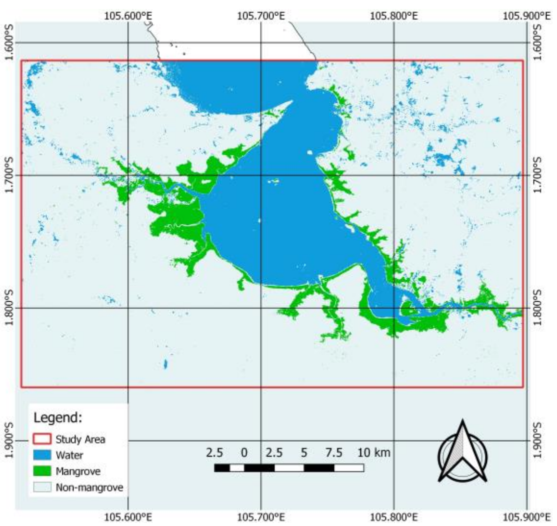

Figure 3-1: RF Classification Results

The accuracy test results may be found in Table 3-1, with a very good overall accuracy of 0.932 (93.2%). The area of mangrove forest detected by the random forest (RF) method is approximately 66.93 ha.

Table 3-1: RF Classification Result Accuracy Test

Data Fields	Classification			Total
	Water bodies	Mangroves	Non-mangroves	
Water bodies	132	0	1	133
Mangroves	1	100	32	133
Non-mangroves	0	0	133	133
Total	133	100	166	399
Overall accuracy				0.932

Furthermore, the classification results obtained using the support vector machine (SVM) algorithm can be seen in Figure 3-2. Figure 3-2 shows that blue indicates waters, green indicates mangrove forests, and gray indicates non-mangroves.

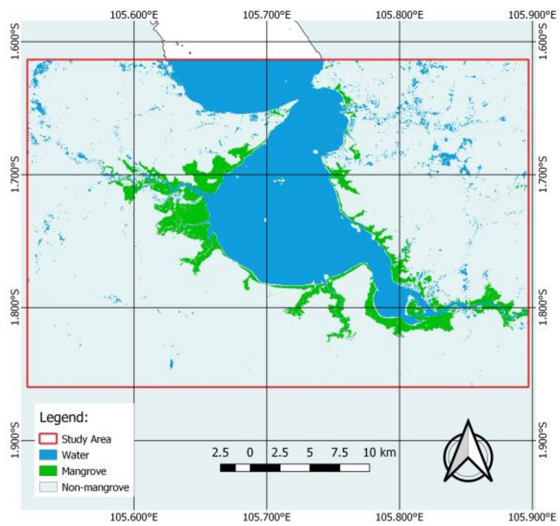

Figure 3-2: SVM Classification Results

The accuracy test results may be found in Table 3-2, with a very good overall accuracy of 0.912 (91.2%). The area of mangrove forests detected by the vector machine (SVM) method is approximately 62.10 ha.

Table 3-2: SVM Classification Result Accuracy Test

Data Fields	Classification			Total
	Water bodies	Mangroves	Non-mangroves	
Water bodies	132	0	1	133
Mangroves	1	100	32	133
Non-mangroves	1	0	132	133
Total	134	100	165	399
Overall accuracy				0.912

The results of the comparison and evaluation of the two algorithms show that these two algorithms can produce data with high accuracy. The random forest (RF) algorithm is slightly superior to the support vector machine (SVM) algorithm in terms of accuracy. However, RF performs faster than SVM in processing; The processing time of the support vector machine (SVM) compared to the random forest (RF) algorithm on the input data that the author uses is around 5-8 times longer.

4 CONCLUSION

Based on the research results, support vector machine (SVM) and random forest (RF) algorithms can be considered for mapping mangrove forests; both can produce data with high accuracy. However, the random forest approach is more recommended because of its processing speed. The accuracy test results of the two algorithms need to be strengthened by carrying out accuracy tests using field data, not high-resolution images from Google Earth Pro. Considering the importance of mangrove forests, further research is needed regarding mangrove forest mapping techniques to support mangrove conservation to support sustainable development.

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