The spatial dynamics of mangrove forest in the Alas Purwo Banyuwangi National Park marine tourism area using remote sensing images

D P Utomo, T Handayani, D Susiloningtyas, M D M Mansessa
Department Geography, University of Indonesia, Depok, Indonesia
E-mail: didik.priyo@ui.ac.id

Abstract. Bedul Mangrove Forest, located in the location of the Alas Purwo Banyuwangi National Park (TNAP). In 2009, the mangrove forest was opened as a tourist area. Although the surrounding community no longer cuts down mangroves, the presence of tourists will affect mangrove growth. This study aims to see the right way to identify mangrove areas, see the dynamics of mangrove trends in TNAP, and adapt it to tourism developments. Remote sensing uses Landsat 8 OLI TRS and Landsat 7 ETM+ imagery data for 2005-2020. The mangrove density analysis used NDVI, grouped into 5 classes, from very dense to very rare. The results showed that the mangrove area's total area was 16.47 km² and was stagnant until the time of determining tourist attractions in 2009. Since the determination until 2020, the mangrove area has decreased to 14.96 km². Overall, mangroves' tendency to experience negative is indicated by an increase in the very dense density class and a decrease in other classes. The composition of mangroves has dramatically increased from 2005 to 2020, from 64% to 87% of the entire class.

1. Introduction
Mangroves or mangroves are plants that live in high tide and low tide areas and form their communities [1]. Mangroves grow along tropical to sub-tropical coastlines, which have an essential function for the environment that contains salt and forms of land in the form of beaches with soil characteristics anaerobes. Therefore, its location in the coastal area and its physical characteristics make mangroves function as shoreline protectors. In broader ecological terms, mangroves also function as animal habitats, prevent seawater intrusion, a source of foodstuffs, breeding grounds, and places for various aquatic biota to grow, as well as protection from tsunamis. From an economic perspective, the people living around the mangrove area can use it as firewood and catch aquatic biotas such as fish and crabs [2].

The abundance of mangrove resources found in the Blok Bedul area in the Alas Purwo National Park has provided various benefits. The surrounding community has long used the abundance of resources found in the Bedul Block as a livelihood. The community's dependence on this ecosystem has made residents even steal marine products and forests, which are the protection and conservation areas of TNAP. Local residents commonly use wood from mangroves for firewood and agriculture. Particular efforts have been made, one of which is the collaboration between Sumberasri Village and TNAP to build an ecotourism area that involves the community. The agreement was made in 2007, and tourism activities began to open in 2009. This collaboration aims to reduce encroachment and change people's habits in utilizing mangrove forests [3].

Until now, remote sensing technology has been widely used in mangrove assessment. Remote sensing in mangrove assessment can be used for species composition, health level, area change, biomass estimation, management design, planning before field methods, rapid information on disaster mitigation, helping to understand ecological and biological relationships and processes, processes, functions, and
dynamics. The behaviour that can be detected is vegetation's sensitivity, especially mangroves, to infrared rays, especially near-infrared. Therefore, mangrove identification can be made by conducting a supervised classification. Supervised classification is the process of categorizing guidance pixels to determine the various types of land cover in an image [4]. The guidance pixel in question is a sample pixel that acts as a guide, usually called the training area [6]. If the land cover has been identified successfully, the next step is to carry out a vegetation analysis. The vegetation analysis that is commonly used is the Normalized Difference Vegetation Index (NDVI). NDVI was built by utilizing NIR (Near Infrared) and Infrared wave calculations because it is suitable for vegetation characteristics in the wave spectrum [5]. By using this principle, this study aims to determine the appropriate algorithm model in identifying mangrove areas, seeing the dynamics of mangrove trends in TNAP, and its relation to tourism development.

2. Materials and methods
2.1. Study area
The research was conducted in the Blok Bedul, Alas Purwo National Park (TNAP), Banyuwangi. The mangroves in TNAP are on the west side. Alas Purwo National Park is a protected area that aims to protect the ecosystem and its uses. Based on measurements on 27 May 1983, the TNAP area was 43,420 ha. TNAP is at an elevation of 0-322 masl with the highest peak, namely Mount Lingga Manis. The coastline is 105 km long from the Grajagan to the Muncar area. The slope varies from 0-40% with the area in the 8-15% interval—rock conditions in limestone and acidic formations. The annual rainfall reaches 1,079 mm (Tegaldlimo) and 1,554 (Muncar). The maximum air temperature ranges from 31.2-34.5 °C. The humidity is relatively small, ranging from 75-81%. The highest wind direction is in the South direction with a speed of 2.3-4.2 knots.

![Figure 1. The appearance of an image that has passed the image preprocessing process. L8 (Landsat 8 OLI TIRS) & L7 (Landsat 7 ETM).](image-url)
only that, but other mangrove areas were also found, such as in Sunglon Ombo, Perpat, Slenggrong, and Buyukan but with a tiny area. According to the Alas Purwo National Park, the area in area I is approximately 866 ha, in region II, it is approximately 198 ha, and in other areas, it is less than 5 Ha [7].

2.2. Data
The research used Landsat 7 ETM and Landsat 8 OLI TIRS imagery acquired from the Google Earth Engine (GEE). Available data is Landsat 7 ETM Tier 1, subjected to radiometric calibration with top-of-atmosphere (TOA). Likewise, the Landsat 8 OLI TIRS imagery available in GEE is a Landsat image that has gone through the TOA radiometric calibration process [8]. Temporally, the data used for Landsat 7, namely the years 2005-2017. For Landsat 8, the data used are 2013-2020.

2.3. Preprocessing image
Using data every year (1-01 to 31-12), the data were analyzed using the median filter method to eliminate the effects of image noise. Median filters work by moving image elements by pixel, replacing each value with neighbouring pixels. The problem is that clouds always cover the image in the area, so it is necessary to erase the cloud using a cloud removing algorithm. This approach aims to remove contaminated portions of satellite imagery and construct information from data that does not use multi-temporal temporal imagery. With these two techniques, the image quality on which the analysis is based will represent the actual situation [9].

2.4. Supervised classification
Supervised classification is the guidance of a specific pixel categorization process, using computer algorithms, numerical descriptions of the various types of land cover found in the image. The classification process makes use of the spectral values contained in the image. The spectral values in each pixel can show the spectral patterns of any land cover; this is known as spatial pattern recognition. This method is very dependent on the interpreter's ability to determine the sample point as a guide. There are at least three stages in conducting supervised classification: (1) the training stage is carried out by taking a representative sample for the training area and building a numerical description of each land cover, (2) the classification stage grouping each pixel value into the most homogeneous class, (3) the output stage the value will be entered into 3 output forms, namely thematic maps, tabular data, and digital data [6].

| Method name | Description | Source |
|-------------|-------------|--------|
| SVM | Boser, Guyon, & Vapnik (1992) as developers of the SVM method. The basic principle of SVM is that a training sample that is close to the boundary of a class will differentiate the class better than any other training sample. | [15] |
| Random Forest | Random Forest is constructed by combining various output decision trees to define new input data based on maximum votes. J. Ross Quinlan designed the Random Forest algorithm. | [15] |
| Naïve Bayes | The way Naïve Bayes works simply predicts future opportunities based on past experiences. | [16] |
| Minimum Distance | This classification technique takes the known identity pixel, and then the closest pixel becomes the training pixel. | [17] |
| GMO Max Entropy | The principle that maximum entropy applies is that a distribution model that satisfies a specific limit must be as uniform as possible. | [18] |
| CART | Classification and Regression Trees (CART) is a model developed by L. Breiman et al. (1984). CART works by identifying and constructing binary decision trees using known training data samples. | [19] |

Table 1. A brief description of the classification methods.
At the training stage, the interpreter's ability to interpret the image is used. Furthermore, at the classification stage, there are various kinds of classification methods that can be used. GEE provides 13 classification methods, which are only used in this study 10 types of classification methods. The 10 classification methods include CART, GMO Max Entropy, Lib SVM, Minimum Distance, Naïve Bayes, Random Forest, Smile CART, Smile Naïve Bayes, Smile Random Forest, and SVM. The use of 10 classification methods aims to find the best classification method for the research area's image characteristics. 4 out of 10 (marked by the use of "Smile" and "Library") methods are the same type of algorithm. It is just that GEE makes local changes that don't affect the functional basis. Given GEE, Google intends to remove 4 old classifiers that have been updated. Then, the output stage used in this study is a thematic map and tabular data. Both are needed to discuss descriptively the phenomena that occur both temporally and spatially.

2.5. Vegetation index
Mangrove identification can be approached with a vegetation index, the Normalized Difference Vegetation Index (NDVI). NDVI was built by utilizing NIR and infrared calculations [10]. For example, in Landsat 8 satellite imagery, where NIR and infrared are in bands 4 and 5 so the formula is:

\[
\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}
\]

The results of the NDVI calculation will produce a number range from -1 to 1. The larger the value indicates, the denser the vegetation canopy is. It also indicates the health of mangroves. According to the Minister of Environment Decree No. 201, the year 2004, solid and rare status is still categorized as good, while the criteria are rarely concluded as damaged.

2.6. Accuracy assessment
In this study, the accuracy assessment used was a confusion matrix or error matrix. A confusion matrix is an accurate assessment that compares each category based on the relationship between reference data and automatic classification results. In this assessment, there are terms known as overall accuracy, producer's accuracy, and consumer's accuracy. Overall accuracy is the ratio between the number of correct pixels in the classification and the total number of reference pixels. The producer's accuracy is the ratio between the number of pixels of the correct classification and the total number of reference pixels in that class. Furthermore, the consumer's accuracy is the ratio between the numbers of correct reference pixels to the total number of classified pixels in that class. Data independence is essential in this accuracy; many cases show the same data for the training area in calculating accuracy. If so, good results only indicate a good classification process in the training area, not the overall classification results [6]. According to the National Space Agency (LAPAN), image data processing accuracy is at least 70%, and after field validation, the accuracy is 90% [11].

3. Result and discussion
3.1. Time-series image analysis
The images that have gone through the image preprocessing stage in the form of a median filter and cloud removal algorithm do not all produce images that are clean from clouds. In 2006, 2010, and 2011 large cloud cover was detected. The entire image is a Landsat 7 ETM image. It makes the image in that year unable to be used as a basis for analysis in assessing mangrove conditions.
3.2. Supervised classification method analysis

The results show that not all methods can classify images with good accuracy. Some methods are also good for classifying Landsat 7 images but not good for classifying Landsat 8 images. These methods are Naïve Bayes and Smile Naïve Bayes. The accuracy of the users of the two methods in detecting mangroves in Landsat 7 imagery is 100% each. However, the accuracy of the users of both methods in detecting mangroves in Landsat 8 imagery is very low, only 9% and 33%. On the other hand, some methods are good in classifying Landsat 8 images but poor in classifying Landsat 7 images. These methods are SVM (Support Vector Machine) and Lib SVM, which are bad for classifying Landsat 7 images. User accuracy of both methods in classifying mangroves on Landsat 7 imagery for 0% each. It means that both methods are not able to classify mangroves on Landsat 7 images. However, the user's accuracy for both methods in classifying mangroves in Landsat 8 images is quite good, namely 91%.

Figure 2. The appearance of the True Color Composite image that has passed the image preprocessing process. L8 (Landsat 8 OLI TIRS) & L7 (Landsat 7 ETM).
Figure 3. Various supervised classification methods have been carried out on Landsat 7 ETM. (a) Smile Random Forest, (b) Smile Naïve Bayes, (c) SVM, (d) Smile CART, (e) Random Forest, (f) Naïve Bayes, (g) Minimum Distance, (h) Lib SVM, (i) GMO Max Entropy, (j) CART.

Figure 4. Various supervised classification methods have been carried out on Landsat 8 OLI TIRS. (a) Smile Random Forest, (b) Smile Naïve Bayes, (c) SVM, (d) Smile CART, (e) Random Forest, (f) Naïve Bayes, (g) Minimum Distance, (h) Lib SVM, (i) GMO Max Entropy, (j) CART.
Based on the accuracy of various methods for each type of image, it can be done to determine the best method for classifying mangroves. The best method for classifying mangroves is Smile Cart and GMO Maximum Entropy, which produce 100% accuracy for each image type. Therefore, in further analysis, one method can be used to assess the extent of mangroves.

3.3. Mangrove area
The mangrove area analysis results have been obtained from 2005 to 2020, which came from 2 types of images, namely Landsat 7 ETM and Landsat 8 OLI TIRS. Based on comparative data for 2013-2017 using Landsat 7 ETM, the mangrove area trend has increased. However, this increase is tiny based on the difference between 2017 and 2013 of only 0.37 km². Data from 2013 - 2020 uses Landsat 8 OLI TIRS, the trend of mangrove area tends to be stagnant. Furthermore, the comparison of Landsat 7 ETM and Landsat 8 OLI TIRS data from 2013-2017 has an average gap of 1.2 km². The difference in sensors between Landsat 7 ETM and Landsat OLI TIRS affects the extensive mangrove network. In line with research conducted by Diniz C. et al. in Brazil, the results showed that there were differences in the results of the area of mangrove areas between Landsat 7 ETM and Landsat 8 OLI TIRS [12].

![Figure 5](image_url). The analysis of the mangrove area in the range of 2005 to 2020 used Landsat 7 ETM and Landsat 8 OLI TIRS imagery.

However, generally without considering the type of image, there is a downward trend. So that in 2005 the area of mangroves was 16.47 km² and was stagnant until the time of determining tourist attractions in 2009. From the time of determination until 2020, the area of mangroves has decreased to 14.96 km². It means that there is a difference of 1.51 km² of the missing mangrove area.

3.4. Mangrove canopy density
Based on the data above, the mangrove density in the Blok Bedul, Alas Purwo National Park has fluctuated from year to year. However, the very dense class is dominated by areas ranging from 60-95%, the smallest class area of 9.06 km² cover 60% in 2012, and the largest area of 15.19 km² cover 95% in 2008.
Based on the temporal analysis, there was an increase in the very dense class density in 2009 for the mangrove Blok Bedul as a tourist attraction from 10.54 km² covered 64% in 2005 to 14.75 km² covered 88% in 2009. However, there was a decrease in density after determining tourist objects to 12.76 km² with a percentage of 87% in 2020. Other classes such as dense, medium, and rare have decreased until the determination of tourist attractions, 4.54 km² (28%); 1.12 km² (7%); and 0.22 km² (1.4%) in 2005 to 1.57 km² (9%); 0.27 km² (2%); and 0.08 km² (0.5%). Then, it tends to be stagnant in 2020 to become 1.57 km² (11%), 0.28 km² (2%); and 0.06 km² (0.4%). For the very rare class, there is no significant dynamic.

Table 2. Tabular data of the canopy density mangrove in the range of 2005 to 2020 used Landsat 7 ETM and Landsat 8 OLI TIRS imagery (in km²).

| Year | Very Rare | Rare | Medium | Dense | Very Dense |
|------|-----------|------|--------|-------|------------|
|      | Area %    | Area % | Area % | Area % | Area %     |
| 2005 | 0.05 0.3% | 0.22 1.4% | 1.12 7% | 4.54 28% | 10.54 64% |
| 2006 | - - -     | - - - | - - - | - - - | - - -     |
| 2007 | 0.00 0.0% | 0.01 0.1% | 0.00 0% | 1.31 9% | 13.95 91% |
| 2008 | 0.05 0.3% | 0.00 0.0% | 0.02 0% | 0.69 4% | 15.19 95% |
| 2009 | 0.06 0.4% | 0.08 0.5% | 0.27 2% | 1.57 9% | 14.75 88% |
| 2010 | - - -     | - - - | - - - | - - - | - - -     |
| 2011 | - - -     | - - - | - - - | - - - | - - -     |
| 2012 | 0.01 0.1% | 0.13 0.9% | 0.96 6% | 4.88 32% | 9.06 60% |
| 2013 | 0.01 0.0% | 0.01 0.0% | 0.06 0% | 2.86 19% | 12.01 80% |
| 2014 | 0.02 0.1% | 0.10 0.6% | 0.79 5% | 2.10 14% | 12.38 80% |
| 2015 | 0.01 0.0% | 0.03 0.2% | 0.30 2% | 2.41 14% | 14.72 84% |
| 2016 | 0.01 0.0% | 0.04 0.3% | 0.39 2% | 2.64 16% | 13.36 81% |
| 2017 | 0.07 0.4% | 0.33 2.0% | 0.99 6% | 2.85 17% | 12.24 74% |
| 2018 | 0.01 0.1% | 0.10 0.7% | 0.61 4% | 4.26 28% | 10.00 67% |
| 2019 | 0.02 0.2% | 0.14 0.9% | 0.41 3% | 1.74 11% | 13.39 85% |
| 2020 | 0.02 0.1% | 0.06 0.4% | 0.28 2% | 1.57 11% | 12.76 87% |

Figure 6. The canopy density mangrove analysis in the range of 2005 to 2020 used Landsat 7 ETM and Landsat 8 OLI TIRS imagery.
Although the mangrove area has decreased, the very dense class composition has increased from 64% to 87% from 2005 to 2020. Meanwhile, other classes tend to experience a decrease in the percentage of area.

3.5. Comparison with manual classification

Manual classification methods using the five senses and interpreter knowledge are also carried out. It is to see the extent to which the classification results can be trusted.

3.5.1. Supervised classification method. Based on the data above, it can be seen that there are differences between the overlapping results of several supervised classification methods with manual classification. The most expansive overlapping area is found in the Minimum Distance method on Landsat 7 ETM, 93%. Meanwhile, in Landsat 8 OLI TIRS, the most expansive overlapping area is in the Naïve Bayes method, which is 100%. However, these results are not valid because the method is excessive in classifying mangroves. It is confirmed by the low level of accuracy of the method in the previous discussion. Then, in the second place, SVM and Lib SVM methods have an overlapping area of 96%.

Figure 7. Mangrove canopy density in Blok Bedul, Banyuwangi from 2005 to 2020. L8 (Landsat 8 OLI TIRS) & L7 (Landsat 7 ETM).
Figure 7. Comparison of supervised classification and manual classification on Landsat 7 ETM. (a) Smile Random Forest, (b) Smile Naïve Bayes, (c) SVM, (d) Smile CART, (e) Random Forest, (f) Naïve Bayes, (g) Minimum Distance, (h) Lib SVM, (i) GMO Max Entropy, (j) CART.

Figure 8. Comparison of supervised classification and manual classification on Landsat 8 OLI TIRS. (a) Smile Random Forest, (b) Smile Naïve Bayes, (c) SVM, (d) Smile CART, (e) Random Forest, (f) Naïve Bayes, (g) Minimum Distance, (h) Lib SVM, (i) GMO Max Entropy, (j) CART.
In general, the overlapping areas' results indicate that the guided classification method is quite good at mapping mangroves. The classification results of the classification are at an overlapping level of 80% - 100%. There are only two methods, namely SVM and Lib SVM on Landsat 7 ETM, and one method, namely Smile Naïve Bayes on Landsat 8 OLI TIRS, below the class value. Then, there is one method, namely Minimum Distance in Landsat 7, and six methods, namely Smile Random Forest, SVM, Naïve Bayes, Minimum Distance, Lib SVM, and CART on Landsat 8 OLI TIRS, which has an overlapping level that is included in the 90% - 100% class.

Table 3. Tabular data of the overlapping area dan percentage comparison between supervised classifications with manual classification mangrove in the range of 2005 to 2020 used Landsat 7 ETM and Landsat 8 OLI TIRS imagery (in km²).

| Method                        | Landsat 7 Overlapping area | Percentage | Landsat 8 Overlapping area | Percentage |
|-------------------------------|----------------------------|------------|----------------------------|------------|
| Smile Random Forest           | 12.53                      | 83%        | 14.37                      | 94%        |
| Smile Naïve Bayes             | 12.67                      | 83%        | 0.00                       | 0%         |
| SVM                           | 0.00                       | 0%         | 14.69                      | 96%        |
| Smile CART                    | 12.31                      | 81%        | 12.99                      | 85%        |
| Random Forest                 | 10.24                      | 68%        | 12.31                      | 81%        |
| Naïve Bayes                   | 12.67                      | 83%        | 15.26                      | 100%       |
| Minimum Distance              | 14.13                      | 93%        | 14.14                      | 93%        |
| Lib SVM                       | 0.00                       | 0%         | 14.58                      | 96%        |
| GMO Maximum Entropy           | 12.96                      | 85%        | 12.52                      | 82%        |
| CART                          | 12.36                      | 81%        | 14.31                      | 94%        |

Figure 9. Time-series comparison of supervised classification and manual classification on Landsat 8 OLI TIRS.
### Table 4. Tabular data of the overlapping area, difference supervised classification, and difference manual classification comparison between time-series supervised classification with manual classification mangrove in the range of 2005 to 2020 used Landsat 7 ETM and Landsat 8 OLI TIRS imagery (in km²).

| Year | Overlapping area | Percentage |
|------|------------------|------------|
| 2005 | 13.03            | 90%        |
| 2007 | 12.31            | 81%        |
| 2008 | 12.33            | 87%        |
| 2009 | 13.44            | 91%        |
| 2012 | 13.08            | 85%        |
| 2013 | 12.70            | 84%        |
| 2014 | 12.21            | 84%        |
| 2015 | 13.60            | 94%        |
| 2016 | 13.71            | 91%        |
| 2017 | 13.94            | 92%        |
| 2018 | 13.08            | 87%        |
| 2019 | 12.99            | 85%        |
| 2020 | 12.70            | 82%        |

3.5.2. *Time-series analysis.* Temporally from 2005 - 2020, the results of overlapping areas show a good percentage. No year has an overlapping area below 80%. There are eight years, namely 2007, 2008, 2012, 2013, 2014, 2018, 2019, and 2020 which are in class 80 - 90%. Furthermore, there are five years, namely 2005, 2009, 2015, 2016, and 2017, in the 90% - 100% class.

4. Conclusion

Based on the analysis above, of the 10 algorithm models used to map mangroves, 2 models have a good level of accuracy for Landsat 7 ETM and Landsat 8 OLI TIRS. The algorithm models are Smile CART and GMO Max Entropy. In total, the mangrove area in the Alas Purwo National Park has decreased since 2005 and 2009 when establishing a tourist attraction. Based on the canopy density analysis, mangrove areas were dominated by very dense classes, followed by dense, medium, rare, and very rare classes. Although the mangrove area is experiencing a decreasing trend, the composition of mangrove density in the very dense class has increased.

References

[1] Noor A R, Khazali Y M, and Suryadiputra I N N 2012 Panduan Pengenalan Mangrove di Indonesia PHKA/WI-IP Bogor 1
[2] Lewis R R, and Streever B 2000 Restoration of mangrove habitat WRP Technical Notes Collection (EDRCTN- WRP-VN-RS-3.2) US Army Engineer Research and Development Centre, Vicksburg MS. www.wes.army.mil/el/wrp
[3] Irfan M 2015 Kemitraan Pengelolaan Ekowisata Mangrove Blok Bedul *Undergraduate Thesis* Faculty of Social and Political Sciences, Department of Administration, University of Jember
[4] Kuenzer C, Bluemel A, Gebhardt S, and Quoc T V and Dech S 2011 Remote sensing of mangrove ecosystems: A review *Remote Sensing* 3 https://doi.org/10.3390/rs3050878
[5] Jensen J R, Ramset E, Davis B A, and Thoenke C W 1991 The measurement of mangrove characteristics in south-west Florida using SPOT multispectral data *Geocartography International* 2 13-21
[6] Lillesan M T, Kiefer W R, and Chipman W J 2015 *Remote Sensing and Image Interpretation* (7th) John Wiley & Sons
[7] Sulastini D, Dyah S M, Susilo U, and Widiastuti R W 2011 *Seri Buku Informasi dan Potensi Mangrove Taman Nasional Alas Purwo*. Balai Taman Nasional Alas Purwo.

[8] Chander G, Markham B L, Helder D L and Ali E 2009 Remote Sensing of Environment Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM +, and EO-1 ALI sensors. *Remote Sensing of Environment* **113**(5) 893–903 https://doi.org/10.1016/j.rse.2009.01.007

[9] Chandran G A J and Jojy C 2016 A Method of Removing and Recovering Clouds in Satellite Images based on Image Inpainting *IJARSET* **3** (3),197–203. https://doi.org/10.17148/IARJSET

[10] Jensen J R 1986 Introductory Digital Image Processing Prentice-Hall Englewood Cliffs NJ p 379

[11] Pusat Pemanfaatan Penginderaan Jauh 2015 *Pedoman Pengolahan Data Penginderaan Jauh Landsat 8 Untuk Mangrove Lembaga Antariksa Nasional*

[12] Diniz C, Cortinhas L, Nerino G, Rodrigues J, Sadeck L, Adami M and Souza-Filho P M W 2019 Brazilian mangrove status: Three decades of satellite data analysis *Remote Sensing* **11**(7) 1-19 https://doi.org/10.3390/rs11070808

[13] Quinlan J R 1992 *C4.5 Programs for Machine Learning* San Mateo, CA: Morgan Kaufmann

[14] Chang C C and Lin C J 2011 LIBSVM: A library for support vector machines ACM *Transactions on Intelligent Systems and Technology* **2**(3) 1–39 https://doi.org/10.1145/1961189.1961199

[15] Shetty S 2019 Analysis of machine learning classifiers for LULC classification on Google Earth Engine 1–65

[16] Sartika D and Indra D 2017 Perbandingan Algoritma Klasifikasi Naïve Bayes, Nearest Neighbour, dan Decision Tree pada Studi Kasus Pengambilan Keputusan Pemilihan Pola Pakaian Jurnal Teknik Informatika dan Sistem Informati **1**(2) 151–161

[17] Murtaza K O and Romshoo S A 2014 Determining the Suitability and Accuracy of Various Statistical Algorithms for Satellite Data Classification *International Journal of Geomatics and Geosciences* **4**(4) 585–599 https://www.researchgate.net/publication/263655149

[18] Phillips S J, Anderson R P, and Schapire R E 2006 Maximum entropy modeling of species geographic distributions *Ecological Modelling* **190** 231–259

[19] Bittencourt H R and Clarke R T 2003 Use of classification and regression trees (cart) to classify remotely-sensed digital images *International Geoscience and Remote Sensing Symposium (IGARSS)* 3751–3753 https://doi.org/10.1109/igarss.2003.1295258

Acknowledgments

The research work reported in this paper was funded by PUTI Grant No. NKB-992/UN2.RST/HKP.05.00/2020 Universitas Indonesia (UI). Thank directorate Research and Community Service Universitas Indonesia.