Mangroves Change Detection using Support Vector Machine Algorithm on Google Earth Engine (A Case Study in Part of Gulf of Bone, South Sulawesi, Indonesia)

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ABSTRACT: Remote sensing data have been proven to be efficient as data source for mangrove mapping and monitoring to support decision making and policy related to mangrove management. One of the key advantages of remote sensing is the temporal availability of the data which allow monitoring of mangrove status from different time period. In line with this advantage, the recent development of Google Earth Engine (GEE) has open wider possibility to work with large image datasets in an online platform for mangrove monitoring. This study aims to develop a method to monitor mangrove cover changes at some parts of Gulf of Bone, South Sulawesi, Indonesia from 2014 to 2018 using a combination of GEE and Support Vector Machine (SVM) algorithm applied to Landsat 8 OLI (30 m pixel size). We used region of interest (ROI) technique to distinguish mangroves, non-mangroves, open area, water bodies, and cloud objects. The result of five classes ROI was for defining all the dataset for data model. The algorithm implementation result shows that the mangrove cover from 2014 to 2015 had decreased significantly along the beach and in several side of fishponds. However, from 2016 to 2018 the mangrove cover had increased especially in the south side of the study area. This change pattern shows the dynamic of mangrove cover in the study area, mainly caused by the development of fish or shrimp ponds and some mangrove restoration efforts. The result shows the potential of SVM and GEE for spatio-temporal data analysis based on Landsat 8 OLI to monitor the mangrove cover changes over the time. Nevertheless, the spectral characteristics of mangroves which is influenced by water bodies or unconsolidated sediment background make the identification of mangroves or non-mangroves area remains challenging.

1. INTRODUCTION

Indonesia is a tropical country that has largest mangrove ecosystem in the world. According to Giri et al. (2011), the total area of mangrove forests in Indonesia is 3,112,989 hectares or 22.6% of the total area of mangroves in the world. Furthermore, Noor et al. (1999) mentioned that there are 202 species of mangroves found in Indonesia alone. These figures substantiate the importance of Indonesia in global context to preserve this highly valuable coastal resource. Mangroves has very important roles in coastal ecosystems, including provide spawning grounds for marine organisms, maintain the food cycle of marine organisms, maintain the quality of coastal waters, preventing sea water intrusion, and preventing coastal abrasion and erosion (Giri et al. 2011; Green et al. 1998). WWF (2015) stated that there was more than 35% reduction in mangrove area. This was mainly caused by the high sea waves so that the mangrove structure was unable to withstand the waves. Another factor that contributed to this loss was human activities that convert mangroves to fishponds or shrimp ponds and other destructive activities so that the mangrove ecosystem is heavily threatened. This loss of mangroves corroborates the need of providing fast, accurate, and up-to-date mangrove maps to support any monitoring and conservation efforts to preserve mangrove ecosystems.

Mapping the location of mangroves is very important to know the status of mangrove areas, both on a local, national and global scale. This data can be used as a baseline in the context of sustainable management and monitoring of mangrove ecosystems. In this case, remote sensing data have been proven to be efficient in producing mangrove maps (Kuenzer et al. 2011; Heumann 2011). Many studies have been done to map and monitor mangroves using remote sensing images from individual mangrove stands to the global extent; from single date to multi-temporal observation. However, most of these studies used conventional approach of image processing. Where each image scene was individually processed using a personal computer to obtain the targeted mangrove information. This approach is ineffective for image-based rapid information derivation that covers large area of observation, including for mangrove monitoring. The presence of cloud processing technologies such as Google Earth Engine (GEE) provides an alternative image processing platform that is more efficient (Diniz et al. 2019). GEE provides a cloud platform for accessing and processing large amounts of freely available satellite imagery. Algorithms developed through GEE can be replicated and applied for image processing over large areas (Gorelick et al. 2017). Regular observation of mangroves change can be efficiently performed with GEE. It has large image data archive and collection of operational algorithms that makes it possible for rapid image processing time over large area of observation.

At the same time, there is growing numbers of studies using support vector machine (SVM) algorithm to classify remote sensing images for various surface land covers. It is one of the machine learning algorithms that allows for rapid and consistent classification of land cover from remote sensing images (Pal & Mather 2005). In this case, combining GEE and SVM would be potentially ideal for providing fast, accurate, and up-to-date mangrove maps for change detection purpose. One of the remote sensing data that is available in GEE platform is Landsat 8 OLI image (30 m pixel size) which have been corrected up to the bottom of atmosphere reflectance. The mangroves in coastal area of Gulf of Bone, South Sulawesi Province, Indonesia, experienced extensive land conversion into fishponds. This study aims to develop a method to monitor mangrove cover changes at some parts of Gulf of Bone, South Sulawesi, Indonesia from 2014 to 2018 using a combination of GEE and SVM algorithm applied to Landsat 8 OLI data.

2. METHODS

2.1 Study Site and Image Data

The study site for this study is part of coastal area of Gulf of Bone, South Sulawesi Province, Indonesia, located at 119^{o}40’0”- 122^{o}40’0” and 2^{o}10’0” 3^{o}30’0” (Figure 1). There are two Landsat 8 OLI scenes covering this study site: Path 114 Row 62 and Path 113 Row 62. The Landsat 8 OLI images used in this study were acquired in 2014, 2015, 2016, 2017, and 2018. All of these images have 20% cloud cover or less over the study site with top of atmosphere (TOA) reflectance correction using GEE image calibration function following Chander et al. (2009) procedure. The first step for this study was to apply an algorithm to identify and select the image with minimum percentage of cloud cover from GEE image database.

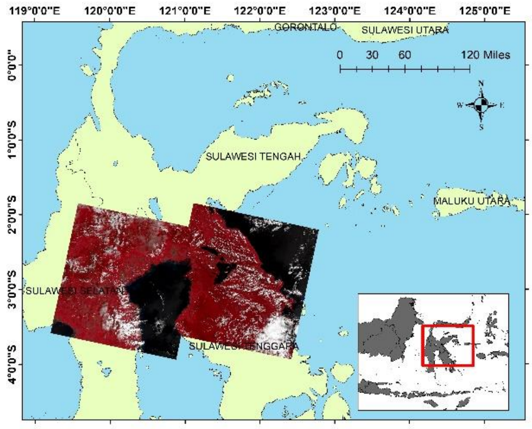


Figure 1. Area of study: Gulf of Bone, South Sulawesi Province, Indonesia (Landsat 8 OLI image composition of 543).

2.2 Machine Learning Algorithm

Machine learning defined as the science of getting computers to learn what humans think and act. This is to improve computers to analyze data and information from human command (Fagella, 2017). Support vector machine (SVM) is one of machine learning algorithm that can be used in Google Earth Engine. SVM is a supervised non-parametric statistical learning algorithm and can be used for both classification or regression. SVM can be using to classifying Mangrove and non-mangrove by detecting pixel reflectance. SVM is responsible for decision boundary from several different class and maximize the margin (distance between the line and dots) and finding the hyper-plane. This can be taken as an example in research conducted by Campomanes (2016) which classifies mangrove cover using the SVM algorithm on the results of segmentation of aerial and lidar photography data where the classification using SVM reaches 83.33%This of course has very good classification results.

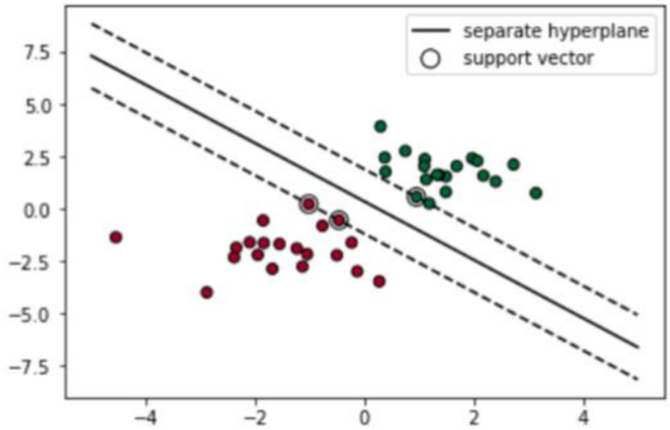


Figure 2. Conceptual hyperplane separation in SVM.

The SVM process is by conducting the training process by entering the training data to the vector space. First, we take training samples in 2018 then the results of sample training on the pixel value in 2018 are extracted then the results of the pixel values are used as a reference in the classification of the image scenes in 2015 and 2014. The results of these classifications are the basis for identifying changes in mangrove cover and we define the optimal hyperplane because it will affect with the result, is it representative or not. The nearest pattern from the training data is called a support vector.

2.3 Training Sample and Mangrove Change Detection and Visualization

Processing with Support Vector Machine is done by using training samples. Mangroves used 422 samples, 592 samples of non-mangrove vegetation, 9 samples of Cloud, and 170 samples of Non-Vegetation. Mangrove samples have the most samples because the focus of this study is on mangroves. Based on the picture, the sample with the blue symbol is mangrove cover, green is non mangrove, purple is cloud cover, and light green is classified as a body of water. The results of the sample training are used as a model for classifying the 2014-2017 recording image scene.

Figure 3. Distribution of sample point used for SVM classification.

3. RESULTS AND DISCUSSION

3.1 Machine Learning Algorithm

SVM algorithm is machine learning algorithm used in this study. SVM algorithm was developed in Google Earth Engine (GEE) used training samples which is obtained from Landsat 8 OLI date acquired in 2018, which then applied for Landsat 8 OLI image date acquired in 2017, 2016, 2015, and 2014. There are six Landsat 8 OLI bands used in this research, these are these are blue (450-510 nm), green (530-590 nm), red (640-670 nm), near infrared (850-880 nm), shortwave infrared 1 (1570-1650 nm), and shortwave infrared 2 (2110-2290 nm) bands. Image scene was used in every year is image scene with cloud condition below 20%, where that function is defined on GEE script.

The algorithm outline on GEE for mangroves change detection from 2014-2018 is applied mangrove sample pixel value on Landsat 8 OLI date acquired in 2018 into the Landsat 8 OLI imagery scene date acquired in 2017-2014. The script starts with the definition for Landsat 8 OLI 2018 selection, then followed by the selection of sample points for SVM algorithm input. SVM algorithm will make tree scheme based on pixel values in each class. Next step is applied tree scheme from SVM algorithm to classify Landsat 8 OLI from 2014 until 2018 (Table 1).

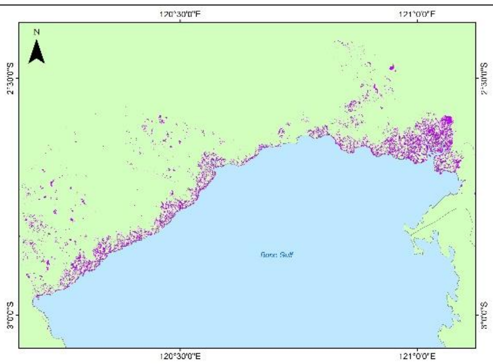
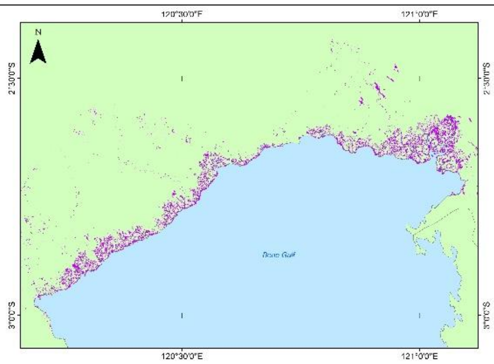
Table 1. GEE script steps summary.

Steps	Task Description
Setting up the model and SVM algorithm	
1	To define Landsat 8 OLI 2018 variable
2	To choose Landsat 8 OLI 2018 scene with parameter cloud cover percentage, region of interest, date acquired, and bands used
3	To change pixel value to be median value
4	To combine sample point in google asset

5	To get pixel value every sample form Landsat 8 OLI 2018
6	To define parameter in SVM algorithm
7	To run SVM algorithm to build tree scheme
8	To classify Landsat 8 OLI 2018 based on tree scheme
9	Set zoom level and map center
10	Export classification result in 2018
Apply SVM tree scheme in Landsat 8 OLI 2017-2014	
1	To define Landsat 8 OLI 2017-2014 variable
2	To choose Landsat 8 OLI 2017-2018 scene with parameter cloud cover percentage, region of interest, date acquired, and bands used
3	To change pixel value to be median value
4	To classify Landsat 8 OLI 2017-2014 based on SVM algorithm tree scheme
5	Set zoom level and map center
6	Export classification result in 2017-2014

3.2 Mangrove Delineation Result

This is the result of the Landsat 8 OLI image classification of the study area recorded in 2014-2018 using the Support Vector Machine algorithm which obtained pixel-based classification results with a spatial resolution of 30 meters. Based on the classification results obtained purple appearance in the form of mangrove cover, non-mangrove green and blue is the body of water. The appearance observed in the study area is the presence of mangroves located on the coast of the Bone Bay while non-mangrove cover tends to be located away from the body of the Bone Bay water. The results also show that there are some misclassifications, especially in mangrove and non-mangrove vegetation, where non-mangrove vegetation is also classified as mangrove vegetation. This is because mangrove vegetation can only live in tidal areas while in the classification results there is a classification of mangroves that have a radius of sea water up to 500 meters. This shows that the classification of mangroves and non-mangrove vegetation is also quite difficult to do so an evaluation of this is needed.

Year	**Results**	**Year**	**Results**
2014		2015	

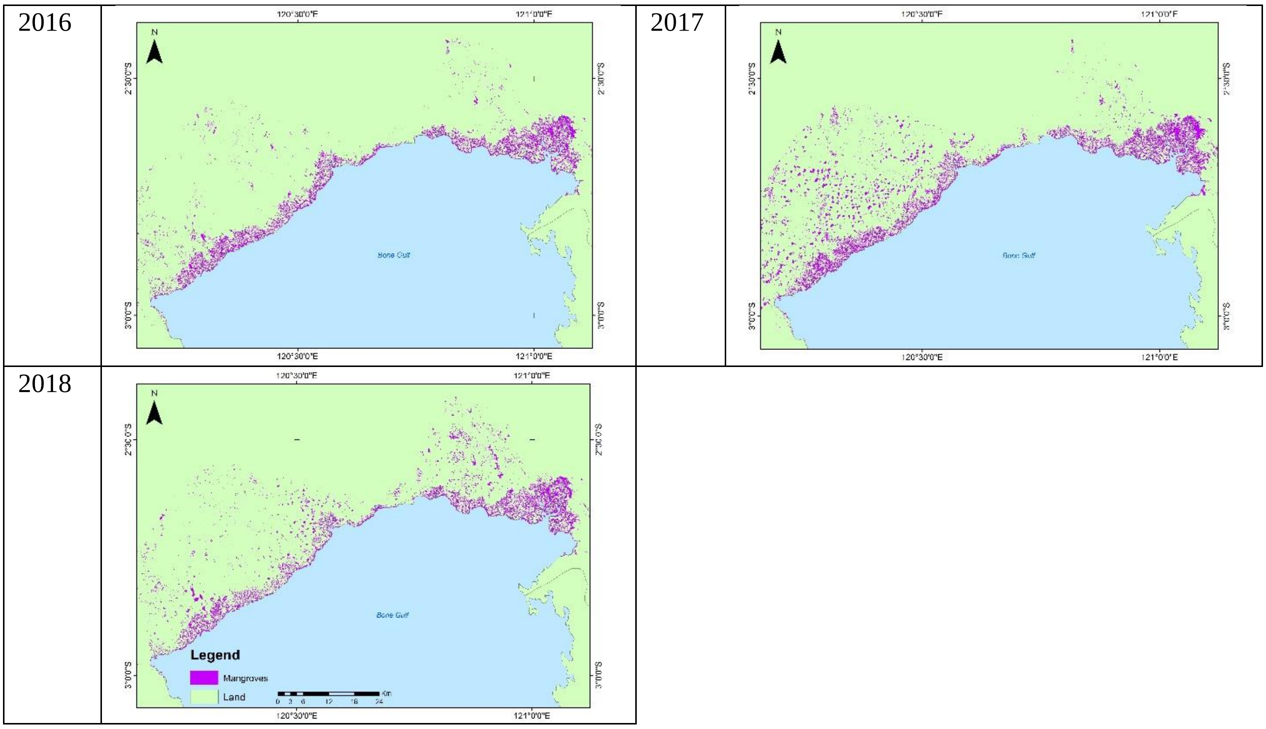


Figure 4. Visualization of mangrove delineation result of 2014-2018.

3.3 Mangrove Change Detection

From Figure 5, its show that there are very dynamic mangroves change over the study area. The Scenes that acquired in 2014 until 2015 there are a decreasing phenomenon. This is caused by a mangrove change. From the picture classified result, in the east side along the river there are a lot area that has a cover change from mangrove cover into fishpond. But in 2016 until 2018, there are an increasing of mangrove area. This happened because mangrove planting was carried out on the embankment (Figure 6). This can be observed where there is a classification of mangroves, especially on pond embankments. This is different from the previous period scene where the classification of pond embankments is entirely non mangrove and water bodies. Mangrove planting is done to maintain the pond so that it does not occur abrasion so that this is good to do, in addition to maintaining the mangrove ecosystem, it also maintains the strength of fish and shrimp ponds.

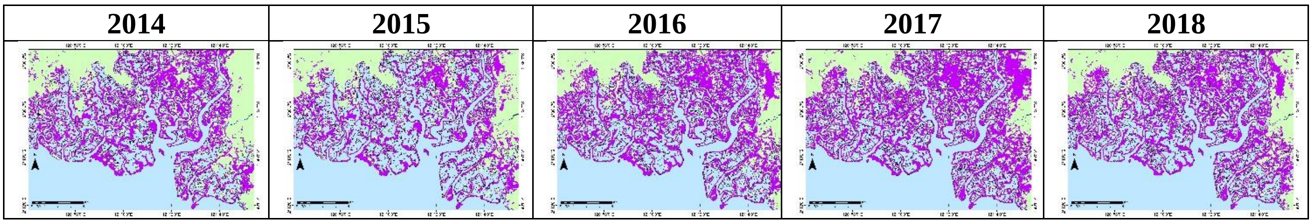


Figure 5. Mangrove change detection from 2014 to 2018
(mangroves are shown in purple color).

Figure 6. Increasing of mangrove areas on the east side of study area as indicated by red circle.

4. CONCLUSION

Mangrove Cover changes can be extracted with Landsat 8 Imagery using Google earth Engine with vector Support Engine Algorithm. There is a very dynamic change in mangroves in the study area. However, the classification remains challenging to distinguish between mangroves, non-mangroves, water bodies, and vacant land. This can be observed in the classification of mangroves where many non-mangrove vegetations are classified as mangroves. so that local knowledge becomes very important to learn especially land cover for mangrove and non-mangrove forests, so that if an error occurs in the classification in the processing results will be able to understand the location of the error to be generated. Based on this evaluation, mangrove welding can be carried out, especially zoning restrictions on the existence of mangroves so that the statistical results contained in the misclassification of quantitative changes can be more representative and closer to truth. Future studies can also examine the thematic accuracy of the classification results that have been carried out so that the accuracy of SVM accuracy results in mangroves can be measured properly.

5. ACKNOWLEDGEMENT

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