International Journal of GEOMATE, Aug., 2022, Vol.23, Issue 96, pp.77-84
ISSN: 2186-2982 (P), 2186-2990 (O), Japan, DOI: https://doi.org/10.21660/2022.96.3312
Geotechnique, Construction Materials and Environment

IDENTIFICATION OF MANGROVE CHANGES IN THE MAHAKAM DELTA IN 2007-2017 USING ALOS/PALSAR AND LANDSAT

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*Corresponding Author, Received: 18 Feb. 2022, Revised: 17 May 2022, Accepted: 12 June 2022

ABSTRACT: The mangrove area in the Mahakam Delta has dynamically changed due to the land-use conversion for various purposes. Various remote sensing data can monitor the changes, for example, ALOS/PALSAR and Landsat imagery. However, there are limited studies that compare the use of both imageries to monitor such changes. This paper aims to compare the ability of two satellite imageries, i.e., ALOS/PALSAR and Landsat, to monitor the dynamic of mangrove areas. Two time-series data of ALOS/PALSAR and Landsat imagery for the acquisition period between 2007 and 2017 were analyzed using the Support Vector Machine (SVM) classification method on the Google Earth Engine (GEE). Landsat analysis results show an increase in the mangrove area of about 17,016 ha and a reduction of about 6,377 ha. ALOS/PALSAR images showed an increase of 15,903 ha and a reduction of 12,713 ha. The change detection results using two different imageries, i.e., Landsat and PALSAR, show slightly different results. Mangrove areas in 2007 and 2017 increased the area as detected from both Landsat and PALSAR. Landsat imaging classification is better at identifying mangroves from non-mangroves, although the 2007 classification results have flaws due to recording errors in striping. Because the quality of PALSAR 2007 and PALSAR 2017 images is not affected, the classification of PALSAR images is deemed more consistent in the area calculation. However, classification results in separating mangrove and non-mangrove near bodies of water are lacking.

Keywords: Mangrove, Mahakam Delta, Google Earth Engine (GEE), ALOS/PALSAR, Landsat.

1. INTRODUCTION

Mangrove ecosystems can adapt to extreme coastal environments but are also very vulnerable to damage related to the use of mangroves without good management policies. For example, mangroves in the Mahakam Delta area have lost about 67% of their total mangrove forest due to conversion to various land uses [1-4]. The existence of oil and natural gas exploration, access to transportation and infrastructure, industrial development, uncontrolled use of natural resources, and changes in cultivation are some examples of factors that influence mangrove changes in the Mahakam Delta [1]. The same conditions could be observed in other water ecosystems affected by weakly regulated anthropogenic activities [5].

Remote sensing provides a powerful ability to monitor land cover [6-8]. Especially, it has been widely used to monitor mangrove cover changes in various regions using various data and approaches [9-18]. For instances; ALOS Prism [9], ALOS-PALSAR [10-11], Landsat [14], and Sentinel 2B [18]. ALOS PALSAR has been used to monitor mangrove covers globally from 1996 to 2010 with an accuracy of 89% [11]. Landsat also has been successfully used to evaluate changes in mangrove forests in the Mahakam Delta for several years, including 1989, 1997, 2004, 2009, and 2015 [10]. However, there are limited studies that compare the results of Machine Learning-based mangrove identification from Landsat and PALSAR data. The result of mangrove identification using Support Vector Machine (SVM), one of the Machine Learning algorithms, has been compared with the decision tree in the other study [18], but how SVM works in various data needs to be explored.

This study aims to compare the results of mangrove cover changes detection from PALSAR and Landsat data using SVM in the Mahakam Delta from 2007 to 2017. The processes were conducted on the Google Earth Engine (GEE). GEE is a cloud computing-based spatial data storage and processing tool that is a solution for today's extensive spatial data [19-21].

2. RESEARCH SIGNIFICANCE

The study of mangroves for the coast is essential in preventing coastal damage caused by seawater abrasion. Besides, mangroves as a habitat for coastal fauna also preserve coastal nature. Mangrove identification can be made quickly using remote sensing technology, and different sensors can produce other information. This study looks at the extent of mangrove changes from two remote sensing sensors, namely radar from PALSAR images and multispectral images from Landsat. The results of this study. The difference in identifying the resulting area and assessing the remote sensing sensor can be seen.

3. MATERIALS AND METHODS

3.1 Study Area

The Delta Mahakam area is in the province of East Kalimantan, with an area of ±110,153 ha based on the Decree of the Minister of Forestry No.674/Menhut-II/2011. This delta is formed by solids flowing along the Mahakam River, and this delta was once known as a Nipah forest (*Nypa fruticans*). Various mangrove species grow in the Mahakam Delta, including Avicennia, Rhizophora, and some rare Sonneratia [1–4].

The study location for mangrove forest changes in 2007-2017 is in the Delta Mahakam area, Kutai Kartanegara Regency, East Kalimantan Province. Geographically, the location of the Mahakam Delta is between 117º14'38.2" - 117º39'45.7" east longitude and 0º20'10.2" - 0º55'43.6" south latitude. Delta Mahakam is included in three sub-districts: Muara Badak District, Anggana District, and Muara Jawa District. Fig. 1 shows the location of the Mahakam Delta as the study area.

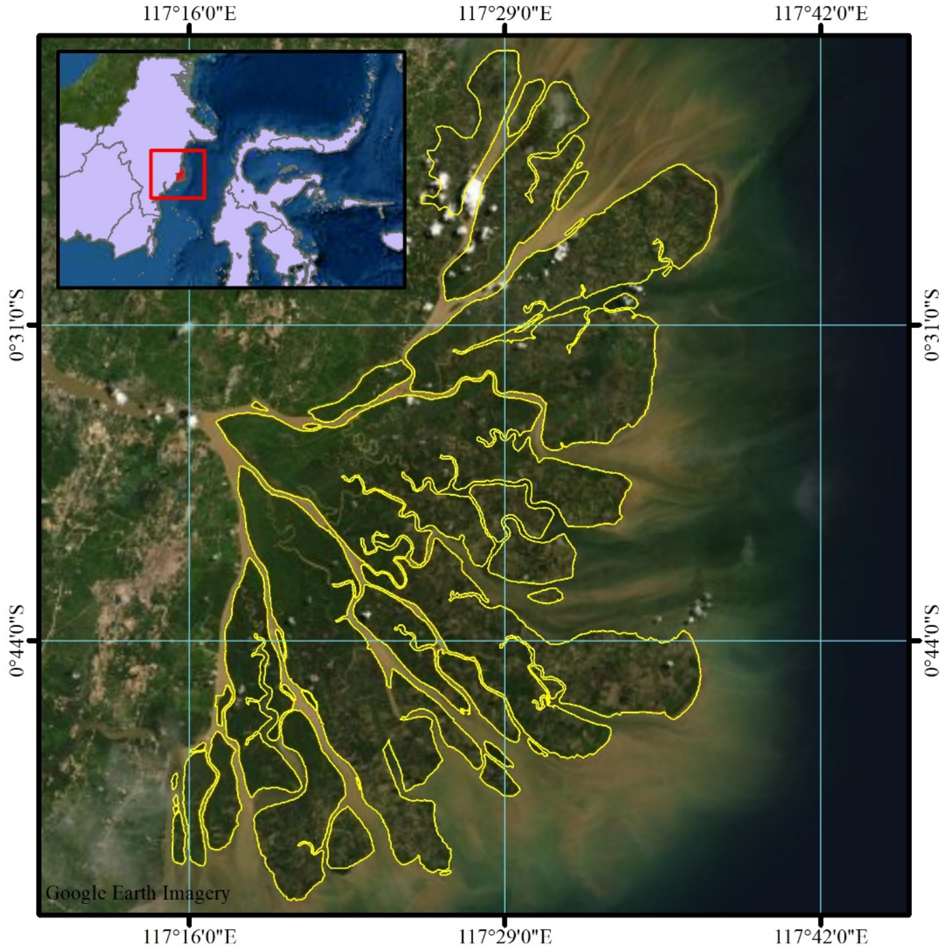

Fig. 1 Location of Study

3.2 Research Framework

The data used in this study are ALOS PALSAR 1/2 and Landsat 7/8 images acquired for the 2007 and 2017 recording years corrected from the GEE platform. The boundary of the study area was taken based on the coordinates of the area of interest (AOI) around the Mahakam Delta mangrove area (Fig. 1). The Mahakam Delta was chosen as the study location because it is the last deposit of the Mahakam River, a large river in East Kalimantan, so changes due to sediment and currents significantly affect the delta environment.

This study uses the Google Earth Engine (GEE) platform to analyze image data and ArcGIS for spatial data processing. The ALOS PALSAR data used is strip mosaic data from the PALSAR 1/2 image that has been mosaiced within one year.

ALOS PALSAR image was chosen to compare the differences in remote sensing sensors in mangrove identification, using a radar sensor, having a spatial resolution of 25 meters and Landsat 30 meters relevant for comparison of identification results. Radar images that have the advantage of recording through clouds are one of the reasons for choosing this image compared to optical images that cannot penetrate clouds in their recording.

While the Landsat 7/8 data used is an atmospheric corrected image that has been mosaiced within one year of recording. Landsat image selection as a multispectral sensor to be processed is considering the resolution that is not much different from PALSAR. Data availability is easy to obtain, the number of channels available is enormous, and Landsat has good temporal data quality compared to other multispectral images.

Furthermore, the sampling of mangroves with non-mangroves was carried out by comparing the samples between the two classes. Sampling was done by visual interpretation of Landsat 7/8 imagery using NIR, SWIR1, and Green composites to distinguish mangrove and non-mangrove forest vegetation, as shown in Fig. 3. In Landsat 7/8 imagery, this composite highlights the differences between mangrove forests and non-mangroves. The number of samples taken is 200 per year of observation by visual interpretation with high imagery, consisting of 100 mangroves and 100 non-mangrove samples. Each sample is divided into training sets to build the model and test sets for accuracy testing with a composition of 50:50.

The next stage is the classification of mangrove and non-mangrove land and the analysis of changes in mangrove land. In this study, the classification with PALSAR 1/2 imagery uses dual-polarization the imagery is shown in Fig. 4, namely HV and HH, and Landsat 7/8 uses blue (B), and green (G), red (R), near-infrared (NIR) bands. Middle infrared 1 (SWIR1), middle infrared 2 (SWIR2), normalized difference vegetation index (NDVI), and enhanced vegetation index (EVI). The normalized difference vegetation index (NDVI) to separate land areas from the ocean emphasize the boundaries of mangrove and non-mangrove classes [14]. EVI can detect changes in mangrove cover, especially in large ecosystems [14].

Classification is carried out using the supervised classification Support Vector Machine (SVM) method using training sample data prepared. In addition, a test set sample with a confusion matrix was carried out to determine the accuracy of the classification results. Each Landsat and PALSAR image recorded in 2017 and 2007 has been classified and then processed further to see changes in mangrove land. The detailed study framework is shown in Fig. 2

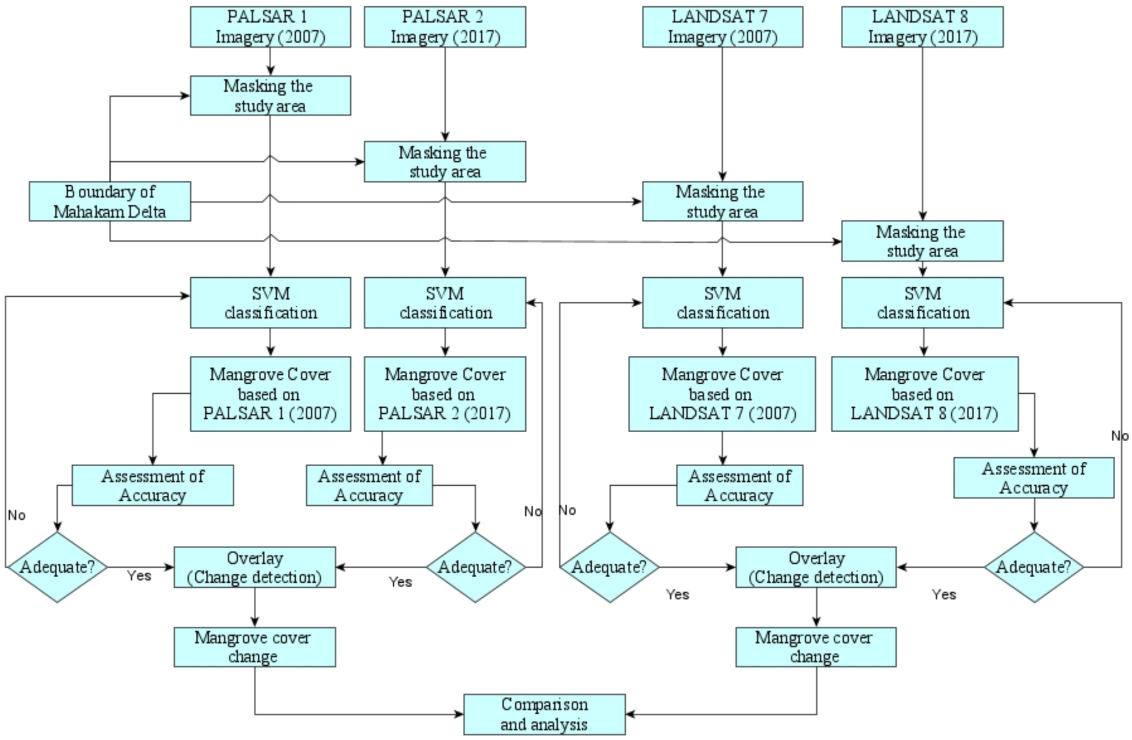

Fig. 2 Research Framework

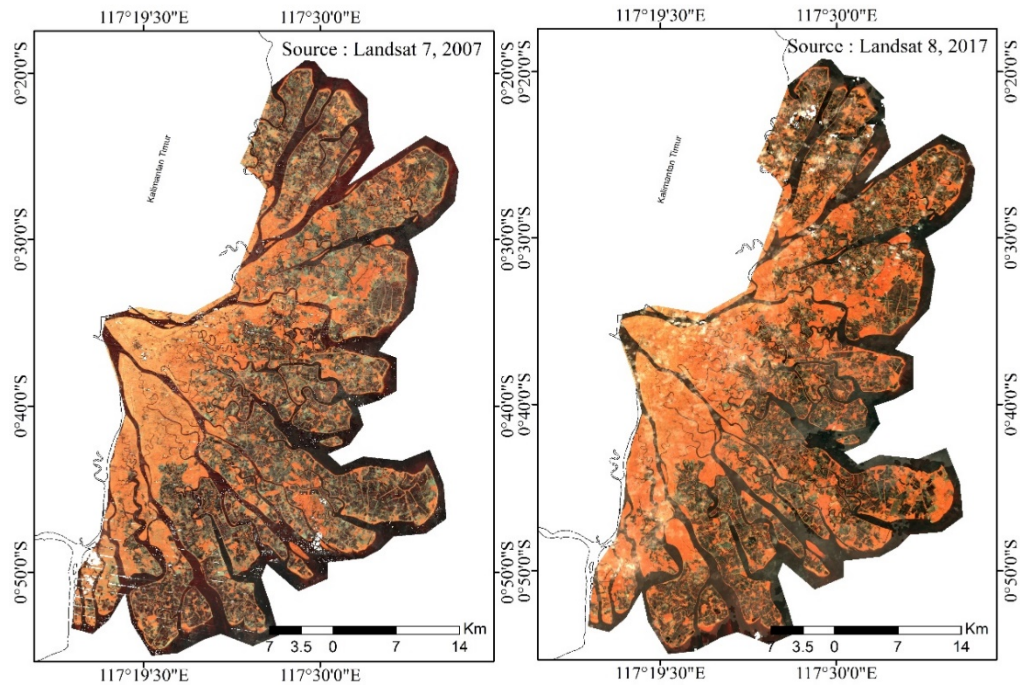

Fig. 3 Landsat Imagery band composite Mahakam River Delta, a) Landsat 7 (left), b) Landsat 8 (right)

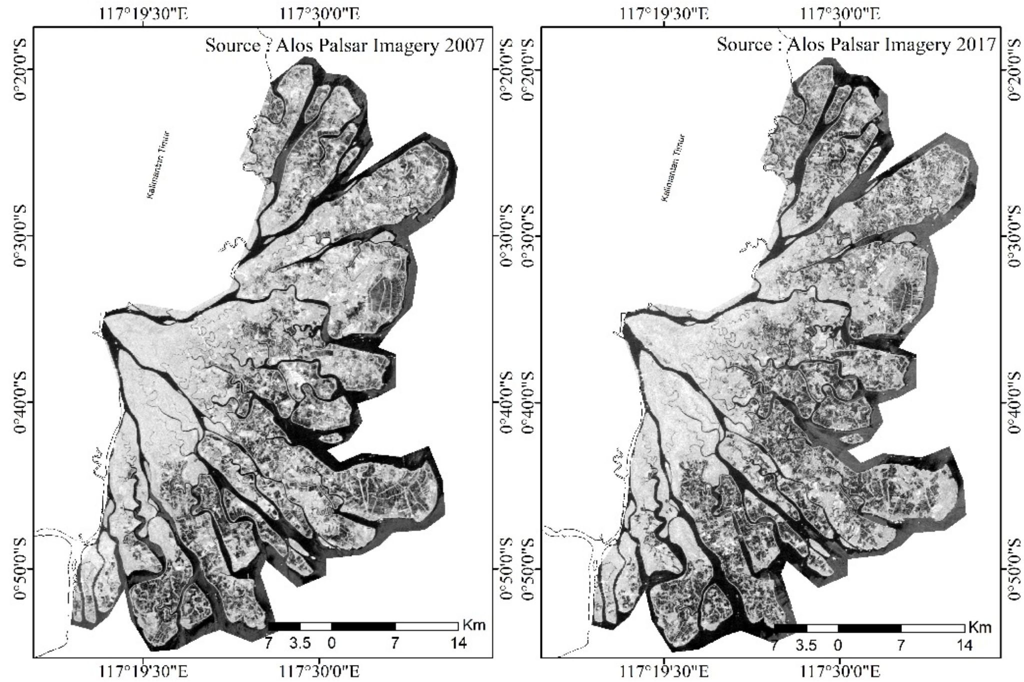

Fig. 4 PALSAR Imagery Mahakam River Delta, a) PALSAR 2007 (left), b) PALSAR 2017 (right)

4. RESULTS AND DISCUSSIONS

Analysis of classification processing at the Mahakam Delta study area was carried out using the SVM method, where class pattern recognition was determined based on the input or examples provided [4]. The samples made consisted of mangrove and non-mangrove samples. The classification results followed the input from the given sample and resulted in two classification classes, namely the mangrove class and the non-mangrove class.

The detection of mangrove changes in the Mahakam Delta increased mangrove areas from 2007 to 2017. The two types of remote sensing sensors used were Landsat 7/8 optical multispectral imagery and PALSAR 1/2 radar imagery, showing an increase in detecting changes in mangrove areas. Landsat image processing in 2007 showed 50,222 ha of mangroves and 130,228 ha of non-mangroves with an accuracy of 87%. In 2017, the results showed 61,580 ha of mangroves and 119,781 non-mangroves with an accuracy of 94%. PALSAR image processing in 2007 showed 73,575 ha of mangroves and 108,231 ha of non-mangroves with an accuracy of 89%. Meanwhile, in 2017 it showed 75,715 ha of mangroves and 106,091 ha of non-mangroves with an accuracy of 84%. The comparison of Landsat and PALSAR image classification results can be seen in Table 1.

The distribution of mangrove changes in the Mahakam Delta from 2007 to 2017 was detected as experiencing many additions in the outer area directly adjacent to the sea. Fig. 5 visually shows the results of Landsat and PALSAR processing which show relatively similar results for the location of the distribution of mangrove enhancement. A complete overview of the usage of PALSAR and Landsat imageries in classifying mangroves based on SWOT analysis is provided in Table 2.

The tendency to provide similar results on the addition of mangrove areas between Landsat and PALSAR but produces different on the increasing and decreasing of mangrove areas. The change detection from Landsat shows 17,016 ha of mangroves and a reduction of 6377 ha of mangroves. In comparison, the PALSAR image shows the addition of 15,903 ha of mangroves and a reduction of 12,713 ha of mangroves. The results of changes in the Landsat and PALSAR mangrove areas can be seen in Table 3.

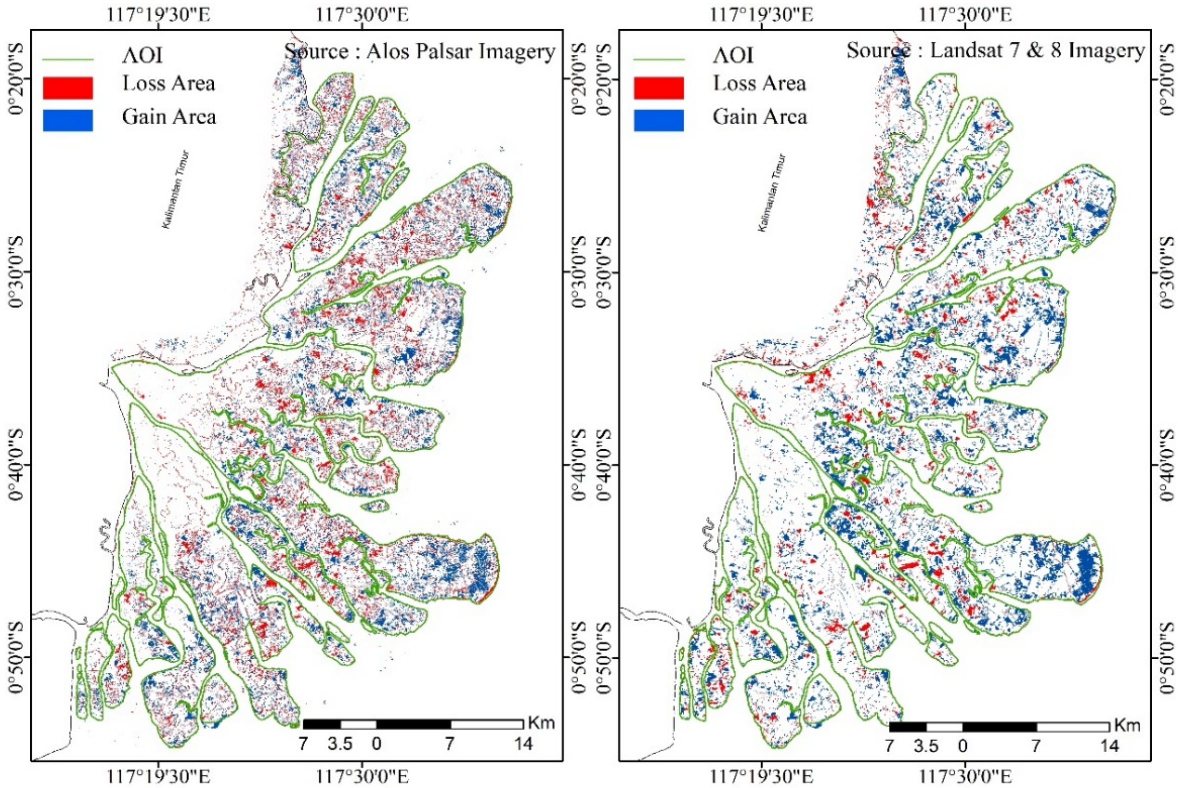

Fig. 5 Map of mangrove change in the Mahakam River Delta 2007-2017, a) using ALOS PALSAR 1 & 2 (left), b) using Landsat 7 & Landsat 8 (right)

Table 1. The extent and accuracy of mangrove and non-mangrove areas in the Mahakam Delta.

Image	Year	Mangrove (ha)	Non-mangrove (ha)	Accuracy
Landsat	2007	50.222	130.228	0.87
	2017	61.580	119.781	0.94
PALSAR	2007	73.575	108.231	0.89
	2017	75.715	106.091	0.84

Table 2. SWOT analysis of Landsat and PALSAR application for mangrove change detection.

Imagery	Internal	External
Landsat	Strengths Has many channels for the identification of mangrove objects	Opportunities Sensitive for mangrove identification & non-mangrove, support for visual interpretation
	Weaknesses Sensor striping issues in Landsat 7 imagery affect data quality	Threats Weather, cloud, and time acquisition affect data quality.
PALSAR	Strengths Using radar waves can operate at any time	Opportunities Data acquisition free affected weather and cloud
	Weaknesses Only has greyscale channels	Threats Not suitable for identifying objects around waters that have a level of wetness

Table 3. Comparison of the increase and decrease in the Mahakam River Delta mangrove area in 2007 and 2017.

Image	Expanded area (ha)	Reduced area (ha)
Landsat	17.016	6.377
PALSAR	15.903	12.713

The cause of the difference in the results of changes between Landsat and PALSAR is due to several things, one of which is the image recording characteristics of the two different images. Landsat is a passive optical image whose recording captures reflections from solar energy so that it is more susceptible to interference when recording in one area. In addition, with the example of cloud disturbance, the image cannot record the earth's surface because clouds cover it. Finally, the shadow of other higher objects affects the quality of multispectral optical images such as Landsat.

Images with multispectral optical sensors will be able to work if the weather is sunny and some objects interfere in the case of mangrove identification. PALSAR is an active radar image considered more consistent in the recording. Imagery with radar sensors can record the condition of the earth's surface without being affected by cloud or weather disturbances such as multispectral optical images. PALSAR image is one of the radar remote sensing images with a good and evenly distributed temporal data set throughout the zone. Although it has the advantage of recording without being limited by cloud and weather conditions, this image does not have as many channels as a multispectral image with several channels. Capable of storing surface information with a range of pixel values, each channel has its characteristics. The radar image produces a greyscale image with polarization according to the sensor used.

Image quality from Landsat in several locations found differences in pixel values even though they were still in the appearance of the same object. Visually, there is a difference between dark and light in locations that indicate a mangrove object, but after classification, the location is classified as a non-mangrove class. The image quality of Landsat 7 is lower; there is striping affecting the size of the area that can be identified shown in Fig. 6 because this disturbance the total area of mangrove and non-mangrove classes in one AOI is different from 2007 and 2017 using Landsat.

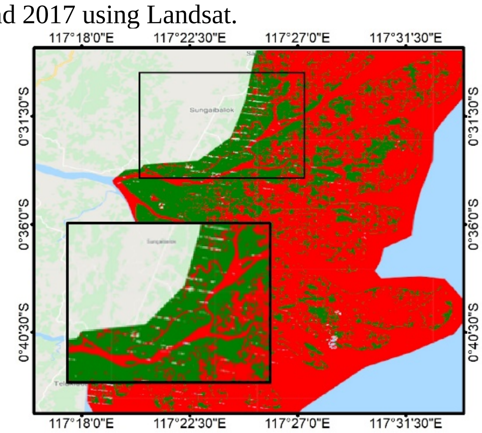

Fig. 6 Striping issues in Landsat 7 recording

The classification produced by PALSAR shows an increase in mangrove area but is also followed by a more significant reduction in mangrove area than Landsat's classification results. The total area of mangrove and non-mangrove classes is more consistent than the results of the Landsat classification. Still, the classification shows poor results when distinguishing mangroves from non-mangroves in areas around water bodies. The non-mangrove class around the water body is not classified well and is included in the mangrove class. Fig. 7 shows that the results of the classification of water bodies in the PALSAR image are not very good, causing an error in the estimation of the mangrove area, especially in areas close to water bodies classified as mang non-mangrove.

The inconsistent results of the classification from PALSAR make the classification results of mangrove classes broader than they should be. In the Landsat classification results, there are weaknesses, namely the results of mangrove areas are not well identified, while in PALSAR, there are weaknesses, namely not being good in classifying mangroves around bodies of water. However, the two satellite images showed the same trend, namely an increase in mangrove areas between 2007 and 2017.

The ability of the radar sensor to identify objects in the waters is one factor in the disturbance of mangrove identification results. The radar sensor will read water bodies easily if there is no cover or solid mixture in the water body. The research location in the Mahakam Delta is an area with high sedimentation. Identification around water bodies can be classified as mangrove and non-mangrove because there is a mixture of objects in pixel recorded.

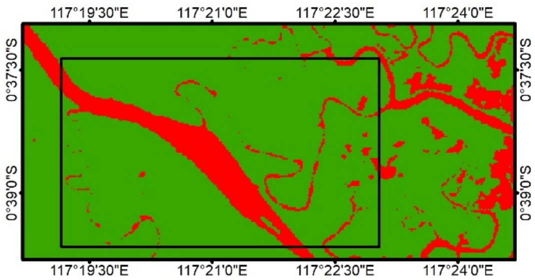

Fig. 7 Poor classification of mangroves in PALSAR around the water body

The selection of remote sensing images as material to determine mangroves must go through a correction phase and optimal data selection to obtain maximum identification and analysis results. Data availability, quality, and conformity with studies are essential in selecting satellite imagery. The advantages and disadvantages of remote sensing image sensors must be considered before processing for a particular theme. The internal factors of the study theme are the key to suitability for the use of remote sensing imagery in research studies.

Results from the identification of mangroves prove that there is mangrove growth, significantly moderate and dense mangroves. Field observations from research [14] explained that the increase in mangrove areas was due to mangroves growing in pond areas that were no longer active. The more significant addition of mangrove land than the reduction of mangrove land in the Mahakam Delta can be attributed to the government's directives in the National Forestry Plan and Provincial Forestry Plan that have designated the Delta Mahakam area a priority area for rehabilitation since 2008.

It is also designed to connect the Mahakam Delta's ecological function with its community's socio-economic development, as supported by the management plan [15]. For example, mangrove land loss in the Mahakam Delta is caused by the conversion of mangroves to aquaculture [6].

5. CONCLUSION

The change detection results are slightly different using two different imageries, Landsat and PALSAR. Mangrove areas in 2007 and 2017 increased the area as detected from both Landsat and PALSAR. The Landsat imagery analysis shows an increase of 17,016 ha, while the PALSAR analysis presents an increase of 15,903 ha. The classification of Landsat imagery is better in distinguishing mangrove and non-mangrove but has shortcomings in the 2007 classification results because of recording errors in the form of striping. This Landsat imagery provides more consistency in the calculation of mangrove areas because the radiometric quality of this imagery is adequate. Compared to PALSAR, this image cannot discern between mangroves and non-mangroves around water bodies.

6. ACKNOWLEDGMENT

The authors would like to acknowledge the anonymous reviewers for their helpful feedback and Pronika Kricella for data analysis support.

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