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ASSESSMENT OF SETTLEMENT AREA DEVELOPMENT IN JEMBER REGENCY AREA BASED ON MULTITEMPORAL LANDSAT 8 OLI-TIRS DATA

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ABSTRACT

Jember is a regency in the province of East Java-Indonesia, experiencing residential or settlement area growth because of increasing population as the main trigger for land use changing. Monitoring the development of settlement areas is important for regional and urban planning. Remote sensing technology provides fast and efective methods of classifying land use and land cover for regional aea, so monitoring the development of settlement area can be identified easily. This study aims to determine the classification of land use and analyse the distribution or evelopment of settlement area in the Jember District based on LANDSAT 8 OLI-TIRS data for the year of 2013, 2015, 2017, 2019 and 2021. The classification was conducted by supervised classification method using a random forest algorithm. The land use is divided into six classes namely vegetation, water body, settlement, bush grass, open land and paddy field. The results showed that settlement area continues to increase every year, meanwhile the area of vegetation, water bodies, bush grass, open land and paddy fields varies every year. The distribution of settlement area in each sub-district showed that the largest area of settlements occur in Ambulu sub-district with 1,447 ha in 2013, 4,064 ha in 2019, and 3,215 ha in 2021. The other years that are 2015 and 2017, Wuluhan sub-district was detected as the largest area of settlement which are 2,950 ha in 2015 and 2,291 ha in 2017. However, this number of settlement area distribution does not really reflect the level of housing density in each sub-district. Thus, the housing density was calcuated by dividing the settlement area to the sub-district area. It found that the highest settlement density in 2021 is located in Kaliwates sub-district with a percentage of 48%, followed by Sumbersari at 44%, Balung at 31%, Ambulu at 30%, and Umbulsari at 29%.

Keywords: remote sensing; settlements; random forest; land use; Jember.

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INTRODUCTION

Jember is a regency located in East Java province with an area of 3.306,69 km^2 and consists of 31 sub-districts. In 2013 Jember district had a population of 2.369.400 people[1], and will increase in 2021 to 2.584.233 people[2]. Population growth can be caused by births and population movement from villages to cities namely urbanization[3]. The increasing population is one of the factors that encourage land use change[4].

Land use changes are usually used as settlements. Excessive land use for settlements will potentially lead to land degradation which will trigger critical land. Changes in land function have an impact on the level of vegetation density which is decreasing, if this is allowed to continue it will affect environmental quality[5].

Identification of land use changing is mostly conducted by land use and land cover (LULC) classification using remote sensing technology because it can reach the entire surface of the earth, without visiting the location directly[6]. The rapid development of remote sensing technology is evidenced by the increasing variety of information vehicles and remote sensing systems available and the large number of types of sensors used[7]. Remote sensing technology employes several satellites data, such as Himawari, NOAA, MODIS, SPOT and Landsat satellites[8].

Since the launch of Landsat 8 with improvements in data quality, the land use and land cover classification based on Landsat satellite data has progressed in science and applications[9]. Landsat 8 OLI-TIRS provides a clearer view of objects on the earth's surface, which will reduce interpretation errors[10]. The common LULC classification methods are supervised and unsupervised learning[11], [12], [13], [14]. The supervised learning method was reported that it has a higher accuracy value than unsupervised learning[15].

The random forest is one of the classification algorithms that combines several independent classification trees (CART). Classification prediction is done by voting from the algorithm flow expressed by random forest. The ensemble method developed by Leo Breiman is to improve classification accuracy[16][17]. Random forest will be combined from each of the existing decision tree techniques, then combined and combined into a model and voting for the final decision results[18].

Random Forest algorithm is carried out in the classification process by training on the data samples. The Random Forest method can produce lower errors and high accuracy in classification[19]. The land use classification that applied random forest algorithms was studied by Papilaya[20]. The classification processes were performed on the Google Earth Engine (GEE) platform. GEE is considered as the effective platform due to all of the processes and calculations are conducted in the cloud so various types of imageries data can be processed without downloading them[20]. GEE can easily analyze land cover changes in time series and large area coverage and provides a collection of satellite images for more than 40 years for the whole world[21].

The increasing population is certainly accompanied by the development of settlement areas that causes changes in land use from vegetation into the non-vegetation areas. Land use monitoring can be analysed through satellite images interpretation[22]. This research was conducted to classify the development of settlements in the Jember district area by utilizing Landsat 8 OLI/TIRS imageries processed in the Google Earth Engine platform. The land use classification processes using one of machine learning algorithm that is Random Forest. This study aims to know the classification of land use and knowing the distribution and the development of residential areas in the Jember district.

METHOD

Location and Datasets

This research was conducted in Jember district, which is one of the districts of East Java Province. The research area can be seen in Figure 1. The data used in this research is secondary data that is Landsat 8 Tiers 1 TOA satellite image data in the range month of May to October every year in 2013, 2015, 2017, 2019 and 2021.

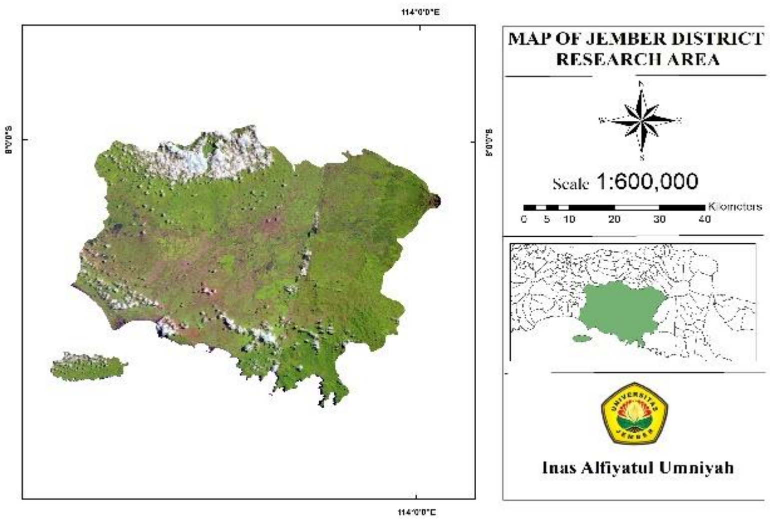

Figure 1. Study Area

Classification

The classification process begins by entering Jember district shapefile data on the GEE platform and create a composite image using bands 6, 5 and 3 in the RGB layers. Next, training samples are made based on the color of pixels into six classes namely green for vegetation, blue for water bodies, red for settlements, yellow for bush grass, brown for built-up land and orange for rice fields. The training sample results will be classified using the supervised classification method with the Random Forest algorithm. The classification results visualize a map of the research area consisting of several colors of object's classes that have been mapped.

Analysis

Data analysis was conducted to determine the development of settlements from the classification results and the distribution area of settlement in the Jember district. The first analysis is to determine the accuracy of the classification process using an accuracy assessment. The calculation of the accuracy value is based on the confusion matrix. The calculated accuracy value is overall accuracy (OA) using equation 1.

$$OA = \frac{Number\ of\ correctly\ classified\ pixels}{The\ total\ number\ of\ pixels\ in\ the\ image} x\ 100\% \quad (1)$$

The next analysis is looking at the changes in the area and distribution of settlements in the Jember district area based on time series data from the LULC classification results. The analysis is formed in the distribution of settlement development in each sub-district and the percentage of settlement development in each sub-district calculated using equation 2.

$$\%\ Density = \frac{Classification\ Area}{Area\ size} x\ 100\% \quad (2)$$

RESULTS AND DISCUSSION

LULC mapping in Jember district was conducted in 31 sub-districts using Landsat 8 OLI/TIRS imagery in 2013, 2015, 2017, 2019 and 2021 from May to October. The mapping process involved pre-processing the Landsat 8 image data, compositing the bands, and cropping the image according to the research area. The method applied in LULC mapping is the random forest algorithm by training samples based on six categories, namely vegetation, water bodies, built-up land, bush grass, open land and rice fields. The creation of training samples was done by utilizing Google Earth available on the GEE (Google Earth Engine) platform, to help identify objects to be classified. The following is a map of the results of the LULC classification that has been carried out.

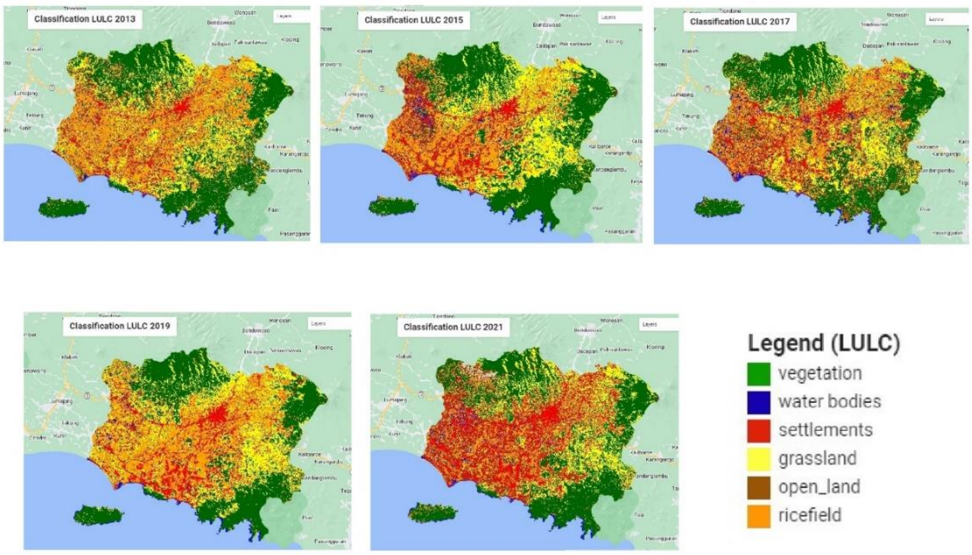

Figure 1. LULC classification map of the study area in 2013, 2015, 2017, 2019 and 2021

The classification focuses on the development of settlements. The area of settlements, including houses, buildings and factories, increases every year. In 2013, the settlement area reached 21,825 ha. This area increased to 27,754 ha in 2015, then continued to grow to 32,664 ha in 2017, and further increased to 43,358 ha in 2019. The built-up area in 2021 reached 45,630 ha. This increase in residential areas can be attributed to population growth in the study area.

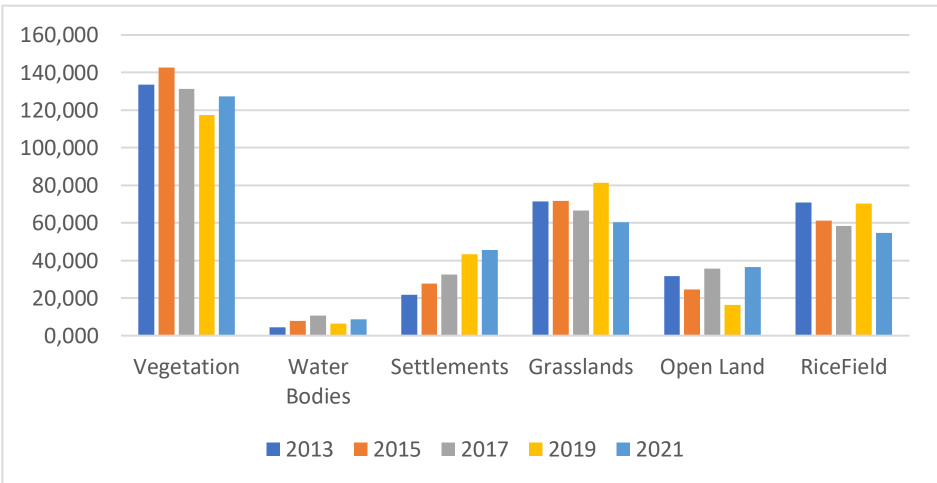

Figure 2. The Area of the Classification Results

Based on Figure 2 above, it can be seen that the vegetation class, water bodies, bush grass, open land and rice fields have wide variations in each year. The vegetation class has a wide variation due to a decrease in soil fertility which can affect plants to grow. The water body class has a wide variation due to the presence of wet rice fields, so it is detected as a water body. Meanwhile, the shrub grass class has a wide variation due to the transformation of plants from having no leaves to plants that have dense leaves. The open land class is due to several areas identified as rice fields and settlements that have similar image characteristics and the rice field class is due to changes in planting and harvesting seasons.

The classification results are tested for accuracy to know how accurate the training samples are in classifying the objects that have been classified. Accuracy tests using the Random Forest method have different kappa coefficient values. The results of the kappa coefficient accuracy test in 2013, 2015, 2017, 2019 and 2021 can be seen in Table 1.

Tabel 1. Accuracy tests

Year	Kappa Coefficient	Percentage %
2013	0,88	90%
2015	0,87	90%
2017	0,87	90%
2019	0,88	91%
2021	0,88	90%

Further analysis was conducted to determine the distribution of settlement development in each sub-district. Based on the results of research on the classification of settlement development, there is a wide distribution in each sub-district in the Jember district area. Distribution information in this study was obtained through processing Landsat 8 images on the GEE platform. The settlement distribution value is shown in the graph in Figure 3.

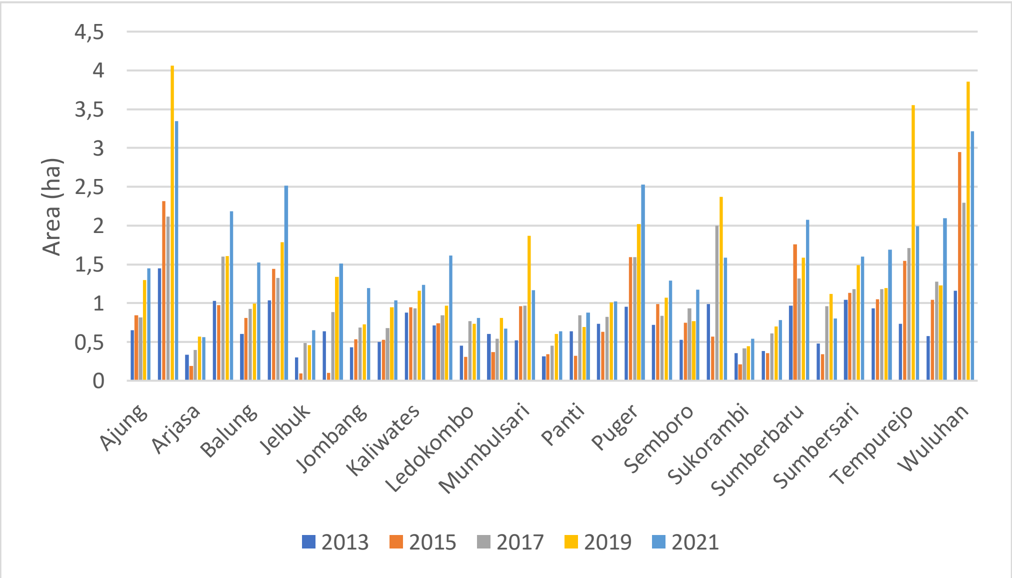

Figure 3. Distribution of Settlement Area Development in Each Sub-district

Based on the figure 4 above, the distribution of settlements in 2013 was highest in Ambulu sub-district with an area of 1,447 ha. In 2015 and 2017 it was located in the Wuluhan sub-district with an area of 2,950 ha in 2015 and 2,291 ha in 2017. In 2019 and 2021 it is located in the Ambulu sub-district with an area of 4,064 ha in 2019 and 3,215 ha in 2021. Factors that cause the distribution of settlement development in each sub-district to occur in Wuluhan and Ambulu sub-districts are due to the development and arrangement of settlements that are not well distributed and not dense.

The distribution of settlement development was further analyzed to determine the density of settlements in each sub-district. The analysis was conducted by calculating the percentage of settlement area against the area of each sub-district to illustrate the level of settlement density as shown in Figure 5.

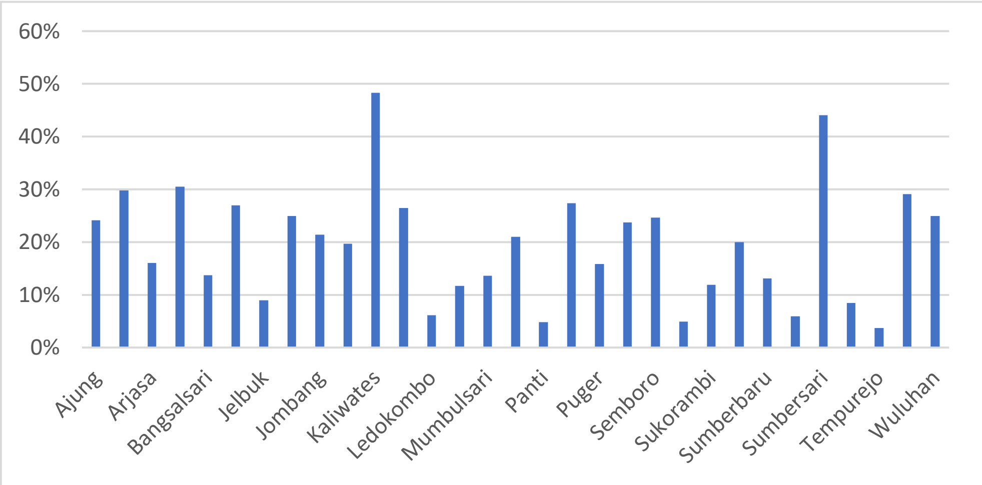

Figure 4. Percentage of Settlement Area Density in 2021

Based on Figure 5, it can be seen that the density of settlements in Jember district varies and two sub-districts have the highest settlement density. The percentage of settlement density in 2021 is located in the Kaliwates sub-district with a percentage of 48%. Furthermore, the second most densely populated settlement is located in the Sumbersari sub-district with a density of 44% and the third density is located in the Balung sub-district with a density of 31%. The fourth density is located in the Ambulu sub-district with a density of 30% and the fifth density is located in the Umbulsari sub-district with a density of 29%. The Kaliwates sub-district has the highest percentage density because the area is located in an urban area with densely populated settlements. The percentage of settlement density is calculated based on the area of the settlement that has been classified divided by the area of each sub-district.

CONCLUSION

This study classifies LULC based on Landsat 8 OLI/TIRS image data in 2013, 2015, 2017, 2019 and 2021 into six classes, namely vegetation, water bodies, settlements, bush grass, open land and rice fields. The classification accuracy value is 90% for the year of 2013, 2015, 2017 and 2021, while the data for 2019 the accuracy value is 91%. The classification results showed increasing area of settlements every year and experience wide variations in other classes. The distribution of residential development in each sub-district conclude with the highest increase of settlement area occur in the Ambulu sub-district in 2013, 2019 and 2021. Whereas, in 2015 and 2017 the widest area of settlement occurred in the Wuluhan sub-district. Inaddition, the analysis of the highest settlement density level in 2021 is located in Kaliwates sub-district with a density of 48%.

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