Land Use Changes Due to Mining Activities in Penajam Paser Utara Regency, East Kalimantan Province

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Abstract. There are coal mines in East Kalimantan Province, one of which is in Penajam Paser Utara Regency. The existence of a coal mine, resulting in changes in land use around it. If there is a change in land use that is not following the land potential, it will have an impact on the surrounding environment. The purpose of this study is to identify changes in land use in 2009-2019 and analyze the relationship between the mining area and the area of change in land use. The data required is in the form of land use in 2009 and 2019, obtained based on interpretation using Landsat imagery and verification of existing land uses. The images used are Landsat 5 TM and SPOT 7 MS ORT images. To identify land use changes, the data processing method used is pixel based image classification with the supervised maximum likelihood classification technique. The analysis method used is an overlay. The result of this research is a decrease in the area of water body, forest, non built area, and farm. There is an increase in the area of built-up area and mining area. There is a relationship between mine area and changes in land use.

1. Introduction

Indonesia itself is a country that has a lot of potential coal natural resources. The mining industry is one of the primary industries for the Indonesian government to earn foreign exchange. However, the mining industry itself requires a lot of labor and capital for regions that process the mining industry. The mining industry also harms the environment and communities living around the mining area [1]. East Kalimantan Province itself is one of the coal-producing provinces. Mining is considered to be the oldest activity in the world after agriculture [2]. Mining has impacts on environmental pollution, ecological damage, and land change due to increased energy demand and large-scale exploitation [3]. Land use change occurs after mining occurs because mining itself begins by removing land to gain access [4].

The land is an area on the surface of the earth that has various characteristics, namely as the biosphere, atmosphere, geological layer, soil, hydrology, plant and animal populations, and the results of human activities both in the past and present [5]. Land use itself is land that has experienced human intervention either permanently or cyclically against a group of natural and artificial resources to fulfill both material and spiritual needs or both [6]. Changes in land use for other activities will have a positive impact on social and economic aspects, but this will have a negative effect on the environment because it will reduce forest area, biodiversity, increase the area of critical land, erosion and landslides if land use changes occur inappropriately [7].
Remote sensing images obtained during a period can provide information about changes in LULC from time to time, and therefore, remote sensing images are an optimal tool that can be used to view mining activities and other human activities that develop and can damage the environment [8].

Research on the existence of mining activities carried out in the Godavari coal mining area, South India [9], and in the Ankroba River basin, Ghana [10] resulted in changes in land use around it. Then there is a study in Darling Range, Western Australia, that uses a supervised method to analyze land use changes caused by mining activities [11]. Based on this background, the purpose of this study is to identify changes in land use area from 2009 to 2019 in Waru Sub-District, Penajam Paser Utara Regency and analyze the relationship between mine area and changes in land use area.

2. Methodology and data

2.1 Research Area
This research was conducted in Waru Sub-District, Penajam Paser Utara Regency, East Kalimantan Province. Astronomically, the capital city of Waru Sub-District is located at 116°37’01.62” East Longitude and 0°23’22.7” South Latitude (Figure 1). Waru Sub-District in the northern part borders Penajam Sub-District. In the east, it is bordered by the Makassar Strait. In the south, it is bordered by Babulu Sub-District. In the west, it is bordered by Penajam Sub-District and Kutai Kartanegara Regency. Waru Sub-District has four villages.

2.2 Data
The data used in this study are temporal land use data for 2009 and 2019. Land use in 2009 was obtained from the results of processing Landsat 5 TM image data with a resolution of 30 x 30 m paths 116 rows 61 and path 117 rows 61, which were downloaded from https://eartexplorer.usgs.gov. Land use in 2019 was obtained from processing the Spot 7 MS ORT image data with a resolution of 1.5 m.

2.3 Method
The atmospheric effect of aerosol particles and atmospheric gases scattered from the earth's surface to the sensor has been widely discussed by several researchers [12, 13]. The initial stage of data processing in this study was to make corrections to Landsat images, which were used both radiometric correction and atmospheric correction. The radiometric correction itself is a correction made to correct the reflectant error due to the position of the sun. Meanwhile, the atmospheric correction itself uses the dark pixel correction method. Dark pixel correction is a correction to the atmosphere done to reduce the presence of shadows in the image caused by atmospheric scattering.

Then the next step is to perform pixel based image classification with supervised classification techniques. Pixel based image classification works on each pixel and extracts information from remote sensing data based on spectral data [14]. Supervised is a technique that involves the classification of pixels using a classification algorithm based on the spectral characteristics of pixels from known information classes [15]. Supervised was carried out on each image used, namely the 2009 Landsat 5 TM and 2019 SPOT 7 MS ORT, to determine the area of land use in each year. This process is carried out using ENVI 5.1.

Then the next step is to overlay the image data that has been supervised. This was done to identify the extent of land use change in Waru Sub-District, Penajam Paser Utara Regency in 2009 and 2019. The classification used in this study non built area, built up area, forests, farm field, water body, and mining area. This process is performed using ArcGIS 10.1.

The analysis technique used to analyze the relationship between mine area and land use change is the Pearson's product moment correlation. The correlation coefficient (r) is between 1 and -1. Variables have a strong correlation if the coefficient of correlation is more significant than 0.5 or less than -0.5. If the correlation coefficient value is positive, the increase in the value of the independent variable is followed by an increase in the value of the dependent variable. If the value of the correlation coefficient is negative, the increase in the value of the independent variable is followed by
a decrease in the value of the dependent variable [16]. The following is the correlation equation for Pearson's product moment used.

\[
r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2]^2[n\sum y^2 - (\sum y)^2]^2}}
\]

(1)

Based on this equation, \( r \) is the correlation coefficient of Pearson's product moment, \( n \) is the amount of data \( x \) and \( y \), \( \sum x \) is the total number of variables \( x \), \( y \) is the total number of variable \( y \), \( x^2 \) is the square of the total number of variables \( x \), and \( \sum y^2 \) is the square of the total number of \( y \) variables. This process is carried out using IBM SPSS Statistics 23 software. The variables used are the mine area and the area of land use change.

![Figure 1. Research area.](image_url)

3. Result and Discussion

3.1 Land Use Change

Based on the interpretation using Landsat 5 TM imagery in 2009 and SPOT 7 MS ORT in 2019, there are six land use classifications used: water body, non built area, built up area, forest, farm field, and mining area (Figure 2).
The most dominant land use classification in Waru Sub-District in 2009 and 2019 is forest. However, the forest area decreased in 2019 by 1354.51 ha. Water bodies are land uses that have the smallest area in both 2009 and 2019. Water body decreased in 2019 by 149.49 ha. The built up area increased in 2019 by 848.67 ha. The non built area decreased in 2019 by 3938.81 ha. This is due to an increase in the mining area by 4734.43 ha. Farm field area decreased by 140.29 ha in 2019. Changes in land use in 2009 and 2019 can be seen in table 1.

The mining area has increased quite a lot. It can be seen in table 1 that there was an increase of 6.4% from 2009 to 2019. The mining area itself is very small in the northwestern part of Waru Sub-District. This is because access to the area is still difficult because forests dominate it. The mining area is quite dominant in the central part of Waru Sub-District. This is because the area has access and was previously dominated by forests. So that there is a change of land function from forest to mining area (Figure 3).

Table 1. The land use area of Waru Sub-District in 2009, and 2019.

| Land Cover   | Area          | 2009    | %  | 2019    | %  |
|--------------|---------------|---------|----|---------|----|
|              | Ha            |         |    | Ha      |    |
| Water Body   | 604,38        | 0.8     |    | 454,89  | 0.6|
| Forest       | 50465,89      | 67.8    |    | 49111,38| 66 |
| Built Up Area| 922,22        | 1.2     |    | 1770,887| 2.4|
| Non Built Area| 7499,35     | 10.1    |    | 3560,54 | 4.8|
| Farm Field   | 12358,84      | 16.6    |    | 12218,55| 16.4|
| Mining Area  | 2547,46       | 3.4     |    | 7281,89 | 9.8|
3.2 The Relationship Between The Mining Area And The Area Of Change In Land Use

The correlation between variables can be seen by looking at sig. (2-tailed). If the value sig. (2-tailed) is less than 0.05, so there is a correlation between variables. If the value is sig. (2-tailed) is more than 0.05, so there is no correlation between variables. Sig value. (2-tailed) is 0.033, which indicates that there is a correlation between mine area and changes in land use. The Pearson correlation value between the mine area and changes in land use is 0.967. This shows that the relationship between mine area and land use change area is a perfect correlation (Table 2). So it can be interpreted that mining affects the extent of land use change.

Table 2. Land cover change transition probability matrix.

|                        | Mining Area | Area of Change in Land Use |
|------------------------|-------------|-----------------------------|
| **Mining Area**        | Pearson Correlation: 0.967 | Sig. (2-tailed): 0.033 |
| **Area of Change in Land Use** | Pearson Correlation: 0.967 | Sig. (2-tailed): 0.033 |

4. Conclusion

The results of this study indicate that there was a decrease in the area of water body, forest, non built area, and farm field from 2009 to 2019. There was an increase in the area of built up area and mining area from 2009 to 2019. Additional mining areas were found in regions with accessibility well. Based on calculations using Pearson's product moment correlation, there is a relationship between the area of...
the mine and the area of land use change and the relationship between these two variables is a perfect correlation.

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