

The Rate of Land Cover Change using Landsat Data in Coal Mining Area of Sawah Lunto City, Indonesia

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Abstract

Sawahlunto city is well-known for coal mining region. As in 2010, there have been at least 12 mining companies exploring coal resources in the region. As time passes, land cover conditions have gradually decreased due to mining activities. This region on which was originally covered by various vegetation and ecosystem have systematically transformed into open areas for coal mining. The use of remote sensing technology for land cover monitoring has been commonly well-developed in accordance with the need for improvement of detailed information about the changes of land use coverage. This study examines the land cover changes using supervised classification method based on Landsat data. The method focuses on four dominant classes of land cover in the region, namely forest, mining, settlement, and water resources. The classification processes were performed based on true-color composite satellite images. The results show that the overall accuracies of classification are 91.68 %, 92.49 %, 93.69 %, and 93.74 % in 2000, 2006, 2011, and 2016 respectively. It was also found that forest is the largest area in the coal mining area which, in some sense, tends to continuously decrease in terms of land cover in the last 15 years. The rate of forest area degradation achieved its maximum between 2006 and 2011.

Keywords: Sawahlunto, coal mining, Landsat, land cover degradation, supervised classification

Laju Perubahan Tutupan Lahan dengan Menggunakan Data Landsat di Area Pertambangan Batubara Kota Sawah Lunto, Indonesia

Abstrak

Kabupaten Sawahlunto terkenal sebagai daerah pertambangan batubara. Pada tahun 2010, setidaknya terdapat 12 perusahaan pertambangan yang mengeksplorasi batubara di kabupaten tersebut. Karena kegiatan penambangan batubara, kondisi tutupan lahan menjadi rusak seiring berjalannya waktu. Area yang semula ditutupi oleh berbagai vegetasi dan ekosistem berubah menjadi area terbuka penambangan batubara. Pemanfaatan teknologi penginderaan jauh untuk memantau tutupan lahan telah berkembang dengan baik tetapi ada kecenderungan untuk meningkatkan kebutuhan akan informasi yang lebih terperinci. Penelitian ini melakukan pemantauan perubahan tutupan lahan menggunakan metode klasifikasi terbimbing berdasarkan data Landsat. Metode klasifikasi ini difokuskan hanya pada empat kelas tutupan lahan yang dominan yaitu hutan, pertambangan, pemukiman, dan air. Proses klasifikasi

dilakukan berdasarkan gambar hasil komposit warna natural (*true color composite*). Hasil penelitian menunjukkan bahwa akurasi keseluruhan (*overall accuracy*) klasifikasi adalah 91,68 %, 92,49 %, 93,69 %, dan 93,74 % pada tahun 2000, 2006, 2011, dan 2016. Data klasifikasi tutupan lahan menginformasikan bahwa hutan adalah area terbesar di penambangan batubara Sawahlunto dan keberadaannya terus menurun selama 15 tahun. Tingkat degradasi kawasan hutan terbesar terjadi antara 2006-2011.

Kata Kunci: *Sawahlunto, pertambangan batubara, Landsat, penurunan tutupan lahan, klasifikasi terbimbing*

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I. INTRODUCTION

The mining sector in Indonesia has been considered as the substantial amount of the state revenue (APBN) by 30 % [1]. There are several types of mining activities that have been conducted in Indonesia such as nickel, gold, silver, bauxite, copper, tin [2], and coal [3]. Coal mining plays a very important role in supplying fuels for small housing business [4] and also integral energy sources for various industries [5] such as textile industry and products (TPT), PT. Indorama Synthetics Tbk, PT. Indo Bharat Rayon [6].

Coal mining sites are commonly found in areas with peat soil types [7]. Peat soil is believed to have very high carbon content [8], and over time, the accumulated soil layer will experience with heat and pressure in a long time so as to form rocks that have a very high carbon content which is widely known as coal.

Sawahlunto is a city located in West Sumatera Province, Indonesia. Coal mining activity in this region is considered as the oldest coal mining exploration in Indonesia because they have been operated since 1891 [9]. This mining is also known as the Ombilin

coal mining [10]. Due to the high income generating activities in this region coming from mining activities, especially coal mining, Sawahlunto is famously called as mining city [11].

As it was 2010, there have been more than 12 coal mining companies operating in Sawahlunto [12]. Sawahlunto city has area of 273.45 km² with more than 27% of this region is hilly area covered by protected forests which belongs to the area of Bukit Barisan in Sumatra [13]. Due to the coal mining activities, the condition of land cover in this area has changed as the most popular method to extract coal deposits is open pit mining [14]. The area that was originally covered by various vegetation and ecosystem has been transformed to open area due to coal mining activities. If the mining activities are running longer, it will further destruct the ecosystem in this region. The area of coal mining area will grow wider, while the area of forest or land cover will decrease and will automatically affect the density level of vegetation in Sawahlunto. Thus, the mining

activities are believed to affect the condition of the environment in this region.

Regarding the issue, it requires such effort to detect the land cover changes in Sawahlunto. The detection on the changes of the earth surface objects, especially monitoring of land cover, can be done by using a remote sensing technology [15,16]. The utilization of remote sensing technology for monitoring land cover has been well-developed, but there is a tendency to increase the need for more detailed information [17]. This technology can be used to obtain information about objects on the surface of the earth by analyzing the data by using the tool without direct contact to the object under study. Obtaining data of the objects may use remote devices such as satellite, spacecraft, and so forth [18].

According to Lilles and Kiefer, there are several ways used in remote sensing technology to detect the changes of earth surface or land cover monitoring; the first is to analyze the changes that occur by knowing the greenness or vegetation index [19]. The vegetation index is one of the parameters used to analyze the vegetation status of one region [20,21]. Furthermore, the technique for monitoring land cover by using remote sensing technology is conducted through classification. The results of the classification will show information about types of land cover on the surface of earth.

The research of investigating land cover of vegetation commonly uses vegetation index such as NDVI (Normalized Difference Vegetation Index); such studies have been conducted by several researchers [22-24]. Sudiana and Diasmara analyzed the condition of vegetation in Kalimantan island using NDVI and EVI (Enhanced Vegetation Index) method [22]. The results showed that, between 2005 and 2006, the vegetation index (EVI) in Kalimantan was about 0.4 and

the EVI score in 2007 increased for more than 0.4 or even almost reached 0.5. Most of detections on the land cover using NDVI have been performed by classifying the land area covered by vegetation and the area which are clear or open from vegetation. Those two classification area can be determined well using NDVI method.

However, NDVI method is quite rare to find in the non-vegetation classification such as arid rangeland and main road. The research to classify arid rangeland, farms, villages, and main roads has been carried out by Al-Ahmadi and Hames [25]. They used satellite images from Landsat-5 TM by applying RGB composite image to do the classification.

Other research of land cover classification has also been done by Irawan and Indarto who conducted a study on land cover classification by utilizing satellite images of Systeme Pour l'Observation de la Terre (SPOT) in the area of Bondowoso Sampean Dam [26]. The results showed that there were nine classes of land cover types with an accuracy level of 84.21 percent.

The other supporting research in detection of area lacking vegetation does not use NDVI, namely the research conducted by Suwarsono and Khomarudin which utilized NDBI (Normalized Difference Build-up Index) to detect the spatial distribution of settlement area in North Sumatra province, Indonesia [27].

Moreover, Catur et al have also conducted a study on the identification of tin mining areas [28]. They found that the characteristic of tin mining land in the Landsat 8 image has bright brown to bright white color, coarse texture, following the river pattern, possessing wide land size and blue water puddle. The accuracy of the research is 90.5 %.

Muchlisin et al also conducted a study on the classification of land cover using data of ALOS (Advanced Land Observing Satellite) in West Java, Indonesia [29]. The results showed that ALOS satellite image data are accurately able to classify into five types of land cover that is man-made object of 38.08 ha, 29.246 ha of open land, 13.98 ha of water, 42.99 ha of rare vegetation, and 70.82 ha of vegetation meeting.

This paper describes monitoring land cover using supervised classification method based on Landsat data imageries. The supervised classification is directed to the four dominant land cover classes in Sawahlunto mining area, i.e. forest, mining, settlement, and water. The classification processes were performed to the true color composite images. This research was conducted by monitoring the land cover of mining area in Sawahlunto city from 2000 to 2016. This research aims to study the changes in forest conversion function into mining area, namely the decreasing amount of forest area and the increase of mining area over the last 15 years.

The coal mining activities in this region which are generally located in the forest area,

inevitably, reduce rampant forest area. The existence of forests that represent land cover as oxygen-producing area will decrease over time as the expanse of coal mining activities opened in this region.

The Landsat data utilized in this research because they have high spatial resolution i.e. 30 m and they can be freely accessed. Even though Landsat data have temporal resolution 16 day but they are still considerable good to be applied in the yearly land cover detection as a focus of investigation in this research.

II. METHOD

Study Area

Sawahlunto city is located within $0^{\circ}33'40''$ to $0^{\circ}43' 33''$ South Latitude and $100^{\circ}43'13''$ to $100^{\circ}50'40''$ East Longitude. This is a case study of land cover changing in the coal mining area in Sawahlunto city, West Sumatra, Indonesia. The research area of interest (RAI) was taken the Sawahlunto city which covers the coal mining area between $0^{\circ}34'30''$ to $0^{\circ}39'00''$ South Latitude and $100^{\circ}43'20''$ to $100^{\circ}49'50''$ East Longitude as shown in Figure 1. In the Landsat data, the RAI consists of 101080 pixels which are formed of 266 rows and 380 columns.

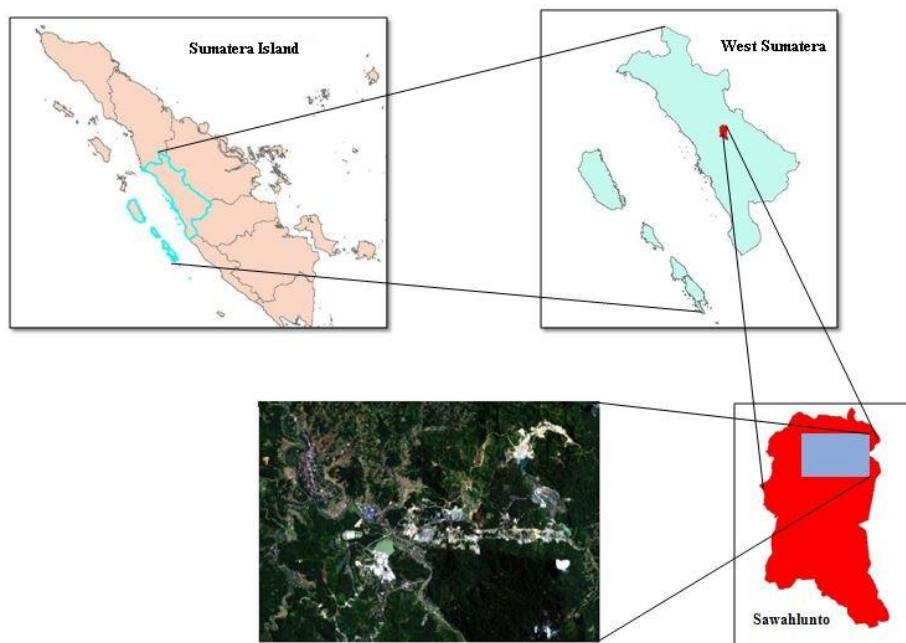


Figure 1. The Research Area of Interest (RAI) of Location

Data Retrieval

The data used in this research are Landsat data which were retrieved from USGS website in years of 2000, 2006, 2011, and 2016. One data which was considered as the best data was chosen for every year. The considered data were only ones which have cloud cover less than 15% to ensure that the data produce most cloud-free area. Those data were retrieved from path 127 and row 060. The path and row represent the region code of an image data. Row is a division of Landsat scenes which refer to the latitude coordinates or a region part from North to South while the path is a division part of Landsat data following the moving of satellite and earth rotation or the sector division through the longitude coordinates from West to East. The utilized data were the ones which were captured at 26 August 2000 from Landsat 5 with 9% cloud cover, 24 July 2006 from Landsat 5 with 11% cloud cover, 6 July 2011 from Landsat 5 with 11% cloud cover, and 14 April 2016 from Landsat 8 with 4% cloud cover. They were then corrected radiometrically to enhance the quality of the data.

Correcting Landsat imagery data

In this research, the correction of image data was conducted by using radiometric correction method. Radiometric correction eliminates the effect of atmospheric dynamics on which radiometric correction is often referred as the Top of Atmosphere (ToA) correction. Radiometric correction was as the first step in this data processing before further analysis would be performed. The radiometric correction process involved correction of sensor-related effects to increase the contrast of each pixel of the image, so that the recorded object is easily interpreted to produce the correct information as same as the real condition of the earth surface viewed. Catur

et al stated that radiometric correction aims to convert digital number of the imagery data into the values of reflectance [28]. The conversion in this research refers to Equation 1 [30]. The values of M_L and Q_L can be obtained from the metadata of each dataset.

$$L_\lambda = (Q_L \times M_L) + A_L \quad (1)$$

where:

L_λ = ToA spectral reflectance

M_L = Reflectance multiplication factor of band x of data

A_L = Reflectance addition (offset value) of band x of data

Q_L = Digital number

In this research, radiometric correction process was done by Quantum GIS software (QGIS). QGIS is the open source data processing software based on Geographic Information System (GIS). GIS is a computer-based information system used to process and to store data or geographic information.

Supervised Classification

The next stage is doing classification of land cover based on the radiometrically-corrected Landsat data using supervised classification method. This method is chosen because controllable accuracy by creating the good training area. The more accurate the training area is made, the higher accuracy can be produced. In this classification, there are four classes of land cover i.e. forest, mining, settlement, and water. In the supervised classification, the result of grouping pixels in the processed imageries is based on the training areas. These areas were determined by doing multi resolution segmentation that aims to create a polygon area or sample image based on the visual features in the imagery. The locations of the object are also confirmed to the high resolution of satellite data such as google earth data in the appropriate time. The process of making polygon as training areas

was performed by using ENVI software. The training areas were determined from the true color composite of Landsat-8 data in the band layer combination of band 3 in red, band 2 in green, and band 1 in the blue layer. Each feature of land cover class was considered through the visual view of true color composite images.

Land cover types were produced by classification process from the corrected data. The process classified the pixels characterized by their color into for classes respecting to the color of each training area. Every data resulted four classes, e.g. forest, mining area, settlement area, and water resources which were represented into four different colors. Determining training areas in the supervised classification would affect the results. The proper training area would produce accurate pixel classification which is shown by the level of accuracy.

Data analysis

The land cover changes

Landsat data have spatial resolution of 30 m. It means that every pixel represents 30 × 30 m area on the real earth surface. The number of pixels in every group in the classification result can be calculated and, therefore, the area of each class also can be determined. By comparing the area from any

data to the other data comes from different year, it can be concluded whether there are changes in any land cover class or not. In this study, there are four classes or groups of land covers in 2000, 2006, 2011, and 2016. This information can be presented in the form of maps. From each of these classification results and to what extent the area has changed of each class can be presented in the form of bar chart; this will describe the land cover change.

Accuracy Assessment

Overall Accuracy (OA) is an accuracy representation of the classification results. Overall accuracy is calculated by dividing the number of pixels which are correctly classified divided by the number of all pixels in the assessed image. In the error matrix of classification as given in Table 1, the number of correctly classified pixels is the sum of values in the main diagonal of that matrix. In the mathematical expression, the formulation to find the overall accuracy is written in Equation 2 as follows [31].

$$OA = \frac{\sum_{i=1}^r x_{ii}}{N} 100\% \tag{2}$$

where:

OA = overall accuracy

N = the total number of pixel

x_{ii} = cell values in the row i and coulomn i

r = the number of row or coulomn in the error matrix.

Table 1. Error Matrix of Classification

		Ground Truth			
		Mining	Forest	Settlement	Water
Assessing Areas	Mining	x_{11}	x_{12}	x_{13}	x_{14}
	Forest	x_{21}	x_{22}	x_{23}	x_{24}
	Settlement	x_{31}	x_{32}	x_{33}	x_{34}
	Water	x_{41}	x_{42}	x_{43}	x_{44}

III. RESULTS AND DISCUSSION

Corrected Data

The number of availability Landsat data with 16-day temporal resolution is more than enough for yearly analysis of land cover change. Even though only best data were chosen in one year for further processing, the atmospheric effect occurred on the acquiring data process, and therefore, further process through radiometric correction to the data were conducted.

One scene of Landsat imagery covers an area of 185×185 km, and the research area was taken by cropping the Landsat data after it was radiometrically-corrected.

To compare the visual view of the Landsat images before and after applying radiometric correction, true color images were made which are composited in the RGB from band 4, band 3, and band 2 of data. The contrast of the corrected image is obviously seen compare to the uncorrected one as shown in Figure 2 and Figure 3. Those two images are Landsat data which were retrieved on 26 August 2000. The results show that the corrected image has high contrast, sharper, and brighter characteristic compared to the uncorrected image.

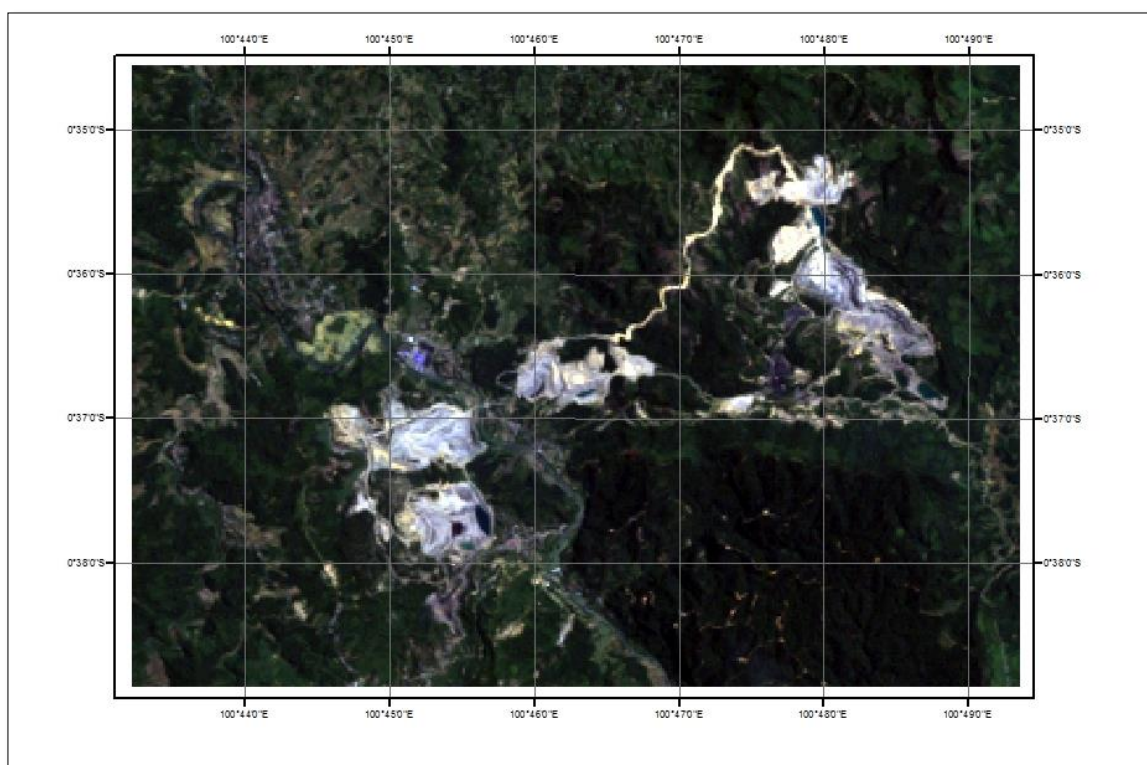


Figure 2. Landsat Imagery Before Radimetrically-Corrected

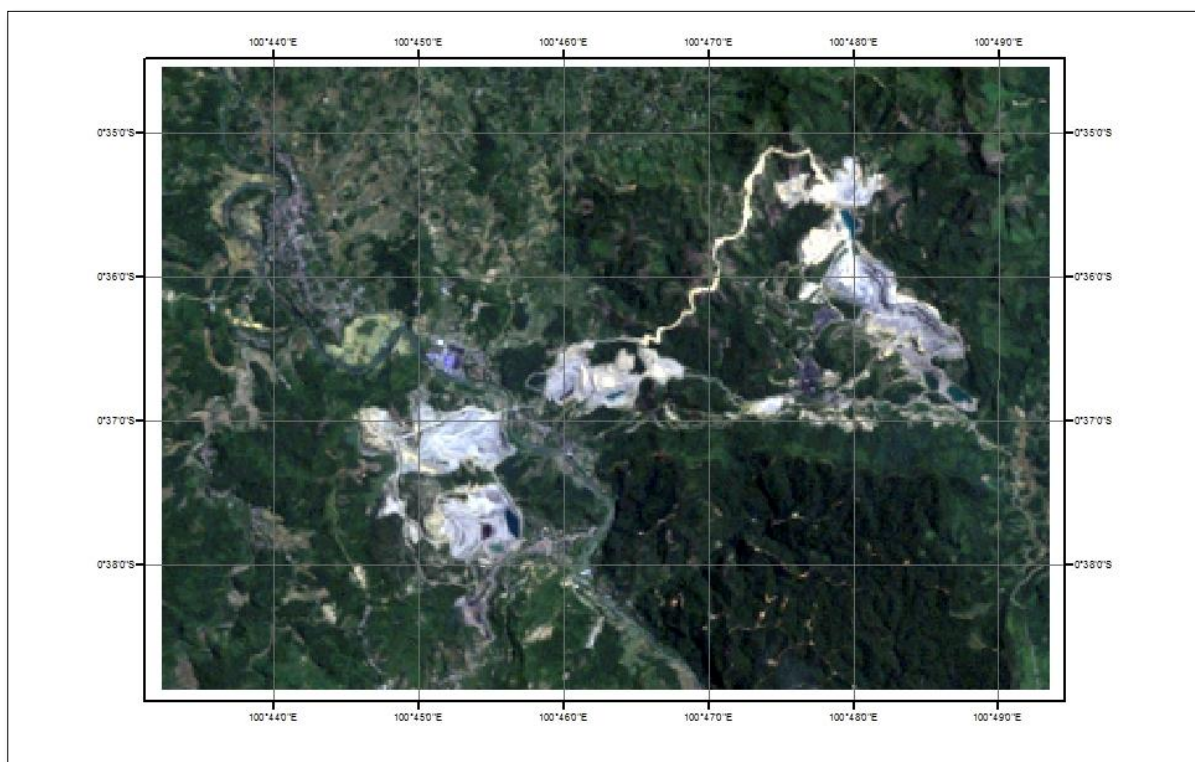


Figure 3. Landsat Imagery After Radimetrically-Corrected

Training Areas

An object on the earth surface can be recognized visually using satellite imagery data through their color composites. To be able to display this color composite image, it requires a combination of three bands namely red, green, and blue or commonly called the combination of RGB layers. As data from Landsat 5 and Landsat 8 were used which have different bands composition, there were also different band to be used in RGB layers in making true colors. True color from Landsat 5 data was created by selecting band 3, 2, and 1 in layer red, green, and blue respectively. Moreover, the true color image from Landsat 8 data was created from band 4, 3, 2 for RGB layers. However, to make classification of several objects, the characteristics of the objects should be recognized such as their texture, shape, and spectral reflectance. In this research the classification of objects was conducted in the mining area of Sawahlunto as a research area

of interest. There are four defined classes like forest, mining area, settlement, and water resource. The classification process was based on the true color of Landsat data which have been corrected. The method of classification was conducted through supervised classification and therefore it needs training area types as much as the defined classes. The visual characteristics of four land cover classifications are given in Table 2.

In this research, training areas were determined by bordering the areas that show visibility characteristics of certain land cover class. For example, the area with blue purple color, dark, and soft texture would be bordered using polygon to be used as training area of water. To make sure that the determination of training areas is correct, further confirmation to Google Earth image in the appropriate location and time is needed. Google Earth images were utilized because they have very high spatial resolution and it is considered easy to differentiate which are

belongs to forest, water (lake or river), housing in the settlement area, and also mining cultivated area. Google Earth imagery data used as references are obtained at 31 December 2000, 31 December 2006, 31 December 2011, and 16 August 2016. The number of training areas in every class was made randomly from the image which shows the un-doubt characteristics of the desired object. The more training areas can be determined confidently, the better accuracy of classification will be resulted. Figure 4 shows the training areas that are utilized in the classification process performing by computer software. Those training areas can be confirmed from Google Earth (Figure 5) which show visual characteristics as described in Table 2.

No	Land cover classes	Visual characteristics
1.	Forest	Green colour Rough texture Irregular patterns
2.	Mine	Brown-white colour Rough texture Regular circular pattern
3.	Settlement	Brown-red colour Slightly bright viewed Slightly rough texture Rectangular patterns Road is obviously seen
4.	Water	Blue-purple colour Dark viewed Soft and smooth texture

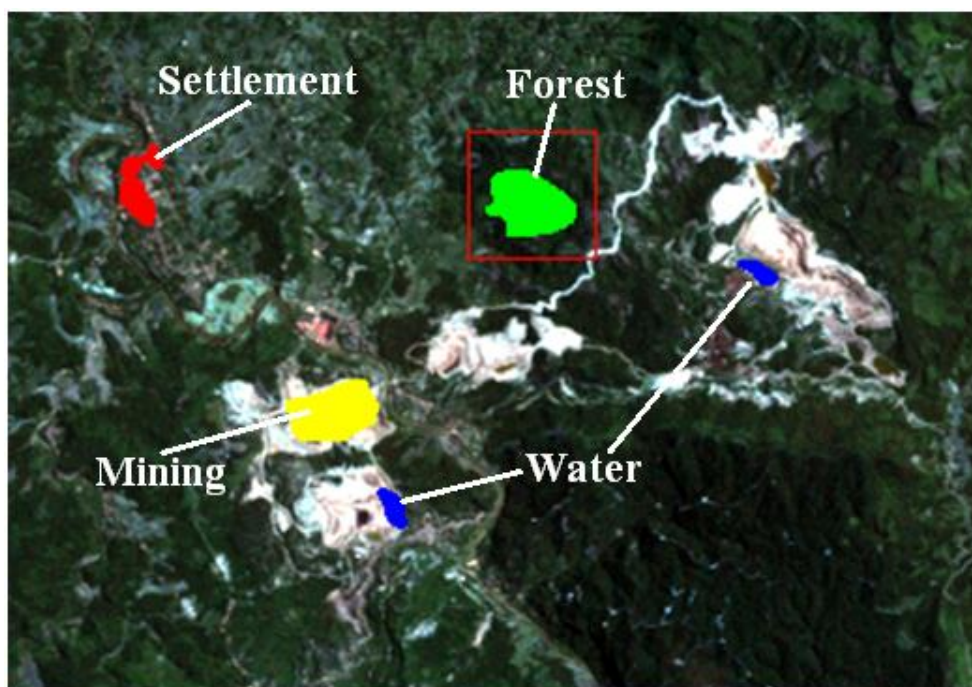


Figure 4. Training Areas which are Determined Using Landsat Data



Figure 5. Visual Confirmation of Training Area Using Google Earth Image

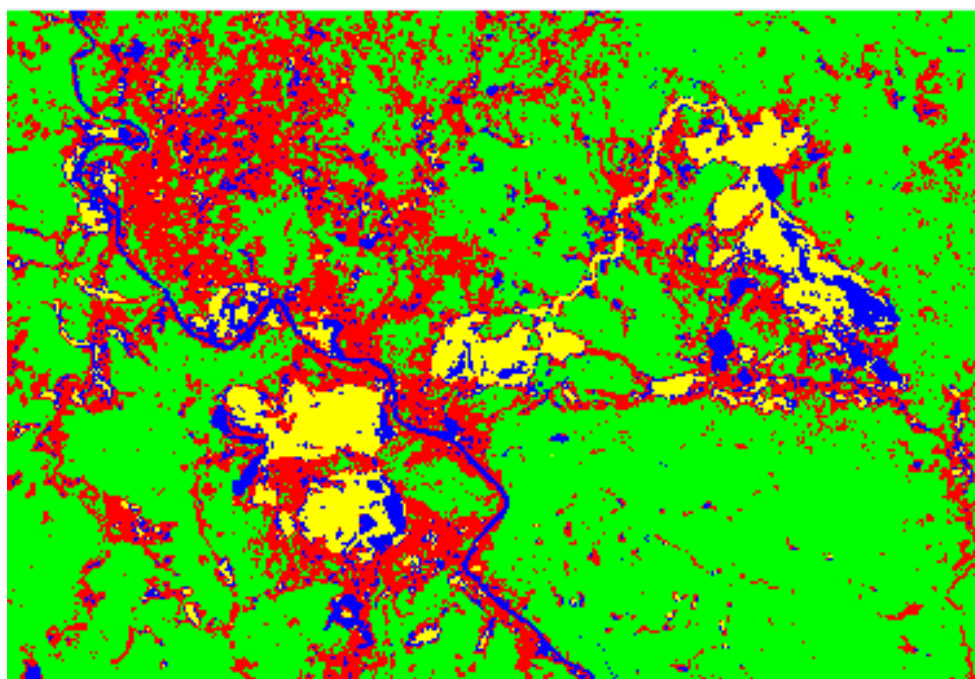


Figure 6. One of the Supervised Classification Results

Data Analysis

Accuracy of Classification

Accuracy assessment is needed in this research because to show the reliability of the information of classification results. The accuracy of the classification was represented

by the Overall Accuracy (OA) value and the to get it has been written in Equation 2. The data of classification pixels were compared to the ground truth given in the confusion matrix in Table 3.

Table 3. Confusion Matrix of Classification Results

Classification Results	Ground Truth (pixel number)				
	Forest	Mining	Settlement	Water	Total
Forest	2199	13	47	0	2259
Mining	1	1360	15	16	1392
Settlement	46	68	566	5	685
Water	20	133	22	126	301
Total	2266	1574	650	147	4637

The data were the outputs from the classification process of the Landsat data in 2000. Using the number of pixels in the main diagonal of that matrix and referring to the Equation 2, the obtained OA value is $4251/4637 = 91.67\%$. Catur et al stated that the overall accuracy value above of 85 % can be categorized as an accurate result, and therefore the classification results in this research are reliable [28].

There are other error analyses called commission error and omission error. Commission error arises when a certain class of land cover has additional pixels because the classification algorithm categorizes an object into wrong class compared to the true data. On the other hand, the omission error come if the object which is truly sit in the certain class is then misclassified on the other class [21]. For example, if the forest pixels are classified as mining, settlement, or water, they are led to the omission error. Conversely if non-forest pixels are classified as forest, then the commission error arise. Based on the data in Table 3 commission error can be calculated by summing the number of pixels above the main diagonal and then it is divided by the number of all pixels of data. Furthermore, the omission error can be found by adding all the number of pixels below the main diagonal and it divided by the number of all pixels. So the number of commission error from Landsat data in 2000 is 1.72% and the omission error is 6.21%.

Table 4. Summary of Accuracy Assessment Results

Year	Overall Accuracy	Commission error	Omission error
2000	91.68 %	1.73 %	6.25 %
2006	92.49 %	3.34 %	3.66 %
2011	93.69 %	1.45 %	4.54 %
2016	93.74 %	2.16 %	3.56 %

All the accuracy assessment steps such as calculating the overall accuracy, commission error, and omission error have been applied to all Landsat data set in 2000, 2006, 2011, and 2016. The accuracy summary of those data is given in Table 4. It is obviously shown that all accuracy values are more than 90 %, which means that all the classification processes produce accurate results of the classified areas.

In the supervised classification, the process of choosing and creating training area has an essential role. The accuracy in determining the training area will have impact to the accuracy results. Additionally, the number of training area also affects the accuracy result. Therefore, the process of making training area is considered as the most important step. This study which showed high accuracy results indicates that the creation of the training area has been performed well.

The rate of changing areas

In order to know to what extent the changes of land cover in Sawahlunto region, the number of pixels in each class from the classification resulted image were counted. The areas of land cover were calculated by multiplying the number of the pixels and the area which is represented by one pixel i.e. 30×30 m or equal to 900 m^2 per pixel. The obtained area of each class of land cover is displayed in Table 5. From the data in Table 5, the forest areas decreased every year.

Table 5. Yearly Changes of Land Cover Area

Year	Classified Areas (hectares)				Total
	Forest	Mining	Settle	Water	
2000	5606.46	563.76	2195.4	731.52	9097.2
2006	5530.32	789.48	2485.3	292.05	9097.2
2011	5004.36	840.60	2891.1	361.08	9097.2
2016	4835.97	870.03	3010.3	380.88	9097.2

Regarding the data presented in Table 5 for one and half decade (2000-2016), the decreasing forest area can be calculated as 770.49 hectares or equals to 8.47 % of total research area of interest. Meanwhile, the area of mining and settlement areas increases by 306.27 and 814.86 hectares, associated with 3.37 % and 8.96 % respectively. The data indicate that the decreasing forest area in Sawahlunto region mostly has been converted to settlements area. The reducing forest area potentially implicates to the increasing temperature on that region. However, the population growth cannot be avoided and the solution of controlling the increasing

temperature can be achieved by planting more trees to restore the function of forest.

In addition, the increasing settlement area is higher than decreasing area of forest. This can be explained that the settlements are possibly constructed in the other area, possibly water resource area. The former water areas have potential risk for flooding the people in the case of heavy rains coming. The flooding may be prevented by creating good drainage systems in this area.

According to the data from the local authority, it is imminent to facilitate such infrastructures as adequate drainage system to the people who reside in the former mining area. The local government should also support with the legal formal rules to the people to conserve the environment. The profiles of land cover changes for the period or research might be easier figured out in a bar chart as displayed in Figure 7.

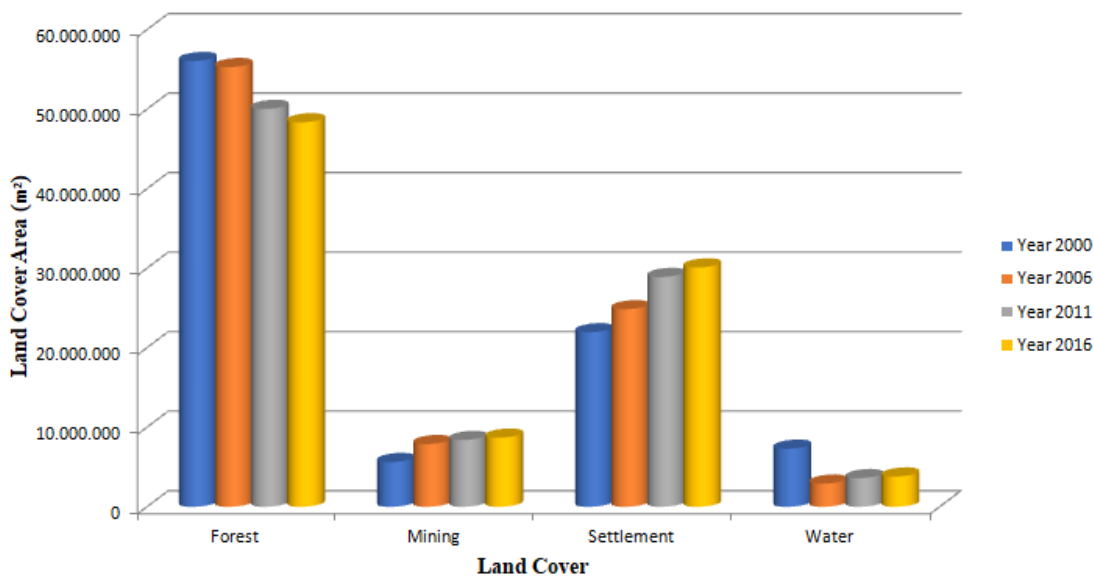


Figure 7. Bar Chart of the Classified Area

Based on the whole results of each land cover as shown in Figure 7, the object that has the largest area in the research area of interest of mining area of Sawahlunto region is forest. Table 5 shows the calculation of the rate of

forest degradation for every 5 years period. In the period of 2000-2006, 2006-2011, and 2011-2016, the rate of forest degradation were 0.84 %, 5.78 %, and 1.85 % respectively.

From those results, the biggest forest degradation rate on the mining area of Sawahlunto occurred between 2006 and 2011. The forest area has been mostly changing to the settlement area in the next 5-year period. In contrast, the least degradation rate of forest happened in the period of 2000 and 2006. There is no published information about the possible reason of this matter. Overall, the patterns of land cover changes have consistent trend, except the water land cover class. Forest area showed consistent decrease from 2000 until 2016. On the contrary, the mining area and settlement display the increasing area consistently in the period of 2000 to 2016. This trend is considered as logical as the expansion of mining exploration area may require more workers, and consequently they need more space to reside by opening forest area used as settlements.

IV. CONCLUSION

The research of land cover classification using Landsat data with the average accuracy of 93 % concludes that in Sawahlunto city from 2000 to 2016 there has been decreasing forest area by 770.5 ha in the rate of 0.86 % per year averagely; this has been converted to mining and settlement areas. However, it was observed that some settlement area came from watered area as well.

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