DETECTING THE AREA DAMAGE DUE TO COAL MINING ACTIVITIES USING LANDSAT MULTITEMPORAL (Case Study: Kutai Kartanegara, East Kalimantan)

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Abstract. Coal is one of the most mining commodities to date, especially to supply both national and international energy needs. Coal mining activities that are not well managed will have an impact on the occurrence of environmental damage. This research tried to utilize the multitemporal Landsat data to analyze the land damage caused by coal mining activities. The research took place at several coal mine sites in East Kalimantan Province. The method developed in this research is the method of change detection. The study tried to know the land damage caused by mining activities using NDVI (Normalized Difference Vegetation Index), NDSI (Normalized Difference Soil Index), NDWI (Normalized Difference Water Index) and GEMI (Global Environment Monitoring Index) parameter based change detection method. The results showed that coal mine area along with the damage that occurred in it can be detected from multitemporal Landsat data using NDSI value-based change detection method. The area damage due to coal mining activities can be classified into high, moderate, and low classes based on the mean and standard deviation of NDSI changes (ΔNDSI). The results of this study are expected to be used to support government efforts and mining managers in post-mining land reclamation activities.

Keywords: *damage area, coal mining, landsat multitemporal*

1 INTRODUCTION

Mining activities cause serious impacts on ecosystems worldwide (Schroeter and Gläber 2011). The Government has a mandate to control pollution and environmental damage based on Indonesia Law Number 32 the Year 2009 on Environmental Protection and Management. According to the Law, environmental protection and management is a systematic and integrated effort undertaken to preserve environmental functions and prevent pollution and/or environmental damage including planning, utilization, control, maintenance, supervision and law enforcement.

One of the activities that have great potential to cause environmental pollution is mining activities. Mining activities have two opposite sides, namely as a carrier of the country's economic prosperity and as an environmental impact carrier that requires considerable energy, thought, and cost for its recovery process (Marganingrum and Noviardi 2010).

Coal is one of the most mining commodities to date, especially to supply both national and international energy needs. Indonesia's coal production has shown a significant increase in production. Indonesia's coal production in 2009 reached about 254 million tons. About 94.4% of them are from Kalimantan, and 75% of the national coal production is exported to abroad (Ginting 2010).

Environmental problems arising from coal mines in Indonesia are, as is generally done by open pit mines, although there are some who use underground mining, it will have an impact on changes in the landscape, physical, chemical, and biological properties of the soil, and generally cause damage to the earth's surface. Thus, this condition will cause disruption to the ecosystem above it (Subardja 2007).

Based on the Act, one of the efforts to protect and manage the environment is to supervise activities that have the potential to cause environmental damage. Remote sensing data can be used to provide the informations about changes in surface water and land cover over time, which is essential for environmental monitoring in mining areas. Remote sensing data are also ideal for environmental impact assessment due to their broad spectral range, affordable cost, and rapid coverage of large areas. Remote sensing data enables the identification, delineating, and monitoring of pollution sources and affected areas, including derelict land, and changes in surface land use and to water bodies (Charou *et al.* 2010). Remote sensing allows for cost- and time-efficient monitoring of landscapes vital to the conservation of natural resources, ecosystems, and biodiversity (Willis 2015). Taking into account the advantages possessed by the use of remote sensing data, the authors are interested to use remote sensing methods to monitor the environmental damage caused by mining activities in Indonesia.

Landsat data is the optical data that historically has the best recording among other data. The existence of this data has been available since Landsat 1 was launched in 1972. Until now, it has been pretty well available Landsat data archive to the latest recording by Landsat 8 the satellite launched since 2013. The results of research at several locations abroad have shown the result that Landsat data is very useful to be used to monitor the impacts of coal mining (Schroeter and Gläber 2011), (Erener 2011) (Chitade and Katyar 2010). In Kütahya Turkey, multi-temporal Landsat TM data sets were used to assist in identifying and monitoring the progress in the rehabilitation field and the evaluation was based on analyzing varying vegetation indices (Erener 2011).

This research tries to raise the topic of utilization of multitemporal Landsat data to know the damaged area caused by coal mining activity in Indonesia region. Research on this topic is rarely done by taking a location in Indonesia.

2 MATERIALS AND METHODOLOGY

2.1 Location and Data

The research took place at several coal mine sites in Kutai Kartanegara, East Kalimantan Province (Figure 1-1). In more detail, these locations can be seen in Figure 3-1. The image data used is a pair of multitemporal Landsat data, namely Landsat 7 path/row 116/060 recording date of May 15, 2000, and Landsat 8 recording dated February 7, 2014.

2.2 Standardization of data

Landsat 8 data were obtained from Remote Sensing Technology and Data Center of Indonesian National Institute of Aeronautics and Space (LAPAN) through website http://landsat-catalog.lapan.go.id/. The data format is GeoTIFF. Level of Landsat 8 is level one terrain-corrected product (L1T). L1T available to users is a radiometrically and geometrically corrected image. The image is also radiometrically corrected to remove relative detector differences, dark current bias, and some artifacts. The level one image is presented in units of Digital Numbers (DNs) which can be easily rescaled to spectral radiance or top of atmosphere (TOA) reflectance (USGS 2015).

Figure 1-1: Location of study area
(source: http://landsat-catalog.lapan.go.id/)

2.3 Methods

The method developed in this research is the method of change detection. By doing a review of many studies, in the context of ecological monitoring, Willis (2015) suggested that change detection has historically been used to look at changes in land use/land cover and disturbance using binary comparisons contrasting conditions during two discrete time periods. In assessing changes in environmental changes, NDVI is a commonly used indicator, especially for monitoring plant phenology changes. The study tried to know the land damage caused by mining activities using NDVI parameter based change detection method. Besides NDVI, this study also extracts other indices such as NDSI, NDWI, and GEMI which will be used for mine area damage analysis.

Processing steps, interpretation, and analysis of data covering three main stages (Figure 2-1), namely:

a. Radiometric correction. The radiometric correction involves converting the DN data into a TOA reflectance both Landsat 7 (USGS 1998) and Landsat 8 (USGS 2015). The atmospheric correction is done by the DOS (Dark Object Subtraction) model (Chavez 1988; 1988; Chavez 1989),
b. Preparation of the Landsat 7 image dataset (bands 2, 3, 4, 5, and 7) and Landsat 8 (bands 3, 4, 5, 6, and 7),
c. Extraction of NDVI, NDSI, NDWI, and GEMI values,
d. Preparation of Landsat 7 RGB-543 color composite image and Landsat 8 RGB-654. Then followed by contrast enhancement and spatial filtering (using high pass filter),
e. Interpretation of mining areas. Done by comparing Landsat 7 image (2000) with Landsat 8 image (2014). The mining area is identified from the image based on the visual visibility changes of Landsat 7 image 2000 and Landsat 8 in 2014, especially the colors, shapes, patterns, and associations,
f. Analysis of mine area damage is done by: sampling, calculation of pixel value statistics, determination of the most sensitive parameters for damage detection, the threshold determination, and classification of the damage level.

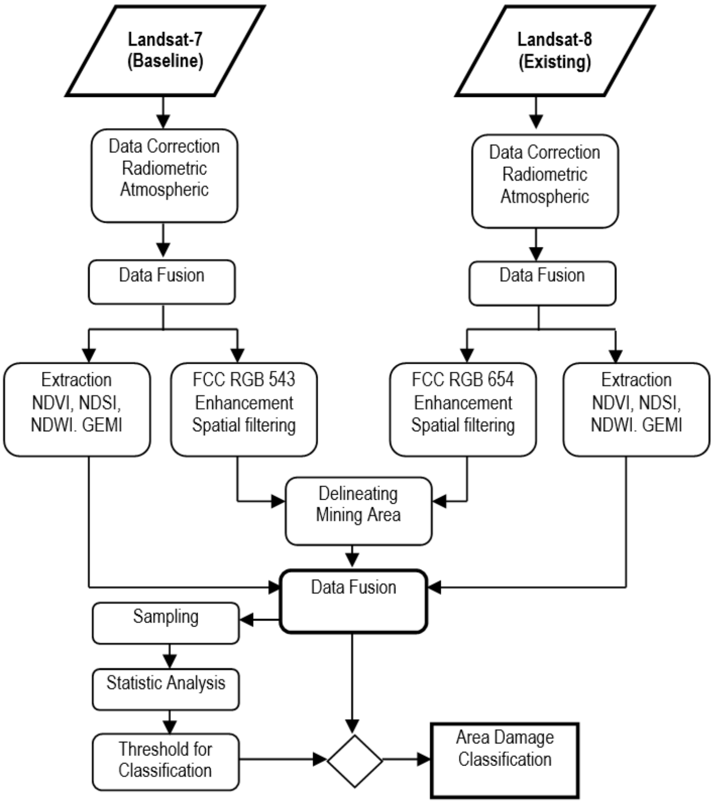


Figure 2-1: Flowchart of processing, interpretation and data analysis

NDVI, NDWI, NDSI, and GEMI values can be derived from Landsat 8 images using the following formula:

a. NDVI is derived from band 4 (Red) and 5 (NIR). The formula was modified from Rouse , *et al* (1974):

$$NDVI = \frac{\rho 5 - \rho 4}{\rho 5 + \rho 4} \qquad (2\text{-}1)$$

b. NDSI is derived from band 4 (Red) and 7 (SWIR). The formula was modified from Rogers and Kearney (2004):

$$NDSI = \frac{\rho 7 - \rho 4}{\rho 7 + \rho 4} \qquad (2\text{-}2)$$

c. NDWI is derived from band 3 (Green) and 5 (NIR). The formula was modified from McFeeters (1996):

$$NDWI = \frac{\rho 3 - \rho 5}{\rho 3 + \rho 5} \qquad (2\text{-}3)$$

d. GEMI is derived from band 4 (Red) and 5 (NIR). The formula was modified from Pinty and Verstraete (1992):

$$GEMI = \delta(1 - 0.25\delta) - \frac{(\rho RED - 0.125)}{(1 - \rho RED)} \qquad (2\text{-}4)$$

$$\delta = \frac{2(\rho NIR^2 - \rho RED^2) + 1.5\rho NIR + 0.5\rho RED}{(\rho NIR + \rho RED + 0.5)}$$

Normalized distances (D-values) were calculated to measure and to test the discrimination ability of the index (Kaufman and Remer 1994). In this research, the D-values > 1 will represent good separability of the index to discriminate the changes of pre-mining and during or post-mining.

$$\mathrm{D} = \left|\frac{\mu 2 - \mu 1}{\sigma 2 + \sigma 1}\right| \qquad (2\text{-}5)$$

where D is Normalized Distance (Kaufman and Remer 1994), µ1 and µ2 are mean values of samples pre-mining and during/post-mining respectively, σ1 and σ2 are the standard deviation of samples pre-mining and during/post-mining respectively. The calculation resulted D-values for all indices which are NDVI, NDSI, NDWI and GEMI.

3 RESULTS AND DISCUSSION

3.1 Identifying the Mining Area

The mining area is identified from the image based on the visual visibility changes of Landsat 7 image 2000 and Landsat 8 in 2014. In general, the mining area can be identified from Landsat 7 (the Year 2000) and Landsat 8 (in 2014). There is a change of color from greenness to redness. In the image of 2000, generally, still greenish color, while in the image of 2014, has undergone many changes, which turned into redness. In the mining area, around red pixels, there are found the dark blue pixels. These pixels are the body of water that was stored. In the Landsat 8 image, the coal outcrop appears to be reddish in color, since this object is dominant to have a high reflectance for the SWIR (Short Wave Infra Red) wavelength. In this composite image, the vegetation is greenish because this object is dominant to have high reflectance for the NIR wavelength. While the object of water for this composite image tends to be blackish black because this dominant object has a high reflectance for the wavelength of Visible (Red) (Figure 3-1).

3.2 Extracting and analyzing the index NDVI, NDSI, NDWI, and GEMI

The results of sampling and statistical measurements, obtained a list of NDVI, NDSI, NDWI and GEMI values at the time pre-mining, while still being mined/post-mining, as presented in Table 3-1, Table 3-2, Table 3-3, and Figure 3-2.

Taking into account the formulas for generating NDVI, NDWI, NDSI, and GEMI, it is known that, respectively, NDVI, NDSI, and NDWI data would be most appropriate for analyzing vegetation objects, open land (coal and soil outcrops), and water. While GEMI data will tend to be similar to NDVI, which is to analyze vegetation objects.

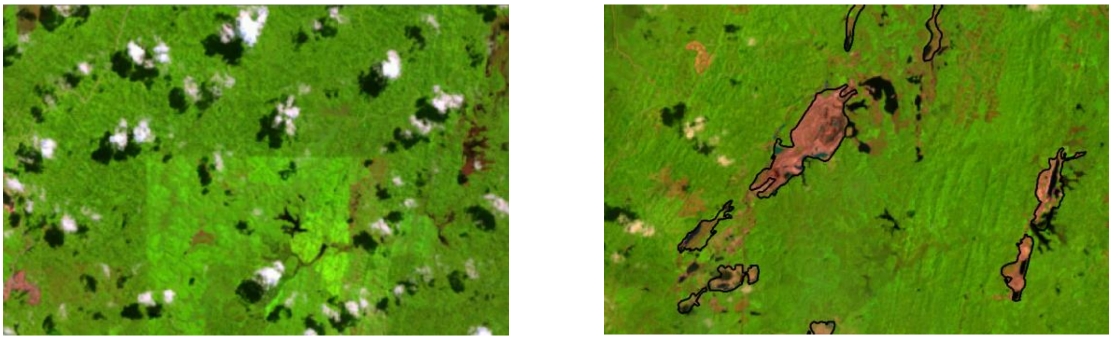
The results of the measurement show that in general, mining activities cause a decrease in the value of NDVI and GEMI. Otherwise for NDSI and NDWI increased.

Based on the results of the measurement of separability, it can be seen that basically NDVI, NDSI, and GEMI have values above 1 and can be used as parameters to measure the extent of damage to mine land. However, since the NDSI value has the highest value, then further to classify the level of mine land damage is used NDSI parameters. Why NDSI has the greatest separability value, this is probably because NDSI is more sensitive to open land objects (coal and soil) than other indices.

By using the assumption of the normal distribution of the value of the increase of NDSI, it can be the classified the estimation of damage level of mining area with criteria based on the mean and standard deviation of NDSI changes (ΔNDSI) as follows:

- High, if $\Delta NDSI_{ij} \geq m\Delta NDSI + 1St.Dev$
- Moderate, if $m\Delta NDSI - 1St.Dev \leq \Delta NDSI_{ij} < m\Delta NDSI + 1St.Dev$
- Low, if $\Delta NDSI_{ij} \leq m\Delta NDSI - 1St.Dev$

Where ΔNDSI is $NDSI_{ij}$ changes of a given pixel, mΔNDSI and St.Dev are the mean and standard deviation of NDSI changes respectively.


Landsat 7 image RGB 543
15 May 2000

Landsat 8 image RGB 654
7 February 2014

Figure 3-1: The results of the mining area identification of Landsat 7 image RGB 543 on 15 May 2000 and Landsat 8 RGB 654 on 7 February 2014. dark polyline shows the boundaries of the mining area

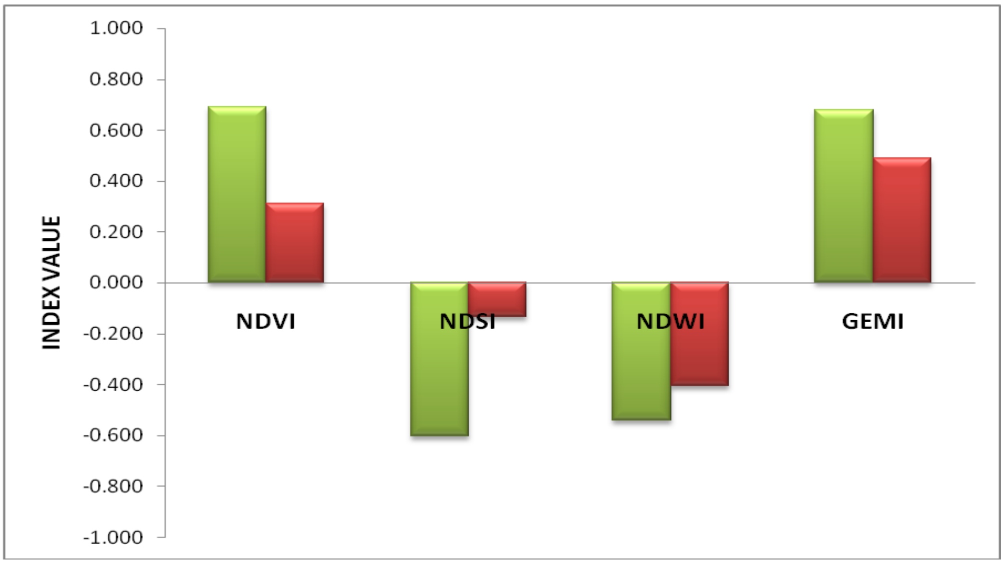


Figure 3-2: Graph of average change of index value, from baseline (green) and existing (red)

Tabel 3-1: Index value at baseline condition, existing and change with sample location of mining areas in East Kalimantan Province

	BASELINE				EXISTING			
INDEX	**NDVI**	**NDSI**	**NDWI**	**GEMI**	**NDVI**	**NDSI**	**NDWI**	**GEMI**
Mean	0.691	-0.602	-0.541	0.678	0.311	-0.136	-0.406	0.488
St.Dev	0.045	0.043	0.032	0.042	0.212	0.199	0.170	0.114

Tabel 3-2: Index value at baseline condition, existing and change with sample location of mining areas in East Kalimantan Province

	CHANGES			
INDEX	**NDVI**	**NDSI**	**NDWI**	**GEMI**
Mean	-0.380	0.467	0.135	-0.191
St.Dev.	0.216	0.201	0.174	0.120

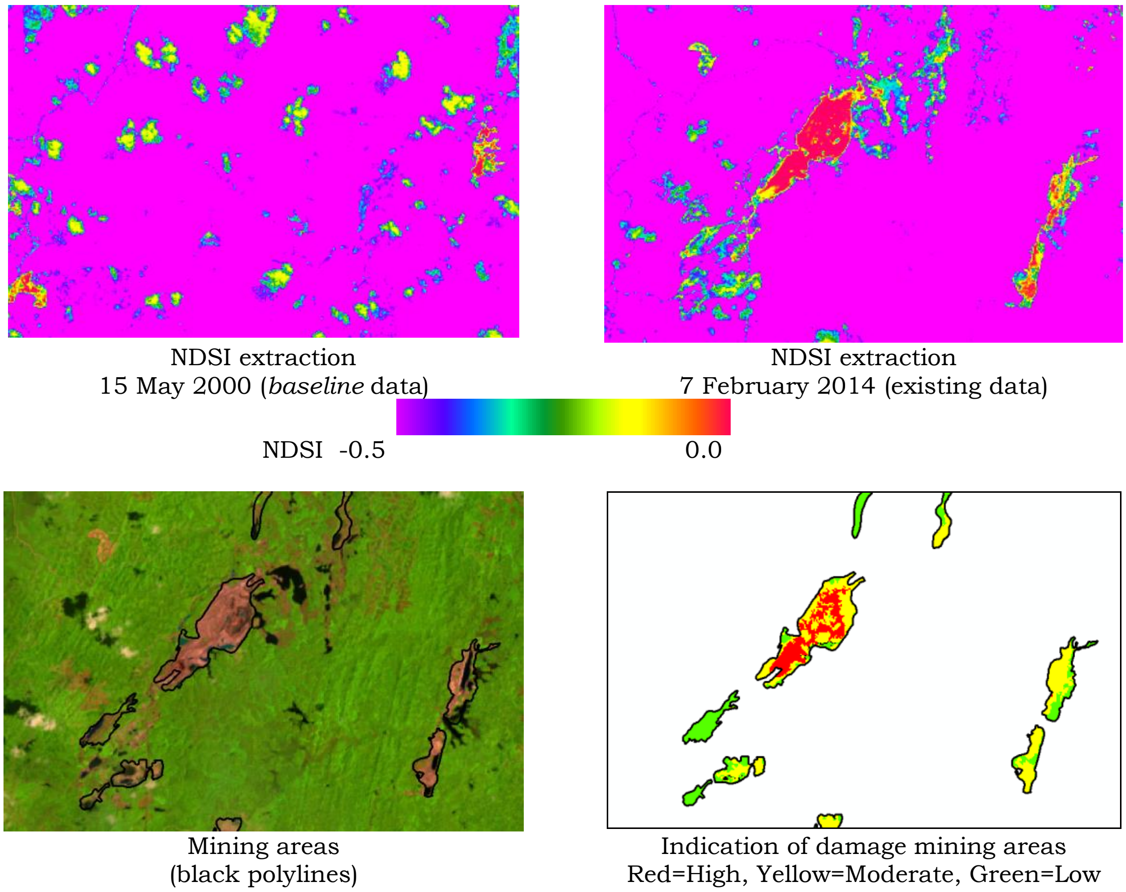


Figure 3-3: Image analysis for mining area identification and indication of damaged area. (location: Kutai Kartanegara)

Tabel 3-3: Separability (D-values) of several indices (NDVI, NDSI, NDWI, and GEMI)

NDVI	NDSI	NDWI	GEMI
-1.477	1.931	0.666	-1.221

Based on above criteria, the indication of mining damage areas in the study area are determined i.e, High if ΔNDSI ≥ 0.668, Medium if 0.266 ≤ ΔNDSI <0.668 and Low if ΔNDSI <0.266. Figure 3-3 shows the result image analysis for the indication of damaged areas in the study area based on ΔNDSI.

The use of NDSI value to know the indication of land damage due to mining activities is based on the understanding that the occurrence of land conversion from vegetation opened to coal excavation will decrease the NIR reflectance and increase SWIR reflectance.

The main weakness in this research is the limitation of spatial resolution of Landsat multitemporal image, which is 30 meters. So the resulting information is not so detailed. With this resolution, Landsat data will only be able to be used to analyze relatively large and extensive mine land. For more detailed analysis or smaller mining areas, a higher resolution image is required, such as SPOT 5, SPOT 6 or SPOT 7. This weakness will be an input for further research.

4 CONCLUSIONS

The results showed that coal mine area along with the damage that occurred in it can be detected from multitemporal Landsat data using NDSI value-based change detection method. The area damage due to coal mining activities can be classified into high, moderate, and low classes based on the mean and standard deviation of NDSI changes (ΔNDSI). The results of this study are expected to be used to support government efforts and mining managers in the post-mining land reclamation activities.

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REFERENCES

Charou E., Stefouli M., Dimitrakopoulos D., *et al.*, (2010), Using Remote Sensing to Assess Impact of Mining Activities on Land and Water Resources. *Mine Water Environ* 29:45–52.

Chavez Jr. PS, (1988), An Improved Dark-Object Subtraction Technique for Atmospheric Scattering Correction of Multispectral Data. *Remote Sensing of Environment* 24:459–79.

Chavez Jr. PS, (1989), Radiometric Calibration of Landsat Thematic Mapper Mutispectral Images. *Photogrammetric Engineering and Remote Sensing* 55(9):1285-1294.

Chitade AZ, Katyar SK, (2010), Impact Analysis of Open Cast Coal Mines on Land Use/Land Cover using Remote Sensing and GIS Technique: A Case Study. International Journal of Engineering Science and Technology 2(12):7171–76.

Erener A., (2011), Remote Sensing of Vegetation Health for Reclaimed Areas of Seyitömer Open Cast Coal Mine. *International Journal of Coal Geology* 86:20–26.

Ginting D., (2010), Makalah Ilmiah. Buletin Sumber Daya Geologi 5(1).

Kaufman YJ, Remer LA, (1994), Detection of Forests using Mid-IR Reflectance: An Application for Aerosol Studies. IEEE 32(3):1994.

Marganingrum D., Noviardi R., (2010), Pencemaran Air Dan Tanah di Kawasan Pertambangan Batubara di PT. Berau Coal, Kalimantan Timur. *Riset Geologi dan Pertambangan* 20(1):11–20.

McFeeters SK, (1996), The Use of the Normalized Difference Water Index (NDWI) in the Delineation of Open Water Features. International Journal of Remote Sensing17(7):1425–1432.

Pinty B., Verstraete MM, (1992), GEMI: A Non-Linear Index to Monitor Global Vegetation from Satellites. Vegetatio 101:15–20.

Rogers AS, Kearney M., (2004), Reducing Signature Variability in Un-Mixing Coastal Marsh Thematic Mapper Scenes using Spectral Indices. International Journal of Remote Sensing 25:2317–2335.

Rouse JW, Haas RW, Schell JA, *et al.*, (1974), Monitoring the Vernal Advancement and Retrogradation (Greenwave effect) of natural vegetation. Greenbelt, MD. USA: NASA/GSFC.

Schroeter L., Gläber C., (2011), Analyses and Monitoring of Lignite Mining Lakes in Eastern Germany with Spectral Signatures of Landsat TM Satellite Data. International Journal of Coal Geology 86:27–39.

Subardja A., (2007), *Pemulihan Kualitas Lingkungan Penambangan Batubara: Karakterisasi dan Pengendalian Air Asam Tambang di Berau*. Laporan Teknis, Puslit Geoteknologi LIPI TA 2007.

USGS, (1998), Landsat 7 Science Data Users Handbook. Sioux Falls, South Dakota.

USGS, (2015), Landsat 8 (L8) Data Users Handbook. version 1. Sioux Falls, South Dakota.

Willis KS, (2015), Remote Sensing Change Detection for Ecological Monitoring in United States Protected Areas. *Biological Conservation* 182:233–42.