MONITORING AND PREDICTING CHANGES OF SURFACE MINING AREA USING IMAGE ANALYSIS OF THE TIME-SERIES IMAGES

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ABSTRACT: Sustainable surface mining needs monitoring changes to identify the long-term influences of mining on environment and land cover. In this sense, remote sensing techniques play important role in monitoring and predicting changes of surface mining area simultaneously and quickly. In this study spatiotemporal change of Emet open pit boron mine area, located in the western part of the Kütahya province of Turkey, in the period 1987–2009 was evaluated using the multi-temporal Landsat TM and ETM+ images. Surface mining area was extracted from pan-sharpened Multispectral Landsat ETM+ imagery by using supervised Support Vector Machine (SVM) classification technique. Furthermore, the classified images were evaluated to detect the potential effect of mining activities in the study area. The results showed that multispectral satellite images and SVM classification method can efficiently be utilized for identifying the spatiotemporal changes in surface mining area.

1. INTRODUCTION

The Emet borate mines were first discovered by J. Gawlik (unpubl.) during lignite exploration work for the Mineral Research and Exploration Institute of Turkey (MTA) in 1956. Numerous studies were subsequently conducted on the geology, mineralogy, origin, and reserve of the borate deposits (Ozpeker, 1969; Helvacı, 1977, 1983, 1984, 1986; Helvacı et al., 1993; Helvacı and Firman, 1976; Kistler and Helvacı, 1994; Yalcın, 1984; Dundar et al., 1986). The major borate mineral is colemanite with minor amounts of ulexite, hydroboracite, veachite-A, teruggite, cahnite, tunellite, and meyerhofferite (Çolak et al., 2000).

Turkey contains 72% boron reserves of the world's known deposits. Reserves placed in the Kütahya-Emet, Eskisehir-Kirka, Balikesir-Bandirma, Balikesir-Bigadiç and Bursa-Kestelek are processed and marked by Eti Mine (Yilmaz 2007).

During the mining activities huge amount of waste material are excavated and removed from one place to another places causing big holes on the land surface. Traditional techniques used for surface mine monitoring, like, topographic measurements and photogrammetric studies are time consuming and labor intensive, therefore, are not efficiently used for a large-scale surface mine area (Anderson et al., 1977). In this instance, remotely sensed satellite data has been used for monitoring and predicting changes of surface mining area. Wen-Bo et al. (2008) classified Landsat TM data using supervised classification technique to determine land use land cover change detection of a coal mining, between year 1995 and 2001. Mengenli (2001) evaluated and monitored the environmental impacts of Eynez surface coal mine using Landsat TM data with maximum likelihood classification technique. Many research studies claimed that supervised classification techniques such as Support Vector Machine (SVM) may often be able to classify a data set to a higher accuracy than conventional classifiers (Foody and Mathur, 2004, Demirel et al., 2011). Demirel et al. (2011) investigated the use of SVM classification methods for identifying, quantifying, and analyzing the spatial response of landscape due to surface mining activities in Goynuk open cast mine, Turkey, from year 2004 to 2008.

In the remotely sensed imageries high reflectance properties of borate minerals make them ideal for detection using remote sensing methods. Spectral measurements of visible, near infrared, and short-wave infrared (0.4-2.5µm) solar reflected energy reveal unique spectral characteristics of the borates that distinguish them for other evaporate minerals (Kratt et.al, 2006). Multispectral satellite data and aerial phots provide information about changes to land cover over time, which is crucial for environmental impact of the mining activities and monitoring of mining areas (Jhanwar 1996; Rathore and Wright 1993). Change analysis of the surface mine are can be evaluated monthly, yearly, or at any other intervals. The Landsat data archive contains more than 25 years of imagery which gives many opportunities for comparison of changes over land surface. While remote sensing technology is not a complete replacement for manual field inspections, it could at least be used to identify areas of interest at mining sites, simplifying the inspection process.

The aim of this study is to investigate how remote sensing images and techniques can be utilized as a tool for monitoring surface mining changes in the Emet open pit boron mine area to evaluate increase of boron production in the period 1987–2009.

2. STUDY AREA AND DATA

Emet boron mine is located at Kütahya Province of Turkey (Fig. 1a). This mine area contains largest boron reserves of Turkey having an estimated reserve of 1.68 billion tonnes of ore grading 28% boron. Its mining sites are located in Hamamköy, 4 km from Hisarcık in the south and in Espey region, 3.5 km from Emet in the north (http://www.etimaden.gov.tr/en/page/production-emet-boron-works). Within the enterprise today, colemanite ores are extracted in 2 open pits namely Hisarcık and Espey, and they are processed in crushing-grinding and concentrator plants (Fig. 1b). Besides, the Boric Acid production is performed in the Boric Acid Plant. Minerals in the Emet borate deposits are summarized in the Table 1.

Table 1. Mineralas in the Emet borate deposits (Helvaci 1976)

Mineral Name	Formula	Location
Colemanite	CaB3O4(OH)3H2O	Espey, Göktepe, Hisarcik, Hamamköy
Ulexite	NaCaB5O6(OH)65(H2O)	Göktepe, Hisarcik
Calestine	SrSO4	Hisarcik
Realgar	AsS	Hisarcik
Orpigment	As2S3	Hisarcik
Gypsum	CaSO42H2O	Göktepe
Calcite	CaCO3	Espey, Göktepe, Hisarcik, hamamköy

In the study area surface mining operations are conducted in a variety of ways depending on geologic factors. In this study, Landsat TM and ETM images belonging to years 1987, 2001 and 2009 were used to monitoring and predicting changes of surface mine area. The image data used in this study were taken from 01 August 1987 for Landsat TM, 12 June 2001 for ETM+ and 07 July 2009 for Landsat TM+ (path 179, row 033). These images were downloaded freely from USGS data archives.

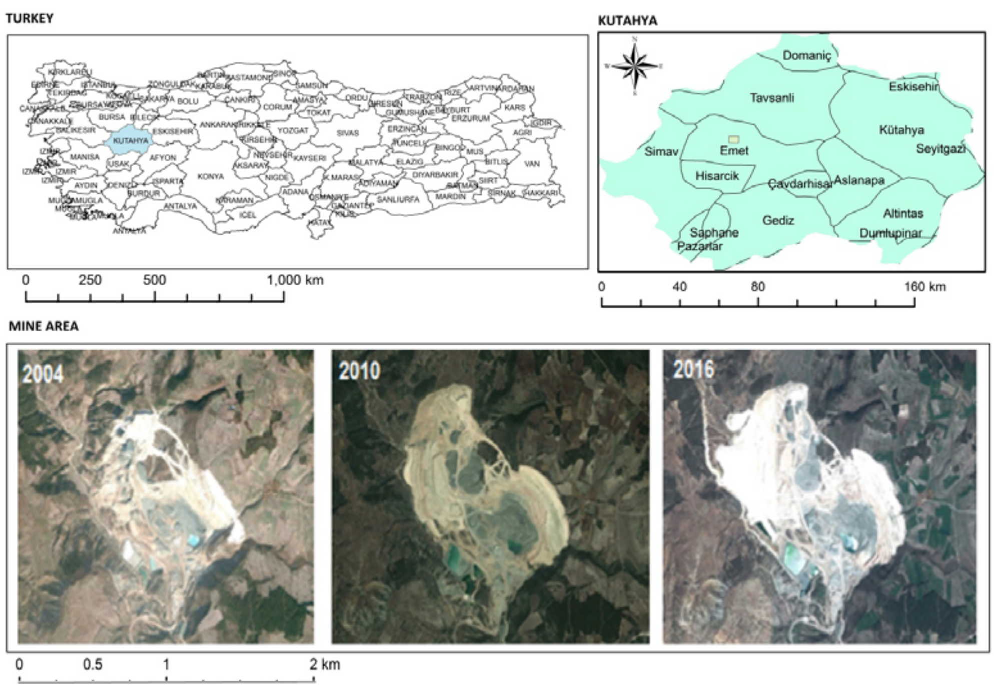

Figure 1. Location of the surface mine area

3. METHOD OF THE STUDY

The process of utilizing Landsat TM data for monitoring surface mining is followed a multi-phase approach. The first phase of analysis consisted of creating classified images using SVM techniques. The second phase of analysis consisted of filtering the artifacts. The final phase of analysis consisted of accuracy assessment and post classification comparison to identify areas of change.

3.1 Support Vector Machines (SVM) Classification

SVM is a supervised learning system and is based on recent advances in statistical learning theory (Cristianini and Shawe-Taylor, 2000). Cortes and Vapnik (1995) developed SVM for binary classification. There are a number of publications for the mathematical formulation of the SVM (e.g. Vapnik 1995, 1998; Burges 1998).
SVM separates the classes with a decision surface that maximizes the margin between the classes. The surface is often called the optimal hyperplane, and the data points, which are closest to the hyperplane, are called support vectors (Fig. 2). The support vectors are the critical elements of the training set (Boser et al., 1992; Cortes and Vapnik 1995; Foody et al., 2007).

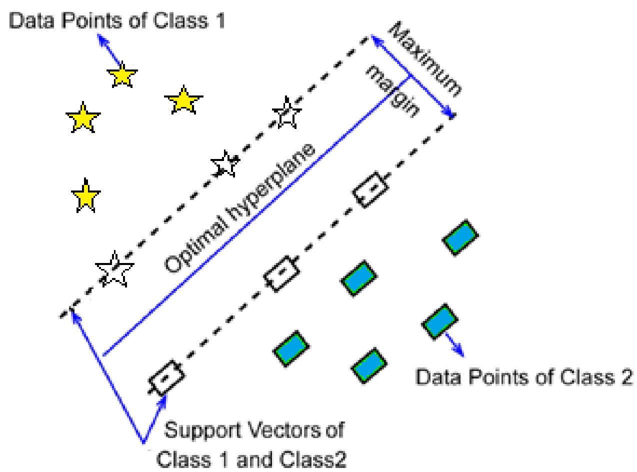

Figure 2. Linear support vector machine example (modified from Burges (1998)).

SVM need training data that optimize the separation of the classes rather than describing the classes themselves (Foody and Mathur, 2004). Using a Radial Basis Function (RBF), class distributions with non-linear boundaries can be mapped into a high dimensional space for linear separation (Huang et al., 2002). Training the SVM with a Gaussian RBF requires setting two parameters: regularization parameter that controls the trade-off between maximizing the margin and minimizing the training error, and kernel width. A small regularization parameter tends to emphasize the margin while ignoring the outliers in the training data, while a large regularization parameter may overfit the training data. A comprehensive description of parameters of SVM can be found in Burges (1998) and Cristianini and Shawe-Taylor (2000).
The 1987 to 2009 series indicates long-term changes that have occurred in them open pit mine area. The 2001 to 2009 series was chosen for detecting short-term changes in the study area. Both of the time series should be useful for revealing mining trends on a mine-by-mine basis. Changes in land cover can be observed and quantified by comparing land cover maps compiled from different dates. Difference images and land cover classifications are useful for determining where land cover has changed within a given period of time.

3.2. Filtering the artifacts

When dealing with the thematic images (and use classification maps), it becomes apparent that there are very tiny land use cluster within a single large land use class. To remove these counterfeit clusters and to produce a more realistic land use class map, Majority Filter is applied to classified data. This considers all the pixels in the convolution window, and assigns the most abundant land class to the central pixel. This results in an output map having smoother and more general trend (http://dst-iget.in/tutorials/IGET_RS_006/IGET_RS_006.pdf).

3.3. Accuracy assessment Post classification comparison

Change detection involves the use of multitemporal data sets to disiciriminate areas of land cover change between datasets of imaging (Lilisant & Kiefer, 1996). One way to discirimінating changes between two datasets of imaging is to employ post-classification comparison. In this approach, two datasets of imagery are independly classified and registered. Then an algorithm can be employed to determine those pixels with a change in classification between dates. Changes in the mine area were detected through making a comparison between two independent classification results. The main advantage of these types of methods is minimizing the effect of radiometric difference between the two data sets (Coppin et al., 2004). However, the accuracy is mainly dependent on the initial classification results of the SVM classification. The change detection between two independent classification results was performed by comparison of classes in the GIS environment.

4. DISCUSSION OF RESULTS

The availability of Landsat data greatly enhances the opportunities for the application of remote sensing techniques to environmental monitoring programs. Utilizing Landsat satellite images through the USGS archive makes it possible to monitor surface mining and reclamation operations, and to characterize land cover changes as a result of mining. The purpose of this study was to demonstrate and evaluate how remote sensing techniques can be utilized as a tool for monitoring surface mining changes, and how they could be integrated into the monitoring process. In addition, this study sought to characterize the effects of increased coal production on the area. Three Landsat images belonging to years 1987-2001 and 2009 were analyzed to detect disturbance caused by mining, and to detect land cover change over the twenty-two year time horizon (Fig. 3). Monitoring the disturbance of ground surface can help assess the risk of adverse environmental effects from mining. The results indicate that remote sensing is a useful tool for monitoring disturbance from surface mining activities, and land cover changes.

Although the spatial resolution of these satellite images are lower than the aerial photos, the additional spectral information like NIR and other bands, allow analyst to better separate vegetation, water and mining areas (Fig. 3). Image data are classified into four categories as vegetation, water, mine area and other classes through SVM classification. The classification training samples were collected from the representative homogeneous areas. The RBF was selected as the kernel method for the SVM classification. This function can handle linearly non-separable problems and works well in most cases (ENVI Manual, 2004). γ was determined as the inverse of the number of bands in the input image and 1000 was taken for the value of the regularization parameter. The results of the classified image data; representing the classes for the 1987- 2001 and 2009 are given in the Fig.3. According to results open pit mine area clearly identified for the years of 2001 and 2009 due to size of the surface mining areas. However, surface mine area is not clearly identified for the years of 1987.

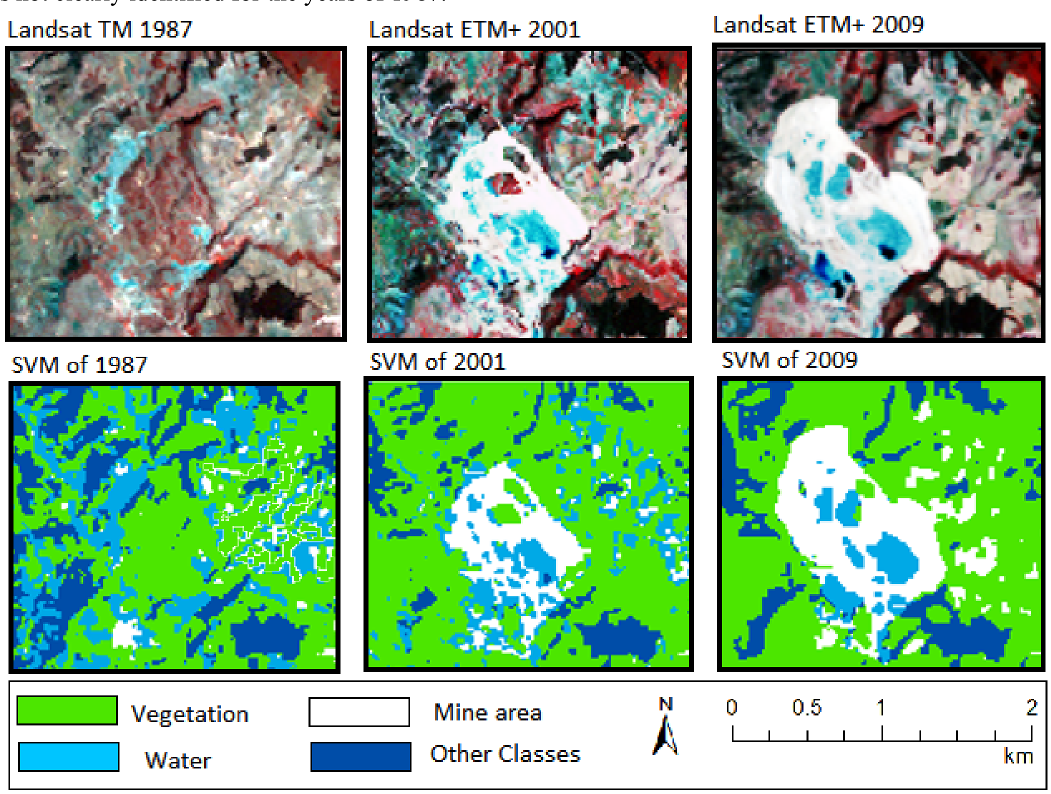

Figure 3. False color combination (432) and SVM classification results of Landsat images 1987-2001-2009.

One of the most common means of expressing classification accuracy is the preparation of a classification error matrix. The error matrix of the year 2009 in the Table 2 indicates an overall accuracy of 98.48 % kappa coefficient 0.97. On the other hand, overall accuracy and kappa coefficient of the year 2001 are 89.73% and 0.86 respectively (Table 3). However, comparing the years 2009 and 2001 the overall accuracy and kappa coefficient of the year 1987 is quite low 59.03 and 0.43 respectively (Table 4). The main reason for this low accuracy is that surface mine area in 1987 is not big enough to determine by 30 m. resolution Landsat image data.

Table 2. Confusion matrix of the SVM classification 2009

Ground Truth	Vegetation	Water	Other Classes	Boron Mine	Total
Vegetation	23	5	0	0	28
Water	0	44	0	0	44
Other classes	0	0	43	0	43
Boron Mine	0	0	0	213	213
Total	23	49	43	213	328
Overall Accuracy = (323/328) 98.48%			**Kappa Coefficient** = 0.97		

Table 3. Confusion matrix of the SVM classification 2001

Ground Truth	Vegetation	Water	Other Classes	Boron Mine	Total
Vegetation	33	0	3	0	36
Water	0	36	0	0	36
Other classes	0	36	0	0	36
Boron Mine	12	0	30	0	42
Total	0	4	0	67	71
Overall Accuracy = (166/185) 89.73%			**Kappa Coefficient** = 0.86		

Table 4: Confusion matrix of the SVM classification 1987

Ground Truth	Vegetation	Water	Other Classes	Boron Mine	Total
Vegetation	56	0	3	0	59
Water	0	29	0	0	29
Other classes	8	0	0	32	40
Boron Mine	0	0	16	0	16
Total	0	29	19	32	144
Overall Accuracy = (85/144) 59.03%			**Kappa Coefficient** = 0.43		

The surface mine area is not clearly observed in the classification results of the Landsat TM of 1987 due to the 30 meter resolution of the data is not enough to determine size of the mine area at that time. For that reason the spatiotemporal changes in surface mining area is made between the period of 2001 and 2009 (Fig.4).

Results showed that the mine area increased by 11.79 % from 2001 to 2009. Vegetation area decreased 13.43 % especially in the north western and south eastern part of the mine area. However, vegetation area is increased by 7.81 % from 2001 to 2009 in the north eastern of the mine area (Table 5).

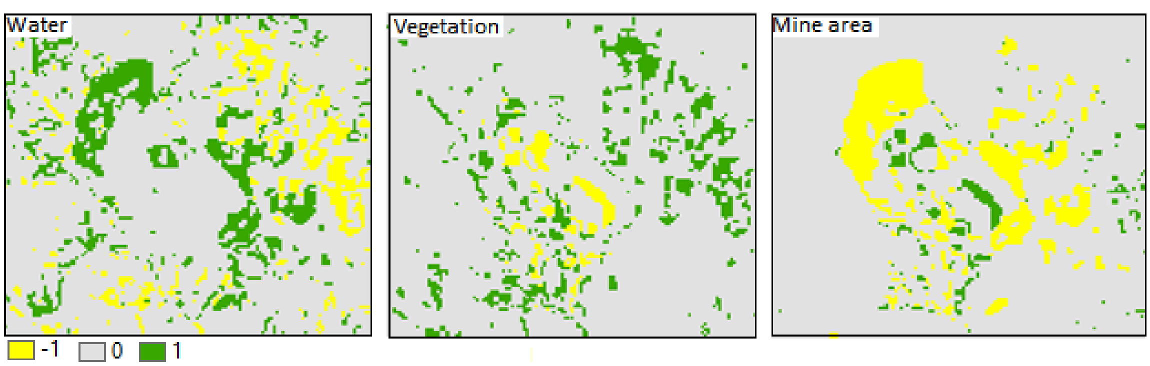

Figure 4. Land cover change map of the study area from 2001 to 2009.

Table 5. Land cover changes from 2001 to 2009.

Value of change from 2001 to 2009	Vegetation		Water		Mine area	
	Pixels	%	Pixels	%	Pixels	%
-1	1119	7.81	356	2.48	1690	11.79
0	11291	78.76	12494	87.15	12225	85.27
1	1926	13.43	1486	10.37	421	2.94
Total	14336	100.00	14336	100.00	14336	100.00

5. CONCLUSIONS

The use of remote sensing images is an inexpensive and effective tool for mapping and monitoring large mining districts and indicating land cover changes, and can be used to supplement data from environmental studies. In this study changes occurred in and around the surface mine area has been successfully identified with the remote sensing data. Research results showed that remotely sensed imagery plays an important role for regional-scale analysis and effective management of environmental impacts induced by surface coal mining activities. SVM classification algorithm was effectively utilized for the classification. The analysis of classification results clearly demonstrates the significance of using satellite data for monitoring the environmental impacts of mining in remote locations even in the mountainous regions despite the cloud cover constraint. Moreover, the use of a multi temporal data allows for the monitoring of the cumulative impacts on land use associated with mining operations.

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