Detecting Landscape Changes Pre- and Post Surface Coal Mining in Indiana, USA

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Abstract

The objective of this study is to gain knowledge about landscape changes on surface coal mines following reclamation in southwestern Indiana, USA using satellite and airborne remote sensing. Three Landsat Thematic Mapper (TM) images acquired in 1989, 2000 and 2006 were used to map the land use/cover pre- and post-surface mining using both unsupervised and supervised classification algorithms. The post-classification comparison change detection algorithm was used to determine the land use/cover changes over time. A portable spectroradiometer was used to record reflectance spectra of vegetated surfaces in the field for calibration and training site selection. The land use/cover maps derived from satellite images were assessed using high-resolution color orthophoto and field-collected data. The overall accuracies for the 1989, 2000 and 2006 land use/cover maps are 91, 90 and 85 percent with kappa statistic of 0.87, 0.86 and 0.80, respectively. Finally, a number of landscape metrics were calculated using FRAGSTATS to characterize pattern changes at the landscape level. The results indicated that the vegetation planted on the mined surfaces in the reclamation process were mainly croplands and grasses, while most of the forest land used for surface coal mining was not reclaimed to its original use.

Keywords

Indiana, landscape metrics, remote sensing, surface coal mining

I. INTRODUCTION

Surface coal mining can potentially result in adverse environmental impacts such as erosion, gully formation, acid mine drainage and increased sediment loading as a result of abandoned and inadequately reclaimed mined lands (Parks, et al., 1987). In addition, spoil piles, destruction and degradation of vegetation and agricultural lands and discharge of effluents from coal washing facilities into nearby water bodies also have had adverse effects on local environments (Rathore,Wright, 1993). Assessing the effects that surface mining activities have on the environment is a major issue in sustainable development and resource management (Latifovic, et al., 2005). Quantification of vegetation conditions pre- and post-mining therefore becomes an important aspect of sustainable land management that requires more sophisticated and comprehensive information on the dynamics of impacts on the environment (Schmidt, Glaesser, 1998). Successful monitoring of landscape changes pre- and post surface coal mining requires observations with frequent temporal coverage over a long period of time. However, such field observations in mined areas are usually not available. For this reason, remote sensing becomes an ideal technology that provides rapid and repetitive monitoring capability on surface coal mining and reclamation success (Rathore, Wright, 1993).

Remote sensing is the science of deriving information about the earth's surface from images acquired at a distance, and has been widely used for land use/cover studies at local, regional and global scales (Chen, 1998; Joshi, et al., 2003; Latifovic, et al., 2005). Kushwaha (1990) investigated the use of satellite remote sensing data in forest-type mapping and change detection in the Western Ghats in Karnataka, India. Normalized difference vegetation index (NDVI) derived from the visible and near-infrared (NIR) bands of satellite imagery, as an important indicator of relative biomass and greenness (Chen, 1998), is often used to calculate primary production, dominant species and anthropogenic impacts when utilized concurrently with field studies (Paruelo, Epstein, 1997; Ricotta, Avena, 1999). In addition, satellite remote sensing provides an important basis for vegetation mapping and landscape monitoring, primarily through the relationships between reflectance and vegetation structure and composition(Joshi, et al., 2003). However, few studies have focused on the assessment of vegetation changes and its impact on the environment pre- and post- surface mining over the long term. Rathore and Wright (1993) reviewed the application of remote sensing on monitoring environmental impacts of surface coal mining in the 1970s and 1980s. Graham et al. (1994) applied the principal component analysis (PCA) on Landsat Thematic Mapper (TM) images to monitor vegetation changes in large areas affected by iron ore mining operations in Noranda, Quebec, Canada. Prakash and Gupta (1998) studied the impact of coal mining on land use changes by using temporal remote sensing data in the Jharia coal field in India. Schmidt and Glaesser (1998) investigated the use of remote sensing data for monitoring environmental impacts of open cast lignite mining in eastern Germany. Recently, a study was conducted using Landsat imagery to assess land use/cover changes resulting from extensive surface mining development in Athabasca, Alta, Canada (Latifovic, et al., 2005).

Indiana was the second state in the United States to enact a reclamation law to regulate surface mining in 1941. The law

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required coal companies to plant trees on spoil banks after mining. However, survival and growth of planted trees was generally poor on the newly reclaimed mine conditions. Many mine operators opted to reclaim to "higher and better" uses such as agriculture, hey land and pastures that are much easier to establish and maintain to meet the stringent erosion control requirements (Purdue University, 2004). Therefore, there is a need for rapid and cost-effective techniques for the evaluation of reclamation success, especially vegetation changes after surface coal mining. The overall goal of this study was to assess the long-term impacts of surface coal mining on vegetation changes in southwestern Indiana, USA using remote sensing. Two specific objectives were: 1) mapping the land use/cover and changes pre- and post-surface coal mining in southwestern Indiana using Landsat TM imagery, and 2) characterizing the landscape patterns and changes of the mined area through spatial analysis.

II. METHODS

A. Study area and data

Surface coal mines investigated in this study are located in the west-central and southwestern portions of the state of Indiana, USA in a large geologic depression known as the Illinois Basin, which originated in tropical wetlands during the Pennsylvanian Period approximately 300 million years ago (Damberger, 1971) (Figure 1). Currently, there are ten active surface coal mines in Indiana that were opened in the 1990s, their names, counties, and areas are presented in Table 1.

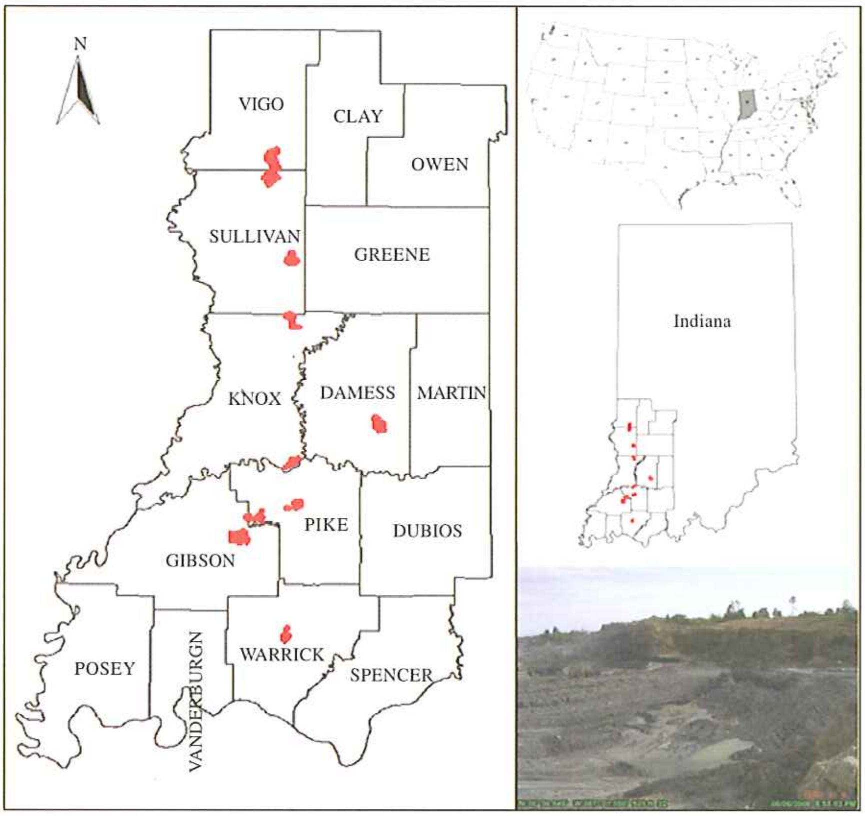

Figure 1. Location of the active surface coal mines opened in the 1990s in southwestern Indiana, USA

Table 1. Indiana active surface coal mines opened in the 1990s

INGS Mine	County Name	Mine Name	Year Start	Area(km^2)
203003	Gibson	Francisco Mine	1996	10.99
203025	Gibson/Pike	Patoka River	1996	4.24
203057	Knox	Freelandville	1996	4.81
203059	Knox	Pride Mine	1996	3.60
203074	Daviess	Midway II	1993	1.15
203239	Sullivan	Penndiana Pit	1994	6.98
203351	Sulivan/Vigo	Farmersburg	1996	21.12
203358	Warrick	Cypress Creek	1998	3.62
203359	Davies	Cannelburg	1997	5.40
203363	Pike	White Church Pit	1996	3.28

Three scenes of Landsat TM images (path22/row33) acquired on the 27th, 17th and 10th of September in 1989, 2000 and 2006, respectively, were purchased through the USGS Earth Resources Observation & Science Data Center and used to map the land use/cover and landscape changes for the study area. Indiana statewide sub-meter color orthophoto obtained in 2005 was used as reference data for training site selection and accuracy assessment. Two field trips were conducted in June 2006 and May 2007 to collect field data using a portable spectroradiometer and a global positioning system (GPS) unit. GPS-based data was projected into a vector layer, which was then overlaid on the Landsat images to integrate the parameters collected in the field with information derived from remotely sensed data at each corresponding 30×30 m grid. In addition, a GPS-based digital camera was used to take pictures of the sampling sites during field trips. Each picture is linked with its latitude/longitude coordinates and directions on a point shapefile and used for image classification and accuracy assessment.

B. Image registration and normalization

Change analysis of satellite images acquired on different dates requires accurate geometric registration in which the root-mean-square-error (RMSE) should be less than one (Prakash, Gupta, 1998). In this study, the image obtained in 2000 was chosen as the reference data in image-to-image registration of the two images acquired in 1989 and 2006. A total of twenty ground control points (GCPs) were selected on each image. The first-order polynomial and nearest neighbor resampling method were used and an average RMSE of 0.54 was obtained. After geometric correction, a normalization method termed histogram matching in ERDAS Imagine® was used to compensate for the effects of differing solar illumination or vegetation growth changes evident on images. Histogram matching is a purely statistical technique that relates the cumulative density function of one image to the density function of another to eliminate the subjectivity problem and reduce the dependence on a geometrically accurate spatial match between multi-date images (Chavez, MacKinnon, 1994).

C. Image classification and accuracy assessment

Both unsupervised and supervised classification algorithms were used to classify the multi-date images into land use/cover maps. Unsupervised classification (or clustering) is an effective method of partitioning remote sensing data in multispectral feature space and extracting land use/cover information (Loveland, et al., 1999; Huang, 2002). In ERDAS Imagine®, unsupervised classification is performed using an algorithm termed the Iterative Self-Organizing Data Analysis Technique (ISODATA). In this study, 30 classes and a 95% confidence threshold were used in the ISODATA unsupervised classification. The classified 30 spectral classes were labeled by geo-linking them with high-resolution orthophoto, which was then used to select training sites for further supervised classification. Considering the study area is dominated by agricultural lands with small portions of forest and water, a five-class classification system was used in this study. The five classes are Water\Wetland (WW), Forested Upland (FU), Agriculture Green (AG) (both crops and re-vegetated grasses), Agriculture Fallow (AF) (both fallow and bare soil before re-vegetating), and Mines\Developed (MD). Since the developed area here includes several roads and few residential, we combined it with the mined area into one class. The training sites are set up to identify the spectral characteristics of each class of interest. At least five training sites were identified from satellite imagery and established for each class based on inspection of the orthophoto and field data. Two supervised classifiers (i.e., maximum likelihood and minimum distance to the means) were then used to compare each pixel to the signatures of training sites and assigned to the class for which the probability is the highest (Wu, Shao, 2002) or the distance is the shortest (Jensen, 2005).

Derived land use/cover maps in 1989, 2000 and 2006 were evaluated using high-resolution orthophoto combined with field inspections. Thirty pixels for each class in the classification maps were selected using a stratified random sampling scheme in accuracy assessment to generate the error matrix. The accuracies of the land use/cover maps were reported by overall accuracy, producer's accuracy, user's accuracy for each class and a more rigorous kappa statistic obtained by a statistical formula that utilizes information in the error matrix (Jensen, 2005). Land use/cover changes during the periods of 1989—2000 and 2000—2006 were detected using the post-classification comparison change detection algorithm, a widely used quantitative change detection method in the field of remote sensing (Civco et al., 2002; Arzandeh, Wang, 2003). This method first classifies the rectified images acquired on different dates separately, then compares and analyzes the classified images to determine the change detection matrix and finally constructs the changes map. Therefore, it is imperative that the individual land use/cover map used in the post-classification change detection be as accurate as possible (Arzandeh, Wang, 2003).

D. Spatial analysis

The spatial pattern of land use/cover and their changes over time at the landscape level were characterized by several landscape metrics calculated using FRAGSTATS, a spatial pattern analysis program for categorical maps (McGarigal, Marks, 1995). The land use/cover maps derived from image classification were used to quantify the areal extent and spatial configuration of patches within a landscape. Class level landscape metrics including Number of Patch (NP), Largest Patch Index (LPI), Total Edge (TE), Clumpiness Index (CLUMPY) and Patch Cohesion Index (COHESION) were calculated for the spatial pattern analysis, for these metrics represent statistically significant changes over time on surface coal mines in this study.

III. RESULTS AND DISCUSSION

A. Image classification and accuracy assessment

The land use/cover of the study area in 1989 before surface coal mining was relatively simple. The land use/cover on Farmersburg, the largest active surface coal mine in Indiana, was covered mainly by agricultural land (69%) and forest (28%), while the developed area covered less than 3 percent (Table 2). In 2000, the mined area increased from 2.6 percent to 10 percent while crops and grasses decreased from 29 percent to 16 percent. In 2006, the mined area kept increasing up to 16.5 percent, which was mainly from forested upland (29 percent down to 17.5 percent) this time rather than from agricultural lands.

Table 2. Areas (km^2) of the four major land use/cover in the Farmersburg site during the years of 1989, 2000 and 2006

Land use/cover	1989		2000		2006	
	km^2	Percent	km^2	Percent	km^2	Percent
Forested Upland (FU)	36.6	28.2%	37.8	29.1%	22.7	17.5%
Agriculture Green (AG)	37.3	28.7%	20.6	15.9%	43.3	33.3%
Agriculture Fallow (AF)	52.9	40.7%	58.1	44.7%	41.5	31.2%
Mines\Developed (MD)	3.43	2.6%	13.1	10.1%	21.5	16.5%

The accuracies of the land use/cover maps in 1989, 2000 and 2006 using maximum likelihood algorithm are presented as error matrixes in Table 3. The overall accuracies of the 1989, 2000 and 2006 land use/cover maps are 91, 90 and 85 percent with a kappa statistic of 0.87, 0.86 and 0.80, respectively. Producer's accuracy of each class was calculated by dividing the correct pixels in that class by the total number of pixels in the corresponding column. This statistic indicates the probability of reference pixels being correctly classified and is a measure of omission error. User's accuracy of each class was calculated by dividing the correct pixels in that class by the total number of pixels in the corresponding row. This statistic is the probability that a pixel classified on the map actually represents that category on the ground and is a measure of commission error. Either as a producer or user of these land use/cover maps, the obtained accuracies are considered satisfactory, especially for forested upland and agricultural lands (AF and AG), most of which are above 90 percent. The relatively low producer's accuracy of the water class is because open water

Table 3. Error matrixes of the 1989, 2000 and 2006 land use/cover maps derived from Landsat TM images

Classification of 1989 image	Reference data					Total	User's Accuracy	Producer's Accuracy
	WW	FU	AG	AF	MD			
Water\Wetland (WW)	2	0	0	0	0	2	100%	67%
Forested Upland (FU)	0	38	0	1	0	39	97%	91%
Agriculture Green (AG)	1	3	38	1	0	43	88%	93%
Agriculture Fallow (AF)	0	1	3	52	3	59	88%	95%
Mines\Developed (MD)	0	0	0	1	6	7	86%	67%
Total	3	42	41	55	9	150		
Overall Accuracy: 91%						Kappa Statistic: 0.87		

Classification of 2000 image	Reference data					Total	User's Accuracy	Producer's Accuracy
	WW	FU	AG	AF	MD			
Water\Wetland (WW)	2	0	0	0	1	3	67%	50%
Forested Upland (FU)	2	34	3	0	1	40	85%	94%
Agriculture Green (AG)	0	1	21	2	1	25	84%	84%
Agriculture Fallow (AF)	0	1	1	59	2	63	94%	97%
Mines\Developed (MD)	0	0	0	0	19	19	100%	79%
Total	4	36	25	61	28	150		
Overall Accuracy: 90%						Kappa Statistic: 0.86		

Classification of 2006 image	Reference data					Total	User's Accuracy	Producer's Accuracy
	WW	FU	AG	AF	MD			
Water\Wetland (WW)	3	0	0	0	1	4	75%	50%
Forested Upland (FU)	0	27	0	0	0	27	100%	77%
Agriculture Green (AG)	1	3	43	1	2	50	86%	92%
Agriculture Fallow (AF)	1	4	2	32	3	42	76%	91%
Mines\Developed (MD)	1	1	1	2	22	27	82%	79%
Total	6	35	46	35	28	150		
Overall Accuracy: 85%						Kappa Statistic: 0.80		

occupies a small portion in this area and resulted in few samples being selected from it, for the number of pixels selected for a class is proportional to the area of this class in a stratified random sampling. Generally speaking, open water is the class with the highest classification accuracy in supervised classification using Landsat imagery, so we are confident that the accuracy of the water class will be higher than it was in this assessment if more water samples are included in future assessment.

The orthophoto used as reference data in accuracy assessment was obtained in 2005, while Landsat images were obtained going back to 1989. The question arises as to how a 2005 orthophoto can be used to assess the classification maps derived from the 1989, 2000 and 2006 satellite images. Since the land use/cover changes were subtle in this area from 2005 to 2006, there is no issue in using the 2005 orthophoto as reference data to evaluate the 2006 land use/cover map. To solve the problem of no reference data available in 1989 and 2000, three TM images of 1989, 2000 and 2006 were displayed in false color composite (RGB=432) and examined carefully through geo-link. No significant difference in the colors of each class was found among them. This is because all three images were acquired in September, in which vegetation and its spectral characteristics are similar. On the other hand, the land use/cover in this area is relatively simple and most changes occurred among those five classes. Therefore, by comparing the false color composite of the 1989 and 2000 images with the 2006 image, one is able to determine the land use/cover on the ground based on its false color in the accuracy assessment.

B. Land use/cover changes

Land use/cover changes among classes during the periods of 1989—2000 and 2000—2006 on the Farmersburg mine are presented in Table 4 as change matrixes, which include the detailed "from-to" information from initial state to final state among the five classes. During the period of 1989—2000, the land used for surface mining was mainly from FU (3.40 km^2), AG (3.49 km^2) and AF (5.06 km^2). At the same time, only one km^2 of the mined land being reclaimed to vegetation (FU or AG). The largest land change in this period was between agricultural lands: approximately 20 km^2 AG changed to AF and 9 km^2 AF to AG. The reason for this is because only part of the cropland used for coal mining was reclaimed to its original use, while some bare soils are not yet re-vegetated. During the period of 2000—2006, the largest land change still occurred between AG and AF, but the direction is opposite, i.e., 26.20 km^2 of AF changed to AG and 8.44 km^2 of AG to AF. The FU used for mining almost doubled (6.33 km^2), meanwhile only 0.34 km^2 of mined area was reclaimed to FU. These results showed that although most of the lands used for surface coal mining were reclaimed to vegetated lands (croplands and grasses), only a small portion was reclaimed to forest land. That is, the vegetation planted on mined surfaces in the reclamation process was mainly crops and grasses, with most of the forested upland used for surface coal mining not being reclaimed to its original use.

Table 4. Change matrixes of the land use/covers (km^2) in the Farmersburg site during the periods of 1989—2000 and 2000—2006

Final state in 2000	Initial state in 1989					Class total
	WW	FU	AG	AF	MD	
Water\Wetland (WW)	1.18	0.58	0.31	0.51	0.09	2.66
Forested Upland (FU)	0.34	28.32	3.85	4.76	0.49	37.77
Agriculture Green (AG)	0.08	1.38	9.74	8.87	0.51	20.58
Agriculture Fallow (AF)	0.08	2.95	19.94	33.70	1.43	58.09
Mines\Developed (MD)	0.20	3.40	3.49	5.06	0.91	13.05
Class Total	1.88	36.62	37.32	52.90	3.43	
Class Changes	0.70	8.30	27.59	19.20	2.53	
Image Difference	0.79	1.15	−16.74	5.19	9.62	
Final state in 2006	**Initial state in 2000**					**Class total**
	WW	FU	AG	AF	MD	
Water\Wetland (WW)	1.53	0.57	0.10	0.43	0.46	3.09
Forested Upland (FU)	0.15	20.92	0.61	0.72	0.34	22.74
Agriculture Green (AG)	0.18	5.20	8.99	26.20	2.72	43.29
Agriculture Fallow (AF)	0.16	4.74	8.44	22.07	6.07	41.49
Mines\Developed (MD)	0.64	6.33	2.43	8.67	3.46	21.54
Class Total	2.66	37.77	20.58	58.09	13.05	
Class Changes	1.13	16.84	11.59	36.02	9.59	
Image Difference	0.43	−15.03	22.71	−16.60	8.49	

C. Landscape metrics by land use/cover

Table 5 lists several landscape metrics computed for each land use/cover class. The metrics were considered by class because each class reveals different information about resource management at surface coal mines. The NP of a particular class is a simple measure of the extent of subdivision or fragmentation of that class. In the five classes, the NP of the class MD increased dramatically from 924 in 1989 to 1664 in 2000 and again to 2418 in 2006. These increases in NP are consistent with the area increases in MD during the same periods: 74 percent for 1989–2000 and 73 percent for 2000–2006 (Table 5). The LPI at the class level quantifies the percentage of total landscape area comprised by the largest patch. As such, it is a measure of dominance. The smaller value of this index reflects the lack of dominance of any land use/cover. In 1989, the dominant land use/covers in this area were FU (LPI = 2.89) and AF (LPI = 2.18); in 2000, the AF continued to be the dominant land use/cover with a LPI of 3.18 while the dominance of FU decreased to 1.09; in 2006, the dominant land use/covers changed to FG (LPI = 2.22) and MD (LPI = 1.55), indicating that while more AF was developed to MD, large portion of the lands were reclaimed to vegetation. The TE at the class level is an absolute measure of total edge length of a particular class. The largest change in TE occurred in FU and MD. The TE of the class FU reduced continuously from 1405 km in 1989 to 1376 km in 2000 and then to 935 km in 2006, while the TE of the MD increased continuously from 231 km in 1989 to 622 km in 2000 and 941 km in 2006. With more lands developed to mines, the TE increased with increasing area and patch numbers. The continuous decrease of the TE of forest land indicated that more and more forested upland has been developed for surface coal mining in the past decade. The CLUMPY is calculated from the adjacency matrix, which shows the frequency in which different pairs of patch types appear side-by-side on the map. The value of CLUMPY equals –1 when the patch type is maximally disaggregated, equals 0 when the focal patch type is distributed randomly and approaches +1 when the patch type is maximally aggregated. All CLUMPY values in this study are positive, ranging from 0.36 for WW in 1989 to 0.59 for MD in 2006. Generally speaking, patch types of the FU, AG and AF were more aggregated than the WW and MD in 1989. With the development of surface coal mines and the needs of water bodies, the patch type of the WW and MD gradually became more aggregated after 2000. The patch cohesion index, COHESION, measures the physical connectedness of the corresponding patch types. Patch cohesion increases as the patch type becomes more clumped or aggregated in its distribution; hence, they are more physically connected. The results of COHESION gave similar results as for CLUMPY described before: the patch type of

Table 5. Landscape metrics for each land use/cover of the Farmersburg site, Indiana in 1989, 2000 and 2006

Land use/cover	Metric	Year		
		1989	2000	2006
Water\Wetland	NP	582	747	749
	LPI	0.02	0.04	0.04
	TE (km)	147.93	207.57	236.37
	CLUMPY	0.36	0.39	0.41
	COHESION	53.58	59.12	64.21
Forested Upland	NP	2161	2248	1791
	LPI	2.89	1.09	0.89
	TE (km)	1404.66	1376.43	934.77
	CLUMPY	0.54	0.54	0.52
	COHESION	93.12	90.83	85.89
Agriculture Green	NP	2693	2931	2539
	LPI	0.27	0.19	2.22
	TE (km)	1612.17	1083.03	1590.12
	CLUMPY	0.47	0.42	0.53
	COHESION	85.21	73.57	92.29
Agriculture Fallow	NP	2175	1625	2872
	LPI	2.18	3.18	1.60
	TE (km)	1855.59	1690.89	1731.54
	CLUMPY	0.52	0.58	0.48
	COHESION	94.21	96.45	90.01
Mines\Developed	NP	924	1664	2418
	LPI	0.05	0.43	1.55
	TE (km)	230.82	621.51	940.83
	CLUMPY	0.39	0.59	0.57
	COHESION	61.29	87.32	90.09

NP(Number of Patch), LPI(Largest Patch Index), TE(Total Edge), CLUMPY(Clumpiness Index), COHESION(Patch Cohesion Index)

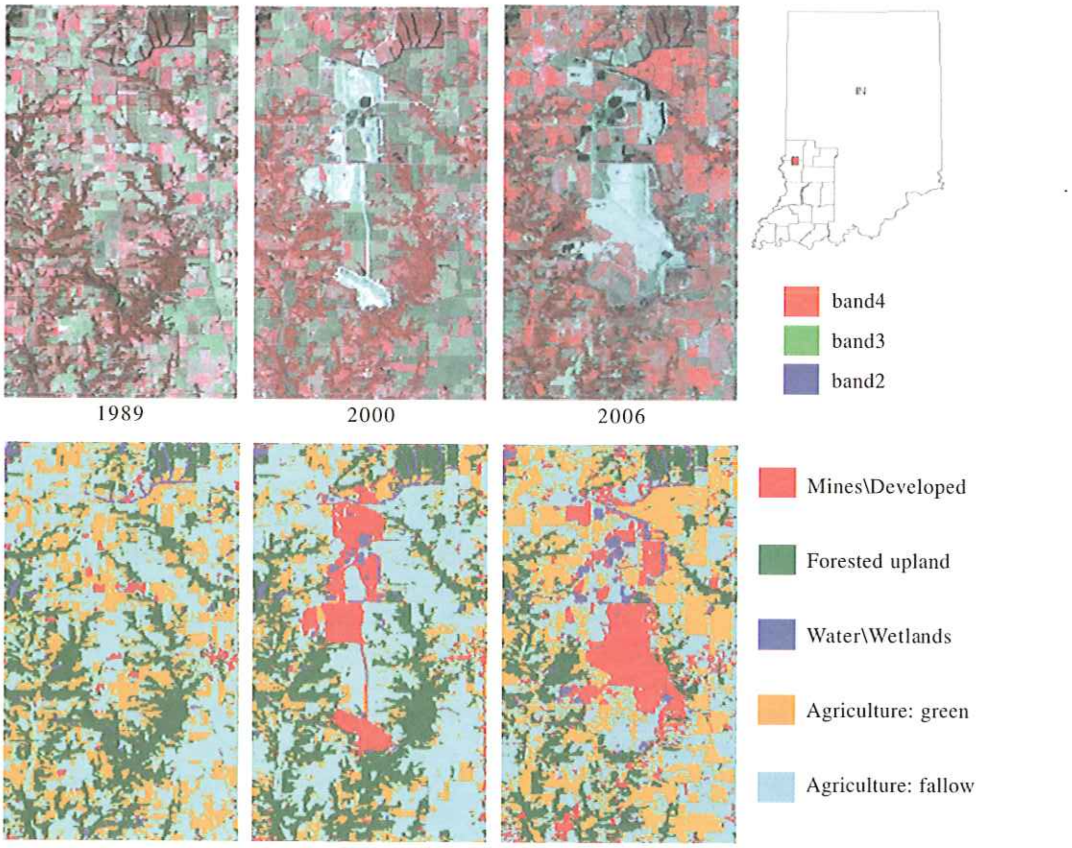

Figure 2. False color composite (RGB=432) of Landsat TM images of the Farmersburg site (above) and their land use/cover maps (below) in 1989, 2000 and 2006, respectively

the FU, AG and AF were more connected than those of the WW and MD but temporally the patch type of the WW and MD became more connected after 2000.

IV. CONCLUSIONS

In comparison with other similar studies, the methods presented in this paper are simple and straightforward yet provide rapid and accurate solutions for detecting land use/cover changes, especially landscapes changes pre- and post-surface coal mining. Satellite remote sensing with high spectral resolution and large geographic coverage provides a better data source and tool in environmental monitoring than traditional data acquisition and interpretation methods. The combination of high spectral resolution satellite imagery, high spatial resolution orthophoto and sufficient field inspection has proven to be an efficient method for monitoring landscape changes on devastated lands and reclamation of surface coal mining.

In addition to area changes, landscape metrics provide more information on land use/cover changes at the landscape level. Examining a suite of landscape metrics over time was useful for summarizing, describing and assessing land use/cover changes on surface coal mines. The program FRAGSTATS is easy to use but powerful enough to compute a wide variety of landscape metrics for categorical maps. Therefore, it is recommended to use landscape metrics to analyze pattern changes of a land when assessing how surface coal mining affects vegetation change and ultimately impacts the environment. The results of this study can be used to understand the broad-scale effects of surface coal mining on vegetation communities pre- and post- mining, and to further provide land mangers insights on land reclamation after surface mining.

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