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Landscape approach for quantifying land use land cover change (1972–2006) and habitat diversity in a mining area in Central India (Bokaro, Jharkhand)

Sumedha Malaviya · Madhushree Munsi · Gracy Oinam · Pawan Kumar Joshi

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Abstract The rate and intensity of land use land cover (LULC) change has increased considerably during the past couple of decades. Mining brings significant alterations in LULC specifically due to its impact on forests. Parts of Central India are well endowed with both forests and minerals. Here, the conflict between human interests and nature has intensified over time. Monitoring and assessment of such conflicts are important for land management and policy making. Remote sensing and Geographical Information System have the potential to serve as accurate tools for environmental monitoring. Understanding the importance of landscape metrics in land use planning is challenging but important. These metrics calculated at landscape, class, and patch level provide an insight into changing spatiotemporal distribution of LULC and ecological connectedness. In the present study, geospatial tools in conjunction with landscape metrics have been used to assess the impact of coal mining on habitat diversity. LULC maps, change detection analysis, and landscape metrics have been computed for the four time periods (1972, 1992, 2001, and 2006). There has been a significant decline in forest cover especially of the Sal-mixed forests, both in area as well as quality, due to flouted mining regulations. Reclamation of mined lands has also been observed in some of the areas since 2001.

Keywords LULCC · Mining · Landscape metrics · Reclamation · Remote sensing · GIS

Introduction

Monitoring and assessing the affects of land use land cover change (LULCC) while sustaining the production of essential resources has become a major priority with researchers, land managers, and policy makers. A number of factors are responsible for LULCC—the most important of these are industrialization, urbanization, and intensification of agriculture. Among the different kinds of land cover changes, deforestation has received greatest scientific attention as it has been shown to be associated with alteration in species distribution, carbon sequestration potential, hydrological regimes, and climate change among others (Townsend et al. 2008). Mining for minerals and fossil fuels causes vast tracts of forested lands to be cleared (Aryee et al. 2003; Sarma 2005). Mining is temporary land use; thus, rehabilitation of mines should be aimed at a clearly defined land use for the area. Mining has altered landscapes all over the world such as

S. Malaviya · M. Munsi · G. Oinam · P. K. Joshi (✉)
TERI University, New Delhi, India
e-mail: pkjoshi27@hotmail.com

forested regions of the Appalachian Mountains (Townsend et al. 2008), Ghana (Yelpaala and Ali 2005), Germany (Huettl 1998), and others. India is also endowed with important mineral resources (Vagholikar et al. 2003; Ghose 2003), and over the years, extraction of these have resulted ecosystem degradation (Ghose 2003; Swer and Singh 2004). Opencast mining of coal in Central India has often caused irreversible alterations in flora, fauna, hydrology, and soil biology and creation of huge overburden dumps (Tiwary and Dhar 1994). Assessing and monitoring the impacts of mining on ecosystems are critical to achieving goals of sustainable development.

Satellite remote sensing techniques, like optical remote sensing (Lattofovic et al. 2005), microwave remote sensing (Almeida-Filho and Shimabukuro 2000), and combinations of both (Voigt et al. 2004), Synthetic Apperture Radar interferometry (Ottl et al. 2002), hyper-spectral remote sensing (Stuart et al. 2000), and many others have been used for mapping disturbances due to mining activities (Kepner et al. 2000). Remote sensing is also the only way of acquiring information about mining-affected remote locations in dense forested tracts which might be inaccessible on ground. Integration of remote sensing with Geographical information systems (GIS) can further strengthen the capabilities of environmental impact assessment of mining activities at both regional and local scales (Chevrel et al. 2001). In India, remote sensing imagery were used by Prakash and Gupta (1998) to detect forest cover changes in the Jharia coal fields; Pranato et al. (2004) has evaluated post-mining reclamation using this technology; Joshi et al. (2006) in the Korba district; Joshi et al. (2008) to understand forest cover fragmentation due to mining and industrialization.

However, the potential of remote sensing in conjunction with GIS largely remains underutilized in environmental monitoring applications (Lattofovic et al. 2005). Fewer studies incorporating geospatial tools for temporal mapping of mining areas, changes in the associated forested ecosystems, and mine reclamation have been reported (Townsend et al. 2008). These are limited to quantification of area only and do not identify spatiotemporal relationships. The discipline of landscape ecology adds a new dimension to land management by incorporating a landscape perspective wherein spatial and temporal relationships are given emphasis (Apan et al. 2002). An understanding of the structural changes in landscape is facilitated by measures of landscape patterns and diversity like landscape metrics which describe pattern through the calculation of a single number. The incorporation of landscape ecology principles into land use plans mitigates the effects of land conversion by guiding such transformations in an ecologically appropriate direction (Golubiewski and Hussein 2007). The present study aims at understanding, developing, and demonstrating a methodology for an integrated application of remote sensing, GIS, and landscape ecological principles in anticipating LULCC due to coal mining in Bokaro District of Jharkhand, in Central India.

Study area

For the present study, an area of 1,256 km^2 was delineated by designating a buffer of 20 km radius at the core of the coal mining area (23°48′ N and 85°50′E) of the Bokaro District in Jharkhand, Central India. Bokaro District forms the central part of the Jharkhand state with its headquarters at the Bokaro steel city. The coal fields extend between the longitudes 85°25′ and 85°65′ E. The coal fields of Bokaro District lying in the Damodar river valley are a continuation of the great strip of coalfields that extend from Raniganj in West Bengal, followed by Jharia, Chandrapura, and Bokaro followed by the South and North Karanpura coalfields in Hazaribagh. The fields are divided into the East and West Bokaro by the Lugu hill, with mining activity concentrated in the East Bokaro and almost completely restricted east of Gumia to the Kargali coal seam of 125 ft thickness. Mining of both underground and open cast kinds has been done in Bokaro District during different time periods (Fig. 1).

The three major forest types of Jharkhand state are the Tropical moist deciduous forests, Tropical dry deciduous forests, and Subtropical Broadleaved hill forests. Sal (*Shorea robusta*)

Fig. 1 Location of study area

is the predominant tree species in the forests of Bokaro. Sal stands exist in association with Bamboo in the hilly areas. Salai (*Boswellia serrata*) and Mahua (*Madhuca latifolia*) are also common in the area. Mining activity is concentrated mostly in region of dense stands of pure Sal forests that have been cleared and destroyed as a prerequisite for mining operations.

Materials and methods

Satellite data used Depending on the availability of satellite data, 1972, 1992, 2001 were downloaded from the Landsat website (http://www.landsat.org). For 2006, IRS P6 LISS III data were borrowed from Biodiversity Characterization project funded by Department of Space and Department of Biotechnology. The details of satellite data used are given in Table 1. The selection of time period was biased to the availability of datasets and to encompass the maximum temporal variability as possible.

Software used All satellite data used were preprocessed using Erdas Imagine version 9.1. The same software was also used for generating change maps. Visual interpretation of satellite data was done using ESRI ArcView version 3.2a. Landscape metrics used in the analysis of change maps were calculated at landscape, class, and patch level using Fragstats version 3.3.

Data processing Data downloaded from Landsat's website was in the form of a zipped folder and each band of data was saved as a separate file.

Table 1 List of satellite data with the sensors

Data used	Path/row	Year	Spectral resolution (μm)	Spatial resolution (m)	Swath (km)
Landsat MSS	150/43, 140/44	1972	Band1 = 0.5–0.6	79	185
			Band2 = 0.6–0.7		
			Band3 = 0.7–0.8		
			Band4 = 0.8–1.1		
Landsat 5 TM	140/44	1992	Band1 = 0.45–0.52	30	185
			Band2 = 0.52–0.60		
			Band3 = 0.63–0.69		
			Band4 = 0.75–0.90		
			Band5 = 1.55–1.75		
			Band7 = 2.09–2.35		
			Band6 = 10.4–12.5	120	
Landsat 7 ETM	140/44	2001	Band1 = 0.45–0.52	30	185
			Band2 = 0.52–0.60		
			Band3 = 0.63–0.69		
			Band4 = 0.75–0.90		
			Band5 = 1.55–1.75		
			Band7 = 2.09–2.35		
			Band6 = 10.4–12.5	120	
IRS P6 LISS III	108/54	2006	Band1 = 0.52–0.59	23.5	141
			Band2 = 0.62–0.68		
			Band3 = 0.77–0.86		
			Band4 = 1.55–0.70	70	

Layer stacking of bands 2, 3, and 4 was done for the Landsat MSS (1972), TM (1992), and ETM+ (2001) data to obtain False Color Composites of three periods using ERDAS IMAGINE 9.1. The Landsat satellite data provided by Global Land Cover Network were radiometrically and geometrically (ortho-rectification with UTM/WGS 84 projection) corrected. The datasets were with sub-pixel level accuracy. For the IRS P6 LISS III data, same principle was applied for radiometric and geometric correction using Erdas Imgaine 9.1 (Joshi et al. 2008). Onscreen visual enhancements like contrast stretching, histogram adjustment techniques, filtering, and changes in band combinations were applied while interpreting the dataset. The enhancement techniques applied were very locale specific to extract the maximum possible information and delineate the boundaries between the LULC classes.

LULCC analysis As satellite data were available at different spatial resolutions, onscreen visual interpretation was done at fixed scale at 1:50,000. Buffer shape file of 20 km radius was overlaid on the raster dataset of 2006, and polygons were digitized. Detailed ground truth information collected for the year 2006 was used to give attributes to the polygons. The interpretation key for LULC mapping is given in Table 2. The interpretation key can be used in the tropical deciduous forest of India and other regions with similar LULC cover type. The 11 LULC classes identified were: Sal-mixed forest (Smx), mixed Sal forest (Mx), scrub (Sc), agriculture (Ag), barren land (Brn), mine (Mn), mined wastelands (Mwl), mining water (Mw), mined reforested areas (Mrf), river (Rv), and reservoir (Rs). The prepared LULC map for year 2006 was compared with the ancillary databases like forest cover map generated by Forest Survey of India, topographic sheets of Survey of India, thematic maps prepared by National Atlas Thematic and Mapping Organization, and maps prepared under biodiversity characterization project (IIRS 2007). The comparison with ancillary database provided refinement in the mapped classes. This shape file was overlaid on 2001 dataset; change areas were identified, and shape and size of polygons were modified.

Table 2 Interpretation key for LULC mapping

LULC	Shape	Size	Tone	Texture	Association	Pattern	Description
Smx	Irregular	Big patches	Light reddish pink	Smooth	–	Regular	These are the dense forest areas dominated by Sal
Mx	Irregular	Small to big patches	Dark red	Smooth–rough	Sal-mixed forest	Irregular	These are relatively open forest with dominant species other than Sal
Sc	Irregular	Small to big patches	Light green-yellow-cyan	Rough	Forests and mine area	Irregular	Open areas less than 10% of tree cover
Ag	Regular	Small patches	Light pink-red	Smooth	Scrub	Regular	Land parcels used for cultivation
Brn	Irregular	Small patches	Dark yellow-cyan	Smooth	Mined wastelands and scrub	Irregular	Open area with partially rocky exposure patches and unutilized land
Mn	Irregular	Large to small patches	Dark black-blue	Smooth	River and mixed Sal forests	Irregular	Strips with active mining
Mwl	Irregular	Small patches	Light gray-cyan	Rough	Active mined areas	Irregular	Land left out after mining
Mw	Regular-oval	Small areas	Black-blue	Smooth	Active mined areas and mined wastelands	Regular	Small water bodies within the mining and mined wastelands, holding water
Mrf	Regular-oval	Small patches	Bright red-pink	Rough–smooth	Mined wastelands	Regular	Small patches of tree cover within the mining landscape, plantation.
Rs	Regular-geometric	Big patches	Bright blue-black	Very Smooth	Forested areas and agricultural areas	Regular	Big water bodies for storing water
Rv	Irregular-linear	Linear shape	Light Cyan-blue	Rough–smooth	Active mined areas and scrub	Regular to irregular	Naturally free flowing water channels

Table 3 List of landscape metrics used for the study

Landscape metrics	Level	Index	Description	Formula
Area/density metrics	Patch	AREA	The area of a patch is limited by the grain and extent of the image.	$\text{Area} = a_{ij}\left(\frac{1}{10,000}\right)$ (a_{ij} = area (m^2) of patch ij)
	Class	NP	Measure of the extent of subdivision or fragmentation of the patch type.	$NP = n_i$ (n_i = number of patches)
	Landscape	NP	Measures the extent of fragmentation of the entire landscape	$NP = N$ (N = total number of patches in the landscape)
		AREA_MN	The area mean is calculated by summing area across all patches in the landscape and dividing by number of patches.	$MN = \frac{\sum_{j=1}^{n} x_{ij}}{n_i}$ (x_{ij} = area (m^2) of patch ij; n_i = number of patches; MN = mean)
		AREA_CV	The coefficient of variation measures relative variability about the mean.	$CV=\frac{SD}{MN} \times 100$ CV = coefficient of variation, MN = mean, SD = standard deviation)
		AREA_SD	It measures the dispersion or variation in area of patches.	$SD = \frac{\sqrt{\sum_{j=1}^{n}\left[[xij] - \left[\frac{\sum_{j=1}^{n} xij}{ni}\right]\right]^2}}{n_i}$ (x_{ij} = area (m^2) of patch ij; n_i = number of patches; SD = standard deviation)
Shape metrics	Class	PAFRAC	It provides an index of patch shape complexity across a wide range of spatial scales (i.e., patch sizes)	$PAFRAC = \frac{2}{\frac{\left(\left[n_i \sum_{j=1}^{n} (\ln p_{ij} - \ln a_{ij})\right] - \left[\sum_{j=1}^{a} \ln p_{ij}\right]\left[\sum_{j=1}^{n} \ln a_{ij}\right]\right)}{\left(ni \sum_{j=1}^{n} \ln p_{ij}^2 - \left(\sum_{j=1}^{n} \ln pij\right)^2\right)}}$ a_{ij} = area (m^2) of patch ij, p_{ij} = perimeter (m) of patch ij, n_i = number of patches in the landscape of patch type (class) i

	Landscape	SHAPE_MN	It measures the complexity of patch shape compared to a standard shape (square or almost square) of the same size,	$\text{SHAPE} = \frac{p_{ij}}{\min p_{ij}}$ (p_{ij} = perimeter of the patch; min p_{ij} = minimum perimeter of patch ij in terms of number of cell surfaces)
Contagion and interspersion metrics	Class	IJI	Measure of class aggregation or clump ness of patches	$\text{IJI} = \frac{\sum_{k=1}^{m}\left[\left(\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right)\ln\left(\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right)\right]}{\ln(m-1)} \times 100$ (e_{ik} = total length of edge in landscape between patch classes, i and k; m = number of patch classes present in landscape including landscape border, if present)
Diversity metrics	Landscape	SHEI	Measure of evenness of patch types and dominance	$\text{SHEI} = \frac{-\sum_{i=1}^{m}(P_i \times \ln P_i)}{\ln m}$ (P_i = proportion of the landscape occupied by patch type (class) i; m = number of patch types (classes) present in the landscape, excluding the landscape border if present)
		SHDI	Higher SHDI indicates greater diversity/fragmentation	$\text{SHDI} = \sum_{i=1}^{m}(P_i \times \ln P_i)$ (P_i = proportion of the landscape occupied by patch type (class) i)

Source: Fragstats Documentation (1995)

Following the same procedure, maps for 2001, 1992, and 1972 were prepared. For change analysis, the vector maps of each year were converted into grid data. Change matrices were prepared for the different time periods to analyze changes in the area covered by different LULC classes. This was done by comparing the number of pixels falling into each category of LULC in one time period with the categorization of the same pixels in same/different class in the previous time period. Three change maps were prepared for these four time periods by overlaying LULC maps of two successive time periods. Changes in LULC classes between each time periods were analyzed through the change maps generated. The rate of change of different classes was calculated using the compound interest formula, suggested by Puyravaud (2003), to calculate change rate as the changes were not linear to the timeline:

$$r = \left[1/\left(t_1 - t_2\right)\right] \times \left[\ln\left(A_2/A_1\right)\right] \times 100$$

where r is the rate of land cover change, and A_1 and A_2 are the forest cover at time t_1 and t_2 respectively.

Landscape analysis and habitat diversity The rate of LULCC is not capable to give a clear picture of the dynamics due to mining and other anthropogenic picture. So landscape metric were calculated to get an overall perspective of these changes. The LULC maps prepared using satellite data interpretation were subjected to landscape analysis tools to assess the changes in the structure of the different cover types at landscape, class, and patch level. Though landscape metrics were computed for all the LULC classes, major emphasis was given on the interpretation of the forest cover classes. This helped to quantify the impact of mining activities on the forest cover, its structure, and organization with the help of habitat diversity indices viz., Shannon diversity and evenness index. For computing landscape parameters, Fragstats version 3.3 was used. A list of parameters used in the present study is given in Table 3. Each metric was computed and analyzed for all possible values. Each computed matrix was compared for each class was compared for the four time periods to understand the impact of mining on LULC.

Results and discussion

Mining has significantly impacted the forest cover in Bokaro District. Analysis of the LULC maps (shown in Fig. 2) generated for the four time periods show changes in forest cover of both the

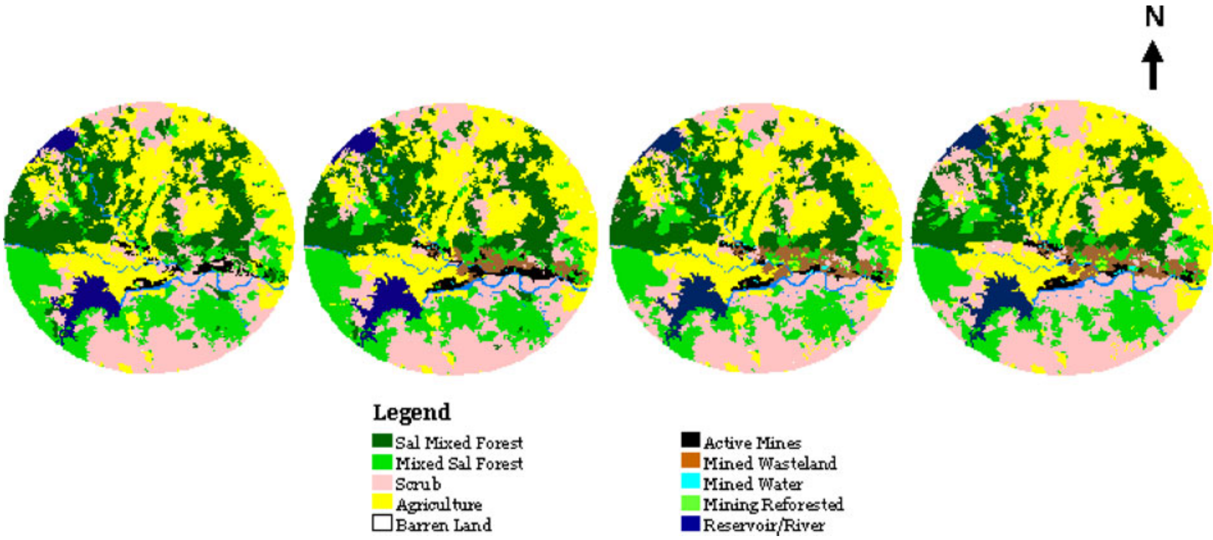

Fig. 2 Temporal land use land cover maps (*1972, 1999, 2001*, and *2006*)

Table 4 Changes in area of LULC classes during 1972–2006

LULC class	1972		1992		2001		2006	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	(%)	Area (km^2)	Area (%)
Smx	305.58	24.44	281.04	22.48	264.91	21.19	254.53	20.36
Mx	219.93	17.59	223.75	17.90	200.76	16.06	196.43	15.71
Sc	279.43	22.35	267.22	21.37	293.63	23.49	335.01	26.80
Ag	356.64	28.53	356.43	28.51	363.41	29.07	335.52	26.84
Brn	0.00	0.00	0.23	0.02	0.36	0.03	1.18	0.09
Mn	20.59	1.65	26.61	2.13	16.82	1.35	17.28	1.38
Mwl	0.00	0.00	26.33	2.11	37.29	2.98	37.44	2.99
Mw	0.00	0.00	0.73	0.06	1.68	0.13	1.68	0.13
Mrf	0.00	0.00	0.00	0.00	3.39	0.27	3.20	0.26
Rs	49.20	3.94	48.89	3.91	48.92	3.91	48.90	3.91
Rv	18.84	1.51	18.97	1.52	19.05	1.52	19.05	1.52

types: Smx and Mx. Smx are characterized by higher density of Sal species, whereas in the Mx, Sal is present but not dominant. At places, forests have also been converted to LULC classes not directly related to the effect of mining like conversion to Ag or Sc. These could be due to an influx of human habitation in adjoining areas and the resultant requirements of a growing human population. The rate of conversion of one LULC class to another is dependent on the proximity of a different LULC class, as well as anthropogenic disturbances. Landscape metrics aided in quantification of structure and composition of the patch types or LULC classes within the landscape.

Land use land cover maps Table 4 represents area occupied by the 11 LULC classes from 1972 to 2006. Significant changes in area of the forested classes both Smx and Mx were observed. Smx declined in area from 305.58 km^2 in 1972 to 254.53 km^2 in 2006. While percentage areas occupied by Mx have declined from 17.59% in 1972 to 15.71% in 2006, the area occupied by the class Sc has also seen major variations over time. This is due to changes in the Mx, variations in the usage of Ag in practice and impact of mining. Percentage area occupied by Sc has increased from 22.35% in 1972 to 26.80% in 2006. Brn, Mn, Mwl, and Mw are the areas resulting from the mining activity in the region. Mining area is very precisely the active mining area. The percentage area occupied by Mwl has increased over time which is also indicated by the decreased area under active mines over time. Reforestation of mined lands was observed from 2001 onwards, wherein 3.39 km^2 of area was reclaimed. Reduction in the area under Rs is due to conversion to Ag. Rv area changes are due to change in river courses over time.

LULC change analysis Table 5 represents rate of change in area of different LULC classes over time. The rate of deforestation has increased in case of Smx. The area under Mx has increased between 1972 and 1992 due to conversion of Smx to Mx and thereafter it has decreased. Rate of change for Smx for 2001–2006 has been highest while for Mx change was highest in the period 1992–2001. The change maps indicate maximum change around the mining area between 1992 and 2001. Between 2001 and 2006, changes have taken place mostly in the Sc and Ag. Rate of conversion to mine has declined over time; conversion to Mn

Table 5 Rate of change in area of different land use/land cover classes over time

LULC class	Rate of change (%)		
	1972–1992	1992–2001	2001–2006
Smx	−0.42	−0.66	−0.80
Mx	0.09	−1.20	−0.44
Sc	−0.22	1.05	−0.44
Ag	0.00	0.22	−1.60
Brn	–	5.09	23.47
Mn	1.28	−5.10	0.54
Mwl	–	3.87	0.08
Mw	–	9.18	0.00
Mrf	–	–	−1.17

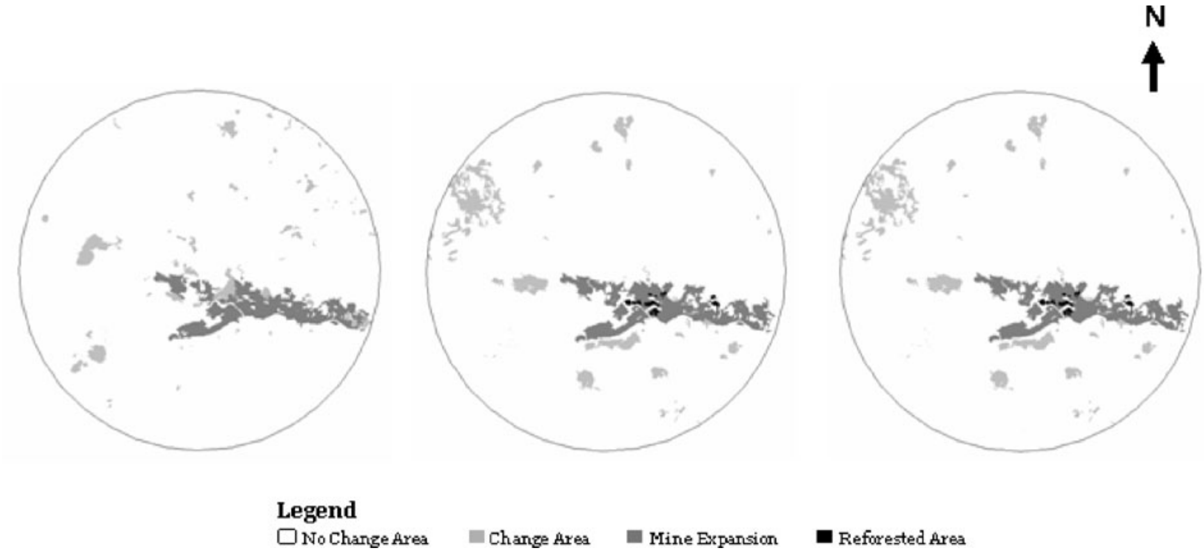

Fig. 3 Temporal land use land cover change maps (*1972–1992, 1992–2001, 2001–2006*)

was slower during 1992–2001 indicated by the high negative value of −5.10%. Figure 3 provides the change areas.

LULC change matrix between 1972 and 1992 is shown in Table 6. The diagonal elements represent areas of no change between 1972 and 1992, while the sub- and supra-diagonal elements indicate change areas. From the total area of 305.54 km^2 occupied by Smx in 1972, only 280 km^2 of the area remains preserved over the 20-year time period. Smx has been mostly converted to Mx (16.65 km^2). For Mx as well, the area has decreased by 14.25 km^2, and conversion of these forests to Mwl (6.02 km^2) and to Mn (2.24 km^2) is observed. Ag has been largely preserved with 6.29 km^2 of land being converted to Mwl. 6.39 km^2 of Sc has also been converted to Mn.

The LULC change matrix for 1992–2001 (Table 7) shows that 5.17 km^2 of Mx has been changed to Mwl while 10.37 km^2 of Smx have been changed to Mx. Mx has converted the maximum to Sc (25.77 km^2). Area occupied by Sc has increased from 267.22 to 293.63 km^2. The Mn has undergone a significant decline in area with 8.96 km^2 of the Mn being converted to Mwl during the 9-year period.

Table 6 LULCC matrix for the time period 1972–1992

	LULC class	Area in 1992 Smx	Mix	Sc	Ag	Brn	Mn	Mwl	Mw	Mrf	Rs	Rv	Total
Area in 1972	Smx	280.88	16.65	0.72	4.62	0.00	0.69	2.02	0.00	0.00	0.00	0.00	305.58
	Mix	0.00	205.68	1.93	4.04	0.00	2.24	6.02	0.02	0.00	0.00	0.00	219.93
	Sc	0.15	1.24	262.56	1.29	0.00	6.39	7.77	0.00	0.00	0.00	0.00	279.43
	Ag	0.00	0.00	1.81	346.17	0.23	2.03	6.29	0.12	0.00	0.00	0.00	356.64
	Brn	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mn	0.00	0.07	0.08	0.17	0.00	15.26	4.22	0.60	0.00	0.00	0.00	20.59
	Mwl	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mw	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mrf	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Rs	0.00	0.00	0.07	0.15	0.00	0.00	0.00	0.00	0.00	48.87	0.00	49.20
	Rv	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	18.78	18.84
	Total	281.04	223.75	267.22	356.43	0.23	26.61	26.33	0.73	0.00	48.89	18.97	1250.21

Table 7 LULCC matrix for the time period 1992–2001

		Area in 2001											
	LULC class	Smx	Mx	Sc	Ag	Brn	Mn	Mwl	Mw	Mrf	Rs	Rv	Total
Area in 1992	Smx	263.12	10.37	2.23	4.85	0.00	0.00	0.48	0.00	0.00	0.00	0.00	281.04
	Mx	0.77	188.98	25.77	1.25	0.00	1.07	5.17	0.06	0.68	0.00	0.00	223.75
	Sc	0.00	0.30	262.93	3.23	0.00	0.31	0.27	0.00	0.00	0.00	0.00	267.22
	Ag	1.02	0.22	1.72	353.43	0.00	0.00	0.00	0.00	0.00	0.04	0.00	356.43
	Brn	0.00	0.00	0.00	0.00	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.23
	Mn	0.00	0.23	0.33	0.64	0.13	15.39	8.96	0.93	0.00	0.00	0.00	26.61
	Mwl	0.00	0.00	0.64	0.00	0.00	0.00	22.42	0.00	2.71	0.00	0.00	26.33
	Mw	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.68	0.00	0.00	0.00	0.73
	Mrf	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Rs	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	48.76	0.00	48.89
	Rv	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	18.97	18.97
	Total	264.91	200.76	293.63	363.41	0.36	16.82	37.29	1.68	3.39	48.92	19.05	1250.21

Between 2001 and 2006 (Table 8), area occupied by Smx has largely changed to Mx. Ag of 28.12 km^2 has been converted to Sc. There have been no significant changes in area occupied by Mwl. Reforestation or reclamation of mined sites has been observed; 3.39 km^2 of area has been reclaimed in 2001 of which a minor 0.19 km^2 has been lost to Mwl in 2006.

Landscape analysis The area density metrics computed at the landscape, class, and patch level are given in Tables 9 and 10. The *number of patches* (NP) at the landscape level has increased from 243 in 1972 to 421 in 2006 indicating that the landscape has undergone considerable fragmentation (Table 9). The number of patches at class level is a measure of the extent of fragmentation of a patch type. It has increased for Smx (32 in 1972 to 66 in 2001) and Mx (77 in 1972 to 105 in 2006), indicating a greater fragmentation of these classes over time (Table 10). The *mean patch area* (AREA_MN) has increased over time, but it does not convey much information as it is sensitive to the number of patches and does not provide information about how many patches are present (Fragstats Documentation 1995). It is the variability or distribution about the mean patch area which is of more use and is indicated by the standard deviation and coefficient of variation. *Patch size standard deviation* (AREA_SD) is a measure of absolute variation. At the landscape level, deviation from mean patch size has increased over time (Table 9). The *patch size coefficient of variation* (AREA_CV) is preferable over patch size standard deviation as it enables comparison between landscapes and measures the

Table 8 LULCC matrix for the time period 2001–2006

		Area in 2006											
	LULC class	Smx	Mx	Sc	Ag	Brn	Mn	Mwl	Mw	Mrf	Rs	Rv	Total
Area in 1992	Smx	254.53	3.68	6.05	0.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	264.91
	Mx	0.00	192.05	7.66	0.00	0.00	0.15	0.89	0.00	0.00	0.00	0.00	200.76
	Sc	0.00	0.21	292.46	0.22	0.13	0.56	0.00	0.00	0.00	0.05	0.00	293.63
	Ag	0.00	0.00	28.12	334.66	0.63	0.00	0.00	0.00	0.00	0.00	0.00	363.41
	Brn	0.00	0.00	0.00	0.00	0.36	0.00	0.00	0.00	0.00	0.00	0.00	0.36
	Mn	0.00	0.00	0.64	0.00	0.06	16.13	0.00	0.00	0.00	0.00	0.00	16.82
	Mwl	0.00	0.50	0.00	0.00	0.00	0.44	36.36	0.00	0.00	0.00	0.00	37.29
	Mw	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.68	0.00	0.00	0.00	1.68
	Mrf	0.00	0.00	0.00	0.00	0.00	0.00	0.19	0.00	3.20	0.00	0.00	3.39
	Rs	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	48.84	0.00	48.92
	Rv	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	19.05	19.05
	Total	254.53	196.43	335.01	335.52	1.18	17.28	37.44	1.68	3.20	48.90	19.05	1,250.21

Table 9 Landscape metrics at the class level

Landscape metrics		1972	1992	2001	2006
Area/density metrics	NP	243	430	439	421
	AREA_MN	221.99	290.75	284.79	296.97
	AREA_CV	412.04	451.78	477.26	476.44
	AREA_SD	914.71	1313.56	1359.21	1414.86
Shape metrics	SHAPE_MN	2.00	2.07	2.08	2.08
Diversity metrics	SHIDI	1.67	1.69	1.7	1.71
	SHEI	0.86	0.73	0.71	0.71

variability about the mean. At the landscape level, patch area coefficient of variation has increased from 412.04 to 476. 44, indicating great variability around mean (Table 9).

The diversity metrics computed by FRAGSTATS are not affected by the spatial configuration of patches. *Shannon diversity index* (SHDI) is used as a relative index for comparing landscapes over time. SHDI values start from 0 which mean that the landscape is composed of only one patch or no diversity. Shannon diversity index has increased from 1.67 in 1972 to 1.71 in 2006 which indicates greater diversity over time or more fragmentation of landscape in time (Table 9). *Shannon evenness index* (SHEI) is a measure of evenness of patch type and ranges from 0 to 1. Values closer to 0 indicate unevenness or greater diversity while 1 indicates that the landscape is highly even being dominated by one patch type. The SHEI values have decreased from 0.86 in 1972 to 0.71 in 2006, thus indicating higher observed diversity in time (Table 9).

Mean shape index (SHAPE_MN) (Table 9) and *Perimeter area fractal dimension index* (PAFRAC) (Table 10) mainly measure the shape complexity. SHAPE_MN value at the landscape level does not have a range, but a value of 1 indicates that the patch is maximally compact. This value has increased from 2 in 1972 to 2.08 in 2006, indicating that patches have become more complex-shaped compared to standard square shape (Table 9). The PAFRAC values range from 1 to 2, 1 for patches with simple perimeters like squares and approaches 2 when patch shapes become more convoluted. For all the LULC classes, PAFRAC values have increased. For Smx, the PAFRAC value has increased from 1.29 in 1972 to 1.42 in 1992, 2001, and 2006. PAFRAC values for some of the LULC classes indicate that either there were patches of the same sizes or there were <10 patches in that class as in the river and reservoir classes (Table 10).

Interspersion juxtaposition index (IJI) at the landscape level is the ratio of observed interspersion to maximum interspersion and is dependent on patch perimeters. IJI approaches 0 when the distribution of adjacencies among unique patch types becomes increasingly uneven. IJI = 100

Table 10 Landscape metrics at the class level

LULC class	NP				Perimeter area fractal dimension index (PAFRAC)				Interspersion juxtaposition index (IJI)			
	1972	1992	2001	2006	1972	1992	2001	2006	1972	1992	2001	2006
Smx	32	52	66	50	1.29	1.42	1.42	1.42	70.10	51.6	53.82	54.86
Mx	77	106	99	105	1.27	1.29	1.29	1.30	74.96	68.52	74.47	69.01
Sc	59	116	123	92	1.29	1.33	1.32	1.28	82.26	67.90	69.89	69.48
Ag	45	93	82	98	1.24	1.29	1.29	1.50	95.70	61.94	63.66	63.55
Brn	0	3	3	10	–	N/A	N/A	1.35	–	51.12	43.57	57.34
Mn	24	20	25	19	1.35	1.39	1.38	1.30	76.44	78.55	80.48	78.48
Mwl	0	10	12	10	–	1.35	1.33	1.53	–	82.66	68.89	82.70
Mw	0	19	11	19	–	1.30	1.41	1.53	–	41.08	19.91	43.68
Mrf	0	11	0	19	–	1.56	–	N/A	–	55.12	–	54.13
Rs	2	6	6	5	N/A	N/A	N/A	N/A	66.79	54.65	57.39	53.97
Rv	5	3	3	3	N/A	N/A	N/A	N/A	75.31	71.56	74.65	71.04

Table 11 Patch area distribution for Sal-mixed forest

Area class (km^2)	Sal-mixed forest				Mixed sal forest			
	1972	1992	2001	2006	1972	1992	2001	2006
0–10	14	14	18	12	27	26	27	28
10–25	3	10	13	10	17	20	23	21
25–100	9	18	23	17	19	36	28	32
100–200	1	2	0	0	6	9	10	7
200–500	2	2	5	4	3	9	3	10
>500	3	6	7	7	5	6	8	7
Total	32	52	66	50	77	106	99	105

when all patch types are equally adjacent to all other patch types (i.e., maximum interspersion and juxtaposition). IJI for mined areas has increased over time (Table 10) indicating that mined patches are highly interspersed with other patches or equally adjacent to other patches. Lowered IJI values for Smx forests does not mean that it is less interspersed, it possibly indicates that over time, patches belonging to this class have been cleared off completely (Table 10). IJI values for Mwl, Mw, Mrf, and Brn are null values for 1972 when number of patch types is less than 3 (Table 10). Patch sizes for Smx and Mx were divided into six categories: area ranging between 0–10, 10–25, 25–100, 100–200, 200–500, and above 500 km^2 to analyze how patches have varied in area. Patch area distribution for all the four time periods is given in the Table 11.

Number of smallest patches (0–10 km^2) has always been high for Smx indicating high degree of fragmentation of this forest type. Numbers of larger patches are higher in later time periods probably because, this forest type has been lost to other land use conversions in a manner, that only large patches of this type remain, which is also indicated by the decline in the total number of patches under this class over time (Table 11). Numbers of patches falling under the 25–100 km^2 class are higher, which suggests a greater degree of fragmentation into smaller sizes of this forest class. Mx has remained very fragmented over time (Table 11) which is indicated by the high number of patches falling under the smallest area category: 0–10 km^2. Patchiness of Mx has also increased due to conversion of Smx to this type. Highest numbers of patches are reported in the 25–100 km^2 class, indicative of breakup of larger patches into smaller ones. For all the four time periods, the number of patches falling under large area class (above 200 km^2) is few, suggesting that Mx are not clumped but rather divided which makes them vulnerable to future disturbances and possibly complete loss of this forest type to other LULC class.

Conclusion

The study demonstrates a methodology for an integrated application of remote sensing, GIS, and landscape ecological principles in anticipating LULCC due to coal mining. This study of the Bokaro District of Jharkhand assesses the impacts of mining on forest cover. Mining for coal has led to loss as well as fragmentation of the forest habitats. Increased diversity during the four time periods is suggestive of the disturbance caused due to mining operations where new land use classes like mine water, mined wasteland areas created by forest, scrub, and agricultural land conversions. Even though mined area has declined over time, the mined wastelands remain and have largely remained unreclaimed except 3.20 km^2 (0.26%) mapped. This is also not well maintained as it has decreased to 3.20 km^2 in 2006 from 3.39 km^2 as in 2001.

The application of satellite remote sensing data in this study provided useful information about the trend of deforestation in the mining landscape. Satellite images with GIS tools proved to be a good data source with useful temporal resolution. Landscape metrics add a quantitative dimension to understand the spatiotemporal changes in a disturbance dominated landscape like a mining landscape. These metrics also create a base for future policy decisions on land use planning. The metrics that proved most useful for the study were the area (patch area), diversity (Shannon's diversity and evenness indices), and the contagion metrics (Interspersion and juxtaposition index). Available software like FRAGSTATS saves time in computing these metrics. This study demonstrates the potential of remotely sensed data and GIS integrated with landscape parameters in monitoring post-mining landscapes and reforestation/reclamation activities. Understanding the patterns of landscape changes are important to environmental managers and environmental scientists.

It is concluded that Central India (most of the districts) as a whole is highly vulnerable landscape that is sensitive to mining due to availability of minerals, rapid industrialization process, and government policies. The continued growth in mining and urbanization has exerted adverse impacts on the landscape. Mapping of mining areas can aid in assessing the impact of mining on land cover and the resultant changes in ecosystem services and processes. Remotely sensed satellite data can be used to assess reclamation or reforestation of abandoned mined areas and also possibly direct the kind of plant species to be planted in the wastelands by incorporating soil layer and other ancillary data in GIS medium. Perhaps one very important application of integrating remotely sensed data with GIS would be in monitoring compliance with mining laws and EIA guidelines. At present, economic development is in direct conflict with the conservation of natural resources. Such a conflict has caused the exploitation of natural resources and generation of issues of climate change. The present sustainable development concept looks forward to the long-term use and management of the resources. For this, eco-restoration and land reclamation practices have to be worked out in the mining landscapes. Similar studies should be carried out regularly to ascertain the magnitude and direction of changes with exact trajectory. These will emphasize on more authentic and sustainable cost benefit analysis of any economic development in tropical region.

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