International Journal of Ecology and Environmental Sciences 49: 549-559, 2023
ISSN: 2320-5199 (Online); https://doi.org/10.55863/ijees.2023.2856

Spatio Temporal Change Analysis of Mining Landscape of the Pakri Barwadi Coal Mining Project and its Buffer Area, Jharkhand, India

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ABSTRACT

The present study aims to assess the surface coal mining dominated land use land cover (LULC) changes concerning the Pakri Barwadih Coal Mining Project (PBCMP) and its surrounding buffer areas in Hazaribagh, Jharkhand. The central mining area covers an area of 39.50 km^2, while the surrounding 2 km and 10 km buffer area including mining area covers 107.06 km^2 and 622.88 km^2, respectively. Five different land use classes i.e. agriculture land, forest cover, mining area, barren land, built-up area, and water bodies in the mining area and adjacent area were analysed for six/ years, i.e., from 2016 to 2022. The changes were detected on a three-year intervals using IRS satellite LISS-IV images. This research depicts the present LULC scenario and the impact of mining on the landscape. In the mining area, there is a drastic reduction in agricultural land (41.26%) and forest land (28.23%). The waste land area recorded sharp increase in mining area (857.13%) and its 2 km surrounding area (138.84%) and 10 km buffer area (119.17%). The increase in built up area recorded for 2 km buffer area was 106.79%, whereas 61.06% for 10 km buffer area. It is expected to reduce the burden on policymakers to prepare an efficient mines development plan and meet sustainable development goal (SDG) 15 (Life on land). The paper highlights the importance of digital change detection techniques for nature and location of the change of the mining area.

Key words: Land use and land cover, coal mining, GIS and remote sensing.

INTRODUCTION

Coal is one of the world's most widely used fossil fuels and provides a significant portion of the energy needed for human consumption. The economic development of many developing countries, such as India, depends heavily on coal mining (Chandrakar 2013, Hassan et al. 2023). Demand and consumption of energy in India has increased dramatically (almost doubled) in the last two decades (Ranjan et al. 2021). Demand for coal for thermal power generation has increased from 630 million tonnes (during 2017-2018) to 735 million tonnes in 2021-2022 and is expected to rise to be 877 million tonnes in 2026-2027 (Anonymous 2019). Geological Survey of India has estimated that as of April, 2022, there were a total of 361.41 billion tonnes of coal resources in the country, of which 5.38 billion tons are prime coking coals, 28.08 billion tons are medium and 1.71 are semi-coking coals. Non-coking coals are 324.65 billion tons and tertiary coals are 1.65 billion tons. Jharkhand state in India listed second in coal resources with coal reserves of 86.66 billion tonnes (Anonymous 2022).

The coal mining area faces a rapidly changing environment due to mining and related activities. The impacts on ecosystems include deforestation, air pollution, land degradation, and displacement (Mishra et al. 2022). Because coal is typically found in ecologically sensitive or forested areas, the excavation of coal and related activities have adverse environmental impacts (Qian et al. 2014). Heavy machinery used in modern mining processes can cause significant ecological and hydrological alternations in the land cover (Turner and Ruscher 2004, Singh 2007). Additional mining operations alter the topography (Manna and Maiti 2014) and drainage pattern (Akiwumi and Butler 2008, Khan and Javed 2012, Manna and Maiti 2016), and major environmental impact are manifested as physical disturbances, such as landscape modification and deterioration (Bajocco et al. 2012, Tadesse et al. 2017), land subsidence (Arifeen et al. 2021), soil erosion and degradation (Saini et al. 2015), and other environmental impacts including vegetation loss (Areendran et al. 2013, Qian et al. 2014), air pollution, ground water contamination (Goswami 2015), and changes in land use and cover classes (Garai and Narayana 2018). In this context, it is crucial to seriously monitor the impact of mining on land use land cover changes in order to minimize the impact of mining on the environment and to ensure efficient land management and decision-making to protect the ecosystem (Bocco et al. 2001, Laskar 2003, Turner et al. 2007, Ranjan et al. 2016, Goparaju et al. 2017).

The information on land use and land cover (LULC) plays a critical role in understanding the interactions between human activities and the natural environment (Shimrah et al. 2022). Land use refers to the development and utilization of land for human purposes, such as residential, commercial, industrial and cultivation uses, whereas land cover refers to the elements of the earth's surface that are covered by natural features as well as man-made objects, such as forests, glaciers, rocks, water bodies, roads, buildings and cultivated areas (He et al. 2022). The LULC study is able to estimate the past status of the LULC pattern across mining/specific regions as well as the current status of the region (Singh et al. 2018, Ranjan and Kanga 2018). In addition, the LULC study in mining area helps in mapping and monitoring mine reclamation activities such as afforestation, land reclamation, etc. Therefore, continuous monitoring and evaluation are required to quantify the impact of mining activity on the LULC patterns; which will assist in the implementation of appropriate land management plans/ programs by relevant authorities and policy makers (Turner et al. 2007).

Remote sensing (RS) and Geographic Information System (GIS) methods are widely used for planning and observing LULC transformation in an area (Zheng et al. 2021). The satellite imagery is used to detect the sensitive land transformation in the Earth's surface (Li et al. 2020). The land transformation information derived from satellite imageries and is more crucial for modelling another natural and cultural process. Remote sensing techniques are used to identify past, present and future LULC change analysis (Li et al. 2014). Remote sensing and GIS methods are more time-saving and cost-effective for the LULCC study (Güler et al. 2007, Erener et al. 2012, Shah 2012). Various earth observations (EO) satellite data are used to monitor changes in the Earth's surface with multiple applications.

The present study aims to quantify the spatio-temporal changes of the LULC pattern over the Pakri Barwadih coal mining region and its 2 and 10 km surrounding areas (including mining area) in the period of 2016, 2019 and 2022. The periodic changes in various landform and land cover changes are studied in detail, and the impact of mining on the dynamics of LULC changes has been registered. The paper highlights the importance of digital change detection techniques for the type and location of change of mining area change.

STUDY AREA

The Pakri Barwadih Coal Block is located in the North Eastern part of North Karanpura Coalfields in Hazaribagh district, Jharkhand. The area is bounded by the coordinates 23°51'30" N to 23°55'30" N latitudes and 85°10' E to 85°15' E longitudes and falls within Survey of India Toposheet No. 73E/1 and 73E/5 (scale 1:50,000). The coal block was allocated in 2004 by the Government of India, Ministry of Coal, New Delhi, to NTPC Limited for captive coal mining. The total project area is 33,194.20 km^2 and the nominal mine capacity is 15 million tonnes per annum. The opening of the mine was announced in May 2016 but active mine operations started in December 2016. The entire study area is categorized into three broad categories i.e mining lease area covering an area of 39.50 km^2, followed by 2 km buffer zone of 107.06 km^2 (including mining area) and 10 km buffer zone of 622.88 km^2 (including mining area) (Fig. 1).

The study area is dominated by mountains and hills with scattered plains and valleys. The altitude range of the area is between 430-560 m above mean sea level. The study area enjoys a tropical to sub-tropical climate. The southwest monsoon contributes almost 80% of the total precipitation in the region. The average annual rainfall of the region is above 1200 mm.

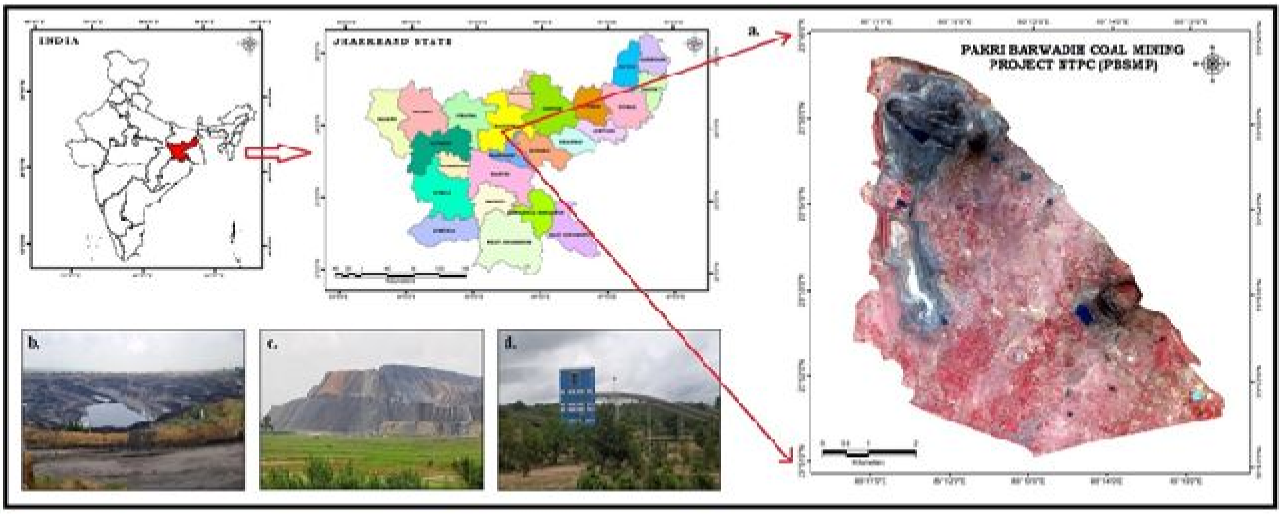

Figure 1. Study area a) Location map of Pakri Barwadi Coal Mining Project (PBCMP) Jharkhand, b) Mining site PBCMP (Open cast mine), c) Mining dump area, d) Ore carrier belt

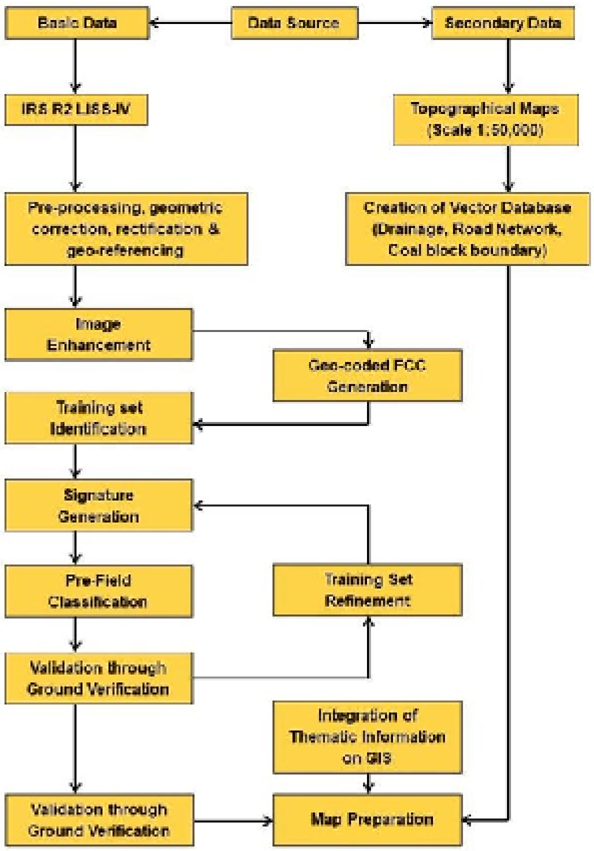

Figure 2. Methodology of Land Use / Land Cover classification used for the study

METHODOLOGY

The main focus of the study was to identify the changes in land use land cover of the mining area by analysing the medium resolution and open-access satellite imagery of different years with a specific time interval. The working methodology is presented in a flow chart (Fig. 2). The workflow of the present study includes multiple steps like satellite data acquisition, image pre-processing, image classification, accuracy assessment, analysis of change detection etc.

Data acquisition

The research was based on the temporal analysis of satellite imagery of the mining area. The satellite imagery data was derived from IRS satellite (LISS-IV sensor) for the year 2016, 2019 and 2022 having path 104 and row 55B was used for land use/ land cover classification. The satellite imageries obtained have been registered to the Universal Transverse Mercator (UTM) map projection with a datum of WGS-84. The study area is located in 45N UTM zone. The characteristics of the satellite data acquired for the study are presented below in Table 1.

Image pre-processing and classification

Image pre-processing, image classification, map preparation, map analysis, etc. were performed using Earth Resource Development Association System (ERDAS) Imagine 2015 software and ArcGIS (version 10.3) software of ESRI (Environmental System Research Institute). The necessary image pre-processing steps (i.e. geometric correction, rectification, layer stacking, geo-referencing, image enhancement, AOI creation and subset) were

Table 1. Description of the Satellite Imageries used for the study

S. No.	Satellite	Sensor	Image acquisition month	Spatial resolution(m)	Spectral resolution(im)	Radiometric resolution(bit)
1	IRS	LISS-IV	April, 2016	5.8	0.28-0.31	10
2	IRS	LISS-IV	April, 2019	5.8	0.25-0.38	10
3	IRS	LISS-IV	March, 2022	5.8	0.27-0.30	10

IRS- Indian Remote Sensing, LISS- Linear Imaging and Self Scanning

performed for satellite images for 2022. A supervised classification methodology using maximum likelihood method taking into consideration the LULC type of the area. Accuracy assessment was carried out by ground truthing and employing the 'Kappa' analysis and images were evaluated.

The satellite images have been divided into five major classes viz. forest area, agricultural land, waste land, build-up area and water body. The classification scheme of the present study is presented in Table 2. The spectral signatures for individual LULC types were recorded by delimiting pixels at the respective training data generation sites. Supervised classification was done in ERDAS software and map compilation was prepared in ArcGIS software. Field survey was conducted in the study area to find out the specific land use category. LULC maps for 2016 and 2019 were used as base map created by PBCMP, NTPC. The thematic maps derived were assessed for change in LULC classes from 2016 to 2022.

Table 2. Land use land cover classification scheme

LULC Classes	Description
Build up land	Village, Town, Industries / Infrastructure Buildings, Roads, Railway Line
Agricultural land	Crop land, Fallow land, Trees grove/ Plantation
Forest area	Dense Mixed Forest, Sparse Mixed Forest, Open Mixed Forest, Degraded Forest, Forest Blank
Waste land	Land with Scrub, Barren / Rocky/ Stony waste, Mining / Dump Area
Water bodies	Tanks / Ponds, Rivers / Streams

LULC dynamics assessment

To account for changes in land cover classes during the study period i.e., from 2016 to 2022, the change matrix was generated by cross-tabulation analysis on a pixel-by-pixel basis. The land use land cover area distribution results were used to compute the trend, net change, percentage change and rate of LULC change between years 2016 and 2019, 2019 and 2022, and for the period 2016 and 2022. To compute the change in percentage, initial and final LULC areal coverage was compared using the following formula:

$$\text{Change (\%)} = \frac{(\text{present LULC area} - \text{previous LULC area})}{\text{previous LULC area}} \times 100$$

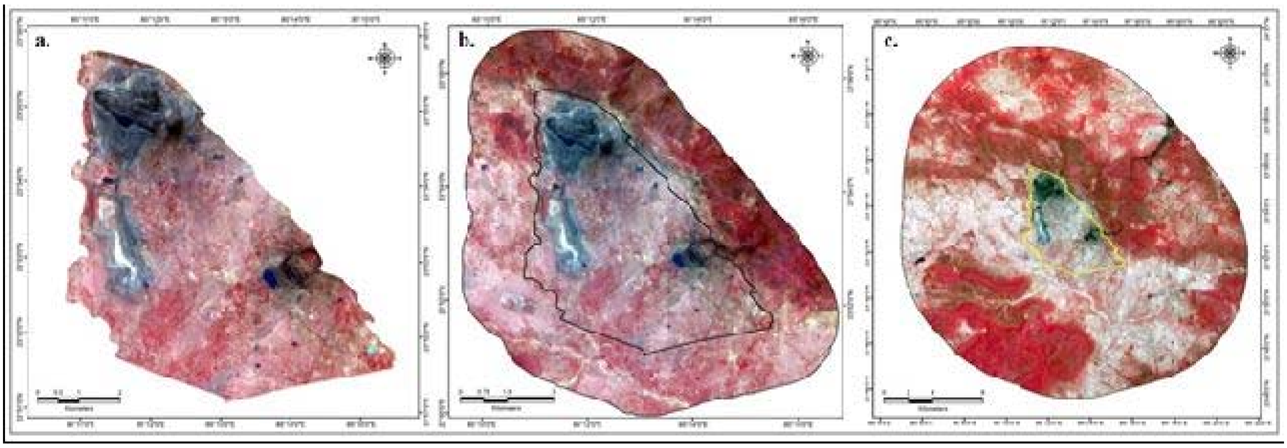

Figure 3. False Colour Composite images (a) Mining lease area, (b) 2 km buffer area, and (c) 10 km buffer area

Table 3. LULC change assessment of mining and its surrounding area on time frame data (2016-2022)

LULC Categories	Area (%)			Area change (%)		
	2016	2019	2022	2016 to 2019	2019 to 2022	2016 to 2022
Mining Lease Area						
Agricultural Land	69.81	65.91	40.99	(-) 5.56	(-) 37.81	(-) 41.26
Forest	18.58	8.81	13.34	(-) 52.58	(+) 51.36	(-) 28.23
Waste Land	2.70	13.52	25.82	(+) 401.13	(+) 91.00	(+) 857.13
Build-Up Land	6.51	9.40	17.16	(+) 44.38	(+) 82.65	(+) 163.71
Water Bodies	2.41	2.37	2.69	(-)1.47	(+) 13.68	(+) 12.00
2 km Buffer Area						
Agricultural Land	54.55	52.57	45.07	(-) 3.95	(-) 14.28	(-) 17.67
Forest	33.11	31.17	29.99	(-) 6.17	(-) 3.80	(-) 9.73
Waste Land	4.04	6.01	9.68	(+) 48.21	(+) 61.15	(+) 138.84
Build-Up Land	5.82	7.71	12.07	(+) 32.14	(+) 56.50	(+) 106.79
Water Bodies	2.49	2.54	3.20	(+) 1.73	(+) 26.07	(+) 28.25
10 km Buffer Area						
Agricultural Land	37.64	37.43	38.48	(-) 0.58	(+) 2.79	(+) 2.19
Forest	55.49	55.03	49.18	(-) 0.83	(-) 10.68	(-) 11.42
Waste Land	2.29	2.59	5.03	(+) 13.02	(+) 93.92	(+) 119.17
Build-Up Land	2.95	3.29	4.75	(+) 11.59	(+) 44.33	(+) 61.06
Water Bodies	1.62	1.66	2.57	(+) 2.33	(+) 54.45	(+) 58.05

Note: All values in percentage. The (+) sign denotes increase and (-) sign denotes decrease of magnitude of change of land use category in different time frame.

Source: LULC map of 2016 and 2019 have been referred from PBCMP, NTPC report and data extraction and compilation for the 2022 satellite imagery done by authors using ArcGIS v 10.3 and ERDAS 2015 software

The correlation analysis of change in different LULC classes with respect to waste land (including mining and dumping area) was carried out by using Microsoft Excel software.

RESULTS

The analysis of spatio-temporal satellite imagery are presented in Figure 4 and Table 3. Correlation analysis of the land use land cover dynamics of the mining area and its surroundings (2 km buffer and 10 km buffer) for 2016, 2019 and 2022 in the month of March-April. The LULC maps of 2016 and 2019 produced by PBCMP, NTPC were used as the base map for the change detection study for 2022 satellite imagery (Fig. 7). Both positive and negative changes occurred in the land use/ cover pattern of the mine and its surrounding buffer areas (Table 3, Fig. 4).

LULC change in the mining area

An area of 39.51 km^2 was under coal mining activity since 2016, and thus LULC status of that year was considered as the baseline for the LULC dynamics study. During the six year period (2016-2022), agricultural area (11.38 km^2) and forest area (2.07 km^2) decreased while wasteland area and built up area increased by 9.14 and 4.21 km^2, respectively. A slight increase in water bodies (12%) was also recorded over this period.

Land use of the area leased for mining shows that it was mainly agricultural land (69.81%) and forest land (18.58%) in 2016. In 2022 only 40.99% agricultural land continued to exist, but Forest land decreased to 13.34%, a net change of 28.82% between 2016 and 2022. Both wasteland and built-up areas are the major land use types expanded due to the mining activity and the associated increase in infrastructure during this period. Wasteland area increased by four folds between 2019 and 2022, mainly consisting of dumping area, mining area and barren land (Fig 5). The rate of decrease of forest area was more pronounced in 2019, but reduced in 2022.

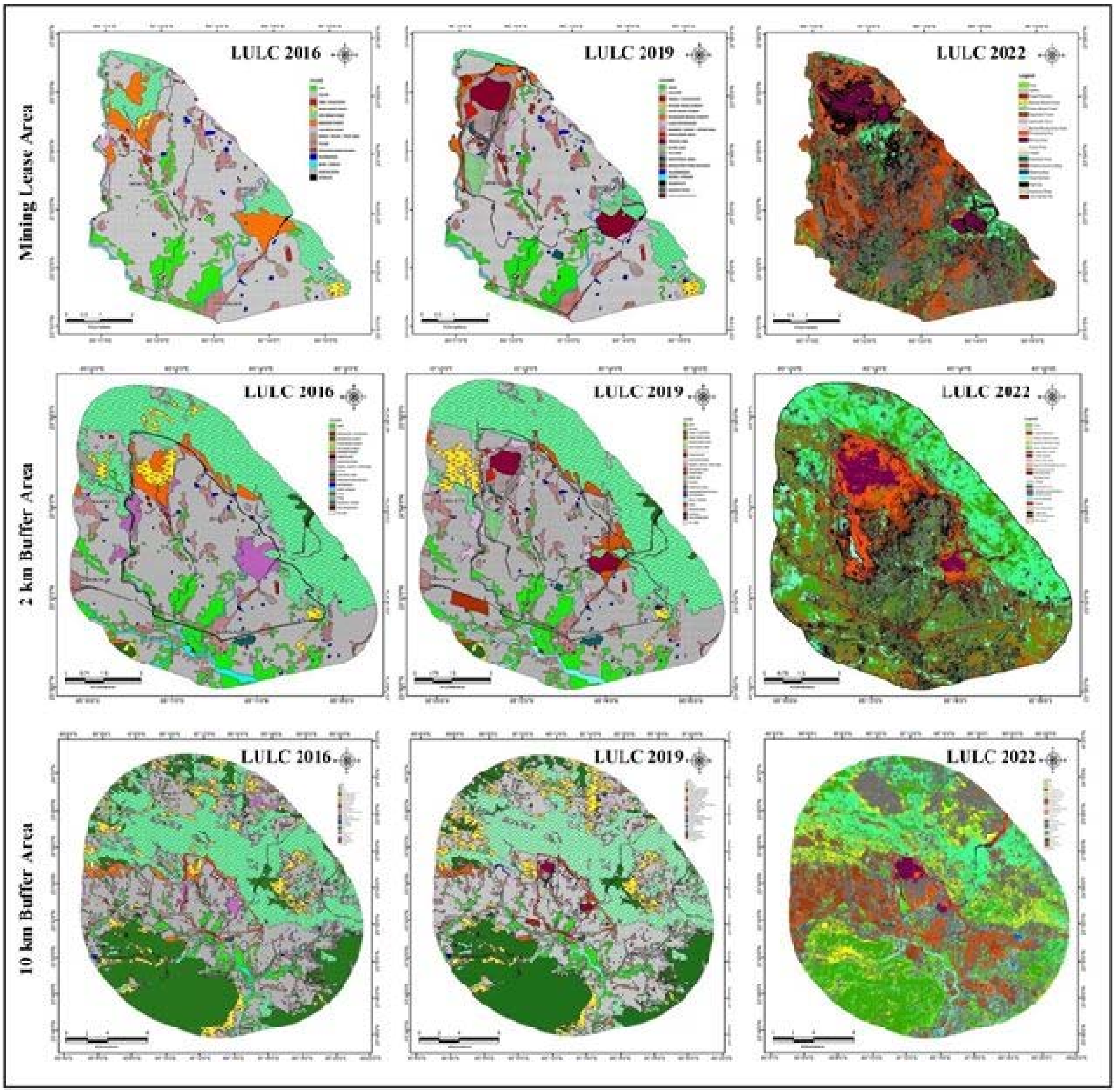

Figure 4. Land use land cover map of (a) mining lease area and its surrounding, (b) 2km buffer area and (c) 10 km buffer area for year 2016, 2019 and 2022 (Source: LULC map of 2016 and 2019 have been referred from PBCMP, NTPC report)

LULC change in buffer area (including mine area)

Geographical area within the 2 km radial buffer area surrounded by mines was dominated by agricultural land (42.67%), followed by forested land (32.37%) in 2016, but gradually decreased. Both built-up area and waste land increased by 106.79 and 138.84%, respectively, during this period (Fig 6).

Geographical area within the 10 km radial buffer area around the mine area cover a total of 622.855 km^2 and was dominated by forest cover (49.57%) followed by agricultural land (37.71%) in 2016. While forest are decreased by 11.42 %, agricultural land, water bodies, built-up area and waste lands increased by 2.19, 58.05, 61.06 and 119.17%, respectively, over these six years (Fig.7).

Correlation analysis of LULC change

Coal mining and associated activities began at the study site in 2016, altered 1.629 km^2 area from other land uses in 2019, and further to 2.104 km^2 by the year 2022. The mining area comprises the opencast (open-pit) coal mines and overburden dumps. As a

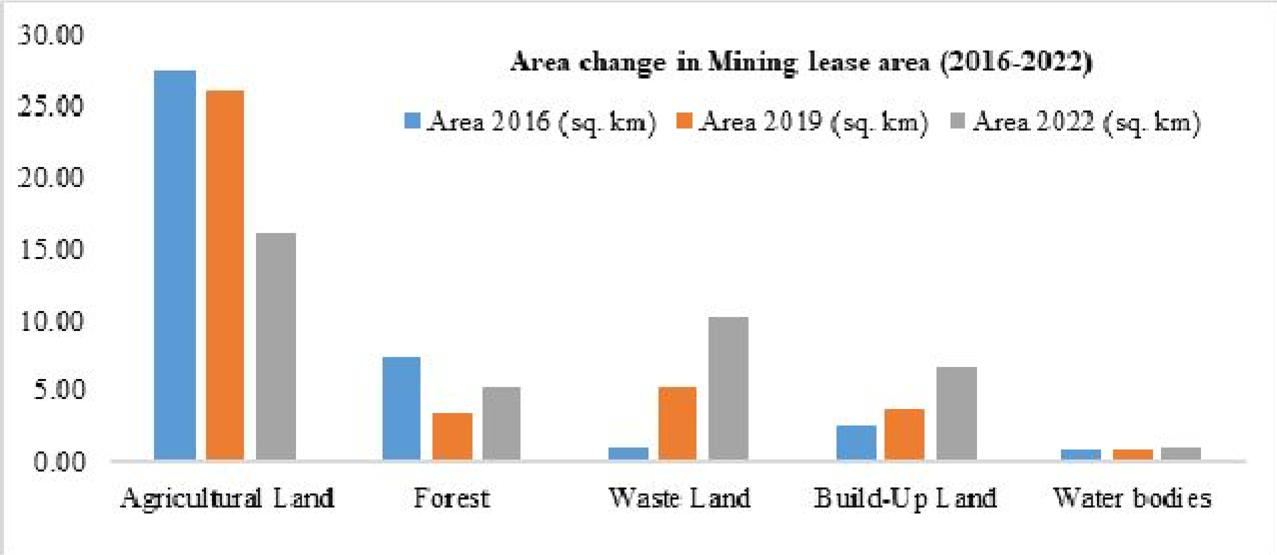

Figure 5. LULC change in the mining area during the study period

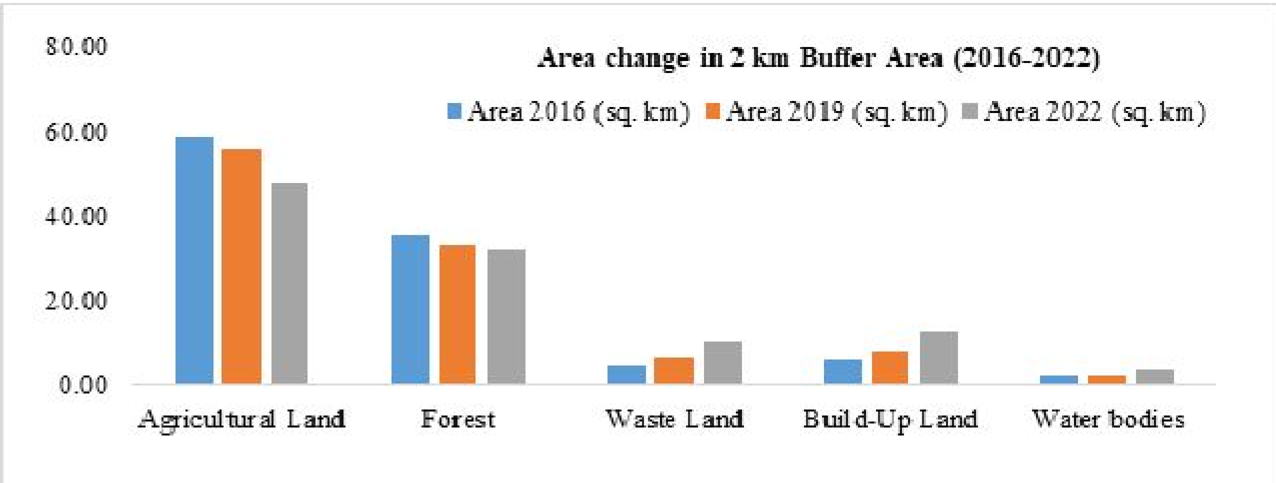

Figure 6. LULC change in the 2 km buffer area (including mining area) during study period

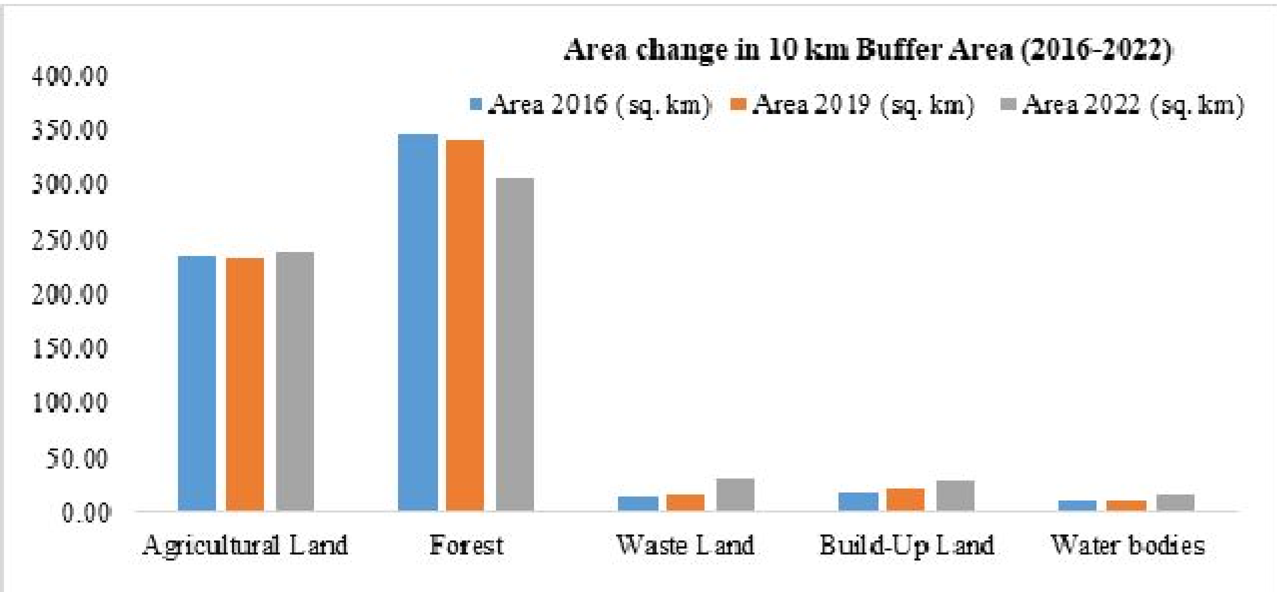

Figure 7. LULC change in the 10 km buffer area (including mining area) during the study period

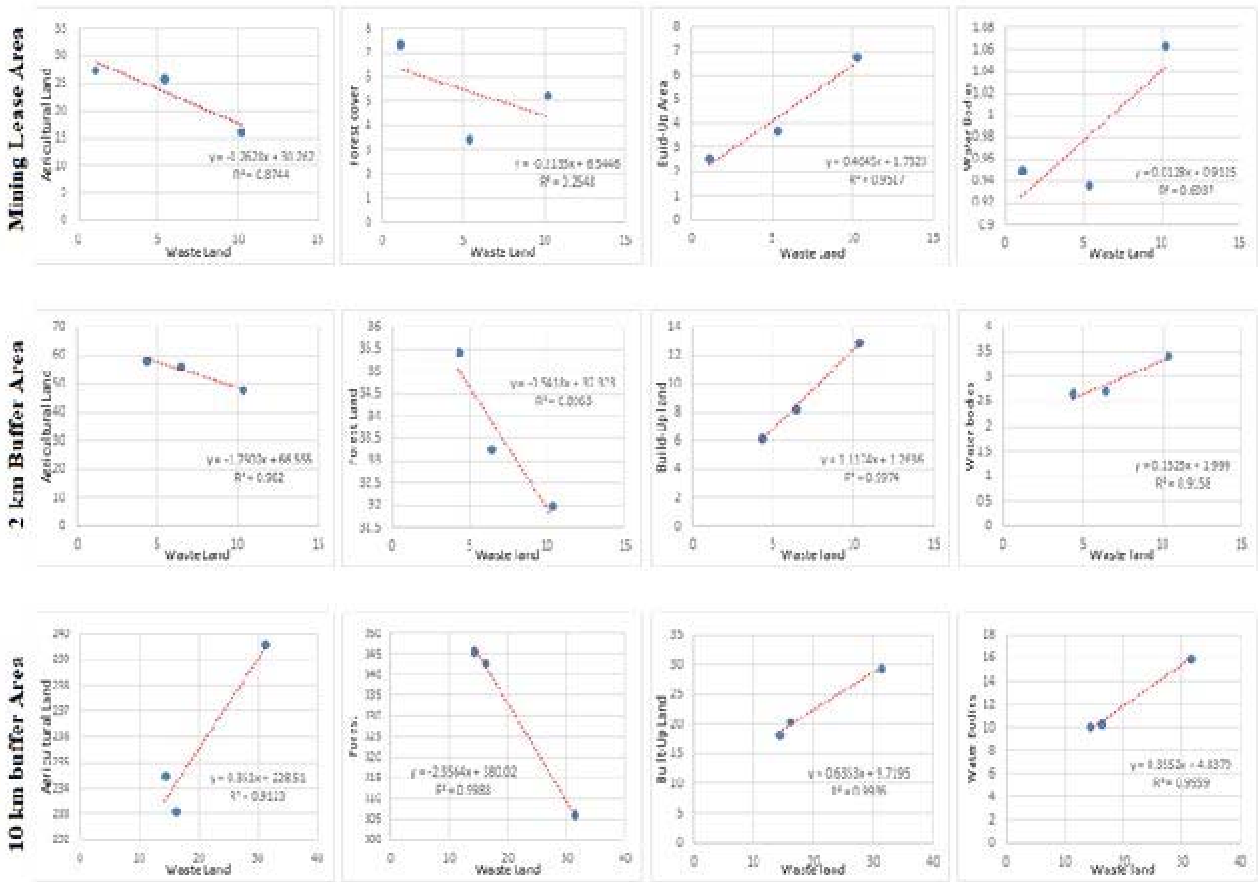

Figure 8. Correlation analysis of LULC changes in study area during study period

consequence, the wasteland area including mining, scrubs, barren, rocky or stony waste and dumping area, increased consistently in their extents during the study period. Built-up area also increased due to the mining activity and the associated increase in infrastructure during this period. The correlative analysis given in Figure 8 shows that in the mining lease area the anthropogenic activity i.e. wasteland and built-up area are positively correlated, while the forest land, water bodies and agricultural land are negatively correlated to the wasteland area. In the 2 km buffer area around the mining area forest cover and agricultural land are negatively correlated, while built-up area and water bodies are positively correlated with the increasing wasteland area. However, analysis of 10 km buffer area indicates that the agriculture land, built-up area and water bodies are positively correlated with the wasteland, while the forest land is negatively correlated to the wasteland area.

DISCUSSION

Coal mining is a dynamic process in which land is regularly changing, with one land use class shifting to another. Besides the LULC change, air pollution, water pollution, coal fires soil pollution were the main drivers that change the environment and productivity of the mining area and its surroundings (Saini et al. 2015). The result shows the rapid change of some LULC classes of the coal mining area from 2016 to 2022. A similar study was conducted for the LULC change in the Jharia coal field between 1999 and 2009 at five-year intervals (Siddiqui and Jain 2022). For the rapidly changing mining area, the LULC study is more suitable for timely management and hazard mitigation (Chamling and Bera 2020). The mining lease area, 2 km buffer zone and 10 km buffer zone have different factors responsible for land use change including topographical, environmental and socio-economic changes in the region (Mundia nad Aniya 2006, Chen and Ju 2014, Zhou et al. 2020). Mining activity in the leased area may cause the changes in the environmental parameters such as water quality, air quality and soil quality in the buffer area (Mondol et al. 2014, Sinha et al. 2019). Similar results were also reported by Gurung et al. (2018) that mining/reclamation activities may have contributed 65% of the overall changes in LULC and indicate drastic decrease in the forest area. Chang et al. (2021) also reported an increase in agricultural land and water bodies in the mining landscape of Shandong Province, China.

Agricultural area decreased in the mining area and its 2 km buffer areas, while in the 10 km buffer area it showed increase. This increase in agricultural area in 10 km buffer area may be due to the increase in the population of the area and their increased needs (Singh et al. 2013). Firozjaei et al. (2021) assessed the impact of mining activities on surface biophysical properties and predicted the future changes in temperature and vegetation cover of the region. In the Pakri Barwadi coal mines area, forest area decreased in mining and its surrounding area. Firozjaei et al. (2021) also reported a decrease in forest cover and expected to further decrease in the near future. Gurung et al. (2018) conducted a detailed study on surface mining and its impact on LULC of watersheds and ecosystem services and reported that surface mining is an important driver of LULC changes in many mountainous areas.

Forest cover has gradually increased in the mining lease area but has decreased in its buffer areas during the study period (2016-2022). This may reflect gradual mining activities and reclamation/plantation in already mined areas and also successive stages of plant growth. Key land use classes such as wasteland and build-up area have increased significantly in the mining sites and their buffer zone. The increase in waste land area is due to the increase in surface mining areas, increased dumping sites, processing units, storage units (Feng et al. 2019, Maiti 2012). Similarly, the built-up area increased due to increase in infrastructure such as offices, settlements, roads, storage units etc. With time there is continuous extraction of natural resources to fulfil human demand, which is causing degradation of natural landscape of the area.

CONCLUSION

The entire mining and its surrounding area are under manifold pressure of mining and agricultural activities. There is slow degradation and fragmentation in forested land and is being converted into various other land uses. This study detected the extent of land use changes in the mining lease area and its 2 km and 10 km buffer areas over the period of six years using the geospatial technology of remote sensing and GIS. The study reveals that the major land use category of the area id agricultural land, followed by forested area. The waste land area has been decreased due to the conversion of barren land settlement. The built up area has increased which led to the expansion of town. Due to better employment opportunities many people also immigrate to the mining and its surrounding buffer areas.

The study will be helpful for further project expansion, land use planning and better management of resources. This simple and inexpensive technique can be used in land use zoning and creation of green belt areas in the buffer zones so as to reduce the impact of coal mining on the surrounding areas. The study will also be beneficial to study the actual status of coal mining and degradation of the area. Further, the published literature can be a database for the policy makers in planning developmental project of the area and also to take appropriate decisions in reclamation of the coal mining sites.

ACKNOWLEDGEMENTS

The authors thank the NTPC Ltd. for providing the consultancy project carried out in the Department of Forestry, Wildlife & Environmental Sciences, Guru Ghasidas Vishwavidayalaya. The authors are also thankful to National Remote Sensing Centre (NRSC), Hydarabad, for providing satellite imagery.

Author's contribution: All authors contributed equally.

Conflict of interest: The authors declare no conflict of interest.

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Received:15th February 2023
Accepted:6th April 2023