**Assessment of Land Cover Changes and fragmentation of mining landscape using Geospatial Technology.**

**Abstract**

*Mining plays an important role in economic development of Jharkhand, India. Simultaneously, it also has significant negative impacts on the environment, ecology, and society. Geospatial technology enables the identification, delineating, and monitoring of change in mining landscape in spatial and temporal scale. The aim of this work was to evaluate the quantitative change in mining landscape using multi-temporal Landsat datasets of 2004 and 2024. The study revealed that mining areas appeared in the 2024 image, which were absent in the 2004 image. Agricultural land has sharply declined due to mining activities. In 2004, it covered 36.41% of the study area, but by 2024, it had dropped to 19.68%. It has observed that number of patch (NP) and patch density (PD)has increase whereas largest patch index (LPI) has decreased. Dense and open forest has also been decrease in this period. The rapid expansion of mining areas over the past decade has raised serious ecological concerns.*

*Key words: Landsat data, mining activity, Geospatial technology, LULC change*

**Introduction**

Mining is a widespread activity conducted in nearly every country globally. In the early 20th century, global mining production experienced a substantial increase, rapidly expanding to meet the growing demands of the population. This growth has led to an extension of acceptable limits for mining operations, largely due to the socio-economic benefits these activities provide (Mishra b2005; Ettler 2016; Maconachie 2012). Despite its importance in the growth and development of a nation's economy mining, in general, and open cast mining in particular raises numerous challenges, destruction and degradation of forest and agricultural lands, soil erosion, acid-mine drainage, air, physical displacement, water, noise, and soil pollution, traditional livelihoods loss and discharge of effluents from mines into nearby water-bodies are some of the other associated problems that have adverse environmental impact (Erener 2011; Zhang et al. 2020).

India is the highest energy-consuming country in the world because of its population and economic growth where coal is the main source of energy. It is second-largest producer and consumer of coal in the world with a total production of 997.83 million tonnes in 2023-24 which was 893.19 million tonnes of coal in 2022-2023, 778.19 million tonnes of coal in 2021-2022, 716.08 million tonnes of coal in 2020-2021 and 730.35 million tonnes of coal in 2018-19 (Ministry of Coal, Govt. of India 2024).

Jharkhand is one of the world’s richest mineral regions, holding approximately 40% of India’s mineral reserves and 29% of its coal reserves. This abundance of natural resources has made mining and mineral extraction are the major industries of the state. With the increase in demand for minerals due to the industrial revolution, illegal and unplanned mining, also increased in this area. Earlier work has demonstrated the wide-ranging impacts of mining in Jharkhand, including deforestation, loss of agricultural land, land subsidence, water pollution, and significant environmental and socio-economic consequences. (Chatterjee et al. 2010; Chatterjee et al. 2015; Pandey et al. 2016; Kumar et al. 2018; Karanam et al. 2021; Joy et al. 2024)

To overcome these challenges continuous monitoring and mapping the dynamic changes in land use land cover patterns are helpful for proper management and developing mitigation strategies. Quantitative studies on mine expansion and related human-induced changes are vital for evaluating the environmental impact of mining activities. Many previous studies have quantified the change in mining landscape using geospatial technologies (Charou et al. 2010; Zhang et al. 2019; Anderson 2020; Patra et al 2022; Ngounouno et al. 2023; Ngueyep et al. 2024). This study aims to evaluate changes in the mining landscape using multi-temporal satellite-based datasets and FRAGSTATS software to quantify the changes.

1. **Study Area**

Barkagaon is a village in Hazaribagh district of Jharkhand is approximately 1,982 feet above the sea level and enjoys tropical climate i.e., it stays hot in summer and moderately cool in winter. Barkagaon is located at coordinates 23.8651°N 85.2167°E and has an area of 447.9sq.km of plains. Hazaribagh town lies on Chota Nagpur plateau. A handful of small hills Sitagarha, Bamanbere and Canary Hill surround the city. The road to Hazaribagh passes through thick forests. The city is famous for its coal and Mica reserves. It has the second largest coal reserve in Jharkhand. The study area has rich forest resources mainly dominated by *Shorea robusta* and bamboo tree. Other species are *Madhuca longifolia*, *Beutea monosperma*, Semal, Mahua, Palas, Kend and Asian pear. Mainly two types of soil are found in Barkagaon. Due to the presence of iron, soil of Hazaribagh is Red in color. Presence of Mica gives the soil a little pink color. Lower layer of soil is yellowish. Sandy loam soil is found around the Damodar River basin. The color of soil is a little red, brown & yellow. Total population of Barkagaon as according to population census 2011 is about 11,689, of which 5,666 females and 6,023 males and a literacy rate of 71.9%. The majority population of the village is Hindi speaking. Santhali is a language of the tribal people of Hazaribagh.

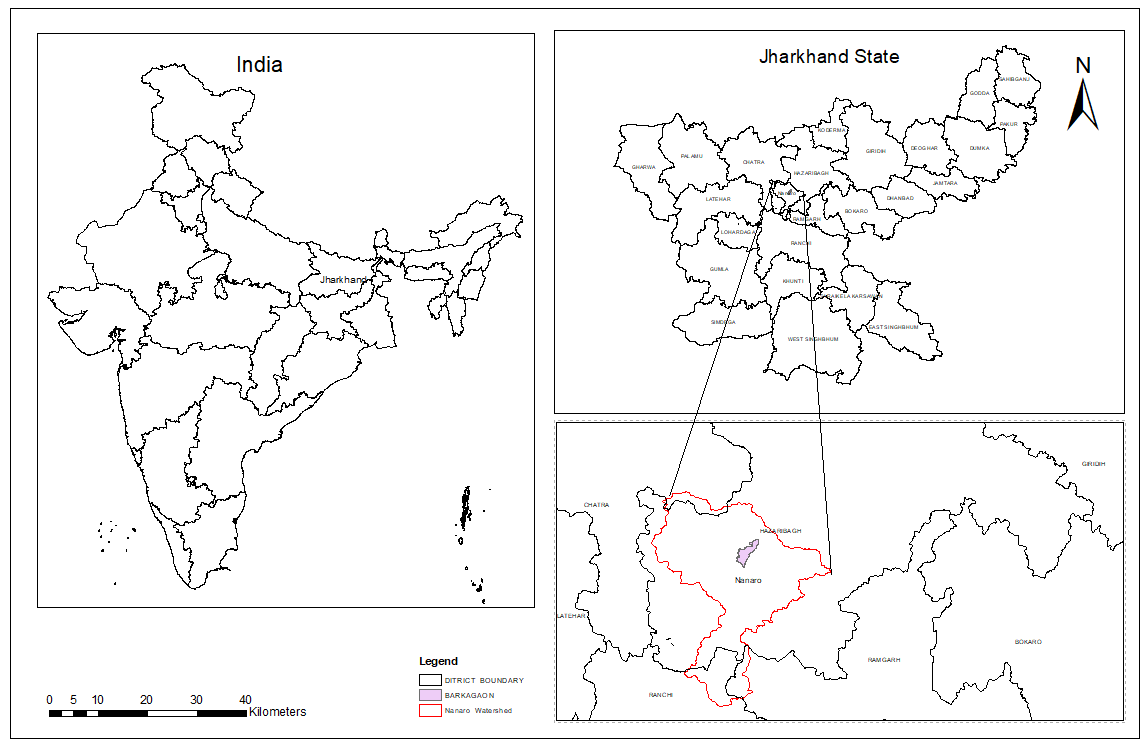


Fig. 1: Location Map of Study Area

1. **Material and Method**

**3.1 Data Used**

Satellite data of Landsat 5/TM and Landsat 8/OLI images were downloaded from [www.usgs.gov.in](http://www.usgs.gov.in). The Landsat image of 2004 and 2024 with spatial resolution of 30m has been used in this study. In this study Landsat 5/ TM band 1-4 i.e. blue, green, red and NIR bands and Landsat 8/ OLI band 2-5 i.e. blue, green, red and NIR bands has been used. Only four bands have been used to reduce the data redundancy.

**Table 1 Details of satellite images**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Satellite/ Sensor | Year/date | Path/row | Bands used | Spatial Resolution(m) |
| Landsat5/TM | 7th March 2004 | 140/44 | 1,2,3,4 | 30 |
| Landsat 8/ OLI | 26th January 2024 | 140/44 | 2,3,4,5 | 30 |

**3.2 Land use and Land cover classification**

LULC maps were prepared using supervised classification method based on training areas and maximum likelihood decision rule. Training polygons are known areas used to classify the remaining part of the image (Jensen 1996). Supervised classification was carried out with GIS software to find out the LULC classes. Land use land cover mapping of the study area using supervised classification is done using the GIS software for different year satellite data which is shown in Table1.Nine LULC classes were prepared (Agricultural land, Open Forest, Dense Forest, Dry riverbed, Barren land, Waterbody, Riverbed, Settlement, Mining area) to understand the change in 20 years.

**3.3 Landscape metrics analysis**

Landscape metrics has been used to observe variability and the impacts of fragmentation. Various studies have already been shown the importance of landscape matrices which can be used to understand the spatial arrangement of LULC and monitoring the spatio-temporal changes (Herzog 2001; Zheng et al.1997; Wei et al 2020; Gabril et al.2019; Mahato et al 2021; Singh et al 2018 ).However, selecting the most appropriate matrix is essential to avoid redundancy in the landscape metrics. Several studies explain the importance of selected matrix for quantification of landscape (Riitters et al. 1995, Cushman et al 2008; Linke and Franklin 2006; Griffith et al 2000; Hargis et al 1998; Cain et al 1997). In this study landscape matrix includes Number of Patches (NP), Patch Density (PD), Largest Patch Index (LPI), Inter-juxtaposition Index (IJI) and MESH were used which is shown in the table 2.

**Table 2: Metrics used at class level to quantify fragmentation (Mc Garigal and Marks, 1995; Kumar et al.2018).**

|  |  |
| --- | --- |
| Metrics and Units |  |
| NP = Total number of patches in this class | NP = 𝑛𝑖  n𝑖= number of patches in the landscape of patch type (class) i. |
| PD- (per unit per ha) Ratio of number of patches and the area of investigated | PD = 𝑛𝑖 /𝐴 (10,000)(100) n𝑖 = number of patches in the landscape of patch type (class) i.  A = total landscape area (𝑚2). |
| LPI –Ratio of largest patch area to investigated area | LPI = max(𝑎𝑖𝑗) 𝑗=1 /𝐴 (100)  a𝑖𝑗= area (𝑚2) of patch ij.  A =total landscape area (𝑚2) |
| IJI- Interspersion-juxtaposition index Degree of interspersion of patches of this class, with all other classes |  |
| MESH, ha (Effective Mesh Size) | MESH= ∑ 𝑎𝑖𝑗2 𝑛 𝑗=1/𝐴 ( 1/10,000 ) a𝑖𝑗 = area (𝑚2) of patch ij.  A = total landscape area (𝑚2). |

1. **Result and discussion**

**4.1 Land use Land cover change analysis**

The landuse maps and statistics of the study area which is generated from satellite data using supervised classification is shown in Table 3 and Fig. 2. In 2004 satellite image, agricultural land emerged as the dominant land cover class, covering approximately 350.29 hectares (ha), or 36.41% of the total area. Dense Forest was the second most prevalent class, spanning about 339.93 ha, or 34.54%. Open Forest covered approximately 200.88 ha, representing 20.41% of the total land area. In comparison, the other land cover classes were significantly smaller. The Dry Riverbed covered 3.69% of the area, Barren Land accounted for 0.45%, Waterbody made up 0.16%, Riverbed comprised 1.68%, and Settlement occupied 2.66% of the total land cover.

However, 2024 satellite image shows that agricultural land covers has decreased dramatically and became 193.68 hectares (19.68%). The Dence forest in the study area has also decreased but to a lesser extent. Significant decrease of open forest has been observed only 151.11 hectares (15.35%), down from 200.88 hectares in 2004. The other land cover classes i.e. Dry Riverbed occupied 0.18 ha (0.02%), Barren Land comprised 4.59 ha (0.47%), Waterbodies covered 17.28 ha (1.76%), Riverbed accounted for 4.23 ha (0.43%) and the Settlement covered 82.71 ha (8.40%) which was only 26.19 ha (2.66%) of total study area. A new land cover class that is Mining Area has been identify in 2024 satellite data covering the second-largest area of 207.9 hectares (21.12%).

Over the last two decades mining industry expanded significantly, resulting in a substantial reduction of agricultural land by 2024. This shift in land use has had profound effects on the region's topography, leading to increased surface instability and damage water drainage pattern. This alteration could ultimately disrupt crop health and productivity. Many previous studies discuss the impact of mining on soil structure and hydrology which ultimately change the overall productivity and sustainability of agriculture productivity and health of crops (Moffat and McNeill, 1994; Hu et al., 1997; Lechner et al., 2014)

**Table 3: Area Statistics of Land Use and Land Cover (LULC) Changes in different Years**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| LU/LC Class | 2004 | | | 2024 | | |
| Area (ha) | Area (%) | Area (ha) | | Area (%) |
| Agriculture Land | 350.29 | 36.41 | 193.68 | | 19.68 |
| Open Forest | 200.88 | 20.41 | 151.11 | | 15.35 |
| Dense Forest | 339.93 | 34.54 | 322.47 | | 32.77 |
| Dry Riverbed | 36.36 | 3.69 | 0.18 | | 0.02 |
| Barren Land | 4.141 | 0.45 | 4.59 | | 0.47 |
| Waterbody | 1.53 | 0.16 | 17.28 | | 1.76 |
| Riverbed | 16.56 | 1.68 | 4.23 | | 0.43 |
| Settlement | 26.19 | 2.66 | 82.71 | | 8.40 |
| Mining Area | 0.00 | 0.00 | 207.9 | | 21.12 |
| **Total Area** | **984.15** | **100** | **984.15** | | **100** |

|  |  |
| --- | --- |
|  |  |
|  |  |

Fig 2. land use land cover map of study area

**4.2 LULC fragmentation and its impact because of mining**

Land use land cover of the study area changed in the period of 2004 to 2024 in terms of landscape fragmentation is shown in the Table4. The landscape metrics-based analysis of the two different years by LULC classes provided information regarding how land cover classes fragmented and changed over time.

The Number of patches for dense and open forest decreased from 34 to 28 and 128 to 92 respectively in studied period. Patch density of the dense and open forests also decrease and, accordingly, LPI decreased, i.e. the larger was the number of patches, the larger became the patch density and the bigger

the largest patches index. The Increase of IJI in 2024 compare to 2004 for dense and open forest is from 42.4778 to 61.275 and 61.6081 to 69.1808 indicating that patched were well interspersed and equally adjacent to all other patch type. Percentage of agriculture land was observed to be dramatic changes in studied period due to mining activities. Decrease in agriculture land with increase in number of patches and decrease LPI indicate the higher fragmentation. A large change can also be observed in case of MESH which decreased to 6.6171ha in 2024 which was 44.3098ha in year 2004.

Settlements formed another important variable patch type, which had a continuous increasing trend with a very high rate. The NP of settlements increased from 64 to 68 and PD increase from 2.4563 per 100 ha to 2.6099 per 100 ha between 2004 and 2024. The decrease of IJI in 2024 compare to 2004 for settlement indicting that patches are not well interspersed or are not equally adjacent to all other patch types.

Table 4 Class-Level Landscape Metrics

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Year | Class | NP | PD | LPI | IJI | MESH |
| 2004 | Agriculture | 50 | 1.919 | 13.0397 | 62.9261 | 44.3098 |
| 2004 | Open Forest | 128 | 4.9127 | 3.6166 | 61.6081 | 3.6857 |
| 2004 | Dence Forest | 34 | 1.3049 | 12.6045 | 42.4778 | 41.4011 |
| 2004 | Settlement | 64 | 2.4563 | 0.266 | 66.8621 | 0.0288 |
| 2004 | Mining Area | 0 | 0 | 0 | 0 | 0 |
|  |  |  |  |  |  |  |
| 2024 | Agriculture | 73 | 2.8018 | 4.6805 | 63.4569 | 6.6171 |
| 2024 | Open Forest | 92 | 3.531 | 2.2245 | 69.1808 | 1.6686 |
| 2024 | Dence Forest | 28 | 1.0746 | 11.9965 | 61.2751 | 37.5011 |
| 2024 | Settlement | 68 | 2.6099 | 1.6891 | 63.7092 | 0.8401 |
| 2024 | Mining Area | 59 | 2.2644 | 7.4231 | 85.2584 | 14.3606 |

**CONCLUSION**

The study examined the spatial-temporal change and fragmentation in LULC of the Barkagaon village in Hazaribagh, Jharkhand using satellite data. In this study Landsat image of year 2004 and 2024 data were used. It was found that in year 2004 does not have mining area whereas year 2024 data shows the mining area. The study reveals that the total area under opencast mines in 2024 was found to be 207.9 ha which is 21.12 percentage of total study area. When comparing the LULC maps of the of 2004 and 2024 it has also been observed that the mining area replaced huge portions of agricultural and forest Lands which was dominated in 2004. FRAGSTATS analysis shows that Forest and agriculture class has become more fragmented and is characterized by increase in human activity during the study period.

Increase settlement, infrastructure development and mining activities have significantly increased pressure on remaining landscapes. The mining activity took over the agriculture/open forest lands showing large destruction. Therefore, if the forest landscape continues to follow the trend, biodiversity of this area likely to decrease. Such change and fragmentation of landscape may disturb soil structure, water quality, ground water and river system of the region. This study will guide policymakers in understanding landscape structure and planning for sustainable development.

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