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ASSESSMENT OF LAND RECLAMATION AND LANDSCAPE DYNAMICS USING GEOSPATIAL TECHNIQUES IN OPEN CAST COAL MINES OF KORBA, CHHATTISGARH, INDIA

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ABSTRACT

Land is the most important natural resource which embodies soil, water, flora-fauna and total ecosystem. All human activities are based on the land which is scarcest natural resource in our country. Mining is a site specific industry and it could not be shifted anywhere else from the location where mineral occurs. It is a fact that surface mining activities do effect the land environment due to ground breaking. Therefore, there is an urgent need to reclaim and restore the mined out land for its productive use for sustainable development of mining. Open cast coal mining and land reclamation is the dominant factor for land cover land use change. In Katghora Tehsil of Korba District. Accurately quantification of the expansion of mining activities is important for assessing how this LCLUC affects ecosystem services such as aesthetics, biodiversity, we used Landsat imagery from 2000, 2010 and 2020 to map the extent of open cast coal mines and land reclamation area, we employed standard image processing and classification techniques in conjunction with a temporal decision tree and GIS maps of mine area to map active and reclaimed mines and track changes through time. For the entire study area, active surface mine extent was highest in between 2010-2020 near about 1.33% area has been increased. And lowest in 2000-2010 near about 0.60% has been changed. Land cover conversion to mines and then reclaimed area after 2010 was almost exclusively from forest plantation. Near about 1.38 % area has been converted into forest plantation area for land reclamation. Accuracy levels for mined and reclaimed cover was above 80% for all time periods, and was generally above 80% for mapping active and reclaimed mines separately, especially for the later time periods in which good accuracy assessment data were available. Our results evidenced the ability of the method under investigation in deriving highly and accurate land use land cover change maps, able to identify the mining areas as well as those in which excavation was replaced by natural vegetation. All in all, the proposed technique showed considerable promise towards the support of a sustainable environmental development and prudent resource management. This work has been attempted to monitor the land reclamation area using geospatial techniques. because it provides better accuracy and decision support system to make a sustainable development of natural resources.
Keywords - Remote sensing, GIS, Land reclamation, LULC. etc

Introduction

Land cover and land use changes (LCLUC) is a key factor of the earth that always shows a very basic correlation between the surrounding environment and anthropogenic activities (Styers *et al*., 2009; Otukei and Blascke, 2010). Rapid Development of societies of human beings, since the revolution in the development of industries, has increased the different types of significant activities that have resulted in a noticeable effect on the land cover and land use (LCLU) (Zhang *et al*., 2010). Removal of the soil layer for mining may cause serious damage to the vegetative cover and can be affect the quality of soil infiltration capacity (Townsend *et al*. 2009; Ranjan *et al*., 2016). After mining activities, an overburden is formed due to excavation and this burden is called as reclaimed area place and it has been shown to be very sensitive to be accelerated soil erosion (Moreno-de las Heras *et al*., 2009) resulting aesthetic degradation of the natural landscape takes place through the massive transfers of overburden material. The latter can be particularly important, especially in touristic destinations. Thus, surface mining is a human activity that has been shown to cause intensive environmental degradation in terms of landscape, vegetation and ecosystems. (Gesch, 2005) in the past few decades remote sensing and GIS has emerged as new technology for monitoring of landscape dynamics, with the help of this satellite data now the days it's possible to observe the mining activities and land reclamation process also because satellite data provide repetitive information of an area (Latifovic *et al*., 2005). Lands at series data has a various advantage that make it very appropriate in mapping mining activity and reclamation. A series of platforms launched since 1972 (i.e. MSS, TM, ETMþ) have allowed the collection at no cost today Rathore and Wright (1993). Producing thematic maps for information extraction related to LULC changes due to mining activity and reclamation using remote sensing data has been based largely on performing digital image classification, by using various thematic map a good decision making plan can be constructed such as suitability mapping of different species for plantation on the overburden area, further which will be helpful to retained the quality of soil again. (e.g. Rathore and Wright 1993; Townsend *et al*., 2009). In this context, our study proposes a method for identifying and analysing the spatial response of landscape dynamics due to the open cast coal mining activities, based on a multi-temporal post-classification change detection scheme. The ability of the technique is evaluated for selected open mining sites located in the Central India and for a period between 2000, 2010 and 2020, during which mining activity occurred in the study areas (Petropoulos *et al*., 2013).

Materials and Methods

Study area

Katghora is a town and nagarpalika in korba district, connecting various states in india through road connectivity. Present study area is located in between 82°28'0.576"E, 22°24'13.327"N and 82°42'6.923"E 22°24'12.728"N and has an average elevation of 312 metres (1,024 ft). Radhasagar is a lake located in the heart of the city. Chak-Chakwa mountain is crown of the Katghora city, which is also known as Hanumangarhi. All the raw materials (coal and water) required for power generation in the district are available in the District of Thermal Power (NTPC KTPS, Balco and BCPP, DSPM, CSEB EAST, CSEB WEST) and 3650 MW of electricity, which are produced by Al- AWA Machadoli is a hydroelectric power station located in vineyards. Coal is available in the district, located in several important coal mine districts of Coal India Limited (SECL). In addition, the aluminium producing company (BALCO) is also located in the district. Rainfall – The Katghora Tehsil of Korba district belongs to the warm temperate climate zone, due to which the district remains very hot and dry. The summer season begins from April to mid-June. Due to the south-west monsoon, the rainy season lasts from the middle of June to the end of September. Major Crops –study area has also persisted for drought conditions. Paddy is the major crop here and mostly depends on the rain. Under most crops,

Methodology

In this research work two sets of clouds cover free satellite data has been used such as Landsat – 8 (OLI) and Landsat–TM for the year 2001, 2010 and 2020 were collected from USGS earth explorer. The United States Geological Survey (USGS, formerly simply Geological Survey) is a scientific agency of the United States government. The scientists of the USGS study the landscape of the United States, its natural resources, and the natural hazards that threaten it. The organization's work spans the disciplines of biology, geography, geology, and hydrology. Base map of the study area was prepared by delineating administrative boundary of study area collected from the Survey of India topo sheets (No. 64j/6, 64j/7, 64j/10, 64j/11, 64j14, 64j15) The base map was rectified with respect to corresponding geometric coordinates in ARC GIS (10.4), later, the administrative boundary was digitized and (.shp) shape file of study area was obtained. The pre-processing of satellite images mainly the radiometric normalization by histogram matching of two images of different dates were done, the layer stacking of different bands was done by combining the individual bands in to a single file in ERDAS Imagine 2015 software. The shape file of administrative boundary (polygon) was overlaid and clipped to extract the study area, while the data outside the polygon was deleted after clipping. Both visible and Infra-red bands were used excluding all other bands and the images were projected in UTM 44N (Universal Transverse Mercator) projection. False color composite (FCC) was generated by using band combination of 4 or 5, 3 and 2 in ERDAS Imagine, image enhancement techniques were employed for increasing brightness of FCCs. "The land use/land cover classification was performed by supervised classification using maximum likelihood algorithm. The algorithm used by the Maximum Likelihood Classification tool is based on two principles:- The cells in each class sample in the multidimensional space being normally distributed, Bayes' theorem of decision making. The tool considers both the variances and covariance's of the class signatures when assigning each cell to one of the classes represented in the signature file. With the assumption that the distribution of a class sample is normal, a class can be characterized by the mean vector and the covariance matrix. Given these two characteristics for each cell value, the statistical probability is computed for each class to determine the membership of the cells to the class. When the default EQUAL option for A priori probability weighting is specified, each cell is assigned to the class to which it has the highest probability of being a member. Process of supervised classification techniques involves the identification of same spectral bands range to create training samples, signature file. The process of classification begins with identifying the spectrally homogenous areas on FCC, which were served as signatures for a particular land cover class. A representative sample of known cover type for each land class was taken by drawing polygons. Such areas are called as training areas '. The training sites were taken in those areas that cover the full range of variability found within a particular land cover to avoid misclassification. The spectrally homogeneous training areas were identified on the basis of reference maps, expertise and GPS observations. Reference data of SOI maps were also used as ancillary data for smoothening classification. Signature files generated for representative training classes used for classifying the entire area. Based on the statistics computed from signature files of training sets on reflection pattern of different land cover classes in different spectral bands, in which a pixel with the maximum likelihood is classified into the corresponding class. out of which a pixel with the maximum likelihood is classified into that corresponding class. The confusion matrix union tool was used for estimating overall accuracy and Kappa coefficient by taking 500 independent random samples of known pixels served as reference points (100 per class) from the original image and derived error matrices for the different classified output images (Congalton, and Green, 1999), while these matrices indicating the concordance of the results of classification and the ground truth data were constructed. The producer's accuracy, user's accuracy and overall accuracy, finally, the kappa coefficient were computed (Congalton, and Green, 2001; Foody, 2008). The post classification comparison technique, which is based on maximum likelihood supervised classification using metrics union in ERDAS Imagine was employed in this study. Two registered and independently classified images were used to calculate the changes in LULC. A two-way cross-matrix was obtained by the application of this procedure and was used to describe the main types of change in the study area. In order to determine the quantity of conversions from a particular land cover to other land cover category and their corresponding area over the evaluated period, cross tabulation analysis on a pixel-by-pixel basis was conducted. Thus, a new thematic layer change map was also produced from the two maps, containing different combinations of ''from– to'' change classes. In this work, five type of land use land cover class have been generated, when we do any kind of research it is very essential to know about the classes that has been covered in the selected study area, they may be forest area, built-up area, agriculture land, fallow land, water body, Mining and industrial area etc. They all are the common type of land used and land cover category and they can be interpretive easily using some image interpretation key such as –size, shape, tone, texture, colour, pattern, shadow and site association. Selected study area has mainly five type of land use land cover classes such as –Forest cover, agriculture crop and fallow land, mining and ashdyke, sandy soil, waterbody. All the classes have been generated for the year during the period of year 2000, 2010 and 2020. After that classified image exported in Arc GIS software for overlay analysis and preparation of final layout map of the study area. During the period of 2000, 2010 to 2020 land use land cover changes have seen in the study area due to open cast coal mining activities.

Results and Discussion

Results on spatial distribution of land use and land cover of the study area during the last twenty years (2000-2020) are summarized in Table 1 and classified maps illustrated in Fig 2 and 3 a, b and c. The five land cover categories *viz.,* Agriculture crop and fallow land, mining and ashdyke areas, sandy soil, forest cover and Water bodies were distributed in a total area of 478.05 Km^2. Initially, the AG_Crop and fallow land (80.94%) was the dominant land cover followed by mining and ashdyke area (8.94%), forest cover (8.10%), water body (8.66%) while sandy soil was spread only in (0.21%) area represented by 1 Km^2. A rapid increase in Mining from 33.5 Km^2 to 42.72 Km^2 and forest cover from 32.12 Km^2 to 38.72 Km^2 areas was observed between 2001 and 2020, Agriculture crop and fallow land from 390.43 Km^2 to 386.95 Km^2 and water bodies from 20.42 Km^2 to 8.66 Km^2 was decreased during this period. Net increases in area of 9.22 Km^2, 6.6 Km^2 were observed under, Mining and, forest cover while the area under agriculture, water body, sandy soil, reduced by 3.48 Km^2 ,11.76 Km^2 0.58 Km^2 within 20 years' period. Accuracy levels of classified images revealed that the user's accuracy for 2001, 2011 and 2020 for various lands uses in the study area ranged between 77–98.9% , 76.3-100% and 75-100%, respectively (Table 1). The range of producer's accuracy of the images for the above corresponding years was 60-100%, 70-100% and 75-98.2% respectively. The overall accuracy was highest (88%) for 2020 followed by 2000 (86.3%) and 2011 (81.2%) classified image and the Kappa coefficients were also followed the similar trend (Table 1).

Results on transition matrix showing the conversion of one land cover to another class between 2000- 2010, 2010-2020 and 2000-2020 are presented in Tables 2-4. The land use/cover change matrix showed the transitions among the five land cover categories in during different periods. Between 2000 and 2010, 13.90 % (66.48 Km^2) of the forest cover was lost to other land uses, out of the 478.09 Km^2 area about 7.22 Km^2 was retained under this class in 2010, whereas a area of 24.29 Km^2 was transferred to agriculture crop and fallow land followed by 0.42 Km^2 to mining land and 0.09 Km^2 to sandy soil(Table 2). At the same time, an extent of 9.5% (45.42 Km^2) of the agriculture crop and fallow land was converted mainly to mining area (14.99 Km^2) and fallow land to forest cover (21.79 Km^2), while 6.15 Km^2 to sandy soil area. And an extent of 3.74% (17.89 Km^2) of the mining and ashdyke area was converted mainly to fallow land (11.78 Km^2) and for land reclamation purpose forest cover (0.99 Km^2), while 1.33 Km^2 to sandy soil area.

In 2000, the largest area of 390.44 Km^2 was under agriculture, which decrease to 389.49 Km^2 in 2010, still 345.02 Km^2 left, while the area of agriculture was lost to mining and ash dyke (14.99 Km^2), forest cover (21.79 Km^2). Similarly, the mining areas increased from 33.51 Km^2 to 36.38 Km^2 and water bodies decreased from 20.43 Km^2 to 12.42 Km^2. Between 2000 and 2011, 14.99 Km^2 of agriculture and 0.42 Km^2 of forest cover were converted to mined areas (Table 2).

Between 2010 and 2020, 6.59% of forest area comprising 12.6 Km^2 was converted to agriculture land (13.73 Km^2), retaining 17.68 Km^2 out of 31.5 Km^2 area under this class (Table 3). However, during at the same period almost 81.48 % of agriculture (389.49 Km^2) was lost to mining area (16.94 Km^2), In contrast, relatively a small area of mining accounting 7.6% (36.37 Km^2) was converted to forest (3.96 Km^2) for land reclamation purpose (Table 3).

Results on transition of land cover classes between 2000 and 2020 are summarized in Table 4. An extent of 6.7 km^2 area under forest, 9.22 km^2 in mining during last 20 years. In contrast, conversion from mining to agriculture was 10.89 km^2 and 6.39 km^2 forest was observed, while there is marked conversion of forest to agriculture during this period was 25.24 km^2. and 6.39 km^2 converted as forest cover for land reclamation purpose (Table 4).

Overall analysis of study area observed that the mining area has been drastically expanded in south direction nearly (9.22 Km^2) from 2000-2020, and forest cover has been expanded nearly (6.6 km^2) from 2000 to 2020. Due to land reclamation in study area.

Recommendations and Conclusions

The study concludes that the reclamation of mining sites after the excavation of coal is a long-term process that includes dumping of waste material and soil, and rocks then plantation of good species of trees to retain the quality of soil again. it's a very serious issue for any mining company to reclaim the area that has been damaged by the mining and it evolves in various stages. However, mining industries has also a social corporate responsibility to all the people living in the surrounding areas of the mining sites. Rehabilitation and reclamation of degraded wasteland caused by the open cast coal mining should be a self-sustain environment and it should be again a source of livelihood related to natural resources. With help of remote sensing and GIS techniques, various thematic layer can be prepared and this layer can be used for site suitability mapping of plant species for Eco restoration with the help of multi criteria decision making (MCDM).

Table 1: Spatio temporal changes in Land Use Land Cover of study area.

	2000		2010		2020		2000-2020
Class Name	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (+Increase, - Decrease)**
Agriculture crop and fallow land	390.43	81.67	389.49	81.48	386.95	80.94	-348
Sandy soil	1.58	0.33	8.29	1.73	1	0.21	-0.58
Waterbody	20.42	4.27	12.41	2.60	8.66	1.81	-11.76
Mining and Ashdyke area	33.5	7.01	36.37	7.61	42.72	8.94	9.22
Forest cover	32.12	6.72	31.48	6.59	38.72	8.10	6.6
Total area	478.05	100.00	478.04	100.00	478.05	100.00	

Table 2 : Cross matrix of Land use / Land cover changes between 2000 and 2010.

			2000				
	Class Name	**Forest cover**	**Agriculture Crop and Fallow Land**	**Mining and Ashdyke area**	**Sandy soil**	**Water body**	**Total area**
	Forest cover	7.22	21.79	0.99	0.03	1.47	**31.5**
	Agriculture Crop and Fallow Land	24.29	345.02	11.78	0.69	7.71	**389.49**
2010	Mining and Ashdyke area	0.42	14.99	15.62	0.42	4.93	**36.38**
	Sandy soil	0.09	6.15	1.33	0.44	0.29	**8.3**
	Water body	0.1	2.49	3.79	0.01	6.03	**12.42**

Table 3: Cross matrix of Land use / Land cover changes between 2010 and 2020.

			2010				
	Class Name	**Forest cover**	**Agriculture Crop and Fallow Land**	**Mining and Ashdyke area**	**Sandy soil**	**Water body**	**Total area**
	Forest cover	17.68	15.04	3.96	0.18	1.86	38.72
	Agriculture Crop and Fallow Land	12.6	354.6	11.53	6.34	1.89	386.96
2020	Mining and Ashdyke area	0.89	16.94	18.94	1.55	4.42	42.74
	Sandy soil	0.03	0.51	0.31	0.14	0.03	1.02
	Water body	0.3	2.41	1.64	0.1	4.21	8.66

Table 4: Cross matrix of Land use / Land cover changes between 2000 and 2020.

			2000				
	Class Name	**Forest cover**	**Agriculture Crop and Fallow Land**	**Mining and Ashdyke area**	**Sandy soil**	**Water body**	**Total area**
	Forest cover	5.93	23.55	6.39	0.12	2.74	38.73
	Agriculture Crop and Fallow Land	25.24	342.97	10.89	0.87	6.89	386.86
2020	Mining and Ashdyke area	0.75	21.36	14.53	0.47	5.62	42.73
	Sandy soil	0.02	0.56	0.29	0.05	0.12	1.04
	Water body	0.09	2	1.41	0.08	5.09	8.67

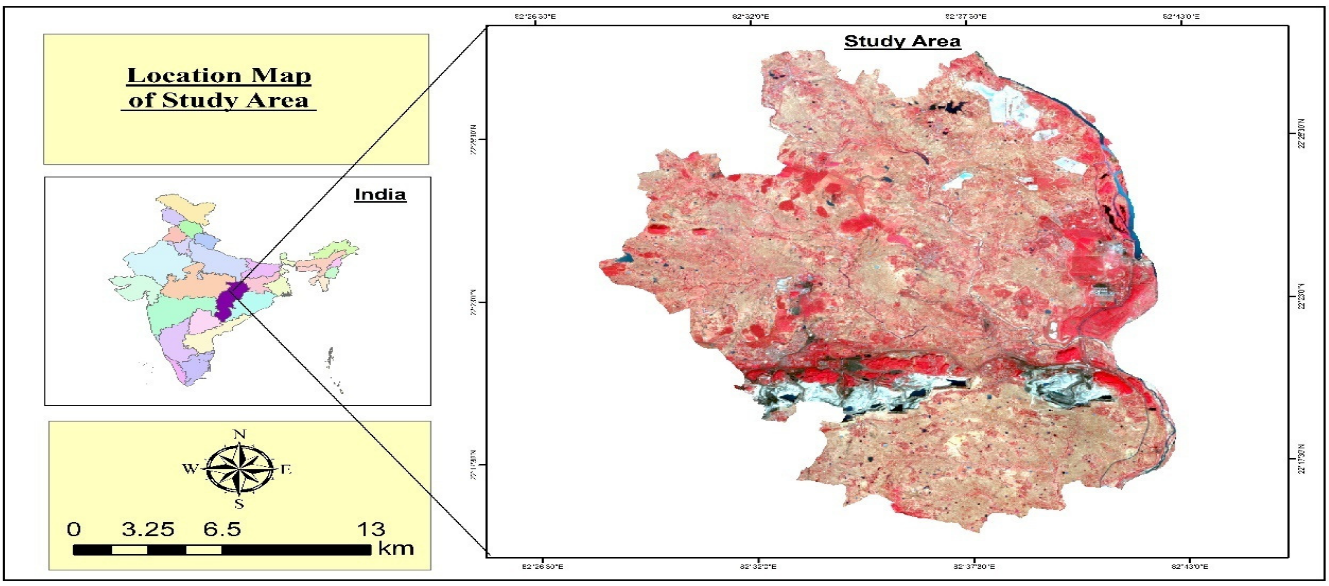

Fig. 1: Location Map of Study Area

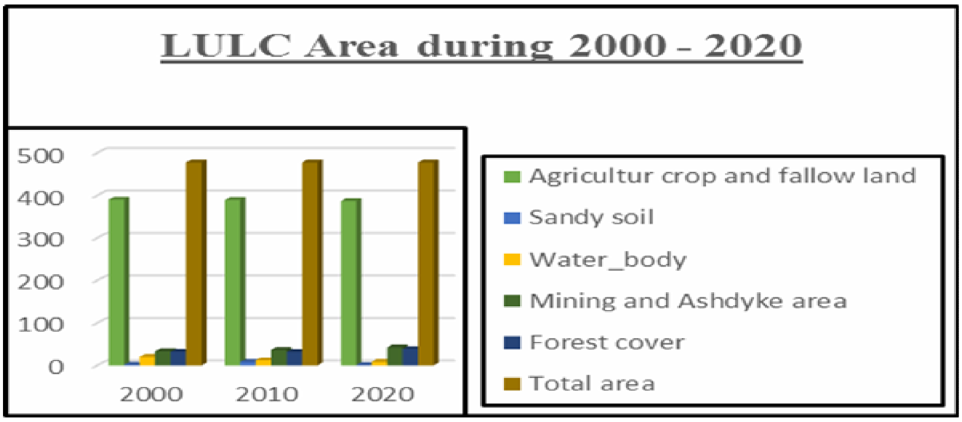

Fig. 2 : Graph of LULC Area during 2000-2020

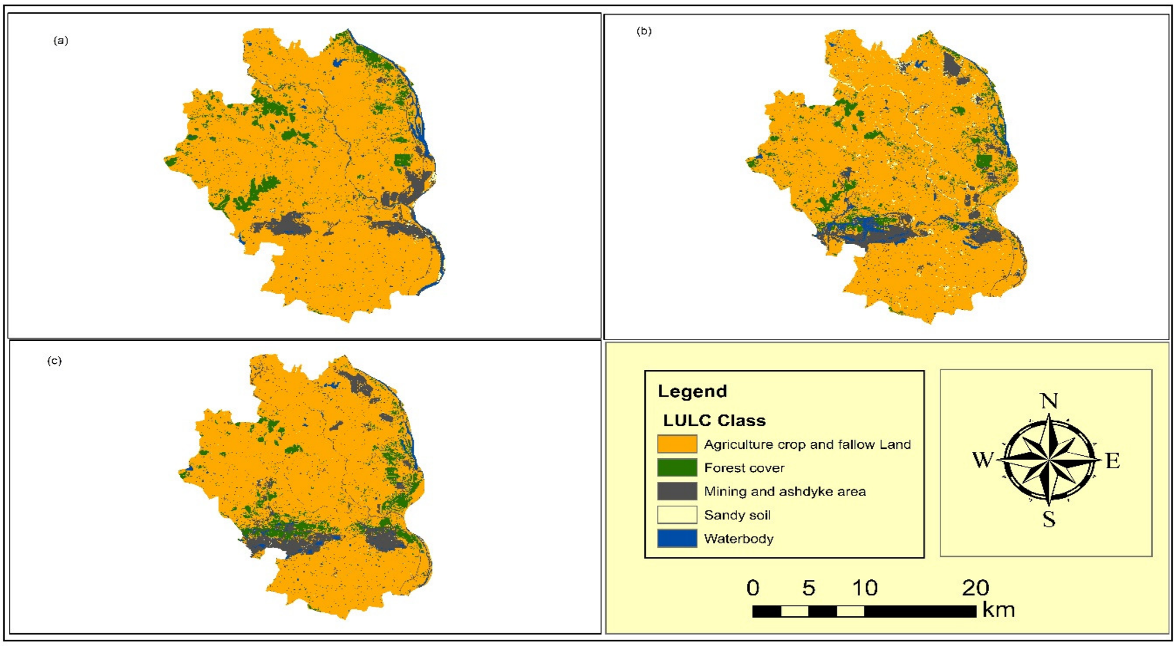

Fig. 3: LULC Map of study area (a) 2000, (b) 2010, (c) 2020

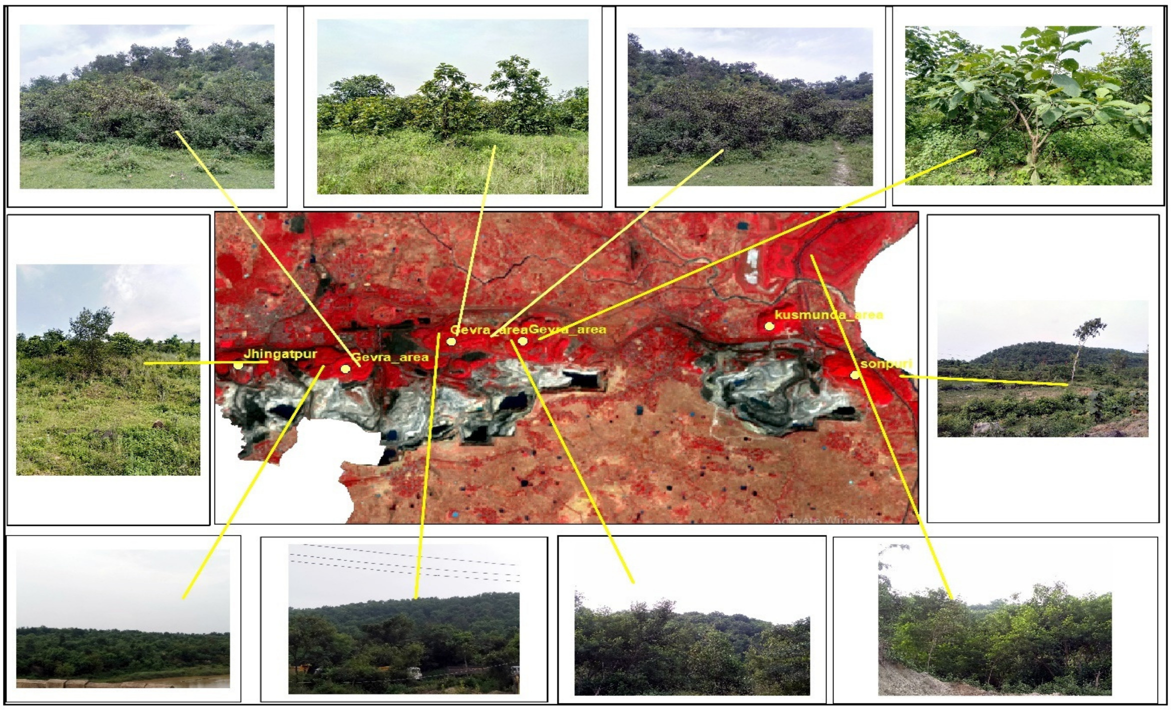

Fig. 4 : Reclaimed area of mining site

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