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Land Use/Land Cover Dynamics During 2001 And 2021 Using Google Earth Engine and GIS in Ramagundam Coal Mining Area, A Part of Pranhita Godavari Valley, Southern India

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Abstract: **Coal is one of the primary sources of energy in India, which are generally extracted through open cast mining. However, coal mining activities, particularly open cast mining methods are known to result in adverse environmental impacts such as vegetation loss, air pollution, ground water contamination along with changes in land use land cover (LULC) features. Hence, reliable temporal data on the impact of mining activities are required to aid in mine reclamation and management efforts. Assessment of LULC changes over the last two decades was carried out in Ramagundam coalfield, using Google Earth Engine (GEE) integrated with Geographical Information System (GIS). Landsat 5 and Landsat 8 multispectral satellite data from 2001 to 2021 with <5% cloud cover was used to classify LULC classes. The different land use classes are classified in GEE through supervised classification using Classification And Regression Tree (CART) classifier. The study indicates that mining area has increased to 298% (from 15.20 km^2 to 60.50 km^2) from 2001 to 2021 and significantly reduces other classes. The outcome of this study could be useful to the coal industry/company to carefully monitoring the effects of mining. This study will aid policy makers and environmentalists in understanding nature of change in LULC features in the area.**

Index Terms: **Classification And Regression Tree, GIS, Google Earth Engine, LULC and Ramagundam Coalfield.**

I. Introduction

The surface of the earth has significantly changed due to both natural phenomena e.g., global warming, greenhouse effect and anthropogenic activities e.g., cultivation of marginal lands, deforestation, mining and industrialization, and overgrazing, (Rathore and Wright, 1993; Hurtt et al., 2011; Areendran et al., 2013). Changes in land use/land cover (LULC) of an area may have positive or negative impact on natural resources at both the local and global levels and its monitoring has become a top priority for policymakers, land managers, and researchers (Malaviya et al., 2010; Mousivand and Arsanjani, 2019). Deforestation, mining and land degradation are negative impact of LULC changes that has resulted in climate change, biodiversity decline, and biophysical characteristics (Li et al., 2016; Mahmood et al., 2016). Regional ecosystems in developing countries are degraded as a result of unplanned land use activities such as unplanned urban expansion, shifting farming, and illegal mining (Mukhopadhyay et al., 2017; Awotwi et al., 2018). Although, mineral resources are most important and fundamental pillars of any country's economy (Sekerin et al., 2019) but unplanned mines and mining operations cause deforestation, land degradation, population displacement and air pollution (Patra and Sethy, 2014; Awotwi et al., 2017).

India is a country with diverse range of mineral resources, and the demand for and consumption of energy related to these resources has more than doubled in the last two decades resulting in expansion of mining industries (Mehta 2002; Ranjan et al., 2021). Coal is India's main resource and primary source of energy, with open cast mining accounting for 75% of the total mines

(Rathore and Wright, 1993). For thermal power generation, coal demand has increased from 630 million tonnes to 735 million tonnes in 2021–22 and is estimated to be 877 million tonnes in 2026–27 (CEA,2018). However, coal is often a necessary source of energy for existing and growing industries but environmental degradation is generally considered as an unavoidable consequence of maintaining overall national development (Chatterjee, et al., 1994). In open cast coal mining, the areas regularly undergo changes with one land use class to another (Saini et al., 2016). Excavation of coal and related activities provide huge energy resource; however, these adversely affect the environment like loss of vegetation, air pollution, ground water contamination along with changes in LULC classes (Ranjan et al., 2021) as these resources are typically found in ecologically sensitive/forested areas (Qian et al., 2014).

Temporal LULC studies aid in the monitoring and mapping of mine reclamation activities such as afforestation and land reclamation and also to quantify consequences of mining activities on the environment (Turner et al., 2007; Ranjan et al., 2021). Regular monitoring and preparing LULC maps by conventional methods is time consuming, expensive, labor intensive, and carrying out ground surveys may also be difficult in some areas due to terrain characteristics (Prakash and Gupta 1998). Further, traditional image classification by user may result in insufficient sample size and poor generalisation (Zhao and Du, 2016). Google Earth Engine (GEE) is widely used platform for LULC classification as it uses Google servers' massive computing functions for high computing power and large storage capacity, along with self-programming classification algorithms, to perform automated LULC classification (Stromann et al., 2020; Pan et al., 2021). Many LULC related studies have been conducted globally using the GEE platform. For example, Xiong et al., (2017) created cropland map of Africa using Sentinel-2 and Landsat-8 Data, Kumaret al., (2021) used Sentinel-2 level-1C data in the RUSLE model for LULC, Pan et al., (2021) classified LULC in Australia and United States using MCD12Q1 Version 6 global land data, Praticò et al., (2021) used Sentinel-2 time-series data to classify Mediterranean Forest Habitats. Therefore, considering its advantages, GEE, a cloud-based platform has been used in this study to classify LULC features employing supervised classification technique.

This study aims to estimate changes occurred in last 20 years due to coal mining in Ramagundam area using GIS and GEE. Ramagundam coalfield have been subjected to extensive and rapid underground and opencast mining since 1974. It is therefore important that a systematic study is to be carried out in this particular coalfield.

II. Study Area

The study area, Ramagundam coalfield is a part of the Pranhita-Godavari valley. The Ramagundam Coal belt is one of the eleven coal belts of Pranhita-Godavari Valley. All the eleven coal belts were operated by Singareni Collieries Company Limited (SCCL). SCCL accounts for around 10 Percent of India's coal production (CEA, 2018). Geologically, the Pranhita-Godavari Valley contains not only one of the largest Gondwana Basins of India but also presents the most complete succession of Gondwana rocks. The Gondwana Basin of Pranhita Godavari Valley has been divided into four sub-basins, namely, i) Godavari, ii) Kothagudem, iii) Chintalapudi and iv) Krishna-Godavari coastal tract (Raja Rao, 1982). The Ramagundam coalfield, which is a part of Godavari sub basin of Pranhita- Godavari Valley exhibits the stratigraphic succession consisting of Talchir, Barakar and Kamithi formations (Singh et al., 2011).

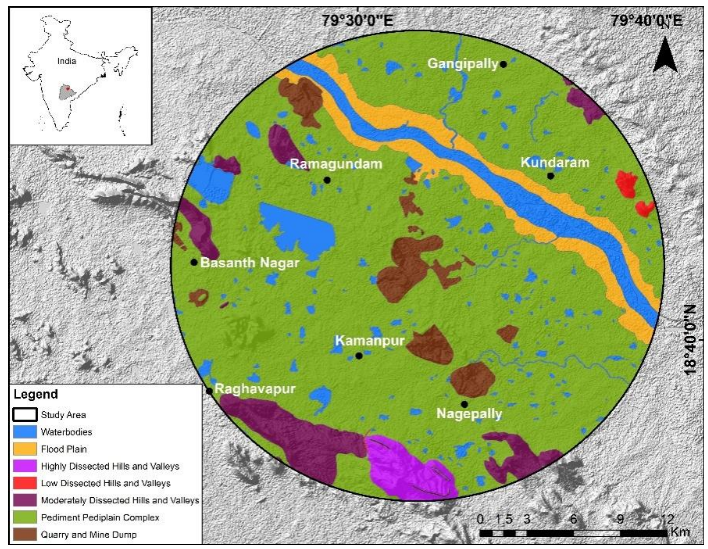


Fig.1: The study area created by 15 km buffer from the Ramagundam coal belt. The area is draped over hillshade created from ALOS-PALSAR DEM.

III. Methodology

The Ramagundam coal belt was identified in the field with its coordinates and later imported in Google earth to digitise its boundary. A buffer of 15-kilometer radius from the centre of the mine has been used to create a buffer zone in QGIS 3.10 software The selected window confined between latitudes 17°11′ N - 17° 12′ N and longitudes 80°46′ E - 80°49′ E in the Karimnagar district of Telangana state, India. To detect the spatial changes, remote sensing data from Landsat 5 for the dates 04/03/2001, 02/03/2006, 01/04/2011, and Landsat 8 satellite data for the dates 13/03/2016 and 11/03/2021 having <5% cloud cover are utilised to classify different LULC classes employing the visible and near infrared bands. Using the base file of Bhuvan-NRSC (National Remote Sensing Centre) several LULC classes such as builtup, agriculture, scrub, forest, water bodies, sandy, barren land and quarry-mine dump classes are used in the supervised classification. To reduce pre-data processing time and uniformity, Google Earth Engine (GEE), a cloud-based platform is used in this study. It combines host of geospatial datasets and computes power for running user algorithms (Python and JavaScript based). LULC specific code in script part of the GEE for pixel-based supervised classification is executed. Total of 50 signature files of each class are added as identified on the Landsat imageries and compared with Google Earth images of same time period for classification. Out of many available classifiers CART (Classification And Regression Tree) is used in the study that creates set of decision trees and produces accurate LULC map (Belgiu and Drăguţ, 2016; Pelletier et al., 2016). Finally, all the LULC thematic maps are exported and areas of various classes mapped have been calculated in GIS environment.

IV. Results And Discussion

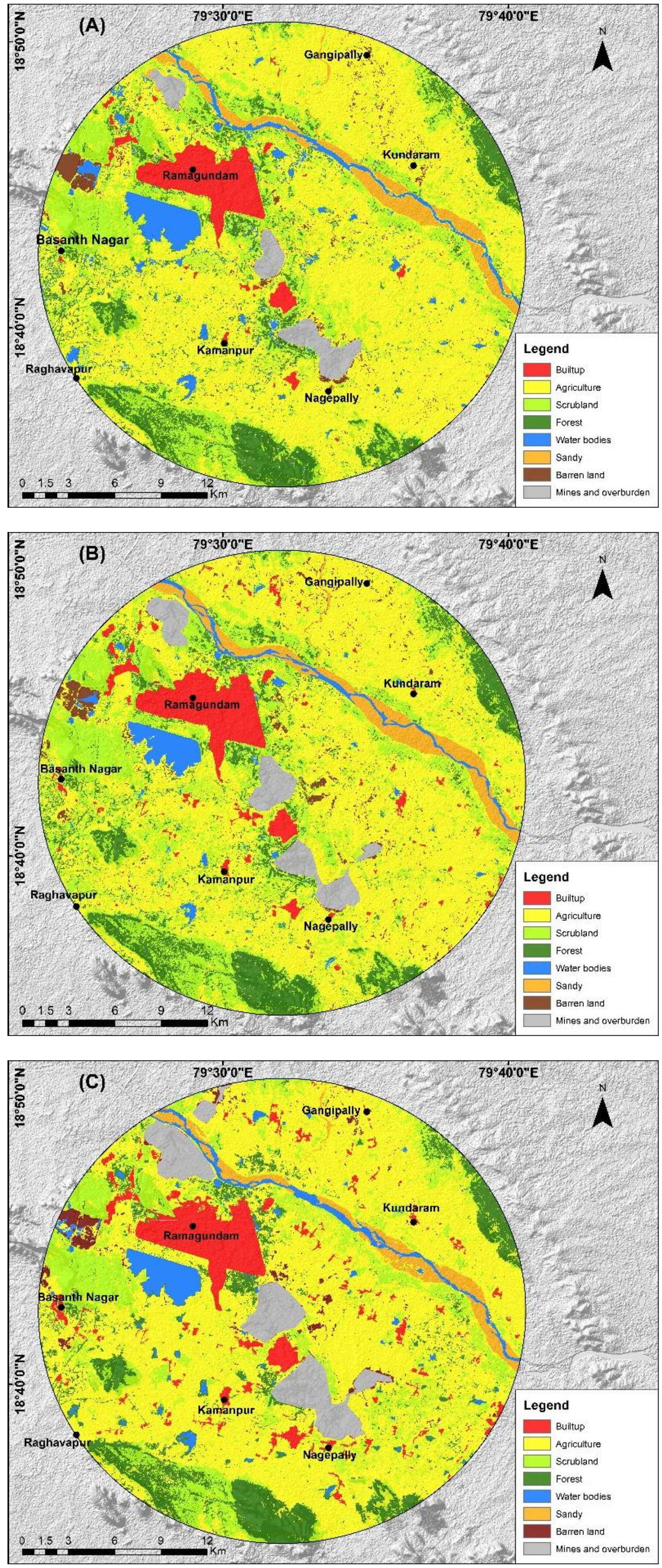
In modern land management, LULC is a critical component to monitor the changes occurred in different time intervals and to minimize their negative impact. Since satellite images have shown to be a trustworthy data source with useful temporal resolution, the comparison of time-sequential data is utilised to analyses changes in land-use patterns using remotely sensed data (Joshi et. al., 2006). Several changes have been observed in the LULC analysis of 2001, 2006, 2011, 2016, and 2021 in the Ramagundam coalfield.

Table 1: Year wise changes in LULC classes (Negative sign indicates reduction).

LULC Class	2001 (Area km^2)	2006 (Area km^2)	2011 (Area km^2)	2016 (Area km^2)	2021 (Area km^2)	% Change from 2001 to 2021
Builtup	28.41	37.21	47.23	62.17	71.31	151
Agriculture	381.81	361.77	401.86	418.42	434.41	13
Scrub	147.5	158.84	102.13	69.1	41.63	-71
Forest	75.43	74.04	69.89	63.6	52.02	-31
Water bodies	27.15	18.38	22.81	13.17	32.49	19
Sandy	20.07	22.58	17.35	23.68	8.21	-59
Barren land	11.33	12.95	9.67	13.03	6.34	-44
Mines and overburden	15.2	21.13	36	43.82	60.5	298
Total	706.9	706.9	706.9	706.9	706.9	

The spatial extent of builtup class has been observed to have increased during the study period 2001 and 2021 from 28.4 km^2 to 71.3 km^2. Agriculture class has decreased from 2001 to 2005 from 381.8 km^2 to 361.7 km^2. But the agriculture class has increased from 2005 to 2021 from 361.7 km^2 to 434.4 km^2 (Table 1, Fig.2).

A drastic decrease is observed in scrub land from 147.5 km^2 to 41.6 km^2 from 2001 to 2021. Forest class has also decreased from 75.4 km^2 to 52 km^2 from 2005 to 2021 and declining trend is observed (Table 1, Fig.2). In case of water bodies, the area has decreased from 27.1 km^2 to ~18.4 km^2 during 2001 and 2006. Its area is observed to have increased in 2011 (22.8 km^2), and a drastic drop in the area has been noticed in the 2016 (~13.2 km^2). But in 2021 increase in the water bodies area (~32.5 km^2) has been noticed.



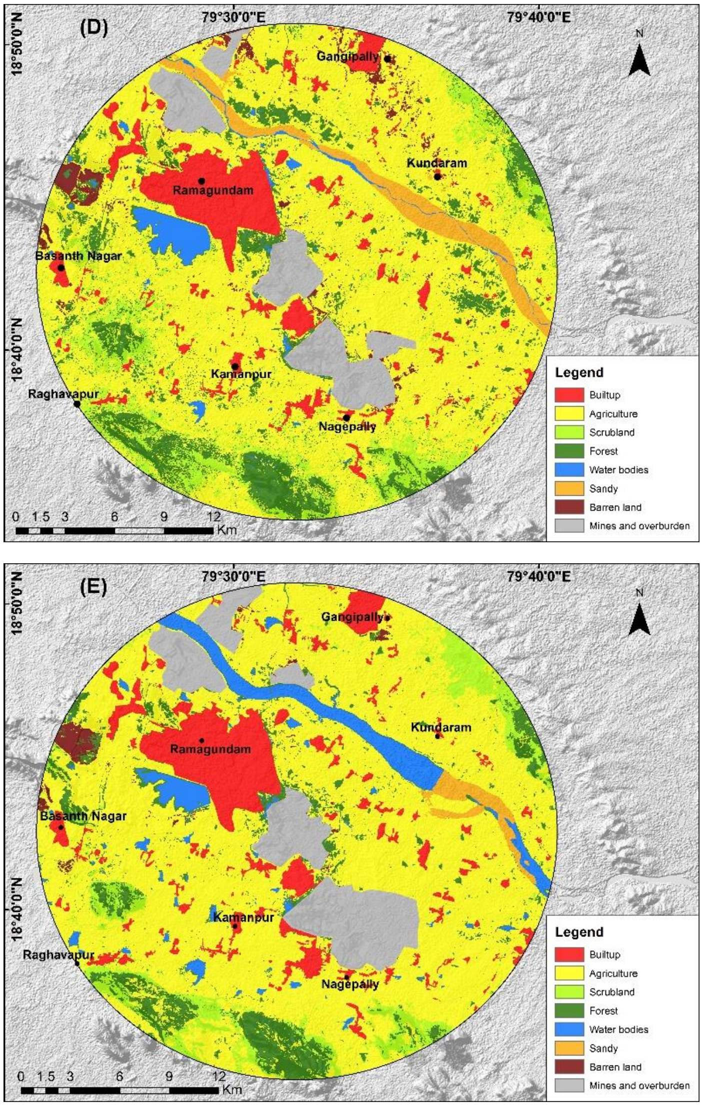


Fig 2: Spatial changes occurred from 2001 to 2021. (A) LULC classes in 2001, (B) LULC classes in 2006, (C) LULC classes in 2011, (D) LULC classes in 2016 and (F) LULC classes in 2021.

Similarly, sandy class has increased from 20.07 km^2 to 22.6 km^2 between 2001 and 2005 and decreased in 2011 (17.3 km^2). Sandy class again increased to ~23.7 km^2 in 2016 and finally decreased to 8.2 km^2 in 2021. Area of barren land class increased in 2006 and declined in 2011. Barren land class again increased to 13 km^2 in 2016 and decreased to 6.3 km^2 in the year 2021. Areas of the mines and overburden area show increasing trend from 15.2 km^2 to 60.5 km^2 in last 20 years (Table 1, Fig.2).

Ramagundam coalfield are the network of many open cast coal mines that are operated by Singareni Collieries Company Limited (SCCL). The field observations (Fig.3a & b) and the LULC maps indicate that mining areas are increasing. The mining area has increased to 298% from 2001 to 2021 but it reduces mainly the scrub land (Fig 4). A total increase of 151% in the builtup area is indication of human habitation. New mining zones need additional manpower, resulting in the establishment of industries

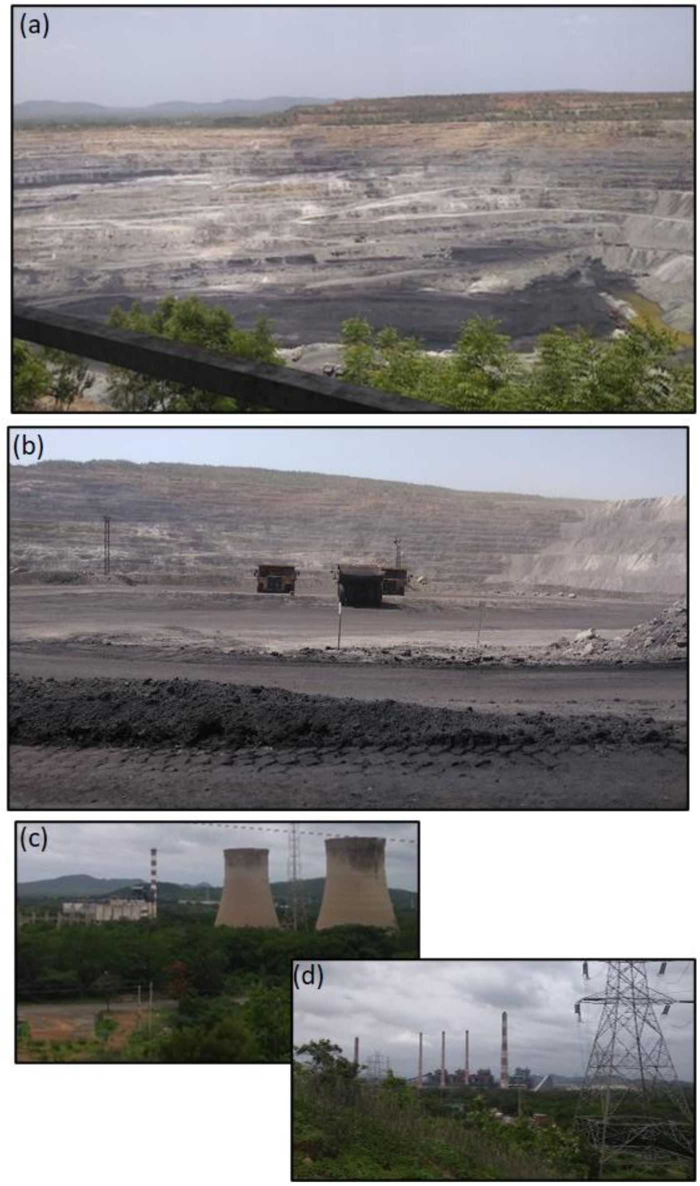


Fig. 3: (a) A panoramic view of the Ramagundam coalfield mining area, (b) Operational coal mining area and (c & d) views of the industrialised area.

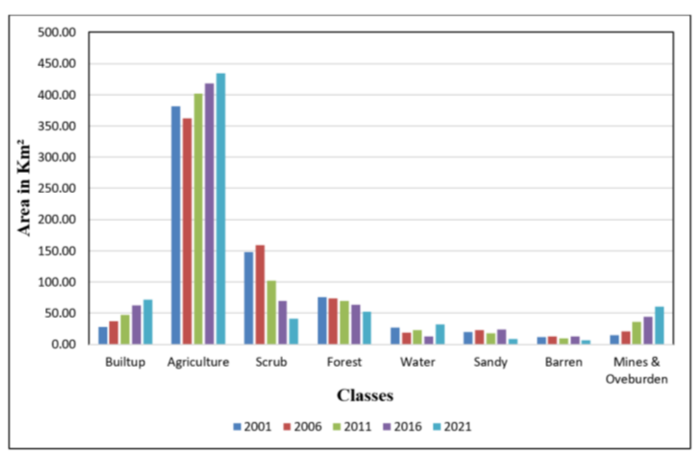


Fig 4: The trend of the different classes during the interval of 20 years.

and habitation that may have increased builtup class (Fig. 3c&d) and declined scrub and barren land class. Due to advance farming policies e.g., inter cropping, mixed cropping, and use of advance machinery, 44% decline in barren land class has been observed that have converted into farming land. A decline of 31% in forest area indicates deforestation. (Fig. 4). Changes in the sandy and water areas are linked, since decrease in one class increases the extent of the other class. These changes were observed to have increased since 2016, when Sundilla dam (also known as Parwati Barrage) was built by Irrigation Department, Government of Telangana, to retain more water in the reservoir (upstream) resulting in exposure of large sand regions in downstream.

Conclusion

Coal is a primary energy source of India which is mined generally through open cast mining. Due to mines direct interaction with atmosphere, it adversely impacts the environmental e.g., vegetation loss, air pollution, ground water contamination and LULC. Hence, reliable temporal data on the impact of mining activities are required to aid in mine reclamation and management efforts. Such study has been carried out in the Ramagundam coalfield, a part of the Pranhita-Godavari valley using Google Earth Engine (GEE) integrated with Geographical Information System (GIS). Temporal data from Landsat 5 and Landsat 8 multispectral satellite data of 2001 and 2021 with <5% cloud cover was used to classify LULC classes. The study shows that there is a total increase of 151% in the builtup area, a decline of 31% in forest area and 44% decline in barren land class. The study indicates that mining area has increased to 298% (from 15.20 km^2 to 60.50 km^2) since 2001 to 2021 and significantly reduces other classes mainly scrub land. The increase in the builtup area can be attributed to the human habitation as a result of increased mining activities. This has also brought negative change in the areas covered under the of forest, scrub and barren land classes. The outcome of this study could be useful to the coal industry/ company to carefully pre-planning the tasks, monitoring the effects of mining and assimilating mined and neighboring areas and can minimise the impact of its activities. This study will aid policy makers and environmentalists in understanding nature of change in LULC features in the area which is an important component for any urban rural planning and environmental management.

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