

ASSESSMENT OF LAND USE/LAND COVER CHANGES FROM 2001 TO 2021 USING GOOGLE EARTH ENGINE IN RAMAGUNDAM MINING AREA, PRANHITA-GODAVARI VALLEY, SOUTHERN INDIA

S. Kiran¹, Rohit Kumar¹ and Kakoli Gogoi¹*

¹Discipline of Geology, School of Sciences Indira Gandhi National Open University, New Delhi-110068

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Abstract

Coal is one of the important primary sources of energy in India, which are generally extracted through open cast mining. However, coal mining activities, particularly open cast mining method 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 this study in Ramagundam coal field, a part of the Pranhita-Godavari valley using Google Earth Engine (GEE) integrated with Geographical Information System (GIS). Landsat 5 and Landsat 8 multispectral satellite data of 2001 and 2021 with <5% cloud cover were used to classify LULC classes. The different land use classes mainly water body, vegetation, builtup and mining area in Ramagundam coal field are classified in GEE through supervised classification using Classification And Regression Tree (CART) classifier. The study reveals that the mining operations increased dramatically between 2001 and 2021. On the other hand, agriculture land has also risen as barren land has been turned to productive land as a result of some effective environmental policies. This study will aid policy makers and environmentalists in understanding nature of change in LULC features in the area so as to plan accordingly.

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Keywords

Ramagundam Coal Field, GEE, GIS, CART, LULC.

INTRODUCTION

Coal is India's most vital resource and principal source of energy, accounting for 0.8 percent of the world's total reserves and producing 40% of the electricity globally (Tiwary, 2001). Coal mining operations are carried out to extract coal from the subsurface using either open cast or underground mining methods. Mineral resources are most important and fundamental pillars of any country's economy (Sekerin et al., 2019) but unplanned mines cause deforestation, land degradation, population displacement and air pollution (Patra and Sethy, 2014; Awotwi et al., 2017). Coal mining activities, particularly open cast mining method are known to result in adverse environmental impacts such as vegetation loss, air pollution, ground water contamination. As a result, appropriate management of mining sites is a critical requirement for environmental preservation, for which required information may be generated through field surveys and utilising satellite data. Field surveys are expensive, time-consuming, and involve a lot of manual work that can be prone to mistake, while satellite remote sensing data based surveys are comparatively less expensive and can be utilised not only for near real-time monitoring of mines but also for historical analysis of changes taking place in a given area. It has been recognised that Land use Land Cover (LULC) maps prepared by satellite data play vital role towards natural resources management (Wentz et al. 2006; Soffianian et al. 2015).

CONTACT *Corresponding author: *kakoligogoi@ignou.ac.in

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LULC mapping using satellite images has become very popular in the last decades (Sen et al. 2015). Remote sensing and GIS tools have been used widely in the mining industry for various purposes such as mineral exploration, modelling, monitoring, mine planning, and environmental impact assessment (Vander Meer et al. 2012; Karan et al. 2016). The need for monitoring and quantifying changes by remote sensing techniques particularly using satellite images has been well recognised. In India, LULC change due to open cast coal mining had been studied in various parts of India such as in Singrauli, MP (Khan and Javed, 2012), Raniganj (Samanta, 2015), Jharia Coalfield (Prakash and Gupta, 1998), etc. However, traditionally used per-pixel satellite image classification for the purpose of LULC mapping by user results in insufficient sample size and poor generalisation (Zhao and Du, 2016). Google Earth Engine (GEE) is now widely used cloud computing platform for LULC classification as GEE uses Google server's 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).

This study tries to measure the changes caused by coal mining in the Ramagundam area during the last 20 years using GIS and GEE. Since 1974, the Coal Fields have been exposed to substantial underground and opencast mining (*The Hindu* April 15, 2018). As a result, it is important to conduct a thorough investigation in this particular coalfield to understand the nature and pattern of changes, if any.

Study Area

The study area, Ramagundam coalfield is a part of Godavari Sub-Basin located in the north-western part of Pranhita-Godavari valley. The Ramagundam Coal belt is oldest coal belt of the eleven coal belts of Pranhita-Godavari Valley. To detect the impact of mining activities the Ramagundam Coal Belt and the surrounding areas a circular region of 15kilometer radius has been identified from the mine area. The selected window is confined between 18°35' N - 18° 50' N latitudes and 79° 25' E - 79° 40' E longitudes in the Karimnagar district of Telangana state, India (Fig 1). The average annual rainfall in the Karimnagar district is 950 mm. Granites, Gneisses, Sandstone, Limestone, Shale, Quartzite's are the major rock types occurring along with the coal seams in the district. The location map of the area is shown in Figure 1. The Gondwana basins of Peninsular India are located along noticeable stream valleys, in particular the Son, Damodar, Mahanadi, Godavari, and Satpura. Prominent lineaments, faults and high heat flow values are the characters of some of these Gonwana basins (Acharya, 2000). The Gondwana Basin of Pranhita-Godavari Valley has been divided into four sub-basins, namely, the i) Godavari, ii) Kothagudem, iii) Chintalapudi, and iv) Krishna-Godavari coastal tract (Raja Rao, 1982). In Ramagundam, the succession of the Lower Gondwana is classified as Talchir, Barakar, Barren and Kamithi Formation. These Lower Gondwana succession overlie either the Archean Gneissic Complex or Sullavai and Pakhal groups of rocks (Raja Rao, 1982).



Figure 1: Location map of the study area. (Source: Google Earth Engine).

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METHODOLOGY

Ramagundam Coal Belt area is digitised and 15km buffer has been created in GIS environment. Landsat 5 and Landsat 8 satellite data dated 04 March 2001, 02 March 2006, and 11 March 2021 with less than 5% cloud cover are used to generate LULC maps of the area. Total of four classes i.e., water body, vegetation, built-up and mining as suggested by Bhuvan-NRSC (National Remote Sensing Centre) are used for supervised classification in GEE platform. GEE is a cloud-based platform that combines host of geospatial datasets and computes power for running user algorithms (Python and JavaScript based). A specific LULC code has been executed to perform pixel-based supervised classification with 50 signature files of each classes. CART (Classification And Regression Tree) classifier has been used that creates set of decision trees and produces accurate LULC map (Belgiu and Drăguț 2016; Pelletier et al., 2016). To enhance the accuracy of the LULC maps Google earth assisted stamping are carried out. Finally, all the LULC thematic maps are exported and there areas have been calculated in GIS environment.

RESULTS AND DISCUSSION

Evaluating LULC is a critical component of modern land management. Since satellite pictures have shown to be a reliable data source with useful temporal resolution, the comparison of time-sequential data is used to study changes in land-use patterns using remotely sensed data, (Garg et al. 1990). The Ramagundam mine's 15-kilometer buffer zone is utilised to delineate various classes in 2001 and 2021 (Figs. 2 and 3). Areas of four classes are tabulated in km² in Table 1. The total net change and percent change of area of the four classes during 2001 – 2021 were determined (Table 1). The net change of classes is also shown in Fig.4.

Table 1: Summary of LULC classification ofRamagundam coalfield area statistics for the years 2001and 2021.

| Class | 2001 (Area in km ²) | 2021 (Area in km ²) | Changes (Area in km ²) |
|----------------------|------------------------------------|------------------------------------|---------------------------------------|
| Built-up | 28.4 | 71.29 | 42.88 |
| Vegetation | 636.14 | 534.38 | -101.76 |
| Mines and overburden | 15.19 | 60.5 | 45.3 |
| Water bodies | 27.15 | 40.7 | 13.55 |

Table 1 clearly depicts that that changes in Land use and Land Cover classes have occurred in Ramagundam Coal Field from 2001 to 2021 (Figs 3 and 4). Mines and overburden have increased from15.19 km² to 60.50 km² indicating that the mining activities have increased. This may be due to discovery of new mines in the area. These mines are strewn over the vegetation, resulting in a loss in vegetation and a greater risk of land degradation. Vegetation area (crop, forest and scrub area are combined into one class) have changed from 636.145 km² to 534.384 km² with the total change of



Figure 2: Photographs of some collection sites. (a-h) in and around TMCH; and (i) inside KCH.



Figure 3: LULC Map of the study area of the year 2021.



Figure 4: Bar diagram showing the net change in LULC classes in the study area during the period from 2001 to 2021.

101.761 km². Negative sign in Table 1 indicate the reduction in the areas. It clearly shows that most of Vegetation class is converted into Built up class and Mines and Overburden Class. Built-up class has increased from 28.4 to 71.29 km² due to population growth in the area during the period of this study. It has been observed that some lands have been turned to either a permeable layer or a barren area with waste building materials. In the case of a water body, there is a minor rise in pond water area. But in the case of river, the dam stores a large quantity of water at the upper reaches in the study region. There is total increase of 13.55 km² have been observed in the area (Figs 2 and 3; Table 1).

CONCLUSION

This study aims to investigate land use/land cover changes occurred in Ramagundam coal field between the years 2001 and 2021 using remote sensing and GIS. Landsat data and GEE were used in this study to highlight the consequences of coal mining in Ramagundam coal field in terms of changes in LULC classes. The main change observed for the time period of 2001-2021 was that the area of the Ramagundam coal field have seen several shifts in land-use patterns, which may be understood in processed Landsat data (Figs 2. 3 and 4). The use of satellite remote sensing data in this study yielded useful information on the deforestation trend in the mining landscape. Some forest regions have been converted to plain lands, either for mining or agriculture. According to the LULC maps, increased mining operations have already had major impact on settlement and forest cover. The results are in tune with the observations of Khan and Javed (2012) who have observed an increase in settlement as a result of population growth and people from other states seeking work. The study reveals that the mining operations increased dramatically between 2001 and 2021 (Figs. 2 and 3). On the other hand, agriculture land has also risen as some of the areas mapped as barren land classhabeen turned to agriculture class. Outcome of this study could also be useful to policy makers and environmentalists in understanding nature of change in LULC features in the area.

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