International Journal of Applied Engineering & Technology

SPATIO TEMPORAL ANALYSIS AROUND RAMAGUNDAM MINING AREA USING RS&GIS TECHNIQUES

Modem Nikhil Kumar[1], Dr Rajni Kant[2], Pranay Moon[3] and Shailendra Bommanwar[4]
[1]Research Scholar, Department of Mining Engineering, BIT, Ballarpur (MS), India
[2]Principal, Ballarpur Institute of Technology Ballarpur Dist-Chandrapur (MS) 442701
[3,4]Assistant Professor, Department of Mining Engineering, BIT, Ballarpur (MS)

ABSTRACT
As industrial activities and pollution contribute to land scarcity, managing land resources efficiently is crucial for environmental protection and sustainable development. This study evaluates land use changes in the Ramagundam mining region using satellite-based change detection techniques like Land Use Land Cover (LULC), Normalized Difference Vegetation Index (NDVI), and Normalized Difference Water Index (NDWI). These tools facilitate surface feature analysis and offer essential data for policymakers, enhancing decision-making, disaster forecasting, and damage assessment.

Keywords: Spatio-Temporal Analysis, Ramagundam Mining Area, Remote Sensing (RS), Geographic Information System (GIS), LULC, NDVI, NDWI

1. INTRODUCTION

1.1 General
The growing demand for energy in India has driven coal mining, significantly affecting ecosystems through deforestation, pollution, and land degradation. This research focuses on quantifying changes in land cover, including forest areas and water bodies, using satellite imagery from 1990 to 2020.

1.2 Remote Sensing
Remote sensing is the acquisition of information about an object or area from a distance, usually using satellite or airborne sensors, without direct contact.

1.3 Principles of Remote Sensing
Remote sensing principles involve capturing and interpreting reflected or emitted electromagnetic radiation from various surfaces on Earth. Different materials reflect distinct wavelengths, which sensors capture for analysis.

1.4 Geographic Information System (GIS)
GIS integrates and analyzes spatial and non-spatial data to produce color-coded maps, helping visualize data patterns. It plays a critical role in geology, environmental management, and land use planning.

1.5 Land Use and Land Cover (LULC)
LULC refers to human activities and natural vegetation coverage on land. Changes in LULC impact sustainable development and environmental protection. Remote sensing provides critical insights into these transformations over time.

1.6 Normalized Difference Vegetation Index (NDVI)
NDVI measures vegetation health by analyzing the absorption and reflection of specific light wavelengths. Healthy plants absorb visible light and reflect near-infrared light, aiding land cover classification.

1.7 Normalized Difference Water Index (NDWI)
NDWI enhances water feature visibility by analyzing green and near-infrared bands. This index helps identify water bodies and assess their changes over time.

2. LITERATURE REVIEW

2.1 Previous Studies on LULC and Mining Impacts

Numerous global studies have used remote sensing to assess the impact of mining on land use and cover. Most studies highlight significant shifts in vegetation, water bodies, and urban expansion due to mining activities.

2.2 Application of Remote Sensing in Coal Mining Areas

Coal mining activities have been studied extensively using Landsat imagery, revealing valuable insights into land degradation and reclamation efforts.

2.3 Remote Sensing and GIS Techniques for Environmental Monitoring

Remote sensing tools, combined with GIS, have emerged as essential techniques for environmental monitoring, offering precise and timely data to evaluate human activities' impact on ecosystems.

3. METHODOLOGY

3.1 Study Area

The study focuses on the Ramagundam coal mining region, located in Peddapalli district of Telangana, India. The area includes parts of the districts of Peddapalli, Mancherial, Adilabad, Nirmal, and Komuram Bheem Asifabad. The coal mining area is primarily managed by "The Singareni Collieries Company Limited" (SCCL). The study's Area of Interest (AOI) is shown in Figure 3.1.

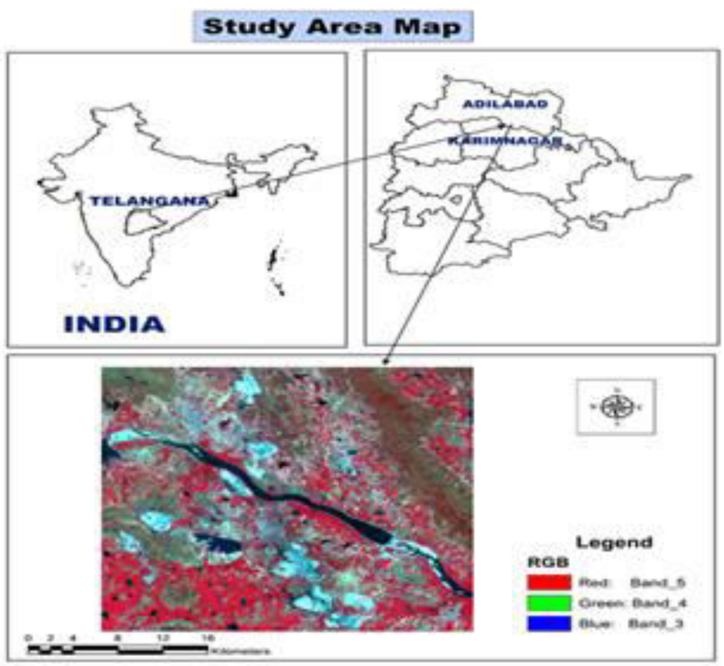

Figure 1 Study Area

3.2 Physiography of Study Area

Ramagundam is a city in Peddapalli district, situated on the banks of the Godavari River at a latitude of 18.759° N and longitude of 79.5134° E, with an elevation of 179 meters. According to the 2011 census, it has an area of 93.87 km² and a population of approximately 2.3 lakhs. The area experiences a climate characterized by hot summers, cold winters, high evaporation rates, and a short rainy season from July to August. Rainfall occurs primarily due to the South-West monsoon, with additional precipitation in September and October due to the North-East monsoon.

3.3 LULC Methodology

The methodology for this study includes various steps such as satellite data acquisition, image pre-processing, digitization, and classification of Land Use Land Cover (LULC).

3.3.1 Data Acquisition and Source

The study uses Landsat satellite images from the years 1990, 1995, 2000, 2005, 2010, 2015, and 2020, obtained from the United States Geological Survey (USGS) Earth Explorer portal. Landsat 4-5 TM and Landsat 8 OLI/TIRS images were used for LULC change analysis . The images were chosen near-anniversary dates to avoid seasonal variability in vegetation cover due to changes in temperature and rainfall.

3.3.2 Image Pre-processing

Pre-processing steps include Layer stacking and AOI creation. Arc GIS (Version 10.4.1) was used for image processing, classification, and map preparation. Pre-processing allows for the accurate alignment and preparation of images for further analysis.

3.3.3 Software and Tools Used

- **Arc GIS (Arc Map 10.4.1):** Used for displaying, processing, and analyzing satellite images, and for LULC classification.
- **Google Earth Pro:** Used as a reference for high-resolution images to assist in the identification of features and mining activities in the study area.

3.3.4 Digitization of Raster Data

Raster data is digitized to convert map information into a digital format. This process allows for the integration of geographic data with other GIS layers, facilitating more comprehensive analysis.

3.3.5 Land Use / Land Cover Classification

A hierarchical classification system with two levels (Level I and Level II) was used. Level I consists of five major classes: Urban Land, Agricultural Land, Forest Land, Water Bodies, and Mining, while Level II includes 17 sub-classes . For example, Urban Land is classified into Built-up and Industrial areas, while Forest Land is divided into Open Forest, Dense Forest, and Shrublands.

3.3.6 LULC Maps

LULC maps were created for the years 1990 to 2020. Each class was identified using a combination of visual interpretation of satellite images and reference data from Google Earth.

3.3.7 Change Detection

A change detection matrix was created using pixel-based cross-tabulation analysis. LULC changes were evaluated for five-year intervals between 1990 and 2020, with the overall change percentage and annual rate of change calculated using the following formulas:

- **LULC Change (%)**

LULCChange(%)={(Present LULC Area−Previous LULC Area) / Previous LULC Area }×100

- **Rate of LULC Change**

Rt=1(t2−t1)×ln(A2/ A1)×100

where A1 and A2 represent the LC areas at times t1 and t2.

3.3.8 Land Use / Land Cover Accuracy Assessment

The accuracy of the classified LULC maps was evaluated by comparing them with reference data such as field visits and high-resolution Google Earth images. Error matrices were generated to assess classification accuracy, and the Kappa Coefficient was used as a measure of agreement between the classified images and the reference data. The accuracy assessment was performed for each time period from 1990 to 2020 (five-year intervals).

3.4 Normalized Difference Vegetation Index (NDVI) Methodology

NDVI is a widely used index for monitoring vegetation health by analyzing the absorption and reflection of light in the red and near-infrared (NIR) bands. The NDVI formula used in the study is:

NDVI=(NIR−Red)/(NIR+Red)

- **For Landsat 4-7:**

NDVI=(Band4−Band3)/(Band4+Band3)

- **For Landsat 8:**

NDVI=(Band5−Band4)/(Band5+Band4)

3.5 Normalized Difference Water Index (NDWI) Methodology

NDWI is used to assess water bodies. It measures the reflectance of water in the green and near-infrared (NIR) bands. The formula for calculating NDWI is:

NDWI=(Green−NIR)/ (Green+NIR)

However, to improve water detection quality, a modified version of the formula (MNDWI) by Xu (2005) was also used, which incorporates the short-wave infrared (SWIR) band.

MNDWI=(Green−SWIR)/ (Green+SWIR)

- **For Landsat 8**

MNDWI=(Band3−Band6)/(Band3+Band6)

3.5.1 NDWI Classification

NDWI values range from -1 to 1. Typically, water bodies have NDWI values above 0.5, while vegetation and built-up areas have much lower or negative values.

4. RESULTS AND DISCUSSION

4.1 General

The study aimed to classify and analyze Land Use/Land Cover (LULC) changes in the Ramagundam coal mining region using Landsat satellite data. Five major LULC categories—Urban Land, Agricultural Land, Forest Cover, Water Bodies, and Mining—were identified. LULC maps for the years 1990, 1995, 2000, 2005, 2010, 2015, and 2020 were generated. The areal statistics of these five categories are shown in Table 4.1, while their percentage distribution is provided in Table 4.2.

Table 4.1: Statistics of Areal Distribution of Level I LULC from 1990 to 2020 (km²)

LULC Classes	1990	1995	2000	2005	2010	2015	2020
Urban land	34.31	34.31	34.31	50.38	55.37	71.57	72.13
Agriculture	722.09	710.65	709.05	688.04	667.6	652.99	643.5
Forest	302.64	293.84	290.39	289.75	290.78	281.44	275.77
Water body	71.11	72.92	72.61	68.68	71.01	71.57	72.21
Mining	9.85	28.28	33.64	43.15	55.22	62.43	76.39

Table 4.2: Areal Distribution of Level I LULC Classes (Percentage)

LULC Classes	1990	1995	2000	2005	2010	2015	2020
Urban land	3	3	3	4.41	4.85	6.27	6.32
Agriculture	63.34	62.33	62.19	60.35	58.56	57.27	56.44
Forest	26.54	25.77	25.47	25.41	25.5	24.68	24.19
Water body	6.23	6.39	6.36	6.02	6.22	6.27	6.33
Mining	0.86	2.48	2.95	3.78	4.84	5.47	6.7

4.2 Areal Distribution of Land Use / Land Cover

The urban land category, which includes built-up and industrial areas, expanded significantly between 1990 and 2020. Urban land area grew from 34.31 km² (3%) in 1990 to 72.13 km² (6.32%) in 2020. This growth was driven by industrialization and population expansion, which occurred largely at the expense of agricultural land.

Agricultural land decreased consistently from 722.09 km² (63.34%) in 1990 to 643.50 km² (56.44%) in 2020 due to increasing urbanization, mining, and industrial activities. Forest cover showed a similar decline, shrinking from 302.64 km² (26.54%) in 1990 to 275.77 km² (24.19%) in 2020.

Mining activities grew steadily, from 9.85 km² (0.86%) in 1990 to 76.39 km² (6.70%) in 2020, due to the opening of new mines and the expansion of existing ones. Water bodies saw only minor fluctuations during the study period, maintaining an area between 6.02% and 6.39%.

4.3 Rate of Change in Land Use / Land Cover

The rate of change in LULC categories is presented in Table 4.3.

Table 4.3: Rate of Change in LULC (% per year)

LULC Classes	90-95	95-00	00-05	05-10	10-15	15-20
Urban land	0	0	7.68	1.88	5.13	0.15
Agriculture	-0.31	-0.04	-0.6	-0.6	-0.44	-0.29
Forest	-0.59	-0.23	-0.04	0.07	-0.65	-0.4
Water body	0.5	-0.08	-1.11	0.66	0.15	0.17
Mining	21.09	3.47	4.97	4.93	2.45	4.03

Urban land grew at the fastest rate between 2000 and 2005 (7.68% per year). Agriculture and forest cover declined consistently over the study period, with the highest decrease in agricultural land occurring between 2000 and 2005 (-0.60% per year). Mining experienced a steady increase, with the most significant growth from 1990 to 1995 (21.09% per year).

4.4 Land Use and Land Cover Accuracy Assessment

Accuracy assessment was conducted using confusion matrices for each year (1990–2020). Tables 4.4 to 4.10 present the confusion matrices for the study period, while Table 4.11 summarizes the overall accuracy and Kappa coefficient values.

Table 4.11: Overall Accuracy and Kappa Coefficient (1990-2020)

Year	1990	1995	2000	2005	2010	2015	2020
Overall Accuracy (%)	89.2	89.6	92.4	96	95.2	94.8	93.6
Kappa Coefficient	0.86	0.86	0.9	0.95	0.94	0.93	0.92

The results showed high classification accuracy, with overall accuracy ranging from 89.2% in 1990 to 96.0% in 2005. Kappa coefficients ranged between 0.86 and 0.95, indicating a strong agreement between classified maps and reference data. Mining, forest, and water bodies were consistently classified with high accuracy.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The study analyzed the impact of mining activities on LULC in the Ramagundam coal mining region between 1990 and 2020. The results show that mining activities led to a significant reduction in agricultural and forest areas, while urban land expanded due to industrialization and population growth.

- The total mining area increased from 9.85 km² in 1990 to 76.39 km² in 2020.
- Agriculture land decreased by approximately 78.59 km², while forest cover declined by 26.87 km² over the study period.

- Urban land expanded by 38 km² from 1990 to 2020.
- Water bodies remained relatively stable throughout the study period, with minor fluctuations in area.

The increase in mining and industrial activities led to environmental degradation, particularly in agricultural and forest areas. However, some positive signs of reclamation were observed, with vegetation cover increasing in certain reclaimed mine areas.

5.2 RECOMMENDATIONS

1. **Comprehensive Knowledge of Study Area:** A thorough understanding of the study area's features is crucial for accurate LULC, NDVI, and NDWI change analysis.
2. **Field-Based Assessments:** While satellite imagery provides valuable data, field-based assessments (e.g., soil and water conditions) are recommended for a more comprehensive analysis.
3. **High-Resolution Data:** Future studies should utilize high-resolution images (5m or better) for more precise LULC classification and change detection, along with monthly data for better temporal accuracy.

REFERENCES

1. Ranjan, A.K., & Parida, B.R. (2019). "Paddy acreage mapping and yield prediction using sentinel-based optical and SAR data in Sahibganj district, Jharkhand (India)." *Spatial Information Research*, 27, 399.
2. Ranjan, A.K., Sahoo, D., & Gorai, A.K. (2020). "Quantitative assessment of landscape transformation due to coal mining activity using earth observation satellite data in Jharsuguda coal mining region, Odisha, India."
3. Thakkar, A.K., Desai, V.R., Patel, A., & Potdar, M.B. (2016). "Post-classification corrections in improving the classification of Land Use/Land Cover of the arid region using RS and GIS: The case of Arjuni watershed, Gujarat, India." *The Egyptian Journal of Remote Sensing and Space Sciences*.
4. Almeida-Filho, R., & Shimabukuro, Y.E. (2000). "Detecting areas disturbed by gold mining activities through JERS-1 SAR images, Roraima State, Brazilian Amazon." *International Journal of Remote Sensing*, 21(17), 3357–3362.
5. Garai, D., & Narayana, A.C. (2018). "Land use/land cover changes in the mining area of Godavari coalfields of southern India." *The Egyptian Journal of Remote Sensing and Space Sciences*.
6. Musaoglu, M., Kaya, S., Seker, D.Z., & Goksel, C. (2002). "A case study of using remote sensing data and GIS for land management: Catalca region." *FIG XXII International Congress*.
7. Yuan, F., Sawaya, K.E., Loeffelholz, B.C., & Bauer, M.E. (2005). "Land cover classification and change analysis of the Twin Cities (Minnesota)." *Remote Sensing of Environment*, 98, 317–328.
8. Chen, J.M. (1996). "Evaluation of vegetation indices and a modified simple ratio for boreal applications." *Canadian Journal of Remote Sensing*, 22(3), 229–242.
9. Koruyan, K., Deliormaanli, A.H., Karaca, Z., Momayez, M., Lu, H., & Yalcin, E. (2012). "Remote sensing in management of mining land and proximate habitat." *The Southern African Institute of Mining and Metallurgy*, 112, 667–672.
10. Zhang, M., Zhou, W., & Li, Y. (2017). "The analysis of object-based change detection in mining area: A case study with Pingshuo Coal Mine." *Remote Sensing and Spatial Information Sciences*, XLII-2/W7, 1017-1023.
11. Tiwari, M.K., & Saxena, A. (2011). "Change detection of land use/land cover pattern in and around Mandideep and Obedullaganj area, using remote sensing and GIS." *International Journal of Technology and Engineering System (IJTES)*, 2(3), 342-350.

12. Singh, N.P., Mukherjee, T.K., & Shrivastava, B.B.P. (1997). "Monitoring the impact of coal mining and thermal power industry on land use pattern in and around Singrauli Coalfield using remote sensing data and GIS." *Journal of the Indian Society of Remote Sensing*, 25(1), 61-72.

13. Singh, N.P., Gupta, V.K., & Singh, A.K. "Geospatial technology for land reclamation monitoring of opencast coal mines in India."

14. Pandian, M., Rajagopal, N., Sakthivel, G., & Amrutha, D.E. (2014). "Land use and land cover change detection using remote sensing and GIS in parts of Coimbatore and Tiruppur districts, Tamil Nadu, India." *International Journal of Remote Sensing & Geosciences (IJRSG)*, 3(1), 15-20.

15. Joshi, P.K., Kumar, M., Midha, N., Vijayanand, & Paliwal, A. (2006). "Assessing areas deforested by coal mining activities through satellite remote sensing images and GIS in parts of Korba, Chhattisgarh." *Journal of the Indian Society of Remote Sensing*, 34(4), 415-422.

16. Mishra, P.K., Rai, A., & Rai, S.C. (2019). "Land use and land cover change detection using geospatial techniques in the Sikkim Himalaya, India." *The Egyptian Journal of Remote Sensing and Space Sciences*.

17. Padmanaban, R., Bhowmik, A.K., & Cabral, P. (2017). "A remote sensing approach to environmental monitoring in a reclaimed mine area." *International Journal of Geo-Information*.

18. Latifovic, R., Fytas, K., Chen, J., & Paraszczak, J. (2004). "Assessing land cover change resulting from large surface mining development." *International Journal of Applied Earth Observation and Geoinformation*, 7, 29–48.

19. Sakthivel, R., Manivel, M., Jawahar raj, N., Pugalanthi, V., Ravichandran, N., & Vijay D., Anand. (2010). "Remote sensing and GIS-based forest cover change detection study in Kalrayan Hills, Tamil Nadu." *Journal of Environmental Biology*, 737-747.

20. Bhandari, S., Phinn, S., & Gill, T. (2012). "Preparing Landsat Image Time Series (LITS) for monitoring changes in vegetation phenology in Queensland, Australia." *Remote Sensing*, Open Access, 1856-1886.

21. Karan, S.K., Samadder, S.R., & Maiti, S.K. (2016). "Assessment of the capability of remote sensing and GIS techniques for monitoring reclamation success in coal mine degraded lands." *Journal of Environmental Management*, 182, 272-283.

22. Bajjali, W. (2018). "Chapter 1: Introduction to GIS." *Springer Science and Business Media LLC*.