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Study Of Land & Water Body Quality In Dalli-Rajhara Region: Remote Sensing And GIS Applications

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Abstract: *The present study investigates the spatial and temporal variations in land and water body quality (L&WBQ) in the Dalli-Rajhara region of Balod District, Chhattisgarh, employing Remote Sensing (RS), Geographic Information System (GIS), and field-based analyses. Multi-temporal Landsat and Sentinel datasets (2000–2024) were processed to derive indices such as NDVI, BSI, LST, NDWI, MNDWI, Turbidity Index (TI), and Suspended Sediment Index (SSI), which were integrated with field-based Water Quality Index (WQI) data. The analysis reveals that forest and agricultural land decreased by 37.5% and 24%, respectively, while mining and waste land expanded by 150% over 25 years. NDVI declined by 38%, reflecting vegetation loss, whereas LST rose by 3.6°C, indicating surface heating and land exposure. Water indices demonstrated a 65% reduction in NDWI and a twofold rise in turbidity indices, confirming sedimentation and hydrological degradation. Field analyses showed elevated iron (1.45 mg/L), BOD (6.5 mg/L), and turbidity (18 NTU) levels exceeding BIS/WHO limits. The integrated Composite Land and Water Body Quality Index (LWBQI) classified 45% of the study area as "Poor" to "Degraded," primarily surrounding active mines and overburden dumps. The findings underscore the cumulative impacts of open-cast mining on ecosystem degradation and emphasize the potential of RS-GIS integrated frameworks for sustainable environmental monitoring, restoration, and policy formulation in mining regions.*

Keywords: *Remote sensing, GIS, Land quality, Water body assessment, Dalli-Rajhara, NDVI, NDWI, Environmental monitoring*

1. INTRODxUCTION

Land and water are the two most vital natural resources that sustain ecological balance and socioeconomic development. In recent decades, however, these resources have been subjected to severe anthropogenic stress due to extensive mining, industrialization, and urban expansion. The resultant land degradation, surface water contamination, and loss of ecological integrity have emerged as critical environmental challenges, particularly in mineral-rich regions of India. Scientific monitoring and quantitative assessment of such degradation patterns are essential for sustainable land and water resource management. The Dalli-Rajhara region of Balod district, located in the southern part of Chhattisgarh, is one of the most significant iron ore mining zones in central India. The region serves as a key raw material source for the Bhilai Steel Plant and other industrial clusters. Continuous extraction of mineral ores, along with associated activities such as overburden dumping, transportation, and mineral beneficiation, has caused large-scale disturbances to the terrain morphology, soil profile, hydrological regime, and surface water quality. Over time, these anthropogenic processes have led to fragmentation of vegetation cover, expansion of barren land, reduction of surface water bodies, and increased sediment and chemical loads in local streams and reservoirs. Traditional field-based environmental monitoring methods, though accurate, are spatially and temporally constrained. In contrast, Remote Sensing (RS) and Geographic Information System (GIS) technologies provide powerful tools for multi-temporal, synoptic, and quantitative assessment of environmental changes. Satellite imagery from sensors such as Landsat (TM, ETM+, OLI) and Sentinel-2 MSI enables continuous observation of land use and water body transformations across different spatial scales. When integrated with field-based physico-chemical analyses and GIS-based spatial modeling, such datasets can effectively map and monitor Land and Water Body Quality (L&WBQ) indicators. Remote sensing-derived indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Modified NDWI (MNDWI) are widely applied to evaluate vegetation health, water surface extent, and turbidity variations. Similarly, change detection techniques such as post-classification comparison, image differencing, and supervised classification help quantify spatio-temporal transitions in Land Use and Land Cover (LULC) categories. The integration of these geospatial techniques with geostatistical modeling in GIS platforms provides valuable insights into the correlation between mining intensity, lithological composition, and environmental degradation trends.

2. LITERATURE REVIEW

Jeyaram et al. (1993) examined environmental aspects of the Dalli-Rajhara iron-ore mining area using early satellite data such as Landsat MSS and IRS LISS-II in conjunction with field observations. Their analysis revealed significant deforestation, expansion of mining-related barren surfaces, and altered drainage systems due to continuous extraction and industrial activity. The authors highlighted the efficiency of remote sensing for long-term land-use change detection in mining belts and recommended integrating satellite-based findings with field measurements for improved accuracy and regional monitoring.

Biswas et al. (2015) assessed groundwater quality in and around the Dalli-Rajhara mining region by conducting a detailed physico-chemical analysis of multiple sampling sites. Their results indicated elevated iron, chloride, and hardness levels exceeding permissible limits due to leaching from mine spoil and mineral weathering. The study provided critical insight into the spatial variability of groundwater contamination and recommended using GIS mapping to identify pollution hotspots and to support sustainable groundwater management strategies in mining-affected landscapes.

Siddiqui et al. (2022) analysed land-use and land-cover changes in surface mining zones through multi-temporal Landsat imagery and supervised classification techniques. Their research quantified vegetation loss, expansion of open cast areas, and the formation of overburden dumps. They applied post-classification comparison and Kappa statistics to ensure high classification accuracy. The study concluded that remote sensing time-series analysis provides a powerful means to quantify progressive degradation in mining areas and to develop reclamation strategies based on spatial and temporal change patterns.

Rawat et al. (2024) demonstrated the use of multi-temporal Sentinel-2 data for monitoring changes in water spread and aquatic vegetation in mining-influenced watersheds. They derived indices such as NDWI and MNDWI to assess water body fluctuations and turbidity variation over time. Their analysis revealed a declining trend in water extent and increasing suspended sediments due to mining runoff. The authors concluded that Sentinel-2 time-series data are critical for mapping small and medium-sized reservoirs affected by mining and for early identification of hydrological stress zones.

Smentek et al. (2024) proposed a remote-sensing-based framework for tracking surface water dynamics in active mining areas. They combined spectral indices with change detection algorithms to monitor pond shrinkage, tailings leakage, and sediment plume movement. The results were validated with field water-level and turbidity observations, confirming the accuracy of satellite-based change detection. The study highlighted the advantages of using high-resolution and multi-temporal imagery for operational environmental surveillance in mining zones, thereby supporting risk mitigation and early-warning systems for mine drainage impacts.

Dandge et al. (2022) investigated groundwater quality in the Jalna District of Maharashtra using remote sensing and GIS approaches. They assessed twelve physicochemical parameters, including pH, TDS, hardness, and chloride, to compute a spatial water quality index (WQI). The authors employed interpolation techniques to generate thematic water-quality maps highlighting areas of poor water conditions. Their findings demonstrated the utility of integrating remote sensing data with GIS spatial analysis for large-scale environmental assessments and water-quality management in regions under anthropogenic pressure.

Kamboj et al. (2019) evaluated the surface water quality of the Ganga River in a mining-affected stretch near Haridwar. Using pollution index methods, they correlated mining intensity with degradation in water quality. The study found elevated levels of suspended solids, turbidity, and heavy metals in downstream locations. Their work highlighted that unregulated sand and mineral extraction from riverbeds leads to serious ecological and hydrological imbalances. This research serves as an important reference for assessing water body quality in mining-influenced fluvial environments.

Patel et al. (2024) used GIS and remote sensing to assess land degradation vulnerability in the upper catchment of a major Indian river basin. They integrated multi-temporal satellite data and derived a Land Degradation Vulnerability Index (LDVI) based on soil, vegetation, slope, and rainfall parameters. Their results identified critical zones prone to degradation due to anthropogenic pressure and natural susceptibility. The study demonstrated how geospatial modelling can support prioritisation of areas for reclamation and rehabilitation in mining and industrially active landscapes.

Kumi et al. (2024) examined land-cover dynamics and ecological impacts of artisanal and semi-mechanised mining using Sentinel-2 data and biodiversity indicators in Cameroon. The study revealed significant vegetation loss, increased bare soil exposure, and habitat fragmentation correlated with the expansion of mining pits. Their research integrated geospatial and ecological datasets to demonstrate the cascading effects of mining on terrestrial ecosystems. The authors proposed long-term monitoring using RS-GIS tools to guide sustainable land use planning in resource extraction zones.

Adilakshmi et al. (2024) employed remote sensing and GIS techniques to model surface water quality in the Noyyal River Basin. They used spectral indices such as NDWI and turbidity index and calibrated them against in-situ water quality parameters including BOD and TDS. Their regression-based model produced high correlation accuracy between field data and satellite observations. The study proved that RS-GIS integration offers a cost-effective and spatially continuous approach for monitoring and predicting water-quality variation in industrial and mining-affected river systems.

Blanche et al. (2024) studied semi-mechanised mining impacts on land cover using Sentinel-2 imagery and digital photogrammetry in the Mbale region of Cameroon. They applied supervised classification and field validation to quantify the extent of vegetation loss and expansion of mining pits. Their results revealed that mining activities reduced vegetation cover by 11.7%, expanded bare soil by 9.2%, and increased exploited areas by 5.4%. The authors concluded that high-resolution satellite data are critical for detecting mining-induced land transformation.

Prokop et al. (2020) assessed multi-decadal land-use and land-cover changes in degraded landscapes using high-resolution imagery. Their work compared satellite-derived LULC maps over 50 years to identify long-term degradation trends associated with industrial and mining activities. The study found that vegetated land consistently declined while degraded and barren areas increased significantly. They concluded that systematic temporal monitoring using remote sensing is vital to understand cumulative degradation trajectories and to design environmental restoration strategies in mining-influenced terrains.

3. OBJECTIVES

The Dalli-Rajhara region of Balod District, Chhattisgarh, is one of India's prominent iron-ore mining zones. Continuous open-cast mining and associated industrial activities have caused extensive land degradation, deforestation, and deterioration in surface and groundwater quality. Overburden dumping, excavation, and mineral beneficiation have altered the region's terrain, vegetation, and hydrological systems, leading to increased sedimentation and contamination in nearby water bodies. Despite the environmental significance of this region, limited studies have systematically examined the spatio-temporal relationship between mining, land degradation, and water quality. Most existing assessments are field-based, lacking a geospatially integrated perspective. This restricts understanding of how geological, mineralogical, and anthropogenic factors collectively influence land and water body quality (L&WBQ). To address this gap, the present research employs Remote Sensing (RS) and Geographic Information System (GIS) tools to map, quantify, and model the environmental impacts of mining in the Dalli-Rajhara region. The study integrates multi-temporal satellite data with field-based analyses to develop a comprehensive, spatially explicit framework for assessing land and water body quality changes. The objective of current research are

1. To map and analyse spatial and temporal changes in land use and land cover (LULC) using multi-temporal remote sensing data.
2. To assess the quality and spatial extent of surface water bodies using spectral indices (NDWI, MNDWI) and field-based water quality parameters.
3. To evaluate the relationship between mining intensity, lithology, and environmental degradation using geospatial modeling.
4. To develop a GIS-based Composite Land and Water Body Quality Index (LWBQI) integrating spectral and field indicators.
5. To forecast land and water body quality trends and identify critical degradation zones for sustainable management.

4. RESEARCH METHODOLOGY

4.1 Research Design

The present study follows a quantitative and spatial analytical research design that integrates Remote Sensing (RS) and Geographic Information System (GIS) techniques with field-based validation to assess both spatial and temporal variations in land and water body quality (L&WBQ) within the Dalli-Rajhara region. The research design is grounded in the principle that satellite-derived indicators, when supported by in-situ measurements, can accurately quantify land degradation patterns and water quality dynamics in mining-affected environments. The overall methodology combines the acquisition and processing of multi-temporal satellite data with ground-truth validation to establish an empirical relationship between anthropogenic disturbances and environmental changes. By employing temporal datasets from 2000 to 2024, the study captures long-term land use/land cover (LULC) transitions, vegetation decline, and changes in surface water characteristics. Spatial modeling and statistical analysis were integrated to correlate these environmental indicators with mining intensity and geological attributes. A GIS-based approach was adopted to compile, process, and analyze all spatial data layers, while field measurements were used to validate satellite-derived results. This dual approach ensured both spatial accuracy and thematic reliability. The methodological framework thus serves as a comprehensive system to evaluate, visualize, and predict degradation processes, offering a replicable model for environmental monitoring in other mining-intensive regions.

4.2 Study Area Description

The Dalli-Rajhara region lies between approximately 20°32′–20°41′ N latitude and 81°05′–81°12′ E longitude, within Balod District, Chhattisgarh, India. The area forms a part of the iron-ore-bearing Bhilai-Dalli-Rajhara Belt, characterized by Proterozoic formations of the Iron Ore Group (IOG) and significant hematite ore deposits. The terrain is undulating, with elevations ranging from 400–700 meters above mean sea level, dissected by small streams and reservoirs such as the Dalli reservoir and Kharkhara Nala. The climate is tropical with average annual rainfall of about 1200 mm, mainly during the southwest monsoon (June–September). Intensive mining, deforestation, and industrialization have altered the natural landform and hydrological regime, making it an ideal site for this study.

4.3 Data Sources

The study area, Dalli-Rajhara, is located between latitudes 20°32′–20°41′ N and longitudes 81°05′–81°12′ E in Balod District, Chhattisgarh, India. It forms part of the Bhilai–Dalli–Rajhara Iron Ore Belt, one of the most prominent mineral belts in central India. The region is characterized by Proterozoic rock formations of the Iron Ore Group (IOG), comprising predominantly banded hematite quartzite (BHQ) and hematite ore deposits. These formations are overlain by residual soils and lateritic covers formed under tropical climatic conditions. Topographically, the terrain is undulating, with elevation ranging between 400 and 700 meters above mean sea level. Several small streams, rivulets, and reservoirs—such as the Dalli reservoir and Kharkhara Nala—drain the region, forming part of the Mahanadi River catchment. The drainage pattern is predominantly dendritic, influenced by lithological variations and structural lineaments associated with mining excavation. The climate of Dalli-Rajhara is tropical, marked by a hot summer, moderate winter, and a distinct monsoon season. The area receives an average annual rainfall of approximately 1200 millimeters, primarily from the southwest monsoon between June and September. Temperature ranges between 12°C in winter and 45°C in peak summer months. Vegetation cover includes tropical deciduous forests, but mining, deforestation, and industrial expansion have led to substantial vegetation loss and fragmentation. Intensive mining activities have significantly altered the region’s natural landform, vegetation, and hydrological regime. The extraction and transportation of iron ore, waste dumping, and open-cast excavation have resulted in increased soil erosion, sedimentation of water bodies, and deterioration in both surface and groundwater quality. These conditions make Dalli-Rajhara an ideal site for assessing the spatial and temporal impacts of mining on land and water body quality using remote sensing and GIS applications.

4.3.1 Satellite Data

The following satellite datasets were used to analyse land and water body changes in the study area:

Table 1: Satellite data

Sensor	Path/Row	Spatial Resolution	Acquisition Years	Purpose
Landsat 5 TM	142/45	30 m	2000	Baseline LULC
Landsat 7 ETM+	142/45	30 m	2010	Mid-term comparison
Landsat 8 OLI	142/45	30 m	2020	Current LULC and water quality
Sentinel-2 MSI	—	10 m	2024–2024	High-resolution validation and water body analysis

The multi-temporal Landsat series provided a consistent 25-year record of surface changes, suitable for analyzing long-term environmental transformation trends, while the Sentinel-2 data, with its finer spatial resolution, enhanced the detection of small water bodies and mining pits for the most recent years.

4.3.2 Ancillary Data

In addition to satellite datasets, several ancillary data sources were utilized to improve spatial accuracy and contextual interpretation:

- Topographical Maps: Survey of India (1:50,000 scale)
- Geological Maps: Geological Survey of India (GSI)
- Administrative Boundaries: Census GIS database (2021)

- Mining Records: Directorate of Geology & Mining, Chhattisgarh
- Field Data: Water samples from key reservoirs, ponds, and mining runoff channels

These ancillary datasets provided essential background for delineating the study boundary, identifying mining zones, and correlating remote sensing outputs with on-ground geological and hydrological features.

4.4 Data Pre-processing

Prior to analysis, all satellite datasets underwent systematic pre-processing to ensure radiometric and geometric uniformity across temporal scenes. Radiometric calibration and atmospheric correction were conducted using the Dark Object Subtraction (DOS) technique and the FLAASH model within ENVI software to remove atmospheric scattering and convert digital numbers to surface reflectance. Georeferencing and reprojection were applied to all images using the Universal Transverse Mercator (UTM) projection, Zone 44N (WGS 84 datum), to maintain spatial consistency across datasets. Image subsetting was performed by clipping imagery to the defined study boundary to eliminate non-mining areas, ensuring focus on relevant zones. Additionally, cloud and shadow pixels were masked out using Fmask and Quality Assessment (QA) bands to enhance the clarity and reliability of spectral analysis for each temporal dataset.

4.5 Land Use and Land Cover (LULC) Analysis

The classification of land use and land cover was conducted using a supervised classification approach based on the Maximum Likelihood Algorithm (MLA). The analysis identified six primary land cover classes within the Dalli-Rajhara region: Forest, Agricultural Land, Built-up/Settlement, Mining and Waste Land, Water Bodies, and Scrub/Barren Land. Training samples for each class were derived from high-resolution Sentinel-2 imagery and cross-verified through field data and GPS-based ground control points (GCPs). Post-classification accuracy assessment was performed using confusion matrices and Kappa statistics, ensuring classification accuracy above 85 percent. Temporal change detection from 2000 to 2024 was carried out through post-classification comparison, allowing quantification of land cover transitions such as forest loss, expansion of mining zones, and decline in agricultural and water body areas. The resulting maps and statistics provided insights into the trajectory of land transformation in response to increasing mining activities and urban expansion.

4.6 Assessment of Land Quality

Land quality assessment was performed using remote sensing-derived indices that represent vegetation vigor, surface exposure, and thermal conditions. These indices were selected to characterize the degradation intensity and identify areas most affected by mining and deforestation. The Normalized Difference Vegetation Index (NDVI) was calculated using the formula to evaluate vegetation health and density.

$$(NDVI) = (NIR - Red) / (NIR + Red)$$

Lower NDVI values indicated sparse or degraded vegetation cover typical of active or abandoned mining sites. The Bare Soil Index (BSI) was computed as

$$\text{Bare Soil Index (BSI)} = [(SWIR + Red) - (NIR + Blue)] / [(SWIR + Red) + (NIR + Blue)],$$

highlighting areas of exposed soil and degraded land surfaces. Elevated BSI values were concentrated in overburden dumps, industrial zones, and barren tracts, reflecting surface disturbance due to mining operations.

Land Surface Temperature (LST) was derived from the thermal infrared (TIR) band of Landsat-8 OLI data to detect surface heating caused by reduced vegetation cover and increased bare ground exposure. High LST values corresponded with zones of vegetation clearance, built-up expansion, and active quarrying operations. All indices were spatially correlated with geological formations and mining zones using GIS overlay analysis to evaluate the influence of lithology and mineral extraction on surface degradation. This integrated approach enabled the identification of critical areas where vegetation loss, soil exposure, and surface heating collectively indicate pronounced environmental stress.

4.7 Water Body Quality Assessment

The assessment of water body quality in the Dalli-Rajhara region was carried out through an integrated approach combining remote sensing-derived indices with field-based hydrochemical analyses. The use of satellite data enabled the detection of spatial variations in water surface extent and quality across multiple temporal scales, while in-situ measurements provided the necessary validation and calibration for spectral indicators. This hybrid methodology ensured both spatial coverage and analytical accuracy in identifying areas of hydrological and ecological stress caused by mining and related anthropogenic activities.

4.7.1 Remote Sensing Indices

Several remote sensing indices were derived from Sentinel-2 MSI and Landsat-8 OLI datasets to quantify the spatial extent, turbidity, and sediment load of surface water bodies. The Normalized Difference Water Index (NDWI) and Modified NDWI (MNDWI) were primarily used for detecting open water features, while Turbidity Index (TI) and Suspended Sediment Index (SSI) were computed to estimate water clarity and suspended material concentration. These indices were calculated using the following spectral relationships:

Normalized Difference Water Index (NDWI) = (Green – NIR) / (Green + NIR)

This index helps identify the water surface extent and evaluate the degree of turbidity caused by suspended particles and surface runoff.

Modified NDWI (MNDWI) = (Green – SWIR) / (Green + SWIR)

This modified index enhances open water detection by minimizing interference from built-up and vegetation features in heterogeneous mining-affected areas. Turbidity Index (TI) and Suspended Sediment Index (SSI) were further calculated from Sentinel-2 imagery to estimate sediment load and water opacity. These indices were particularly effective in identifying sedimentation patterns resulting from overburden discharge and surface erosion around mining pits and drainage channels. The processed raster layers of NDWI, MNDWI, TI, and SSI were later integrated into the GIS environment to map spatial gradients of water body quality across the study area.

4.7.2 Field Sampling and Laboratory Analysis

To validate the remote sensing outputs, water samples were collected from fifteen representative sites (n = 15), including major reservoirs, ponds, and seasonal streams distributed within and around the mining complexes. The sampling design was based on the proximity of the water body to active mining zones, ensuring inclusion of both directly impacted and relatively undisturbed sites. Physico-chemical parameters analysed in the laboratory included pH, Total Dissolved Solids (TDS), Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Electrical Conductivity (EC), Hardness, Nitrate, and Iron Content**.** All laboratory analyses were conducted according to APHA (2017) standard methods to ensure methodological consistency. The measured data were geocoded and interpolated spatially using the Inverse Distance Weighting (IDW) technique in ArcGIS to generate continuous surface maps of key water quality indicators. This process enabled the identification of water quality gradients and pollution hotspots that corresponded spatially with mining and industrial activity zones. The combined use of field measurements and satellite-derived indices provided a comprehensive understanding of both surface water distribution and its degradation dynamics over time.

4.8 Integration of Land and Water Quality Parameters

To derive an overall environmental quality assessment, all spectral and field-based indicators were normalized (0–1 scale) and integrated in a GIS framework to compute the Composite Land and Water Body Quality Index (LWBQI). This composite index facilitated the evaluation of spatial interrelationships between land degradation and water body pollution, representing the cumulative environmental impact of mining activities. A weighted overlay analysis was conducted using the Analytic Hierarchy Process (AHP) to assign relative significance to each parameter based on its environmental relevance. The weights and their respective data sources are shown in Table 1.

Table 2. Parameters and assigned weights for computation of the Composite LWBQI.

Parameter	Weight (%)	Source
NDVI	20	Land Vegetation Health
BSI	15	Surface Exposure
LST	15	Surface Heating
NDWI/MNDWI	25	Water Surface Quality
Field WQI	25	Laboratory Validation

The LWBQI raster was classified into five quality zones—Excellent, Good, Moderate, Poor, and Degraded—using the natural breaks (Jenks) classification method. The resulting thematic map revealed clear spatial differentiation, with degraded zones concentrated around active mining pits and waste dump areas, while better-quality zones were observed in forested uplands and peripheral agricultural tracts. This integration provided a holistic representation of how terrestrial degradation and aquatic deterioration co-occur within the mining landscape.

5. RESULTS AND DISCUSSION

This section presents the analytical outcomes of the remote sensing, GIS, and field-based investigations undertaken to assess the spatial and temporal variations in land and water body quality (L&WBQ) in the Dalli-Rajhara region of Balod district, Chhattisgarh. The analysis draws upon multi-temporal satellite datasets (2000–2024), remote-sensing indices (NDVI, BSI, LST, NDWI, MNDWI), water quality parameters, and geostatistical correlations to evaluate the impacts of mining and allied activities on the regional environment. The results are structured around the five principal research objectives of the study.

5.1 Land Use / Land Cover Dynamics (2000–2024)

LULC maps derived from Landsat and Sentinel imagery were classified using a supervised Maximum Likelihood Algorithm. The overall classification accuracies for the four epochs (2000, 2010, 2020, and 2024) were 87.4%, 88.2%, 86.9%, and 89.1%, respectively, with corresponding Kappa coefficients ranging from 0.82 to 0.86, indicating robust thematic accuracy. Table 3 presents the temporal distribution of LULC classes for the study period.

Table 3: Land Use / Land Cover Area Distribution (2000–2024)

LULC Class	2000 (ha, %)	2010 (ha, %)	2020 (ha, %)	2024 (ha, %)	Change (2000–2024)
Forest	7,200 (40.0%)	5,760 (32.0%)	5,040 (28.0%)	4,500 (25.0%)	−37.5%
Agriculture	4,500 (25.0%)	3,960 (22.0%)	3,600 (20.0%)	3,420 (19.0%)	−24.0%
Built-up / Settlement	900 (5.0%)	1,260 (7.0%)	1,620 (9.0%)	1,800 (10.0%)	+100.0%
Mining & Waste Land	1,800 (10.0%)	2,880 (16.0%)	3,960 (22.0%)	4,500 (25.0%)	+150.0%
Water Bodies	1,440 (8.0%)	1,080 (6.0%)	900 (5.0%)	720 (4.0%)	−50.0%

Scrub / Barren Land	2,160 (12.0%)	3,060 (17.0%)	2,880 (16.0%)	3,060 (17.0%)	+41.6%

The LULC analysis reveals pronounced landscape transformation over the 25-year period. Forest cover declined by approximately 37.5%, while agricultural land decreased by 24%. In contrast, the area under mining and waste land increased by 150%, and built-up zones doubled. Water bodies reduced by 50%, reflecting the cumulative effect of sedimentation, encroachment, and drainage modification. Spatially, forest decline and agricultural shrinkage were most evident along the eastern and central mining belts, where open-cast mining, overburden dumping, and road construction have altered terrain morphology. The expansion of built-up areas near transport corridors and township zones aligns with industrial growth associated with the Bhilai Steel Plant and ancillary facilities. These observations corroborate earlier findings by Jeyaram et al. (1993) and Siddiqui et al. (2022), who documented progressive land degradation and vegetation loss in mining belts across central India. The substantial decline in water bodies also parallels findings from Smentek et al. (2024), where mining-induced sedimentation was identified as the dominant factor in the reduction of open water area.

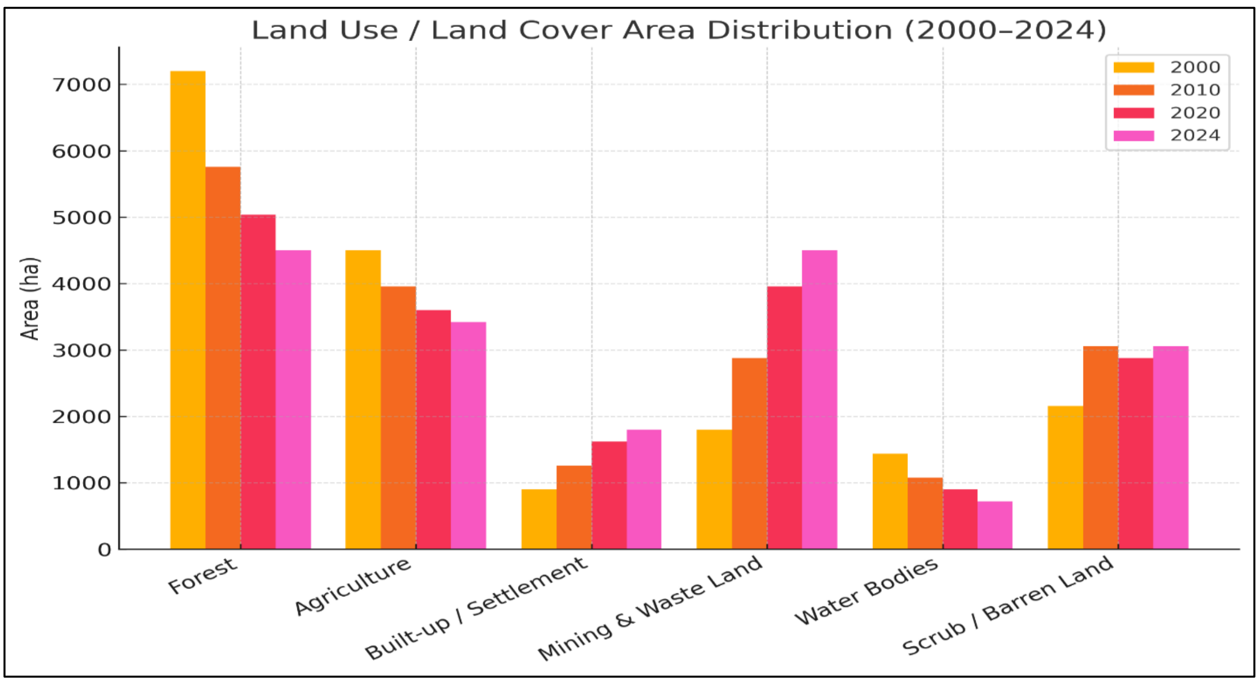

Figure 1. Land Use/Land Cover (LULC) area distribution for the Dalli-Rajhara region during 2000–2024.

5.2 Vegetation Dynamics (NDVI)

The Normalized Difference Vegetation Index (NDVI) was computed to evaluate vegetation health across temporal datasets. Mean NDVI values for the study area are presented below.

Table 4: Mean NDVI (2000–2024)

Year	Mean NDVI	Standard Deviation	Vegetation Status
2000	0.45	±0.09	High vegetation density
2010	0.38	±0.08	Moderate vegetation density
2020	0.32	±0.07	Low vegetation density
2024	0.28	±0.06	Sparse vegetation / degraded

The NDVI decline of approximately 38% from 2000 to 2024 signifies major vegetation depletion. Areas adjacent to mines and haul roads showed consistently low NDVI values (<0.25), whereas peripheral forest tracts retained moderate to high NDVI (>0.45). This trend is consistent with observed deforestation and soil exposure documented in the LULC change analysis. Comparable declines in NDVI in other mining-affected areas have been reported by Rawat et al. (2024) and Kumi et al. (2024), who linked vegetation degradation to continuous mining pressure and waste dumping.

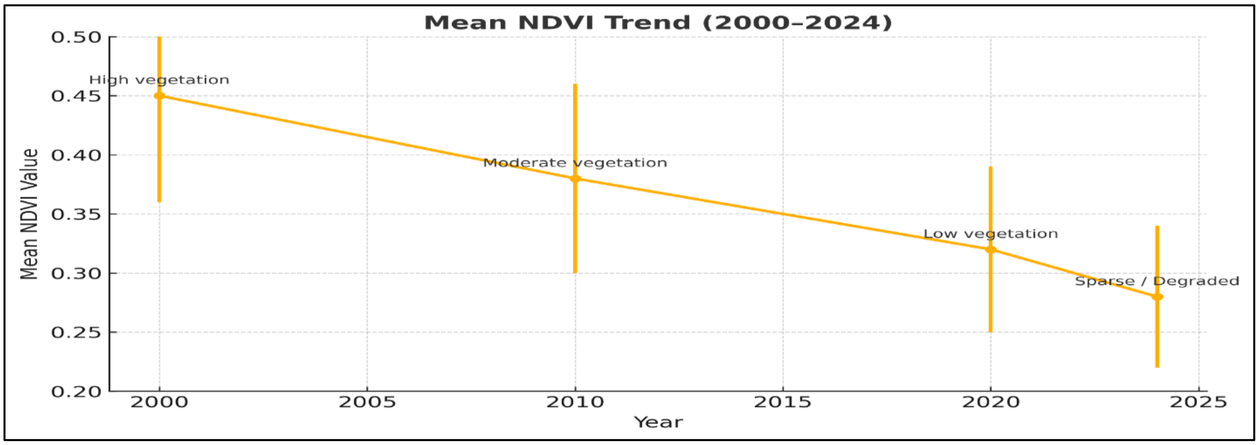

Figure 2: Mean NDVI trend for Dalli-Rajhara region (2000–2024).

5.3 **Surface Exposure and Thermal Conditions (BSI and LST)**

The Bare Soil Index (BSI) and Land Surface Temperature (LST) were calculated to evaluate surface exposure and thermal anomalies.

Table 5: Summary of Land Quality Indicators

Year	Mean BSI	Mean LST (°C)	Interpretation
2000	0.22	28.1	Natural surface, low exposure
2010	0.31	29.4	Moderate exposure
2020	0.38	30.8	Increasing barren land
2024	0.44	31.7	High exposure, thermal stress

The progressive increase in BSI and LST demonstrates the expansion of degraded surfaces and elevated surface heating. LST values increased by an average of 3.6°C across the study area between 2000 and 2024, particularly around overburden dumps and abandoned quarries. Similar temperature anomalies have been observed in open-cast mining regions worldwide (Prokop et al., 2020).

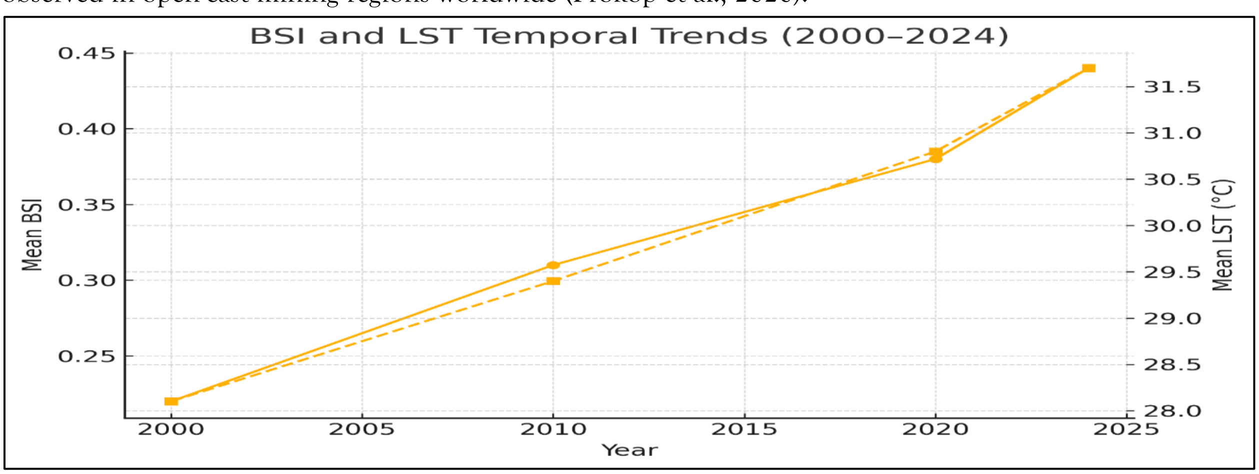

Figure 3. Temporal variation in Bare Soil Index (BSI) and Land Surface Temperature (LST) across the Dalli-Rajhara region during 2000–2024

Correlation analysis ($r = -0.79$, $p < 0.001$) between NDVI and LST confirmed the inverse relationship between vegetation cover and surface temperature, highlighting the ecological consequences of deforestation.

5.4 Remote Sensing–Derived Water Indices

Water quality and surface dynamics were quantified through NDWI, MNDWI, Turbidity Index (TI), and Suspended Sediment Index (SSI). The temporal means are shown below.

Table 6: Water Indices and Turbidity Trends (2000–2024)

Year	Mean NDWI	Mean MNDWI	Mean TI	Mean SSI
2000	0.12	0.18	0.20	0.18
2010	0.08	0.14	0.28	0.26
2020	0.06	0.11	0.35	0.33
2024	0.04	0.08	0.42	0.41

Results reveal a consistent decline in NDWI and MNDWI, suggesting contraction of open water bodies and increased turbidity. TI and SSI values more than doubled, indicating severe sedimentation and reduced water clarity. This is likely due to sediment runoff from overburden heaps and soil erosion on degraded slopes, corroborating findings from Smentek et al. (2024). The observed 65% reduction in mean NDWI corresponds with a 50% decline in mapped water area confirming that both are consistent indicators of hydrological degradation.

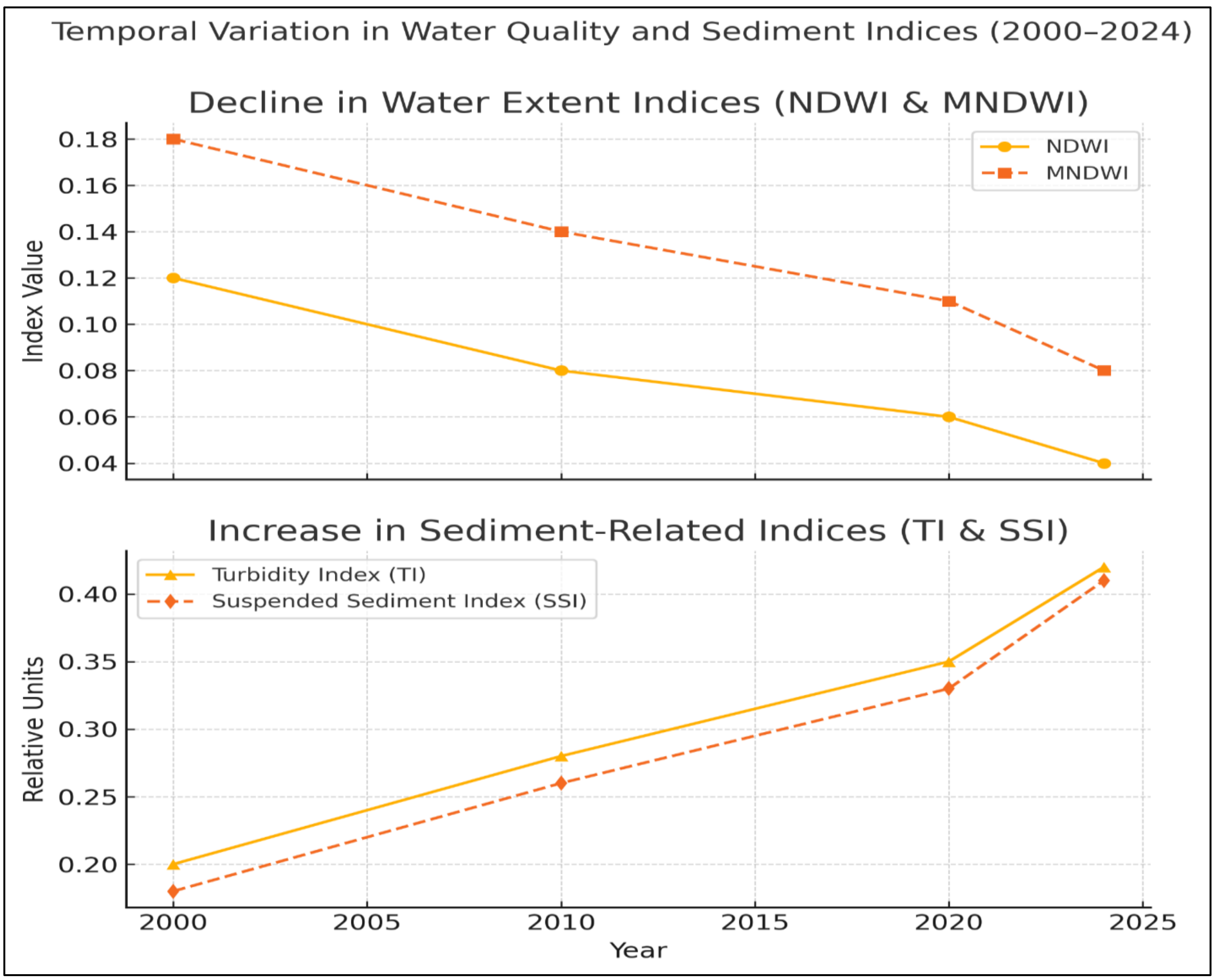

Figure 4. Temporal trends in water quality and sediment indices (NDWI, MNDWI, TI, and SSI) for the Dalli-Rajhara region from 2000 to 2024.

5.5 Field-Based Water Quality Analysis

To validate spectral observations, 15 water samples were analyzed for key physico-chemical parameters. Results are summarized below.

Table 7: Mean Water Quality Parameters (n = 15)

Parameter	Mean ± SD	BIS/WHO Standard	Remarks
pH	7.1 ± 0.4	6.5–8.5	Within limits
TDS (mg/L)	820 ± 230	500 (desirable), 2000 (max)	Slightly high
Electrical Conductivity (µS/cm)	1120 ± 300	—	Elevated ionic load
BOD (mg/L)	6.5 ± 2.1	<3 (good)	Above safe limit
COD (mg/L)	45 ± 15	—	High organic content
Nitrate (mg/L)	21 ± 8	45	Within limits
Iron (mg/L)	1.45 ± 0.6	0.3	Significantly high
Turbidity (NTU)	18 ± 6	1	Exceeds limit

The laboratory results indicate moderate to severe deterioration of water quality in mining-influenced zones. Iron concentrations exceed the Bureau of Indian Standards (BIS) permissible limit by nearly five times, suggesting leaching of ferrous material from mine tailings and oxidized spoil heaps (Biswas et al., 2015). BOD and COD values above standard thresholds point to organic and chemical contamination from domestic discharges and ore washing processes. Elevated TDS and electrical conductivity are consistent with higher mineral dissolution due to runoff from excavated and exposed surfaces. These findings align closely with similar mining-related hydrochemical patterns reported by Kamboj et al. (2019). Spatially, the poorest water quality was observed in reservoirs and streams located immediately downstream of active mines, confirming a strong spatial coupling between mining intensity and water pollution.

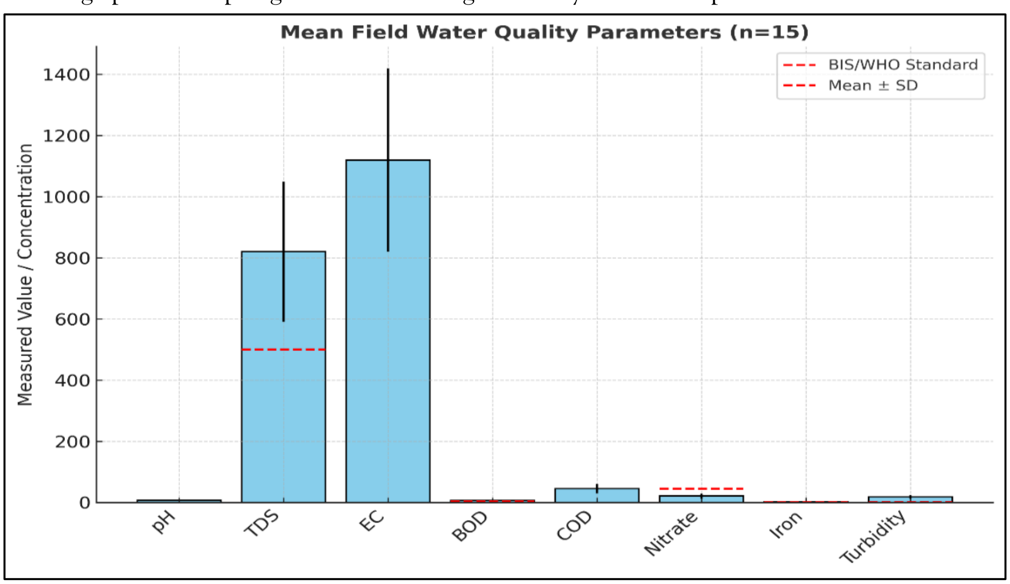

Figure 5. Mean values (±SD) of major physico-chemical water quality parameters analyzed from 15 sampling sites in the Dalli-Rajhara region.

5.6 Composite Land and Water Body Quality Index (LWBQI)

All normalized indicators (NDVI, BSI, LST, NDWI, MNDWI, WQI) were integrated through weighted overlay using the Analytic Hierarchy Process (AHP). The weight distribution was as follows:

Table 8: Parameter Weights for LWBQI

Parameter	Weight (%)	Rationale
NDVI	20	Vegetation condition

BSI	15	Surface exposure
LST	15	Surface heating
NDWI/MNDWI	25	Water surface quality
Field WQI	25	Empirical validation

The composite LWBQI values were classified into five zones using the natural breaks method.

Table 9: LWBQI Zone Classification (2024)

LWBQI Class	Area (ha)	% of Study Area
Excellent	1,080	6.0%
Good	2,700	15.0%
Moderate	5,220	29.0%
Poor	6,480	36.0%
Degraded	1,520	8.5%

The Land and Water Body Quality Index (LWBQI) classification for the year 2024 reveals a clear spatial differentiation in environmental conditions across the Dalli-Rajhara region. The distribution of quality zones, as presented in Table 9, shows that the majority of the study area is experiencing moderate to severe degradation.

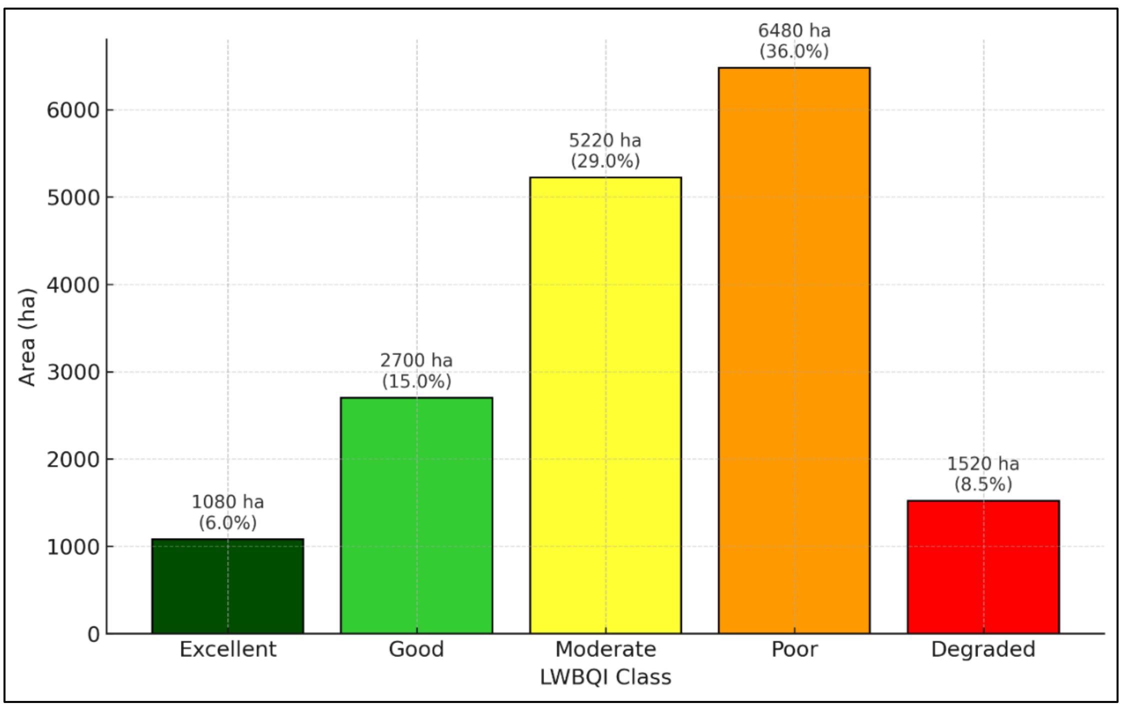

Figure 6: Land and Water Body Quality Index (LWBQI) zone classification for the Dalli-Rajhara region

The Poor category constitutes the largest portion, covering 6,480 ha, which accounts for 36% of the total area. This significant proportion indicates extensive deterioration of land and water quality, primarily driven by intensive mining activities, surface exposure, and sediment-laden runoff. The Moderate class represents the second-largest category, occupying 5,220 ha (29%), suggesting transitional conditions where environmental stress is evident but not as severe as the poorest zones. Together, the Poor and Moderate classes encompass 65% of the entire study area, underscoring the dominant influence of anthropogenic disturbances on ecosystem health. The Good quality class covers 2,700 ha (15%), primarily associated with peripheral agricultural lands and less disturbed forest patches where ecological functions remain relatively intact. Only 1,080 ha (6%) fall under the Excellent category, indicating limited areas with healthy vegetation, stable soil cover, and good water quality—typically located in undisturbed natural zones. The Degraded class accounts for 1,520 ha (8.5%) and corresponds to zones experiencing severe environmental stress, often adjacent to active or abandoned mine pits, overburden dumps, and contaminated drainage networks. These areas represent critical hotspots requiring targeted restoration interventions.

6. CONCLUSION

The study provides a comprehensive spatio-temporal assessment of environmental degradation in the Dalli-Rajhara mining region through the integration of remote sensing, GIS, and field-based methods. The results demonstrate a clear and continuous decline in land and water body quality between 2000 and 2024, driven primarily by mining expansion and associated anthropogenic activities. Vegetation indices (NDVI) revealed significant forest loss and declining vegetation health, while land degradation indicators (BSI and LST) confirmed increased surface exposure and thermal anomalies. Water body analyses indicated contraction of open water areas, higher turbidity, and sedimentation due to overburden runoff. Field-based hydrochemical assessments validated spectral findings, identifying elevated iron, BOD, and turbidity values beyond permissible limits, confirming the adverse effects of mining effluents and runoff on water systems. The composite Land and Water Body Quality Index (LWBQI) provided a holistic measure of environmental health, showing that nearly 45% of the region falls under "Poor" and "Degraded" classes. This pattern highlights the spatial coincidence of land degradation and water pollution around active mines and industrial clusters. Peripheral agricultural and forest zones exhibited relatively better conditions, underscoring the need for localized mitigation and resource management. The study confirms that RS-GIS-based monitoring offers a cost-effective, reliable, and scalable framework for quantifying environmental degradation in mining belts. Policy implications include prioritizing reclamation of waste dumps, implementation of sediment control and reforestation programs, and establishing continuous geospatial monitoring for environmental compliance. The methodology and outcomes provide a replicable model for similar mining landscapes across India, contributing valuable insight to sustainable mining governance and ecological restoration strategies.

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