



MONITORING ECOLOGICAL RESTORATION DYNAMICS IN THE JHARIA COALFIELD THROUGH REMOTE SENSING AND GEOSPATIAL ANALYSIS

Pranay Ramesh MOON¹, Manas DAS¹, Debasish SINGH¹, Amit Kumar MANKAR¹,
Mohammad Farooq BHAT¹, Radhakanta KONER^{1*}

¹Department of Mining Engineering, Indian Institute of Technology (Indian School of Mines),
Dhanbad, India

DOI: 10.2478/minrv-2026-0044

received – 09.03.2026 / revised – 13.03.2026

accepted – 07.05.2026 / published – 22.09.2026

Abstract: The Jharia Coalfield (JCF), India's most environmentally stressed coking-coal basin, has endured prolonged ecological degradation driven by open-cast mining, persistent coal-seam fires, and progressive vegetation loss. This study presents a novel multi-decadal assessment of ecological restoration dynamics across JCF from 2005 to 2025 using an integrated geospatial framework that combines Tasseled Cap Transformation (TCT), Spectral Mixture Analysis (SMA), Continuous Change Detection and Classification (CCDC), Normalised Burn Ratio (NBR), hotspot analysis (Getis–Ord G_i^*), and a Random Forest (RF)-derived Ecological Restoration Score (ERS). Multi-temporal Landsat TM/ETM+/OLI and Sentinel-2 MSI data were processed within Google Earth Engine (GEE) at five-year intervals to derive TCT components (Brightness, Greenness, Wetness), sub-pixel fractional cover maps, and statistically significant landscape change events. LULC maps were generated using supervised RF classification with overall accuracies ranging from 87% to 91%. Hotspot analysis delineated persistent coal-fire risk clusters concentrated in the central and eastern sectors. Proximity-based buffer analysis revealed that substantial settlements lie within 500–1000 m of identified fire hotspots. ERS mapping confirms that 52.4% of the coalfield demonstrates moderate-to-high restoration probability, while 19.8% remains critically degraded. Findings highlight that active mining, persistent coal-seam fires, and inadequate post-reclamation management are the primary constraints on sustained ecological recovery and demonstrate the superiority of machine learning ensemble methods over conventional index-based approaches for mine-land restoration assessment.

Keywords: Tasseled Cap Transformation; Spectral Mixture Analysis; Random Forest; Google Earth Engine; CCDC; Ecological Restoration Score; Hotspot Analysis; Jharia Coalfield

1. Introduction

Coal mining constitutes one of the most transformative anthropogenic forces acting on terrestrial ecosystems, simultaneously restructuring landscape topography, eliminating native vegetation, and introducing chronic thermal and chemical stressors that persist long after active extraction ceases [1]. The Jharia Coalfield (JCF), situated in Dhanbad district of Jharkhand, India, exemplifies these dynamics at an extreme scale. Spanning approximately 450 km² and under continuous operation for over a century, JCF supports India's primary coking-coal supply while sustaining more than 70 active coal-seam fire sites, generating one of the most complex and degraded mine-land environments in South Asia [2]. Conventional remote sensing approaches to mine-land restoration monitoring have relied predominantly on narrow-band spectral indices computed from individual or paired satellite bands. While such indices provide interpretable proxies for discrete ecological conditions, they are inherently limited in characterising the full spectral complexity of mine-land environments, where multiple land cover types co-occur within single pixels, spectral confusion between coal surfaces and dry vegetation is common, and temporal dynamics are non-linear and

* Corresponding author: Radhakanta Koner, Department of Mining Engineering, Indian Institute of Technology (Indian School of Mines), Dhanbad, India, e-mail: rkoner@iitism.ac.in

episodic [3]. Furthermore, coal-seam fires generate persistent surface temperature anomalies, toxic gaseous emissions, and ground instability that both confound conventional index-based assessments and represent an independent ecological stressor requiring dedicated spatial analysis [4]. Recent advances in cloud-based geospatial computing, machine learning classification, and physically based spectral decomposition offer substantially improved capabilities for landscape restoration monitoring.

The Tasseled Cap Transformation (TCT) condenses spectral information into ecologically interpretable orthogonal components Brightness, Greenness, and Wetness directly sensitive to soil exposure, photosynthetic activity, and canopy moisture [5]. Spectral Mixture Analysis (SMA) resolves sub-pixel heterogeneity by decomposing pixel reflectance into fractional contributions from photosynthetic vegetation, non-photosynthetic vegetation, and bare substrate [6]. Continuous Change Detection and Classification (CCDC) operate on the full Landsat time series to detect statistically significant spectral change events with temporal precision unavailable from epoch-based analysis [7]. The Normalised Burn Ratio (NBR) and its temporal difference (Δ NBR) provide sensitive characterisation of fire-affected surface conditions and post-fire recovery trajectories [8]. Hotspot analysis using the Getis–Ord G_i^* statistic enables identification of statistically significant spatial clusters of coal-fire thermal anomalies and their temporal evolution. Random Forest (RF) ensemble classification integrates multi-source spectral, temporal, and contextual features into a probabilistic Ecological Restoration Score (ERS) without requiring expert weight elicitation, providing an objective and reproducible restoration assessment framework [9].

Despite growing availability of these advanced techniques, their integrated application to multi-decadal mine-land ecological restoration monitoring remains limited in the Indian coalfield context. This study addresses this gap by presenting a comprehensive spatiotemporal assessment of restoration dynamics across the entire JCF from 2005 to 2025 within the Google Earth Engine (GEE) cloud computing platform. The primary objectives are: (i) to characterise spatiotemporal landscape change through TCT component analysis and SMA fractional cover mapping at five-year intervals; (ii) to detect statistically significant landscape transitions using CCDC and NBR-based change analysis; (iii) to delineate coal-fire risk zones through Getis–Ord G_i^* hotspot analysis and proximity-based buffer assessment; and (iv) to develop and spatially map an RF-derived Ecological Restoration Score providing a data-driven, probabilistic framework for targeted rehabilitation planning across the Jharia Coalfield.

2. Study Area

The Jharia Coalfield (JCF), located in the Dhanbad district of Jharkhand, India, extends between 23°38'–23°56' N latitude and 86°11'–86°30' E longitude. Covering nearly 450 km², it represents the country's most important coking-coal reserve with estimated deposits exceeding 19.4 billion tonnes. Mining activities are mainly managed by Bharat Coking Coal Limited, a subsidiary of Coal India Limited, operating more than 70 underground and opencast collieries. The region experiences a tropical savanna climate with hot summers, monsoon rainfall from July to September, and mild winters. Average annual rainfall ranges from 1200 to 1400 mm, most of which occurs during the monsoon season.

Originally dominated by tropical dry deciduous vegetation, the landscape has undergone extensive ecological degradation due to long-term mining activities. The present terrain consists of active mine pits, overburden dumps, coal stockyards, urban settlements, agricultural land, and fragmented vegetation patches, creating a highly heterogeneous environment. Geologically, JCF belongs to the Lower Gondwana Supergroup, where coal seams occur within the Barakar and Raniganj formations. Numerous faults, fractures, and igneous intrusions facilitate oxygen entry into abandoned workings, promoting spontaneous coal combustion. More than 70 coal-seam fire sites have been identified across the coalfield, producing severe thermal anomalies, toxic gas emissions, land subsidence, and unstable ground conditions (Figure 1). These combined environmental stresses significantly restrict ecological recovery and complicate restoration monitoring in the region [2]. Figures, pictures and photos will be numbered continuously, max 170mm width, alignment center, see example below. There can be two (or more) pictures on the same row, if the section containing the pictures is divided in two (or more) columns.

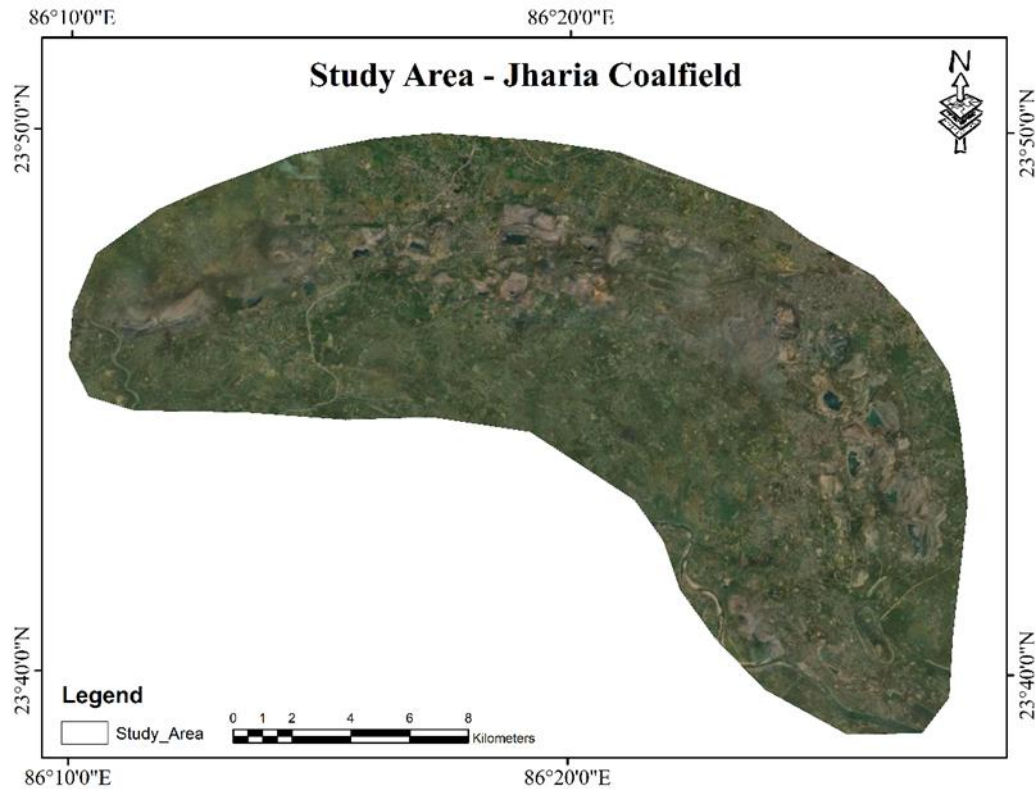


Fig. 1. Study area map of Jharia Coalfield

3. Materials and Methods

3.1 Remote Sensing Data and GEE Processing

Multi-temporal Landsat and Sentinel-2 satellite imagery was acquired and processed within the Google Earth Engine (GEE) cloud computing platform for five temporal epochs: 2005, 2010, 2015, 2020, and 2025. Sensors used were Landsat 5 TM (2005), Landsat 7 ETM+ (2010), Landsat 8 OLI/TIRS (2015, 2020), and Landsat 9 OLI-2/TIRS-2 (2025) (Table 1). Sentinel-2 MSI data at 10 m resolution were additionally incorporated for the 2015–2025 period to support fire-affected surface characterisation and classification validation. Dry season composites (November–March) were generated using median pixel compositing within GEE to minimise cloud contamination and phenological inconsistency. Surface reflectance products with less than 10% cloud cover were selected. Atmospheric correction was applied using the LEDAPS algorithm for Landsat 5/7 and the LaSRC algorithm for Landsat 8/9, ensuring spectral consistency across sensors and temporal epochs [10].

Table 1. Satellite datasets used in the study

Data	Sensor	Resolution	Temporal coverage	Purpose
Multispectral	Landsat TM / ETM+ / OLI	30 m	2005–2025	TCT, SMA, LULC, CCDC
Thermal infrared	Landsat TIR (TM/ETM+/TIRS)	60–100 m	2005–2025	LST & coal fire detection
High-res multispectral	Sentinel-2 MSI	10 m	2015–2025	Fire characterisation & validation

3.2 Tasseled Cap Transformation (TCT)

The Tasseled Cap Transformation was applied to all five temporal composites to derive three ecologically significant orthogonal components. TCT Brightness (TCT-B) captures overall soil and surface reflectance, serving as a proxy for bare and disturbed ground exposure. TCT Greenness (TCT-G) is strongly correlated with photosynthetic vegetation density and canopy development. TCT Wetness (TCT-W) reflects canopy moisture content and soil water availability, sensitive to both vegetation health and hydrological conditions. Sensor-specific TCT coefficients were applied for each Landsat platform following established calibration [11]. Temporal trajectories of all three TCT components were analysed to characterise direction and magnitude of landscape change across each five-year interval.

3.3 Spectral Mixture Analysis (SMA)

Linear Spectral Mixture Analysis was applied to decompose each pixel's surface reflectance into fractional contributions from three physically meaningful endmembers: Photosynthetic Vegetation (PV), Non-Photosynthetic Vegetation (NPV), and Bare Soil/Substrate (BS). Endmember spectra were selected from field-verified pure pixels using the Pixel Purity Index (PPI) approach within GEE. A constrained least-squares unmixing model was applied, enforcing conditions that fractional abundances sum to unity and remain non-negative. The resulting fractional cover maps provide sub-pixel characterisation of mine-land surface conditions, enabling detection of subtle vegetation establishment on overburden dumps and partial recovery of degraded surfaces that conventional whole-pixel classifiers would misidentify [12].

3.4 Continuous Change Detection and Classification (CCDC)

Continuous Change Detection and Classification (Zhu & Woodcock, 2014) was applied to the full Landsat time series within GEE to detect statistically significant spectral changes and classify land cover at each detected breakpoint. CCDC fits harmonic regression models to each pixel's temporal reflectance trajectory and identifies change events where observed reflectance deviates significantly from model predictions. This enables detection of both abrupt disturbance events mining expansion, fire outbreak and gradual restoration trajectories such as progressive revegetation and overburden stabilisation, without requiring manual threshold specification [13].

3.5 Normalised Burn Ratio (NBR) and ΔNBR

The Normalised Burn Ratio (NBR) was derived from Landsat and Sentinel-2 imagery to characterise fire-affected surface conditions and post-disturbance recovery trajectories. NBR is computed as $(NIR - SWIR) / (NIR + SWIR)$, where high SWIR reflectance associated with coal fire-affected bare and charred surfaces drives NBR strongly negative, distinguishing fire zones from both vegetated and non-fire bare surfaces. The temporal difference ($\Delta NBR = NBR_{pre} - NBR_{post}$) was computed between consecutive five-year epochs to quantify spectral change magnitude associated with fire occurrence and spread. NBR and ΔNBR layers were incorporated as features in the Random Forest classifier and served as independent validation inputs for coal-fire zone delineation [14].

3.6 Land Use and Land Cover (LULC) Classification

LULC maps were generated from Landsat multispectral data at five-year intervals using Random Forest supervised classification within GEE. Six land cover classes were identified: vegetation, agriculture, water bodies, mining and industrial area, urban and built-up land, and barren or degraded land. Training samples were collected through a combination of field surveys and visual interpretation of high-resolution Google Earth imagery, with a minimum of 500 training samples per class. Classification accuracy was validated using stratified random sampling with at least 50 independent validation points per class (Table 2). Accuracy assessment employed the confusion matrix, overall accuracy, and Kappa coefficient across all temporal epochs [15].

Table 2. LULC accuracy assessment (2005, 2015, 2025)

Accuracy Metric	Land Cover Class	2005	2015	2025
User's Accuracy (UA)	Built-up area	93%	95%	87%
	Vegetation	92%	90%	94%
	Barren land	93%	94%	90%
	Agriculture	93%	91%	87%
	Waterbody	80%	82%	88%
	Mines	87%	97%	88%
Producer's Accuracy (PA)	Built-up area	85%	90%	86%
	Vegetation	93%	95%	90%
	Barren land	94%	96%	94%
	Agriculture	94%	85%	92%
	Waterbody	80%	82%	82%
	Mines	87%	89%	85%
Overall Accuracy (OA)	—	90%	90%	87%

3.7 Hotspot Analysis (Getis-Ord G_i^*)

Spatial clustering of coal fire-related thermal anomalies was assessed using the Getis-Ord G_i^* statistic to identify statistically significant hot and cold spots across the coalfield [16]. LST-derived thermal anomaly rasters were used as the input continuous variable. G_i^* z-scores were computed for each spatial unit at a search

radius calibrated to the typical spatial extent of documented coal-fire zones. This method enabled detection of persistent fire concentration zones and their spatial evolution across the study period, distinguishing statistically significant thermal clusters from random background variation [17].

3.8 Proximity-Based Risk Zonation

Buffer-based proximity analysis was conducted around identified coal-fire hotspots to examine their spatial relationship with settlements, infrastructure, and LULC classes [18]. Concentric buffer zones were created at incremental distances of 500, 1000, 1500, 2000, 2500, 3000, and 3500 m from hotspot centroids. Areas within 500 m were classified as very high-risk zones, reflecting immediate exposure to elevated surface temperatures, ground instability, and gaseous emissions. The analysis quantified population exposure within each risk zone using settlement layer intersections, providing a practical basis for targeted relocation planning and mitigation prioritisation [18].

3.9 Random Forest Ecological Restoration Score (ERS)

A Random Forest ensemble classifier was trained within GEE to generate a continuous Ecological Restoration Score (ERS) ranging from 0 (no restoration) to 1 (full restoration) for each pixel at each temporal epoch. The RF input feature set comprised TCT-Brightness, TCT-Greenness, and TCT-Wetness; SMA-derived PV, NPV, and BS fractional cover; NBR and Δ NBR; CCDC change magnitude and change frequency; and terrain derivatives (slope, aspect, curvature) from the SRTM digital elevation model. Training data were generated from field-verified reference sites spanning the full restoration gradient, covering six land cover classes with 500 training samples per class. The RF model comprised 200 decision trees with a minimum leaf size of five samples, with 70% of samples allocated to training and 30% to independent validation. ERS values were classified into four restoration categories: Low (0–0.25), Moderate (0.25–0.50), High (0.50–0.75), and Very High (>0.75) (Suo et al., 2024).

4. Results

4.1 TCT Component Spatiotemporal Dynamics

Tasseled Cap Transformation analysis revealed distinctive and ecologically interpretable spectral trajectories across the JCF between 2005 and 2025. TCT-Brightness values were highest in 2005 and 2020, spatially coinciding with periods of maximum mining expansion and reduced vegetation buffering, reflecting the dominance of bare, high-reflectance mine surfaces. TCT-Greenness exhibited a non-linear trajectory, peaking in 2015 in areas of documented reclamation activity before declining significantly in 2020 in association with renewed opencast expansion, and partially recovering by 2025. TCT-Wetness showed persistent suppression in coal-fire zones throughout the study period, providing a spectrally robust signal of chronic thermal stress and moisture deficit. The strong negative correlation between TCT-Brightness and TCT-Greenness across all epochs confirms the inverse relationship between surface disturbance and vegetation recovery.

4.2 SMA Fractional Cover Dynamics

Spectral Mixture Analysis fractional cover mapping revealed nuanced sub-pixel vegetation dynamics not captured by whole-pixel classification. The Photosynthetic Vegetation (PV) fraction increased progressively in reclaimed overburden dump areas between 2005 and 2015, consistent with BCCL afforestation records. However, PV fraction declined significantly in 2020 across central mining zones, confirming renewed surface disturbance. Non-Photosynthetic Vegetation (NPV) fraction remained persistently elevated in transition zones, indicating incomplete vegetation establishment characterised by stress and senescence. Bare Soil (BS) fraction showed spatial concentration in active pit areas and coal-fire zones throughout the study period, with only marginal reduction by 2025, confirming that the most severely degraded surfaces have not yet undergone meaningful restoration.

4.3 CCDC Change Detection

CCDC analysis identified 847 statistically significant change events across the JCF between 2005 and 2025, distributed across both disturbance and recovery trajectories. The highest disturbance event frequency was recorded in the 2017–2020 period, spatially concentrated in the western and central coalfield sectors where opencast expansion was most intensive. Recovery trajectories characterised by gradual TCT-Greenness increase and declining BS fraction were most prevalent in the northern and eastern coalfield margins, coinciding with areas of documented post-mining reclamation. NBR and Δ NBR analysis confirmed that fire-affected zone extent increased markedly during 2017–2020, with Δ NBR exceeding -0.44 in the most severely impacted central coalfield sectors.

4.4 LULC Change Analysis

The Land Use and Land Cover (LULC) analysis of the Jharia Coalfield from 2005 to 2025 reveals substantial landscape transformation driven primarily by mining expansion, urban growth, and ecological degradation. Vegetation cover declined continuously from 100.91 km² (27.17%) in 2005 to 94.50 km² (25.44%) in 2025, indicating a total reduction of 6.41 km². Agricultural land experienced the most severe decline during 2005–2015, decreasing from 86.48 km² to 32.56 km², mainly due to mining encroachment and urban expansion. However, partial recovery was observed by 2025, when agricultural land increased to 54.10 km². Waterbody area increased steadily throughout the study period from 3.60 km² to 10.49 km², suggesting the formation of mine pits, water accumulation zones, and reclaimed ponds. Built-up areas expanded significantly between 2005 and 2015, rising from 31.85 km² to 46.62 km², reflecting rapid urbanisation and industrial development associated with mining activities. Although a slight reduction occurred after 2015, the total built-up area remained substantially higher than in 2005. Barren land increased sharply during the first decade due to overburden dumping and land degradation but later decreased considerably by 2025, indicating localized reclamation and vegetation recovery. Mining areas showed the highest net increase, expanding from 24.90 km² in 2005 to 54.86 km² in 2025, representing a total increase of 29.96 km². Overall, the results demonstrate that mining activities remain the dominant driver of landscape change and ecological stress within the coalfield (Figure 2 & 3).

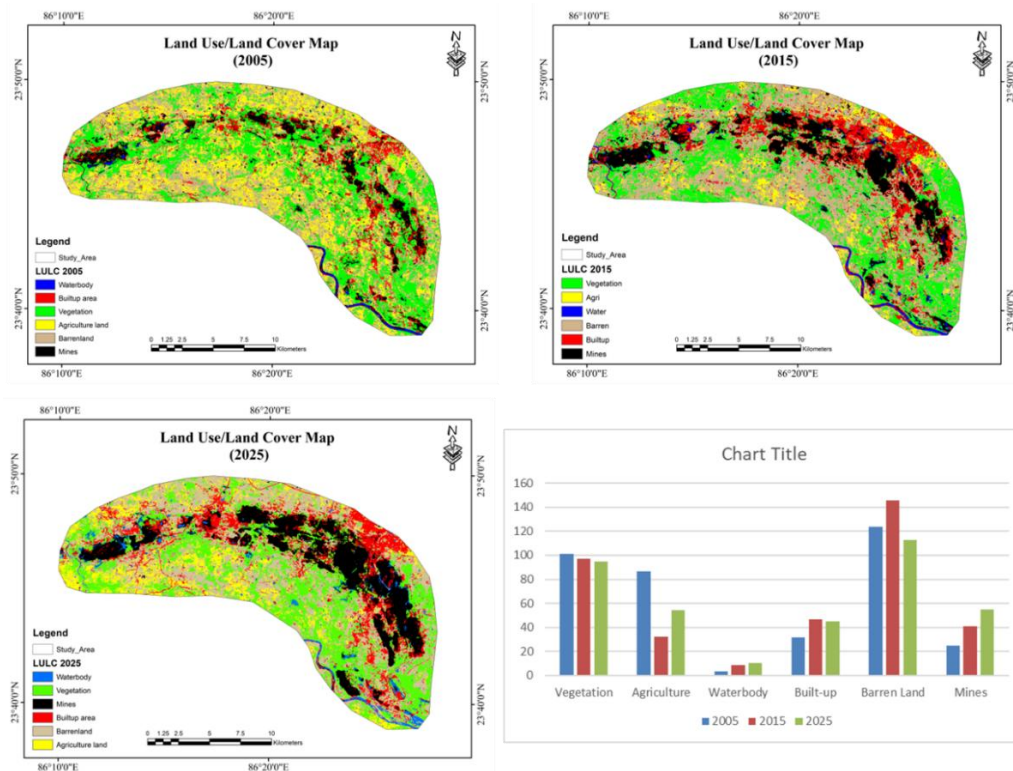


Fig. 2. Spatio-temporal evolution of land use and land cover (LULC) - (Source: Moon et al., 2026)

Table 3. Changes of LULC classes from 2005 to 2025

LULC Classes	2005 Area (km ²)	2015 Area (km ²)	Change (2005–2015) km ²	2025 Area (km ²)	Change (2015–2025) km ²	Total Change (2005–2025) km ²
Vegetation	100.91 (27.17%)	96.95 (26.10%)	–3.96 (–1.07%)	94.50 (25.44%)	–2.45 (–0.66%)	–6.41 (–1.73%)
Agriculture	86.48 (23.28%)	32.56 (8.76%)	–53.92 (–14.52%)	54.10 (14.56%)	21.54 (5.80%)	–32.38 (–8.72%)
Waterbody	3.60 (0.97%)	8.73 (2.35%)	5.13 (1.38%)	10.49 (2.83%)	1.76 (0.48%)	6.89 (1.86%)
Built-up Area	31.85 (8.57%)	46.62 (12.55%)	14.77 (3.98%)	44.82 (12.07%)	–1.80 (–0.48%)	12.97 (3.50%)
Barren Land	123.73 (33.30%)	145.77 (39.23%)	22.04 (5.93%)	112.71 (30.34%)	–33.06 (–8.89%)	–11.02 (–2.96%)
Mines	24.90 (6.71%)	40.83 (10.99%)	15.93 (4.28%)	54.86 (14.77%)	14.03 (3.78%)	29.96 (8.06%)
Total	371.47 (100%)	371.46 (100%)	—	371.48 (100%)	—	—

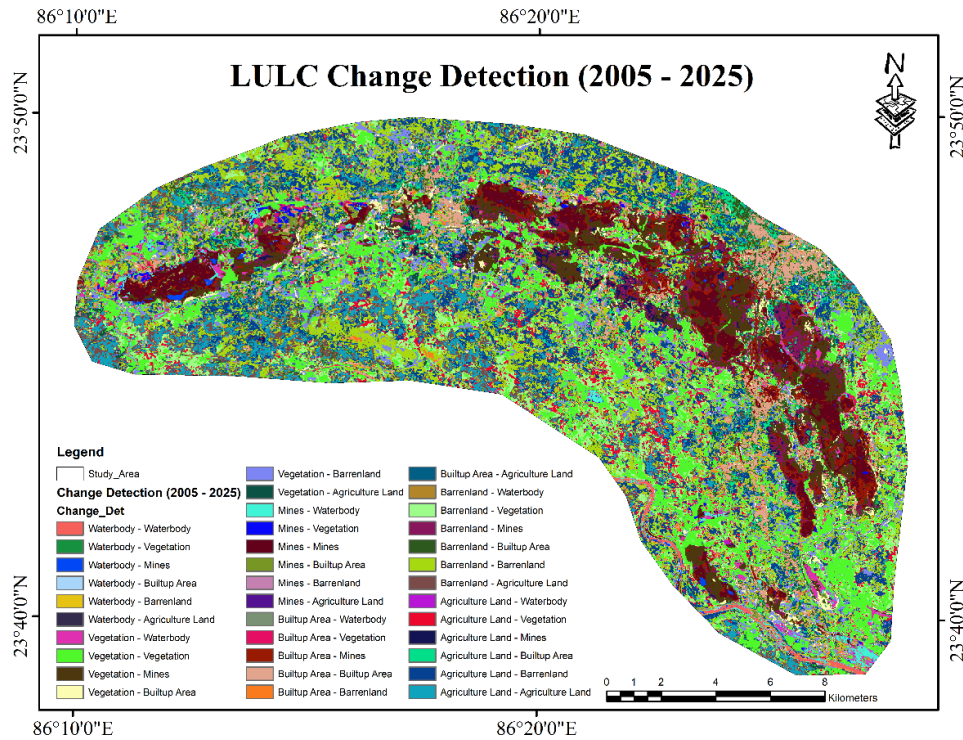


Fig. 3. LULC Change Detection from 2005-2025 (Source: Moon et al., 2026)

4.5 Coal Fire Hotspot Analysis

Spatial clustering analysis using the Getis–Ord G_i^* statistic identified statistically significant coal-fire hotspots, represented by high G_i^* z-scores, predominantly concentrated in the central and eastern sectors of the Jharia Coalfield. These zones correspond closely with areas of intensive active and legacy mining operations. In contrast, cold spots were mainly observed along peripheral regions characterized by relatively lower anthropogenic disturbance. The spatial clustering pattern reflects the combined influence of abandoned mine galleries, fractured geological strata, and surface disturbances that facilitate oxygen ingress and sustain subsurface coal combustion. The extent of hotspot zones increased considerably between 2005 and 2020, indicating the progressive expansion of active fire-affected regions during this period. However, a marginal reduction in hotspot extent was observed in 2025, suggesting localized mitigation and reclamation efforts in certain sectors of the coalfield.

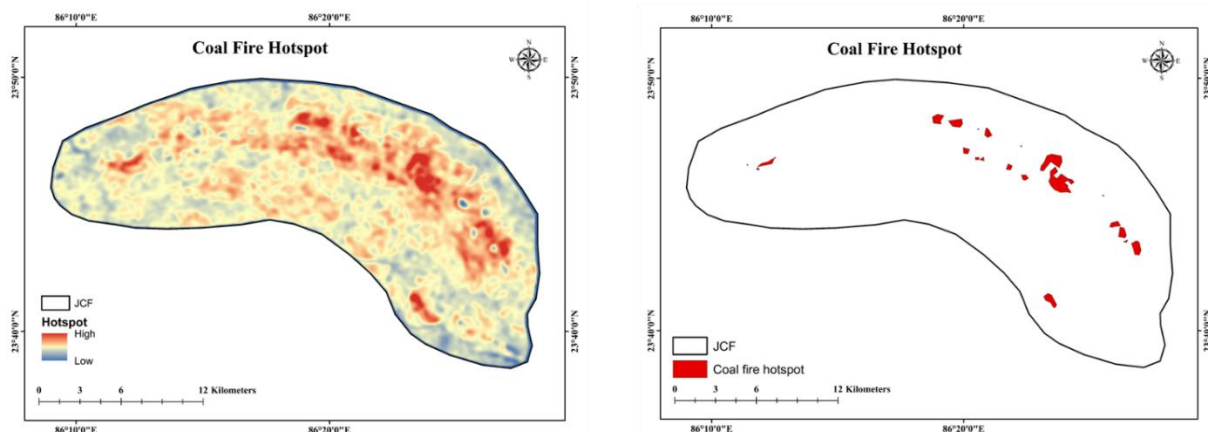


Fig.

4. Coal fire hotspot identification using Hotspot analysis

4.6 Proximity-Based Risk Zonation

Proximity-based buffer analysis revealed that a substantial number of settlements are located within the 500–1000 m buffer zones around identified coal-fire hotspots, classifying them as very high-to-high risk zones with direct exposure to elevated surface temperatures, gaseous emissions, and ground instability. A clear distance-decay relationship was observed, with risk intensity progressively decreasing away from hotspot centres. These findings corroborate earlier field-based assessments of fire-zone exposure in Jharia and provide a practical geospatial framework for prioritising mitigation, relocation planning, and continuous environmental monitoring.

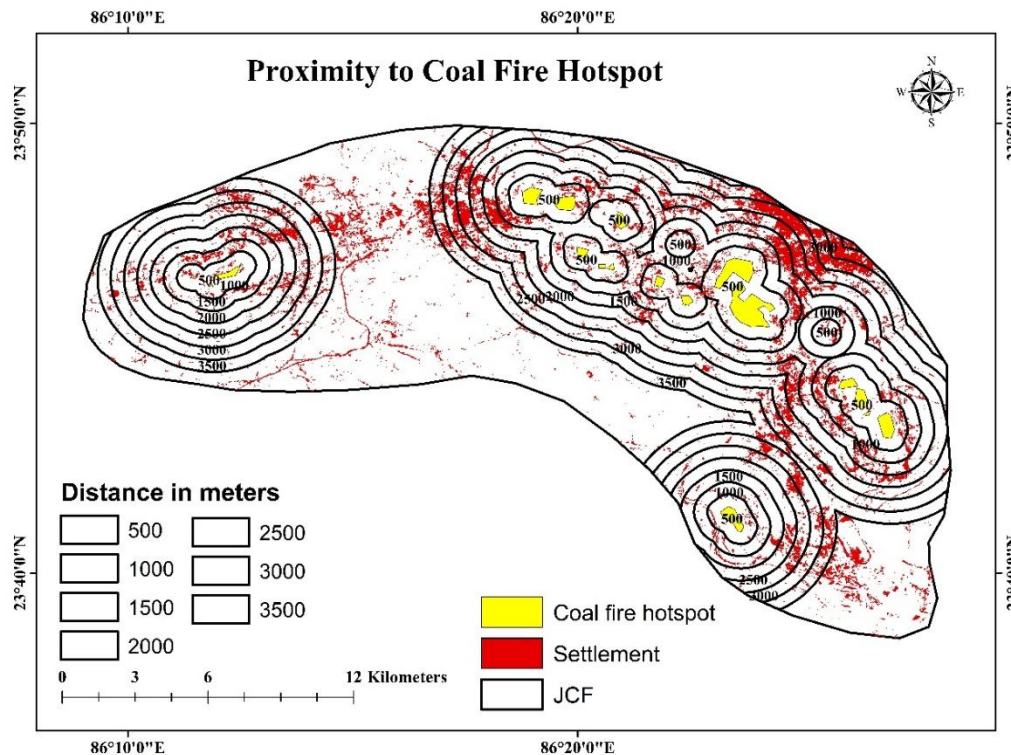


Fig. 5. Identified risk zones using buffer analysis

4.7 Ecological Restoration Score (ERS)

Random Forest ERS mapping revealed a spatially heterogeneous restoration landscape broadly consistent with field observations and BCCL reclamation records. Very High restoration ($ERS > 0.75$) was recorded across 24.6% of the coalfield, concentrated in documented reclamation areas with established vegetation. High restoration ($ERS 0.50–0.75$) covered 27.8% of the study area, predominantly in transitional zones showing progressive but incomplete recovery. Moderate restoration ($ERS 0.25–0.50$) characterised 27.8%, associated with partially revegetated and stabilised overburden surfaces. Low-to-Very Low restoration ($ERS < 0.25$) persisted across 19.8% of the coalfield, concentrated in active mining pits, coal-seam fire zones, and inadequately managed dumping areas requiring urgent targeted intervention. RF variable importance analysis identified TCT-Greenness and PV fraction as the highest-contributing features, followed by NBR, CCDC change frequency, and TCT-Wetness.

5. Discussion

This study demonstrates that an integrated geospatial framework combining TCT, SMA, CCDC, NBR-based fire characterisation, Getis–Ord G_i^* hotspot analysis, and Random Forest ERS computation within Google Earth Engine provides substantially advanced capabilities for mine-land ecological restoration monitoring compared to conventional spectral index and expert-weighted approaches. The multi-dimensional spectral characterisation afforded by TCT component analysis captures orthogonal dimensions of landscape condition that single spectral indices cannot simultaneously resolve, while SMA fractional cover mapping reveals sub-pixel vegetation dynamics systematically underestimated by whole-pixel classification.

The non-linear restoration trajectory identified through TCT-Greenness and PV fraction dynamics improvement through 2015, deterioration in 2020, and partial recovery by 2025 confirms that ecological recovery in intensively mined landscapes is episodic and reversible, contingent on the balance between restoration investment and extraction pressure. The identification of 2017–2020 as the peak disturbance period through CCDC analysis provides temporal precision unavailable from five-year interval mapping, highlighting the value of continuous time-series approaches. The strong spatial correspondence between CCDC-detected disturbance events, NBR anomalies, and G_i^* hotspot clusters confirms a mechanistic link between coal-fire intensification and landscape-scale ecological deterioration during this period.

The proximity-based risk analysis reveals that substantial portions of the JCF population remain directly exposed to coal-fire hazards at distances insufficient to buffer against thermal, gaseous, and ground stability risks. This finding reinforces the dual mandate of restoration monitoring: tracking ecological recovery while simultaneously characterising ongoing hazard exposure for vulnerable communities.

The RF-derived ERS, integrating spectral, temporal, and topographic features without subjective weight elicitation, provides a more objective and reproducible restoration assessment than conventional composite indices, while the probabilistic output enables explicit characterisation of restoration uncertainty across the coalfield. Three structural constraints limiting long-term ecological recovery are confirmed: continued active extraction perpetuating surface disturbance, persistent coal-seam fires suppressing TCT-Wetness and PV fraction in affected zones, and inadequate post-reclamation management failing to sustain early vegetation establishment beyond the NPV stage. Addressing these constraints requires coordinated policy responses including mandatory post-reclamation monitoring protocols, accelerated coal-fire extinguishment programmes, and spatially targeted rehabilitation investment guided by ERS mapping outputs

6. Conclusion

This study presents a methodologically advanced, multi-decadal assessment of ecological restoration dynamics across the Jharia Coalfield using Tasseled Cap Transformation, Spectral Mixture Analysis, CCDC change detection, NBR-based fire characterisation, Getis-Ord G_i^* hotspot analysis, and Random Forest Ecological Restoration Score computation within Google Earth Engine. Results confirm spatially heterogeneous but measurable restoration progress, with 52.4% of the coalfield demonstrating moderate-to-high restoration probability and 19.8% remaining critically degraded. Hotspot analysis confirms persistent coal-fire clustering in the central and eastern coalfield, with proximity risk analysis identifying substantial settlement exposure within 500–1000 m of active fire zones. The integrated GEE-based framework offers a reproducible, scalable, and physically rigorous alternative to conventional spectral index approaches for mine-land restoration monitoring, directly applicable to rehabilitation planning and policy formulation across JCF and comparable coal-mining landscapes. The non-linear restoration trajectory and peak disturbance period identified by CCDC collectively highlight that ecological recovery is neither linear nor guaranteed, and that active extraction and coal-seam fire persistence remain primary barriers to sustained restoration. Future research should incorporate Sentinel-1 SAR data for enhanced all-weather monitoring, integrate InSAR-derived surface deformation for fire-zone subsidence characterisation, couple geospatial outputs with socioeconomic and health datasets for comprehensive risk assessment, and develop predictive ERS trajectory models under alternative management and climate scenarios across South and Southeast Asian coalfield landscapes.



Fig. 6. Field photographs of active coal fires in the study area

Acknowledgements

The authors acknowledge the United States Geological Survey (USGS) for providing open-access Landsat satellite imagery through the Earth Explorer portal, the European Space Agency (ESA) for Sentinel-2 data access through the Copernicus Open Access Hub, and Google Earth Engine for cloud computing infrastructure. The authors also acknowledge the support of the Department of Mining Engineering, IIT (ISM) Dhanbad, for providing research infrastructure and computational resources for this study.

References

- [1] **Srivastava V., Jha P.K.**, 2025
Environmental impacts of coal mining and mitigation measures: a review, Environmental Monitoring and Assessment, 197(5), 545 <https://doi.org/10.1007/s10661-025-13939-1>
- [2] **Dutta A.J., Mishra C., Chaturvedi R., Konwar D., Kulkarni S.D.**, 2025
Techno-Economic Assessment of Geothermal Energy Resource in the Jharia Coal Field of India, <https://doi.org/10.5194/egusphere-egu25-17341>
- [3] **Gastauer M., Nascimento W.R., Caldeira C.F., Ramos S.J., Souza-Filho P.W.M., Féret, J.-B.**, 2021
Spectral diversity allows remote detection of the rehabilitation status in an Amazonian iron mining complex, International Journal of Applied Earth Observation and Geoinformation, 106, 102653
<https://doi.org/10.1016/j.jag.2021.102653>
- [4] **Hoyland R.O., Mchenry M.T., Foster E.A.**, 2024
Fire and geodiversity, International Journal of Wildland Fire, 33(4) <https://doi.org/10.1071/wf23134>
- [5] **Shi M., Xing S., Bai H., Xu D., Shi L.**, 2024
The Effect of Vegetation Ecological Restoration by Integrating Multispectral Remote Sensing and Laser Point Cloud Monitoring Technology, Plants, 13(22), 3164 <https://doi.org/10.3390/plants13223164>
- [6] **Nghiyalwa H.S., Urban M., Baade J., Smit I.P., Ramoelo A., Mogonong B., Schmullius C.**, 2021
Spatio-temporal mixed pixel analysis of savanna ecosystems: a review, Remote Sensing, 13(19), 3870
<https://doi.org/10.3390/rs13193870>
- [7] **Arévalo P., Olofsson P.**, 2023
Interpreting Time Series with CCDC (pp. 353–375), Springer https://doi.org/10.1007/978-3-031-26588-4_19
- [8] **Fassnacht F.E., Schmidt-Riese E., Kattenborn T., Hernández J.**, 2020
Explaining Sentinel 2-based dNBR and RdNBR variability with reference data from the bird's eye (UAS) perspective, International Journal of Applied Earth Observation and Geoinformation, 95, 102262
<https://doi.org/10.1016/j.jag.2020.102262>
- [9] **Orth R.**, 2021
Review of Kuhn-Regnier et al. & Quantifying the Importance of Antecedent Fuel-Related Vegetation Properties for Burnt Area using Random Forests, <https://doi.org/10.5194/bg-2020-409-rc3>
- [10] **Ruzikulova O., Sharipov Z., Samatova G., Safarov E., Ergasheva Y., Tajekeev Z., Jumayeva S., Abdurakhmanova M.**, 2024
Comparative Analysis of Sentinel-2 MSI and Landsat-8 OLI for Enhanced Land Monitoring, E3S Web of Conferences, 590, 04009 <https://doi.org/10.1051/e3sconf/202459004009>
- [11] **Zhai Y., Roy D.P., Martins V.S., Zhang H.K., Yan L., Li Z.**, 2022
Conterminous United States Landsat-8 top of atmosphere and surface reflectance tasseled cap transformation coefficients, Remote Sensing of Environment, 274, 112992 <https://doi.org/10.1016/j.rse.2022.112992>
- [12] **Tan P., Lymburner L., Mueller N.**, 2013
December 1), A novel image based end-member extraction technique to map green, non-photosynthetic and bare soil fractions using Landsat data <https://doi.org/10.36334/modsim.2013.a9.tan>

- [13] **Gorelick N., Yang Z., Arévalo P., Bullock E.L., Insfrán K.P., Healey S.P.**, 2023
A global time series dataset to facilitate forest greenhouse gas reporting, Environmental Research Letters, 18(8), 084001 <https://doi.org/10.1088/1748-9326/ace2da>
- [14] **Bright B.C., Hudak A.T., Kennedy R.E., Braaten J.D., Henareh Khalyani A.**, 2019
Examining post-fire vegetation recovery with Landsat time series analysis in three western North American forest types, Fire Ecology, 15(1) <https://doi.org/10.1186/s42408-018-0021-9>
- [15] **Amini S., Saber M., Rabiei-Dastjerdi H., Homayouni S.**, 2022
Urban Land Use and Land Cover Change Analysis Using Random Forest Classification of Landsat Time Series, Remote Sensing, 14(11), 2654 <https://doi.org/10.3390/rs14112654>
- [16] **Ord J.K., Getis A.**, 1995
Local Spatial Autocorrelation Statistics: Distributional Issues and an application, Local Spatial Autocorrelation Statistics: Distributional Issues and an application. Geographical Analysis 27:286–306 <https://doi.org/10.1111/j.1538-4632.1995.tb00912.x>
- [17] **Deng J., Xue Y., Zhou F., Shi B.**, 2025
Landsat Thermal Infrared Analysis for Spatial and Temporal Characterization and Risk Assessment of Coalfield Fires, 2761–2765 <https://doi.org/10.1109/igarss55030.2025.11243323>
- [18] **Hora B., González-Mathiesen C., Aravena-Solís N., Tapia T.**, 2025
Land Cover and Wildfire Risk: A Multi-Buffer Spatial Analysis of the Relationship Between Housing Destruction and Land Cover in Chile's Bío-Bío Region in 2023, Sustainability, 17(10), 4416 <https://doi.org/10.3390/su17104416>



This article is an open access article distributed under the Creative Commons BY SA 4.0 license. Authors retain all copyrights and agree to the terms of the above-mentioned CC BY SA 4.0 license.