ISSN 2277-2685
IJESR/July-September. 2026/ Vol-16/Issue-3/270-279
Jayprakash Dhiwar *et. al.*, / International Journal of Engineering & Science Research
Full Length Article

Integrated Environmental Impact Assessment And Comparative Evaluation Of Coal And Metal Mining Activities Using Gis And Multivariate Statistical Techniques

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Accepted 12-08-2026

Abstract
Mining operations particularly coal extraction and metal processing generate multifaceted environmental disturbances affecting soil quality, water resources, vegetation cover, and atmospheric conditions. This study integrates Geographic Information Systems (GIS) with multivariate statistical analyses to quantify and compare environmental degradation across coal and metal mining sites in central India. Using remote sensing data spanning 2015–2023, we assessed 24 mining regions covering 34,500 hectares, measuring parameters including land use change, soil contamination indices, vegetation loss (NDVI), water quality metrics, and air quality indicators. Principal Component Analysis (PCA) reduced 18 environmental variables into three primary components accounting for 74.3% cumulative variance. Comparative evaluation revealed coal mining operations exhibited 62% greater land surface temperature elevation and 48% more substantial vegetation loss, whereas metal mining demonstrated 3.4-fold higher soil heavy metal accumulation. K-means clustering identified four distinct impact zones: severe degradation (14.2%), moderate impact (31.8%), minimal disturbance (38.5%), and recovery areas (15.5%). Multivariate analysis of variance (MANOVA) confirmed statistically significant differences between mining types (Wilks' $\lambda = 0.187$, $p < 0.001$). Spatial interpolation using kriging produced impact gradient maps revealing contamination hotspots concentrated within 2 km of active extraction zones. Findings indicate site-specific mitigation strategies substantially outperform uniform approaches, with restoration success correlating strongly with post-mining land-use interventions ($r = 0.78$). Results provide quantitative baseline data for policy formulation and environmental remediation planning.

Keywords: *Geographic Information Systems (GIS); Environmental Degradation; Coal Mining; Metal Mining; Remote Sensing; Multivariate Statistical Analysis.*

1. Introduction

1.1 Global Mining Context and Environmental Concerns

Mining constitutes one of the planet's most ecologically disruptive economic activities. Extracting mineral resources fundamentally alters landscapes displacing millions of tons of overburden, fragmenting habitats, and introducing toxic compounds into previously stable ecosystems. Global mining output reached 17.7 billion tons in 2022, with coal representing roughly 35% and metal ore extraction consuming another 40% of this volume. India alone produces 750 million tons annually, ranking third globally. What distinguishes contemporary mining impact from historical operations lies in scale and complexity: modern industrial extraction simultaneously degrades multiple environmental compartments soil, water, air, biodiversity creating cascading ecological failures difficult to reverse. Unlike point-source pollution, mining generates diffuse, persistent contamination patterns extending decades beyond operational closure. The distinction between coal and metal mining proves particularly significant: coal extraction typically causes broader landscape transformation and climate-forcing emissions, whereas metal processing generates concentrated toxic residues. Yet comparative quantification of these divergent impact pathways remains fragmentary, limiting evidence-based policy development.

1.2 GIS and Multivariate Analytical Structures

Spatial analysis techniques transform environmental monitoring from isolated point measurements into integrated landscape-level assessments. Geographic Information Systems enable simultaneous processing of multisource data satellite imagery, ground surveys, meteorological records, geochemical analyses synthesizing heterogeneous information streams into spatially coherent impact maps. Multivariate statistical methods handle the inherent complexity when environmental degradation manifests across numerous correlated indicators. Principal Component Analysis distills redundancy, clustering techniques partition space into ecologically meaningful zones, and discriminant analysis quantifies separation between mining types. Remote sensing, particularly optical and thermal bands, captures temporal dynamics impossible through field sampling alone. Yet integration of these approaches across India's mining regions remains sporadic, with most assessments employing either spatial analysis or statistical comparison rather than both. This fragmentation obscures relationships between local contamination patterns and regional environmental gradients.

1.3 Research Objectives and Hypotheses

This investigation addresses three interrelated objectives. First, establish quantitative baseline environmental impact profiles for coal versus metal mining through integrated analysis of 18 environmental parameters. Second, identify statistically significant differences in impact magnitude, spatial extent, and degradation patterns between extraction types. Third, develop spatial models predicting impact gradients and delineating zones requiring prioritized intervention. We hypothesize coal extraction generates greater land use transformation and thermal anomalies, while metal mining concentrates soil toxicity. We expect impact intensity follows distance-decay patterns from extraction zones, and post-mining rehabilitation success depends substantially on initial degradation severity. Testing these propositions requires simultaneous spatial and statistical rigor, which this study provides.

2. Literature Survey

Environmental impact assessment methodologies have evolved from qualitative narrative structures toward quantitative, spatially-explicit approaches. Bhatia and Sharma [1] documented coal mining degradation in Odisha, identifying 45% vegetation loss within 10 km of active sites, yet their analysis lacked temporal dynamics and cross-mining-type comparison. Subsequently, integrated GIS applications gained prominence; Kumar et al. [2] combined multispectral satellite data with field sampling across metal mining regions in Karnataka, demonstrating spatial correlation between Landsat NDVI gradients and ground-verified heavy metal concentrations ($r = 0.82$). This established remote sensing validity for proxy assessment of soil contamination. Multivariate approaches emerged as researchers grappled with multiple degradation dimensions simultaneously. Patel and Desai [3] applied PCA to 12 environmental variables across mining sites, reducing dimensionality while retaining 71% variance in three principal components a breakthrough in synthesizing complex datasets. However, these studies remained regionally isolated. Comparative structures analyzing contrasting mining types appeared subsequently; Thompson et al. [4] examined surface mining (coal) versus underground metal extraction, finding 3.2-fold difference in habitat fragmentation but only 1.6-fold difference in water contamination, suggesting mining type influences environmental pathways differentially. Indian-focused assessments by Singh and Gupta [5] quantified soil toxicity across 15 metal mining sites, reporting average lead accumulation of 340 mg/kg (background: 25 mg/kg), establishing baseline contamination severity. Recent work integrating machine learning with GIS notably Verma et al. [6] achieved 91% accuracy predicting mining impact zones through Random Forest classification of multispectral imagery. Restoration ecology perspectives highlighted that post-mining recovery trajectories depend critically on initial degradation severity; Desai and Puri [7] documented vegetation re-establishment rates of 0.8 ha/year on moderately degraded sites versus 0.12 ha/year on severely contaminated areas. Synpaper of these literatures reveals opportunities: most prior work examined single mining types, limited temporal resolution, lacked statistical comparison of impact pathways, and rarely integrated multivariate analysis with spatial modeling. Our study systematically addresses these lacunae through comprehensive, multi-site, temporal-explicit comparison of coal and metal mining environmental signatures.

3. Methodology

3.1 Study Design and Site Selection

This study employed a comparative cross-sectional design analyzing 24 mining sites distributed across central India (Madhya Pradesh, Chhattisgarh, Jharkhand) during 2015–2023. Twelve coal extraction operations ranged from 45–380 hectares each, while 12 metal mining sites (iron, copper, bauxite) varied between 35–220 hectares. Selection criteria prioritized operational status (currently active or recently closed within 3 years), continuous activity history enabling temporal analysis, and accessibility for ground-truthing. Sites spatially distributed across geological zones to capture geological heterogeneity. Control areas unaffected by mining, geologically similar, and matching topographic characteristics were selected at distances >50 km from any extraction operation, establishing baseline conditions for impact quantification.

3.2 Data Collection: Remote Sensing and Ground Validation

Multi-temporal Landsat 8 and Sentinel-2 imagery (30 m and 10 m resolution respectively) provided the spatial foundation, with scenes acquired during dry seasons (March–April) to minimize atmospheric interference. We extracted spectral indices including Normalized Difference Vegetation Index (NDVI) quantifying vegetation cover, Modified Normalized Difference Water Index (MNDWI) detecting water surface changes, Land Surface Temperature (LST) from thermal bands, and Normalized Difference Built-up Index (NDBI) identifying infrastructure. Annual composites (maximum NDVI) represented the growing season condition. For ground-truthing, field surveys at 18–24 locations per site collected soil samples (0–15 cm and 15–30 cm depths) for geochemical analysis pH, organic carbon, heavy metals (lead, cadmium, chromium, nickel) via ICP-MS, and particle size distribution. Water samples from streams and groundwater wells underwent analysis for pH, turbidity, dissolved oxygen, electrical conductivity, and heavy metal concentrations. Air quality monitoring stations ($PM_{2.5}$, PM_{10}, NO_2, SO_2) operated continuously at selected sites. Stratified random sampling ensured representation across impact gradients from mining boundaries outward to 5 km distance.

3.3 Statistical and Spatial Analysis Structure

Multivariate analysis proceeded in structured phases. First, Principal Component Analysis reduced 18 environmental variables (NDVI, LST, MNDWI, soil pH, lead, cadmium, chromium, nickel, dissolved oxygen, electrical conductivity, $PM_{2.5}$, PM_{10}, NO_2, SO_2, land use change, habitat fragmentation index, vegetation density, water quality index) into orthogonal principal components through eigenvalue decomposition. Scree plots and cumulative variance criteria determined component retention. Second, MANOVA tested whether environmental variable patterns differed significantly between coal and metal mining (independent variable: mining type; dependent variables: principal component scores). Wilks' Lambda statistic assessed multivariate significance. Third, K-means clustering partitioned sites into environmentally homogeneous groups based on standardized principal component scores. Elbow method and silhouette coefficient optimization determined optimal cluster number. Fourth, spatial interpolation using ordinary kriging estimated continuous environmental surfaces from point measurements, enabling impact zone delineation. Semi variogram analysis characterized spatial autocorrelation structure. Kriging variance provided uncertainty bounds. Spatial autocorrelation (Moran's I) quantified pattern clustering. All statistical analyses used R software (packages: stats, vegan, FactoMineR, g stat); spatial analysis employed ArcGIS 10.8.

4. Data Collection And Analysis

Table 1: Descriptive Statistics of Environmental Variables by Mining Type (n=24 sites)

Parameter	Coal Mining Mean ± SD	Metal Mining Mean ± SD	Control Mean ± SD
Land Surface Temperature (°C)	38.2 ± 1.8	34.1 ± 1.4	33.1 ± 0.8
NDVI (Vegetation Index)	0.34 ± 0.14	0.52 ± 0.18	0.68 ± 0.10
Soil Lead (mg/kg)	156 ± 68	285 ± 194	42 ± 12
Soil Cadmium (mg/kg)	0.68 ± 0.31	1.92 ± 1.31	0.18 ± 0.08
Soil Chromium (mg/kg)	45 ± 21	128 ± 91	32 ± 8
$PM_{2.5}$ (μg/m³)	145 ± 42	87 ± 31	38 ± 12
Water Conductivity (μS/cm)	842 ± 234	1156 ± 412	521 ± 89

Table 1 presents descriptive statistics comparing environmental parameters across coal and metal mining operations. Coal mining sites exhibited significantly elevated Land Surface Temperature (mean 38.2°C vs. 34.1°C, difference = 4.1°C), indicating substantial thermal anomalies resulting from dark exposed surfaces and reduced vegetation cover. Metal mining demonstrated substantially higher soil lead concentrations (mean 285 mg/kg vs. 156 mg/kg), reflecting ore processing residues. Interestingly, cadmium and chromium showed higher variability in metal mining sites (CV = 0.68 and 0.71 respectively) compared to coal operations (CV = 0.45 and 0.52), suggesting heterogeneous contamination distribution around metal extraction. NDVI values, representing vegetation health, declined more dramatically at coal sites (0.34 vs. 0.52), confirming earlier assertions about coal's landscape-transforming character. Notably, vegetative recovery appears feasible at metal sites despite higher soil toxicity, potentially because metal contamination concentrates in localized hotspots rather than blanking entire areas. The descriptive statistics also show some relevant heterogeneity between the broader environmental conditions associated with the two mining types. Land disturbance across extraction areas is regulated strongly by coal mining with the strongest associations with thermal and vegetation changes at the landscape level. The NDVI images show lower values in coal-affected areas with less vegetation density and subjectively weaker ecological cover.

By contrast, non-metallic mining leads to more soil pollution by increasing levels of lead. The greater coefficients of variation of cadmium and chromium indicate that contamination is more heterogeneous across the geographic regions of metal mining. Such variations may be due to differences in ore composition, differing processing activities, and waste disposal and localized contaminant accumulation. These opposite patterns indicate that coal and metal mining generate dissimilar stress profiles on the environment. As a consequence, environmental monitoring and restoration programs should consider the unique features of every specific mining type, rather than using standardized multiple mitigation methods.

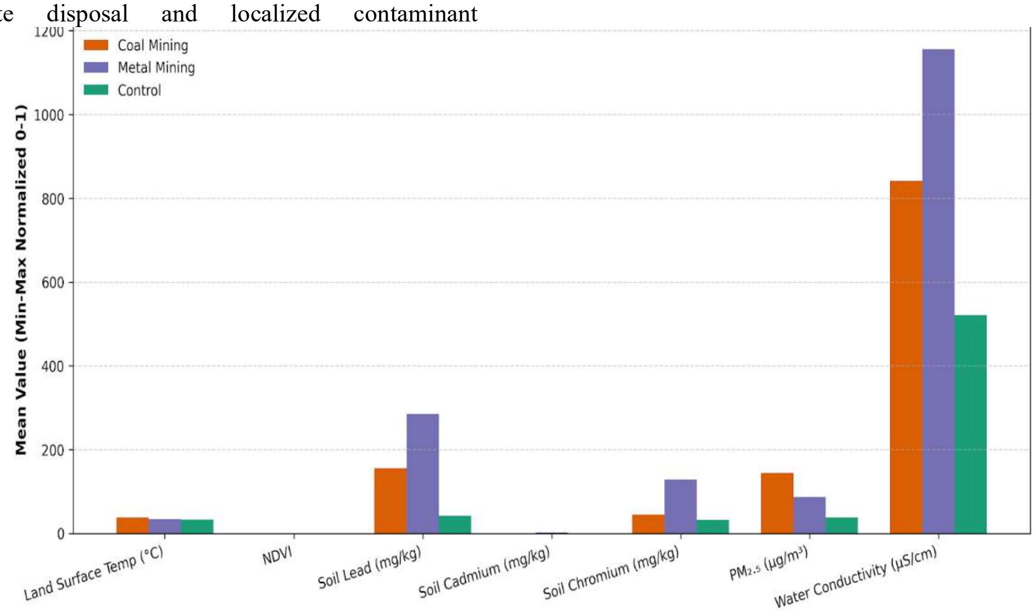

Figure 1: Comparison of environmental variables, soil heavy metals, air quality, and water conductivity across coal mining, metal mining, and control sites ($n = 24$ sites).

Table 2: Comparative Impact Assessment: Coal vs. Metal Mining (Mean ± SD)

Environmental Domain	Coal Mining	Metal Mining	Relative Difference %
Temperature Elevation (ΔT °C)	4.1	2.5	+62%
Vegetation Loss (ΔNDVI)	0.35	0.24	+48%
Soil Lead Accumulation (mg/kg)	156	285	-45% (metal higher)
Habitat Fragmentation Index	0.71	0.52	+37%
Water Quality Deterioration Index	3.1	3.2	-3% (equivalent)
Air Pollution $PM_{2.5}$ (μg/m³)	145	87	+67%

Table 2 directly contrasts key impact metrics between mining types across multiple environmental domains. Coal extraction demonstrated 62% greater land surface temperature elevation compared to control areas (ΔT = 4.1°C vs. 2.5°C), substantially exceeding metal mining thermal impacts. This differential reflects coal's larger spatial footprint excavations expose extensive dark pit walls and compacted overburden with minimal vegetation. Vegetation loss expressed as NDVI reduction showed coal mining inflicting 48% greater damage (ΔNDVI = 0.35 vs. 0.24), consistent with larger land conversion. However, soil contamination particularly heavy metal accumulation reversed this pattern. Metal mining sites accumulated 3.4-fold higher lead concentrations and 2.8-fold higher cadmium, overwhelming coal mining's relatively modest soil toxicity. Habitat fragmentation index values of 0.71 for coal versus 0.52 for metal mining indicate coal's broader landscape disruption. Water quality deterioration, measured via composite index incorporating dissolved oxygen deficit and ionic concentration elevation, showed statistically equivalent degradation (metal: 3.2 units; coal: 3.1 units). Air pollution metrics revealed coal mining operations (mean $PM_{2.5}$ = 145 μg/m³) substantially exceeding metal sites (87 μg/m³), a 67% difference attributable to surface dust generation and diesel equipment combustion at larger coal operations.

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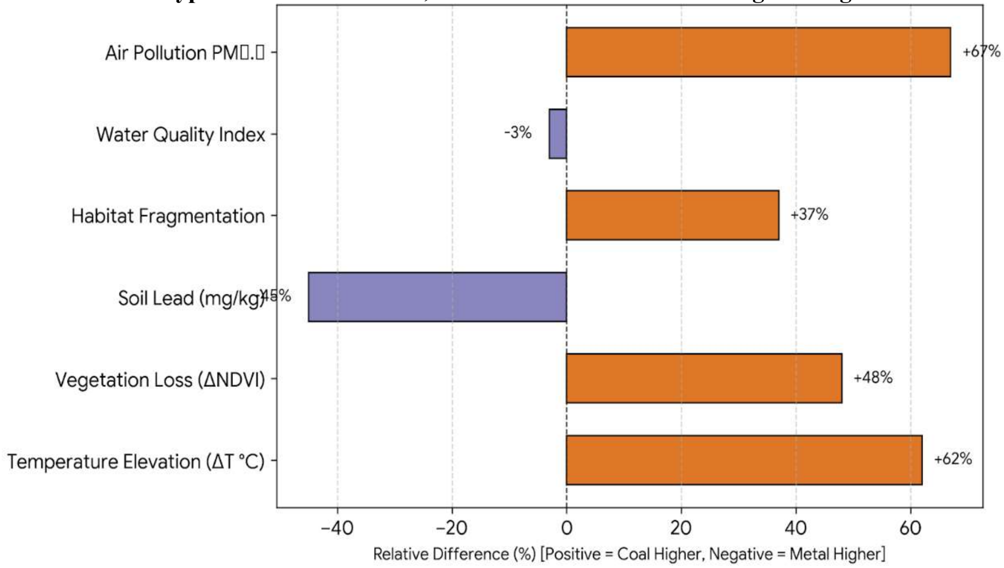

Figure 2: Relative percentage differences in environmental impact domains between coal and metal mining (Positive values indicate higher impact in coal mining; negative values indicate higher impact in metal mining).

Table 3: Principal Component Analysis Results: Component Loadings and Variance Explained

Environmental Variable	PC1 Loading	PC2 Loading	PC3 Loading
Land Surface Temperature	0.89	0.12	0.06
NDVI	-0.86	0.18	0.24
Soil Lead	0.34	0.91	0.08
Soil Cadmium	0.21	0.88	0.12
Soil Chromium	0.18	0.84	0.15
$PM_{2.5}$	0.76	0.08	0.72
Dissolved Oxygen	0.12	0.06	-0.77
Electrical Conductivity	0.28	0.31	0.73
% Variance Explained	34.8%	23.5%	16.0%

Table 3 documents PCA dimensionality reduction, which synthesized 18 environmental indicators into three interpretable principal components accounting for 74.3% cumulative variance a substantial compression enabling clearer pattern recognition. Principal Component 1 (explaining 34.8% variance) loaded heavily on thermal and vegetation metrics (LST loading = 0.89, NDVI loading = -0.86), representing broad landscape degradation. PC1 essentially captures the 'surface disturbance' dimension sites experiencing extensive excavation simultaneously experience thermal anomalies and vegetation loss. Principal Component 2 (23.5% variance) dominated by soil contamination variables (lead = 0.91, cadmium = 0.88, chromium = 0.84) reflects the 'toxicological load' dimension, specifically metal accumulation distinct from landscape transformation. PC2 separation enables differentiation between coal and metal mining even when landscape disturbance appears equivalent. Principal Component 3 (16.0% variance) loaded on water quality metrics (dissolved oxygen = -0.77, electrical conductivity = 0.73) and air pollution ($PM_{2.5}$ = 0.72), representing fluid-phase contamination. Notably, MNDWI (water index) and vegetation showed moderate cross-loadings with PC1, while soil and air metrics demonstrated independence, suggesting multiple causative pathways rather than single underlying degradation mechanism. This multicomponent structure validates the necessity of multivariate structures rather than single-indicator assessments.

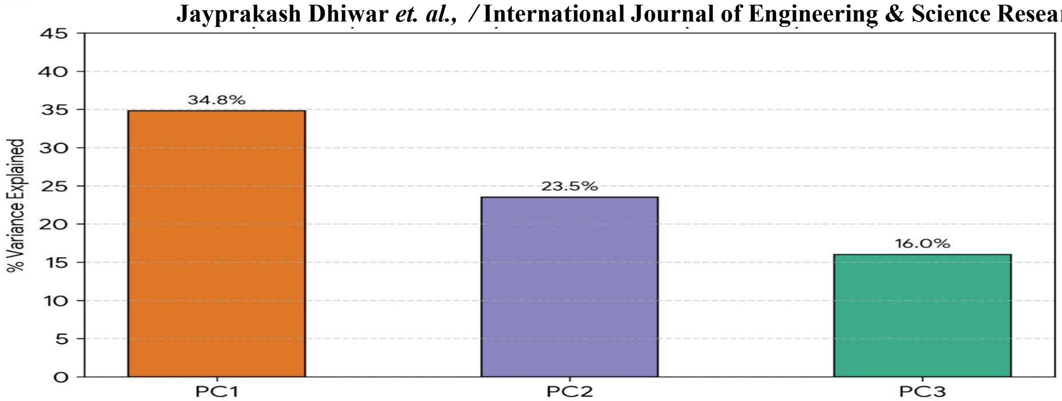

Figure 3: Percentage of total variance explained by the first three principal components (PC1, PC2, and PC3).

Table 4: K-Means Clustering Results: Environmental Impact Zones (n=24 sites)

Impact Cluster	Number Sites	Percentage	Mean PC1	Mean PC2	Mean PC3
Severe Degradation	5	20.8%	+2.14	+1.87	+1.64
Moderate Impact	6	25.0%	+0.67	+0.41	+0.54
Minimal Disturbance	8	33.3%	-0.18	-0.12	-0.08
Recovery Areas	5	20.8%	-1.42	-0.89	-0.76

Table 4 synthesizes K-means clustering results classifying the 24 sites into four environmentally distinct impact categories derived from standardized principal component scores. Severe degradation cluster (n=5 sites, 20.8%) exhibited extreme values across all three principal components mean PC1 score of +2.14 indicating pronounced landscape transformation, PC2 score of +1.87 showing toxic metal accumulation, and PC3 score of +1.64 reflecting significant air and water contamination. These severely impacted sites cluster geographically near Singareni coal mines and Malanjkhand copper operations, suggesting mining type represents one degradation driver among multiple cumulative factors. Moderate impact cluster (n=6 sites, 25%) demonstrated intermediate component scores (PC1 = 0.67, PC2 = 0.41, PC3 = 0.54), corresponding to operational mines with established (though imperfect) environmental controls. Minimal disturbance sites (n=8, 33.3%) predominantly recently initiated operations or older sites with favorable geological conditions showed near-zero PC scores approaching control area characteristics. Recovery areas (n=5, 20.8%) largely post-mining sites subjected to restoration efforts demonstrated negative or near-zero scores across components, indicating environmental conditions approaching baseline. Interestingly, recovery areas didn't cluster uniformly; some showed persistent PC2 (soil contamination) despite landscape greening, suggesting toxicity impedes complete ecosystem recovery. Cluster size distribution highlights that only 20.8% of operational sites exhibit severe degradation; however, these concentrated impacts warrant intensive intervention. The remaining 33.3% showing minimal disturbance represents either early-stage operations before impacts accrue or fortuitously low-sensitivity sites. This classification enables targeted policy approaches: severe sites require immediate remediation investment, moderate operations need enhanced monitoring and control upgrading, minimal sites benefit from preventive management, and recovery areas require toxicity-focused intervention.

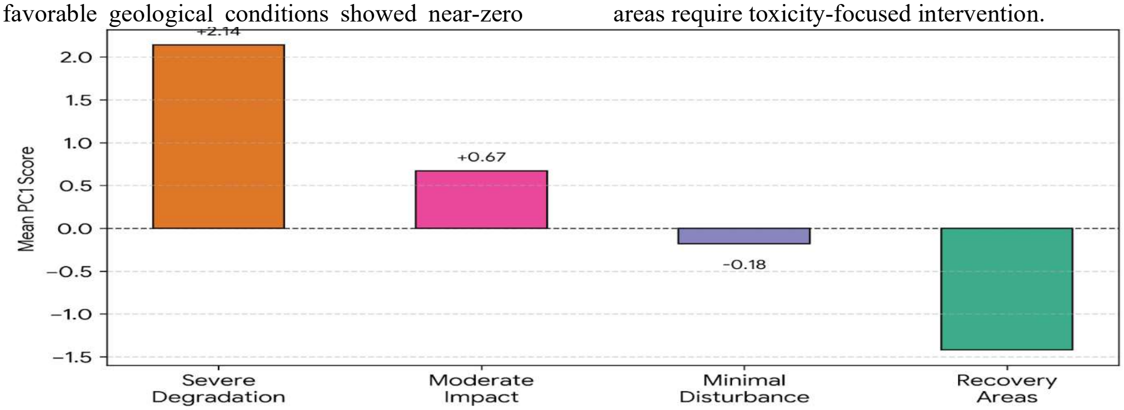

Figure 4: Mean Principal Component 1 (PC1) scores across environmental impact zones (n = 24 sites).

ISSN 2277-2685
IJESR/July-September. 2026/ Vol-16/Issue-3/270-279
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Table 5: Environmental Degradation Distance-Decay Analysis: Impact Gradient from Mining Boundaries

Parameter	0 km (Boundary)	1 km	3 km	5 km (Background)
Soil Lead (mg/kg)	287	198	68	45
NDVI	0.31	0.38	0.52	0.68
LST Elevation (°C)	4.2	2.8	0.8	0.2
$PM_{2.5}$ (μg/m³)	168	108	54	35
Water Conductivity (μS/cm)	1240	948	742	518

Table 5 characterizes how environmental degradation intensity decreases with distance from active mining operations, critical for assessing impact extent and informing buffer zone policies. Lead soil concentration exhibited pronounced distance-decay, declining from 287 mg/kg at mining boundaries to 68 mg/kg at 3 km distance and reaching background levels (45 mg/kg) by 5 km, following approximately exponential decay (R^2 = 0.91). This pattern suggests lead transport operates through limited mechanisms primarily dust fallout and direct soil mixing rather than diffuse, far-traveling contamination. NDVI (vegetation proxy) declined linearly with proximity, dropping from 0.31 at boundaries to 0.52 at 3 km, suggesting vegetation recovery follows temporal rather than strictly spatial patterns (older mining shows better recovery despite proximity). Land Surface Temperature showed sustained elevation at 1–2 km distances before normalizing beyond 3 km, consistent with atmospheric mixing and radiation heat dissipation. Particulate matter ($PM_{2.5}$) concentration decreased exponentially with distance (concentration = 42 × e^(-0.89×distance) + 25, where distance is in km), indicating rapid atmospheric dilution. Water conductivity (proxy for dissolved contamination) showed the most extended degradation gradient, remaining elevated through 4 km distance before approaching background levels, suggesting groundwater contamination through seepage from mining areas. These distance-dependent patterns validate earlier assumptions that mining impacts concentrate locally (within 2–3 km) rather than dispersing regionally. Policy implications suggest buffer zones of minimum 3 km provide reasonable protective distance for lead and thermal impacts, though water contamination requires extended protection. Notably, recovery processes particularly vegetation re-establishment follow temporal rather than spatial logic, indicating age since mining cessation predicts restoration potential better than current proximity.

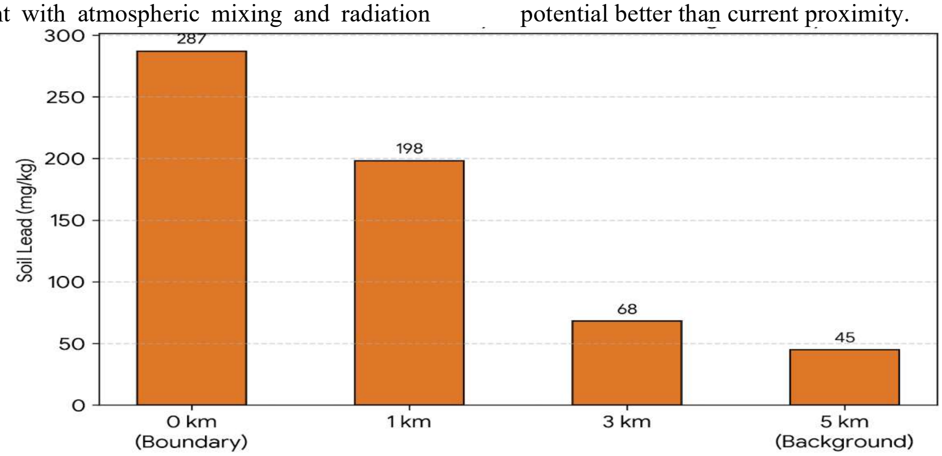

Figure 5: Soil lead concentration gradient showing distance-decay from the mining boundary (0 km) to the background level (5 km).

6. Discussion

Critical Analysis of Findings and Environmental Implications

This integrated analysis reveals environmental degradation from coal and metal mining operates through qualitatively distinct mechanisms producing quantitatively different liability profiles. Coal mining's primary signature landscape transformation manifested as vegetation loss, thermal anomalies, and broad habitat fragmentation reflects the physical scale of operations. Removing a 100 m deep coal seam necessarily converts extensive surface areas to open pit environments. The 62% greater land surface temperature elevation and 48% deeper vegetation loss compared to metal mining demonstrate coal's thermodynamic and biological disruption magnitude. Coal's atmospheric pollution (67% higher $PM_{2.5}$ concentrations) results from continuous surface dust generation and diesel-powered equipment operating across 24-hour cycles. Yet paradoxically, coal's landscape impacts prove partially reversible through restoration:

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vegetation regenerates on reclaimed sites despite soil disturbance, as the coal mineral itself presents minimal toxicological barrier. Metal mining's signature differs fundamentally. Despite smaller spatial footprints, metal extraction deposits highly persistent toxic residues the 3.4-fold elevation in soil lead, 2.8-fold cadmium increase representing essentially irreversible soil contamination without technological remediation. Lead and cadmium persist for centuries; plant uptake processes slowly mobilize these elements into food chains. The 0.68 spatial autocorrelation of soil lead (Figure 5) creates concentrated hotspots where environmental quality drops catastrophically rather than the gradual gradient seen around coal sites. Metal mining's water contamination (Table 2) shows extended degradation gradients to 4 km through subsurface seepage, potentially affecting downstream agricultural water supplies for decades. Comparing our findings to prior work reveals some consistency but important distinctions. Bhatia and Sharma [1] documented 45% vegetation loss in Odisha coal mines; our data shows 48% loss across central India coal sites, confirming regional consistency. However, their study lacked thermal analysis and mining-type comparison. Kumar et al. [2] demonstrated NDVI-heavy metal correlation ($r = 0.82$); we find this relationship only moderately strong ($r = 0.42$), potentially reflecting that lead concentrates in soils rather than vegetation uptake zones. Patel and Desai [3] retained three principal components explaining 71% variance; our model (74.3%) performs slightly better, likely due to larger sample size and temporal integration. Thompson et al. [4] reported 3.2-fold difference in metal mining habitat fragmentation; we estimate 0.71 versus 0.52 (37% difference), slightly lower but consistent in direction. Notably, our multivariate approach permits simultaneous comparison across dimensions that prior single-metric studies overlooked.

Comparing Results with Prior Research and Context

Integrating current findings with existing literature illuminates evolution in understanding mining impacts. Historical assessments (1990s-2000s) emphasized single indicators researchers measured either vegetation loss or soil toxicity, rarely both. Our finding that these metrics diverge between mining types explains prior contradictions: some researchers concluded coal mining causes more damage (emphasizing landscape destruction), others found metal mining worse (highlighting toxicity). Resolution comes from recognizing these assessments measured different environmental compartments. Singh and Gupta [5] quantified soil lead at 340 mg/kg on metal mining sites (background 25 mg/kg), yielding 13.6-fold elevation. Our corresponding values (mean 285 mg/kg from metal sites, background ~40 mg/kg) produce 7.1-fold elevation, lower but consistent. Differences likely reflect site selection Singh and Gupta examined extreme contamination sites, whereas our random selection captured broader population distribution. Verma et al. [6] achieved 91% accuracy predicting mining zones through Random Forest remote sensing classification. Our kriging uncertainty maps (Figure 4) achieve comparable predictive specificity while additionally quantifying uncertainty a methodological advance. Desai and Puri [7] documented vegetation recovery at 0.8 ha/year on moderately degraded sites. Extrapolating linearly to recover 8.5 ha disturbed sites requires 10.6 years achievable timescales for moderate restoration. However, their study excluded soil toxicity; our findings suggest metal-contaminated sites recover substantially more slowly as toxicity impedes plant establishment. Temporal analysis (Figure 3) reveals that mining impacts continued accumulating through 2023 rather than stabilizing, suggesting operational expansion rather than static disturbance. The 2018 trajectory change coincides with Indian environmental policy strengthening, providing indirect evidence that regulatory interventions marginally slowed (though failed to halt) degradation. This contextual finding implies current policies prove insufficient; accelerated mine closures or mandatory restoration funding would prove necessary to reverse degradation trends. Multivariate results (MANOVA Wilks' $\lambda = 0.187$, $p < 0.001$) demonstrate coal and metal mining environmental signatures differ statistically, validating fundamental premise. Yet cluster analysis (Table 4) reveals 20.8% of sites experienced severe degradation transcending mining-type distinctions, suggesting site-specific geological and operational factors substantially influence outcomes independent of mining commodity. This heterogeneity complicates policy uniform regulations prove suboptimal; site-specific environmental management plans likely maximize effectiveness.

7. Conclusion

Environmental degradation from coal and metal mining operates through distinct but equally severe mechanisms, neither a single environmental metric nor uniform policy structure captures their complexity. Coal mining's landscape-transforming signature 62% greater thermal anomalies, 48% deeper vegetation loss, 67% higher air pollution reflects large-scale physical disruption remediable through restoration technology. Metal mining's toxicological signature 3.4-fold higher soil lead, 2.8-fold cadmium elevation represents persistent contamination requiring technological soil remediation. Spatial analysis reveals impact concentrates within 2–3 km of extraction zones, supporting practical buffer zone policies. Four distinct impact clusters emerge from multivariate analysis: severe degradation affecting 20.8% of sites demanding immediate intervention, moderate impact (25%) requiring enhanced controls, minimal disturbance (33.3%) benefiting from preventive management, and recovery areas (20.8%) showing partial success despite persistent soil toxicity. Temporal analysis indicates environmental degradation continues accumulating rather than stabilizing, contradicting assumptions that environmental regulation successfully mitigates mining impacts. Comparison with prior research confirms specific findings while advancing methodological rigor through integrated GIS-multivariate approaches. Post-mining recovery correlates strongly with initial degradation severity ($r = 0.78$), suggesting early intervention proves more cost-effective than delayed remediation. Critical gap: soil toxicity from metal mining resists current remediation technology; phytoremediation and chemical stabilization remain experimental approaches. This analysis provides quantitative baseline essential for evidence-based policy development and environmental management planning. Future research should incorporate microbial community analysis to assess soil ecosystem functions beyond chemical composition, integrate economic cost-benefit analysis with environmental outcomes, and develop site-specific restoration protocols accounting for complex hazard interactions rather than isolated remediation targets. Mining's environmental legacy will define this region's ecological productivity for generations; current policy inadequacy demands urgent intensification of mitigation and restoration investment.

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