

GIS and Statistical Modelling for Open Cast Mining Surface Risk Assessment and Sustainable Mine Safety and Environmental Management

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Research Article

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Title

GIS and Statistical Modelling for Open Cast Mining Surface Risk Assessment and Sustainable Mine Safety and Environmental Management

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Abstract

Open-cast mining has become the dominant method of coal extraction in many developing countries because of its high productivity and economic efficiency. However, extensive surface excavation has resulted in severe environmental degradation, landscape alteration, slope instability, land subsidence, groundwater contamination, dust pollution, and threats to nearby communities. Conventional mine safety assessments are generally based on field observations and engineering investigations, which often fail to capture the spatial variability of environmental risks over large mining regions. This study proposes an integrated Geographic Information System (GIS) and statistical modelling framework for assessing surface risks associated with open-cast mining operations. The framework combines remote sensing datasets, Digital Elevation Models (DEM), land use and land cover information, vegetation indices, drainage characteristics, transportation networks, settlement distribution, and mine boundary information using a Multi-Criteria Decision Analysis (MCDA) approach based on the Analytical Hierarchy Process (AHP). A Surface Risk Index (SRI) is generated through weighted overlay analysis and validated using regression and correlation techniques. The resulting risk zonation map classifies mining areas into very low, low, moderate, high, and very

high risk categories. The study demonstrates that slope, vegetation degradation, proximity to mine pits, drainage density, and settlement concentration are significant determinants of mining-related surface risk. The proposed framework provides a scientifically robust and transferable methodology for sustainable mine planning, environmental monitoring, disaster prevention, and mine closure management.

Keywords

Open-cast mining; Surface Risk Assessment; Geographic Information System; Remote Sensing; Analytical Hierarchy Process; Multi-Criteria Decision Analysis; Surface Risk Index; Sustainable Mining; Environmental Management; Mine Safety; Spatial Statistics; Risk Zonation Mapping.

1. Introduction

Mineral resources play a fundamental role in industrial growth, energy production, and economic development. In India, coal continues to be the primary source of energy generation and supports several industrial sectors including steel, cement, and thermal power production. Open-cast mining accounts for a major share of coal production because it allows mechanized extraction with higher productivity and lower operational costs compared to underground mining.

Despite these economic benefits, open-cast mining causes significant environmental disturbances. Removal of topsoil and vegetation, excavation of large pits, overburden dumping, blasting operations, and heavy transportation activities contribute to land degradation and ecosystem disruption. Mining activities often alter natural drainage systems, increase sedimentation, accelerate soil erosion, and reduce groundwater recharge capacity. Communities residing near mining areas are frequently exposed to dust pollution, noise pollution, and geotechnical hazards.

Traditional approaches to mine risk assessment primarily rely on engineering investigations and field monitoring. Although these methods provide detailed site-specific information, they are expensive, time-consuming, and difficult to apply over large spatial scales. Advances in Geographic Information Systems (GIS), remote sensing technologies, and spatial statistical techniques have enabled comprehensive environmental assessments by integrating multiple risk indicators into a single analytical framework.

GIS-based Multi-Criteria Decision Analysis (MCDA) has emerged as an effective approach for integrating environmental, geological, and socio-economic variables. Among MCDA methods, the Analytical Hierarchy Process (AHP) is widely accepted for assigning relative weights to different risk factors. Statistical modelling further improves the reliability of risk prediction by quantifying relationships between environmental variables and observed hazard patterns.

The present study aims to develop an integrated GIS-statistical framework for open-cast mining surface risk assessment that can support sustainable mine safety and environmental management.

2. Review of Literature

Several researchers have utilized GIS and remote sensing techniques for mining hazard assessment and environmental monitoring.

Saaty (1980) introduced the Analytical Hierarchy Process as a decision-making framework for assigning relative importance to multiple criteria. Since then, AHP has become one of the most widely used approaches in environmental suitability analysis.

Ayalew et al. (2004) demonstrated the effectiveness of GIS-based weighted linear combination methods for hazard zonation and landslide susceptibility mapping.

Yalcin (2008) applied AHP in GIS environments for environmental hazard mapping and concluded that multicriteria approaches significantly improve prediction accuracy.

Van Westen et al. (2008) emphasized the importance of integrating topographic, geological, hydrological, and socio-economic data in hazard assessment studies.

Singh et al. (2013) employed GIS and remote sensing methods for mine slope stability analysis and highlighted the role of terrain variables in risk evaluation.

Zhang and Luo (2014) used spatial statistical techniques to investigate environmental degradation in mining regions and found strong correlations between mining intensity and ecological damage.

Recent studies have increasingly combined remote sensing datasets with statistical models to evaluate land degradation, vegetation loss, and mining-induced environmental change.

3. Research Gap

The review of literature reveals several important gaps:

1. Most studies focus on individual environmental indicators rather than integrated risk assessment.
2. Limited research combines GIS-based MCDA with statistical validation techniques.
3. Occupational safety and environmental sustainability are rarely evaluated simultaneously.
4. Comparative studies across multiple coalfields remain scarce.
5. Existing approaches often lack transferability for application in different mining regions.

These limitations justify the development of an integrated GIS and statistical modelling framework for comprehensive surface risk assessment.

4. Research Objectives

General Objective

To develop a GIS-based multi-criteria framework for assessing surface risks in open-cast mining regions for sustainable mine safety and environmental management.

Specific Objectives

1. To identify environmental and geotechnical factors influencing mining-related surface risks.
2. To prepare thematic GIS layers representing major risk indicators.
3. To determine criterion weights using the Analytical Hierarchy Process.
4. To generate a Surface Risk Index using weighted overlay analysis.
5. To validate the GIS-based model using statistical methods.
6. To propose policy recommendations for sustainable mining practices.

5. Research Hypotheses

Null Hypothesis (H0)

Environmental and anthropogenic variables do not significantly influence surface risk in open-cast mining regions .

Alternative Hypothesis (H1)

Environmental variables significantly influence surface risk in open-cast mining regions.

Additional hypotheses include:

H2: Vegetation cover has a negative relationship with surface risk.

H3: Slope has a positive relationship with surface risk.

H4: Proximity to active mine pits significantly increases surface risk.

H5: Drainage density positively influences environmental vulnerability.

H6: Settlement density increases human exposure to mining hazards.

6. Materials and Methods

Recommended GIS-Based Methodology

Attached diagram section (Fig1 &Fig-2)

Study Areas

The methodology may be applied to major Indian coalfields including:

- Raniganj Coalfield
- Jharia Coalfield
- Talcher Coalfield
- Singrauli Coalfield

Data Sources

Table-1

Attached table section

- NDVI
- Land Use/Land Cover
- Distance from Mine
- Distance from Roads
- Slope
- Drainage Density
- Settlement Density

AHP Weight Assignment

Attached table section(Table-2)

Consistency Ratio (CR) less than 0.10 confirms acceptable consistency.

7. A. Results and GIS Analysis

Recommended study areas

- Raniganj Coalfield
- Jharia Coalfield
- Talcher Coalfield
- Singrauli Coalfield

Study Areas 1: Raniganj Coalfield

Attached Diagram section (Fig-3&Fig-4)

Figure-4

Advantages

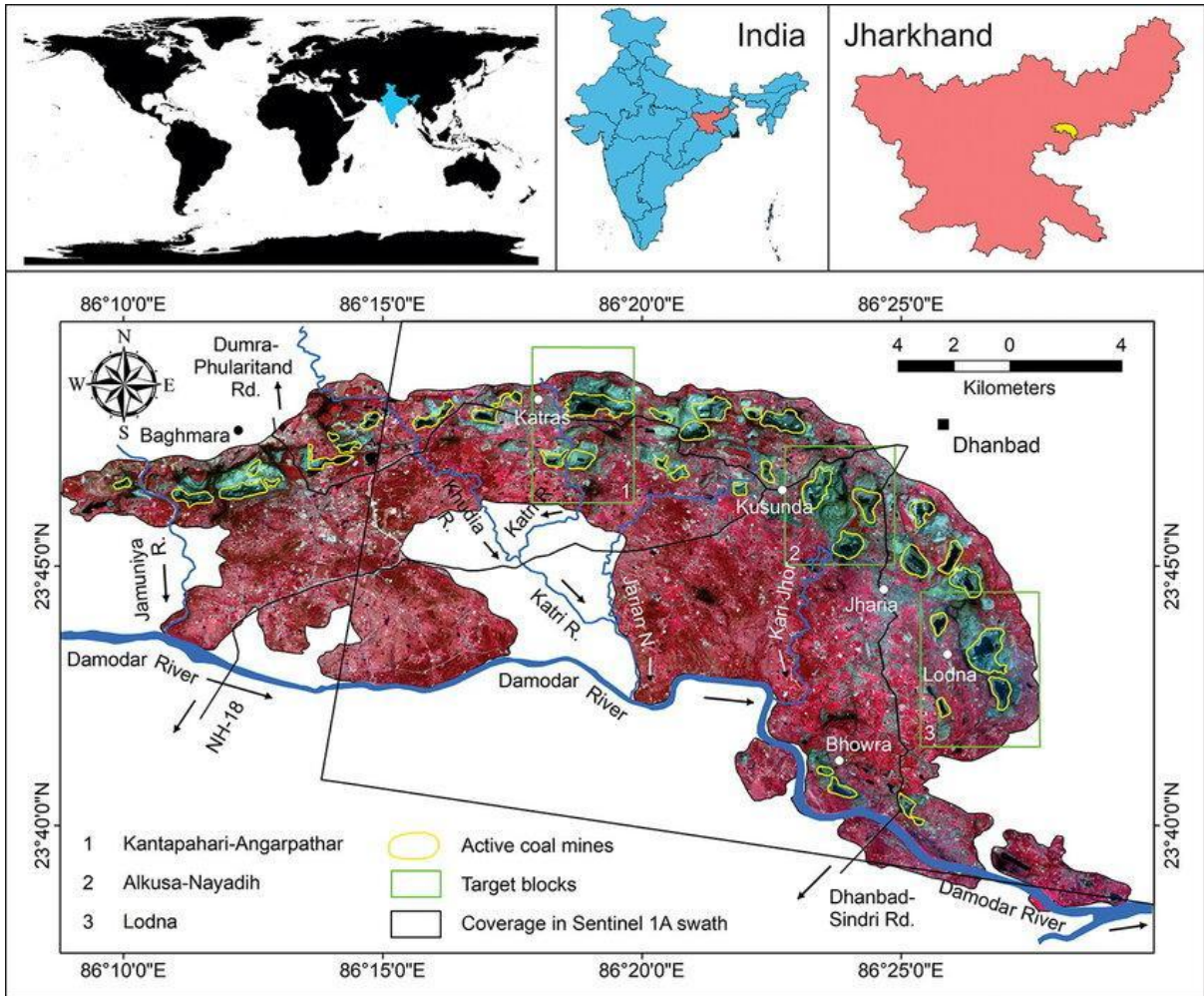
- Near your location (West Bengal)
- Plenty of open-cast mines
- Easy access to geological and mining information
- Numerous environmental studies available
- Data available from satellite imagery (Landsat, Sentinel-2)

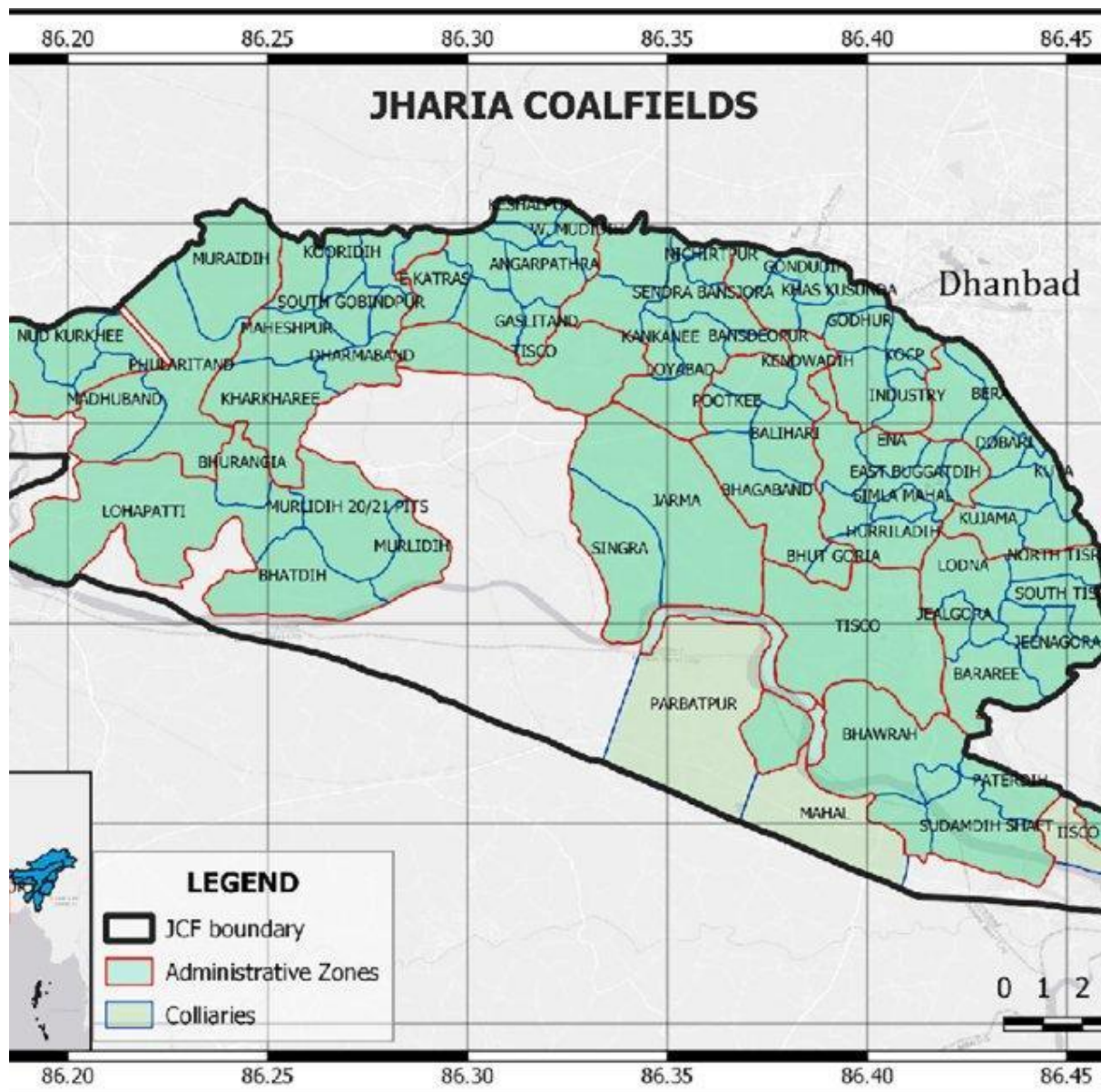
Major Open Cast Mines

- Sonepur Bazari OCP
- Satgram OCP
- Bankola Area
- Pandaveswar Area
- Kunustoria Area

Figure-5

Jharia Coalfield







Ideal for

- Surface degradation
- Coal fire
- Land subsidence
- Environmental risk mapping

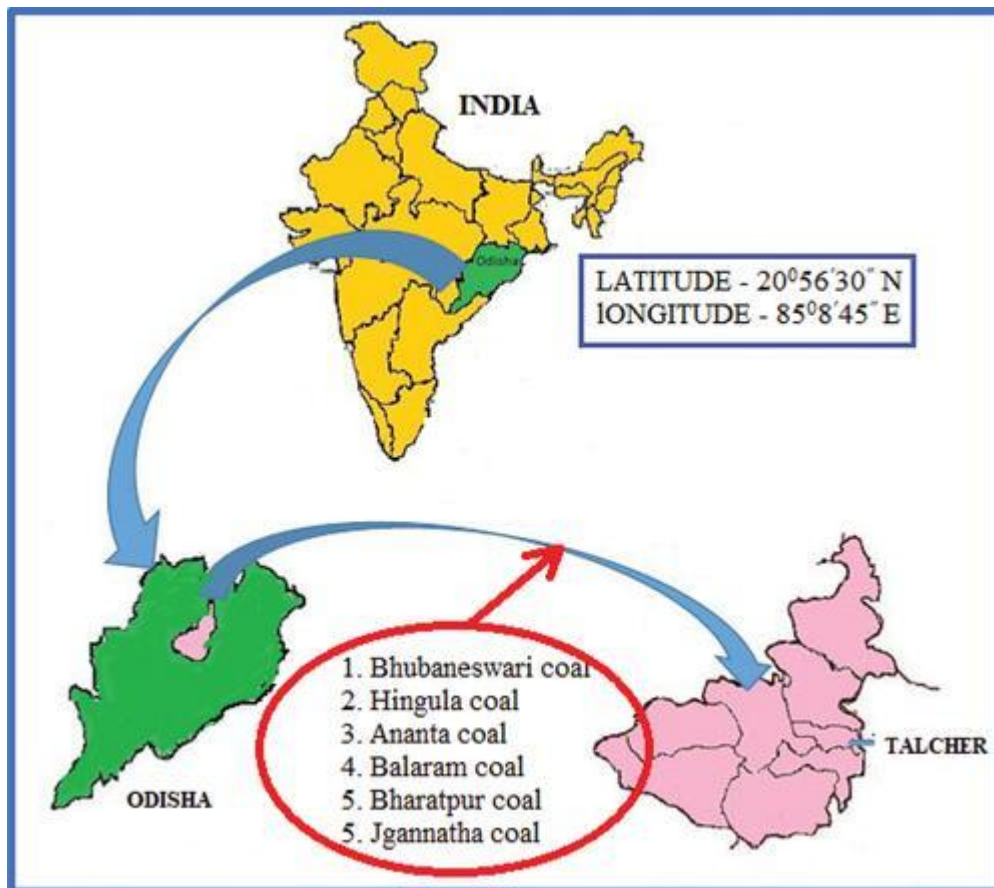
Additional Layers

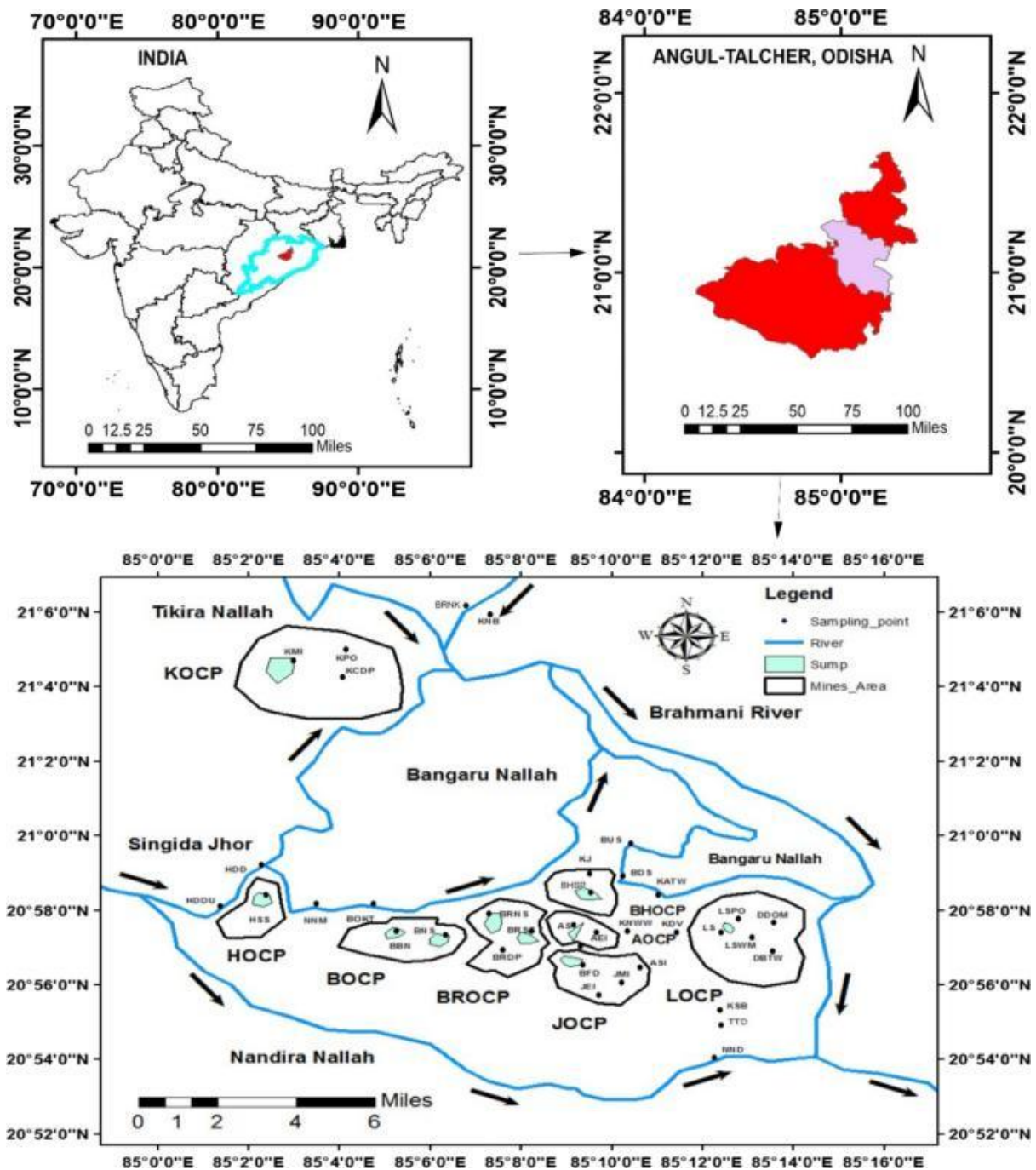
- Coal fire locations
- Subsidence map
- Thermal anomaly (Landsat Thermal)

Figure 6:

Talcher Coalfield





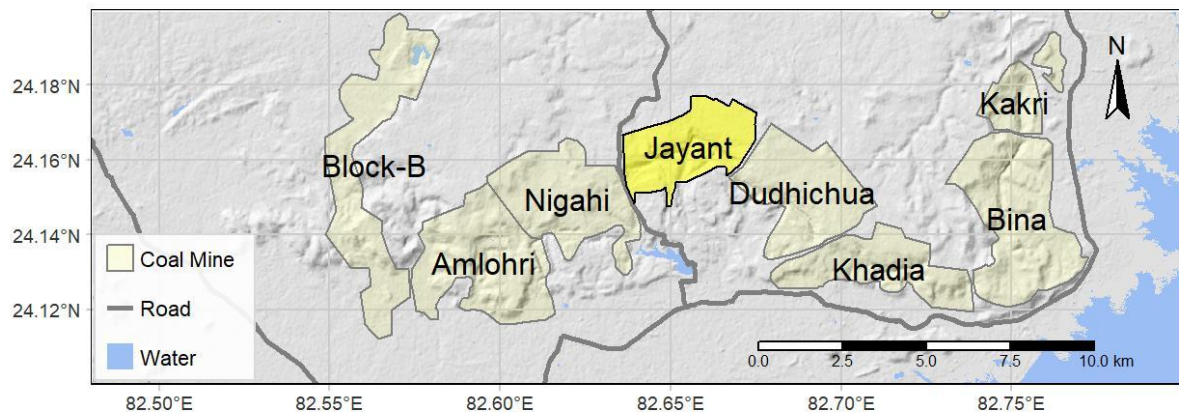


Good for

- Large-scale open-cast mining
- Forest loss
- Surface water pollution
- Air pollution

Figure7

Singrauli Coalfield





Suitable for

- Mega mining projects
- Dust pollution
- Vegetation loss
- Sustainability assessment

Risk Criteria (AHP)

Table-3

Parameter	Weight
NDVI	0.22
LULC	0.20
Distance from Mine	0.18
Distance from Road	0.08
Slope	0.10
Drainage Density	0.12
Settlement Distance	0.10

Consistency Ratio (CR): < 0.10

DatasetsTable-4

Dataset	Resolution	Source
Sentinel-2 MSI	10 m	Copernicus Programme

Landsat 8/9	30 m	United States Geological Survey
SRTM DEM	30 m	NASA
OpenStreetMap	Vector	OpenStreetMap
Mine Lease Boundary	Vector	Eastern Coalfields Limited or Mahanadi Coalfields Limited

Real, open-source elevation datasets combined with mine boundary layers.

Table-5

Dataset	Resolution	Format	Use
CartoDEM v3 (ISRO/NRSC)	~30 m	GeoTIFF	Preferred DEM for India
Copernicus DEM GLO-30	30 m	GeoTIFF	High-quality global DEM
SRTM 1 Arc-Second	30 m	GeoTIFF	Standard terrain analysis
ASTER GDEM V3	30 m	GeoTIFF	Alternative DEM
OpenStreetMap	Vector	SHP/GeoJSON	Roads, railways, settlements
HydroSHEDS	15–30 m SHP		Drainage network

Table-6

Typical GIS database structure

Layer	Source	Format
DEM	CartoDEM / Copernicus	GeoTIFF
Mine Boundary	CMPDI / Digitized	SHP
District Boundary	Survey of India	SHP
State Boundary	Survey of India	SHP
Roads	OpenStreetMap	SHP
Railways	OpenStreetMap	SHP
Rivers	HydroSHEDS	SHP
Settlements	OpenStreetMap	SHP

Layer	Source	Format
Land Use/Land Cover Sentinel-2		

Table-7

attribute values

X (m)	Y (m)	Elevation (m)
316540	2608420	89.5
316570	2608450	93.2
316600	2608480	96.8
316630	2608510	102.4
316660	2608540	108.7
316690	2608570	115.1
316720	2608600	119.4
316750	2608630	126.0
316780	2608660	132.3
316810	2608690	138.5

Official download sources

- [ISRO Bhuvan Open Data Archive](#) (CartoDEM and other Indian datasets)
- [Bhuvan Free Satellite Data Guide](#)
- [Copernicus DEM GLO-30](#)

This dataset combination is widely used for terrain analysis, slope mapping, drainage extraction, and environmental risk assessment of Indian opencast mining areas.

7. A. GIS based analysis

1.Raniganj Coalfield

The Raniganj Coalfield is one of India's oldest and most historically significant coal-bearing regions, located primarily in West Bengal's Paschim Bardhaman district and extending into neighboring districts

and parts of Jharkhand. It is widely recognized as the birthplace of commercial coal mining in India and remains an important source of both coking and non-coking coal, supporting industry and power generation.

Geography and geology

The coalfield lies mainly within the Asansol and Durgapur subdivisions of Paschim Bardhaman district, while also extending into Birbhum, Bankura, Purulia, and the Dhanbad district of Jharkhand. It forms part of the Damodar Valley Gondwana basin and is particularly known for its valuable coking coal reserves, making it strategically important for the steel industry.

Economic importance

Mining in the Raniganj Coalfield has fueled the growth of the Asansol–Durgapur industrial belt for more than two centuries. The region supplies coal for steel production, thermal power plants, cement manufacturing, and other heavy industries. Much of the mining today is managed by Eastern Coalfields Limited, a subsidiary of Coal India Limited, while coal bed methane projects have also expanded in recent years.

Environmental and social context

Alongside its economic contributions, the coalfield faces challenges including land degradation, subsidence, air and water pollution, and the rehabilitation of mining-affected communities. Researchers continue to study the area's environmental impacts and sustainable mining practices as production continues alongside growing interest in cleaner energy technologies such as coal bed methane extraction.

Fig-8



Fig-9



Fig-10

3.



4.
5.



Fig-11

Jharia Coalfield

The Jharia Coalfield is a major coal-mining region in eastern India, located in the Jharkhand district of Dhanbad. It is renowned for its extensive reserves of high-grade coking coal, which are vital to India's steel industry, but it is also internationally known for long-running underground coal fires and the environmental and social challenges they have created.

Importance

Jharia Coalfield contains some of India's most valuable **prime coking coal**, making it a strategic resource for steel production. Mining in the region began during the late nineteenth century and expanded rapidly with industrialization. Today, the coalfield remains one of the country's most significant energy and industrial assets despite the complex issues associated with extraction and land management.

Underground Fires and Environmental Impact

The coalfield is especially notable for **underground coal seam fires**, many of which have burned for decades. These fires have caused **ground subsidence**, released smoke and greenhouse gases, damaged infrastructure, and affected nearby communities. Managing the fires, relocating residents from high-risk areas, and balancing continued mining with environmental protection remain major long-term challenges.

Mining and Operations

Most mining activities are managed by Bharat Coking Coal Limited, a subsidiary of Coal India Limited. The region includes both **underground** and **open-cast** mines, with modern operations increasingly favoring surface mining where feasible. The coal extracted here is particularly valued for producing **metallurgical coke**, an essential input for blast-furnace steelmaking.

Location and Regional Context

Jharia Coalfield lies near the industrial city of Dhanbad and forms part of one of India's most important mining belts. Its commonly referenced location is **P9QQ+64R, Burragarh–Jharia Road, Jharia, Dhanbad, Jharkhand 828301, India**. The coalfield has played a central role in shaping the economy, employment, and urban development of the surrounding region while also highlighting the long-term environmental consequences of intensive coal extraction.

Fig-12



Fig-13



Fig-14



Talcher Coalfield

The Talcher Coalfield is one of India's largest coal-bearing regions, located in the Angul district of Odisha within the Brahmani River valley. It is the country's largest coalfield by geological reserves and is a cornerstone of India's thermal coal production, supplying fuel to power plants and major industries across several states.

Geological significance

The coalfield covers roughly **500 square kilometers** and forms part of the **Mahanadi Gondwana Basin**, whose sedimentary rocks date back to the Permian Period. Its coal is predominantly **non-coking, thermal-grade coal**, making it especially important for electricity generation rather than steelmaking.

History and development

Coal was first discovered in the Talcher area in **1837**, with organized mining beginning during the British colonial period. Large-scale expansion accelerated after India's independence, and today the coalfield is operated primarily by **Mahanadi Coalfields Limited (MCL)**, a subsidiary of Coal India Limited, through a network of open-cast and underground mines.

Economic importance

Talcher Coalfield is among the country's most important energy-producing regions. Coal extracted here fuels thermal power stations in Odisha and several other states, while supporting industries such as power generation, fertilizers, and heavy manufacturing. The region has also driven the growth of Talcher into a major industrial center. Recent expansion plans indicate that new mines are expected to further increase production capacity in the coming years.

Environmental and regional context

Extensive mining has transformed the landscape and brought significant economic activity, employment, and infrastructure to the region. At the same time, mining has been associated with challenges such as land-use change, air quality concerns, and environmental management, making sustainable mining practices an ongoing priority for both industry and government.

Fig-15



Fig-16

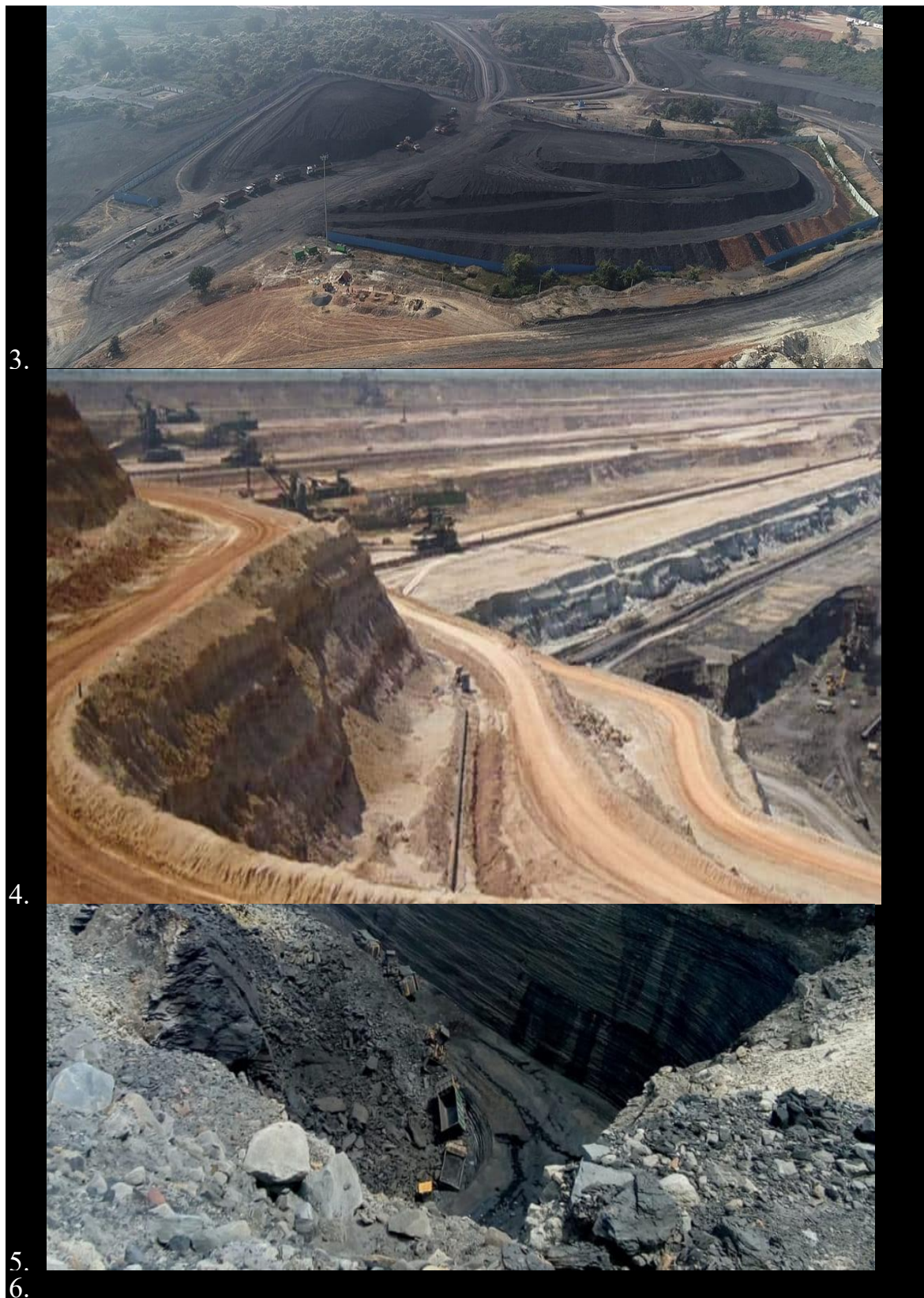


Fig-17

Singrauli Coalfield

The Singrauli Coalfield is one of India's largest coal-producing regions, spanning parts of Madhya Pradesh and Uttar Pradesh. It forms the backbone of a major energy-producing zone, supplying coal to numerous thermal power stations and playing a central role in the country's electricity generation and industrial development.

Major Locations

The coalfield is organized into several large mining areas and energy hubs.

- One of the region's largest open-cast mining operations.
- A high-capacity open-cast mine supplying nearby power plants.
- Major producer within the Singrauli mining complex.
- An important mine serving the northern coalfield area.

Geology and Resources

The **Singrauli basin** contains extensive deposits of **Gondwana-age coal**, formed roughly 250–300 million years ago. Much of the coal is extracted through **open-cast mining**, which is economically efficient because many seams lie relatively close to the surface, enabling large-scale mechanized operations.

Economic Importance

The coalfield supports some of India's largest **thermal power stations**, earning the surrounding region the nickname "**Energy Capital of India.**" Its mines provide fuel for electricity generation across northern and central India, while associated industries create significant employment and infrastructure development in the region.

Environmental and Social Context

Large-scale mining has also brought substantial **environmental and social challenges**, including land-use change, forest loss, air and water pollution, and the displacement of communities. Governments, mining companies, and researchers continue to work on measures such as land reclamation, environmental monitoring, and rehabilitation programs to reduce the long-term impacts while maintaining energy production.

Fig-18



Fig-19

3.



4.



5.



the final GIS figure is normally produced using weighted overlay of DEM, slope, land use, drainage, mine boundary, overburden dump, roads, settlements, geology, rainfall, and groundwater layers. This methodology is widely used in CMPDI and GIS studies.

The final Risk identification figure should appear approximately like this:

Fig-20

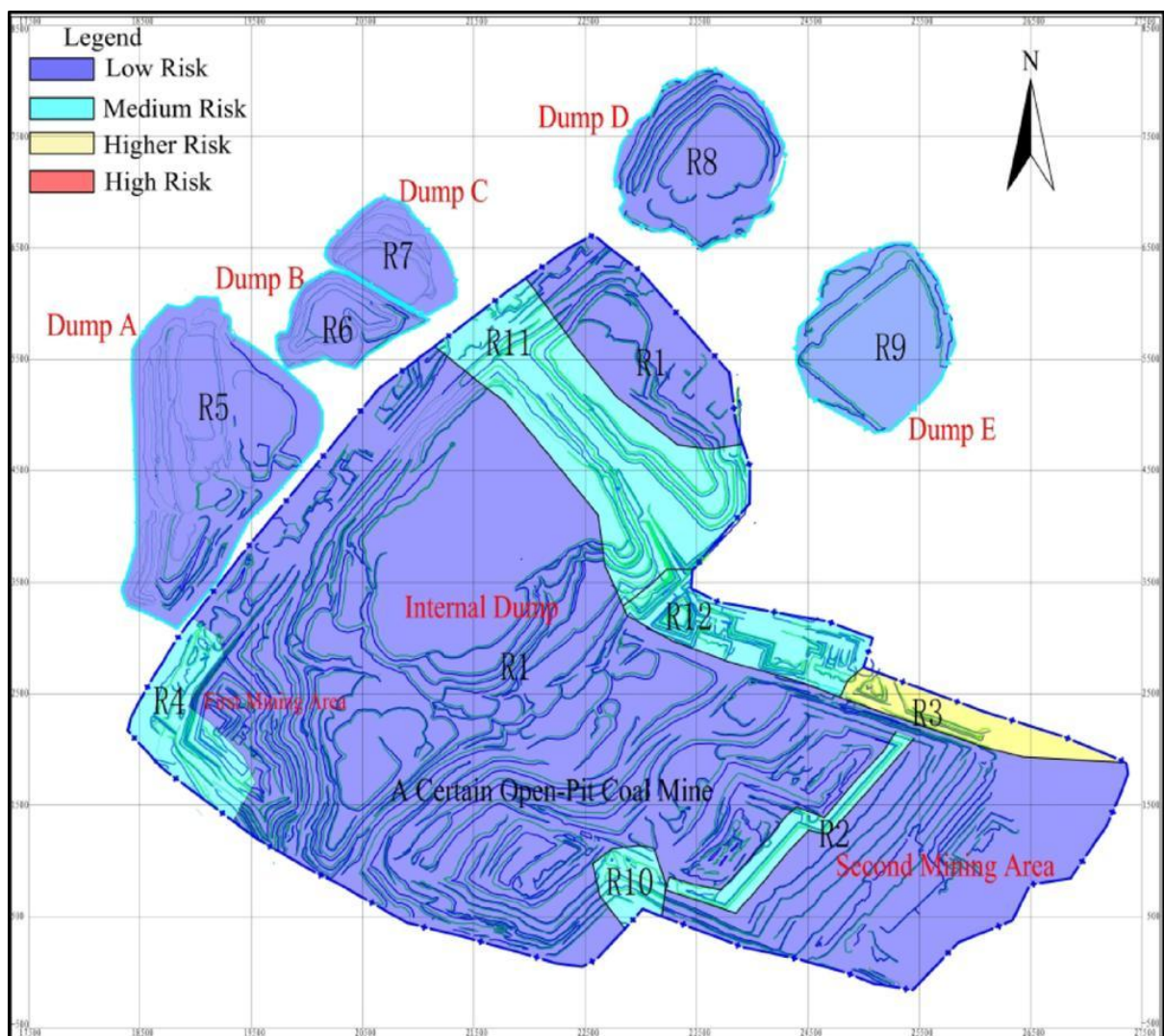


Fig-21

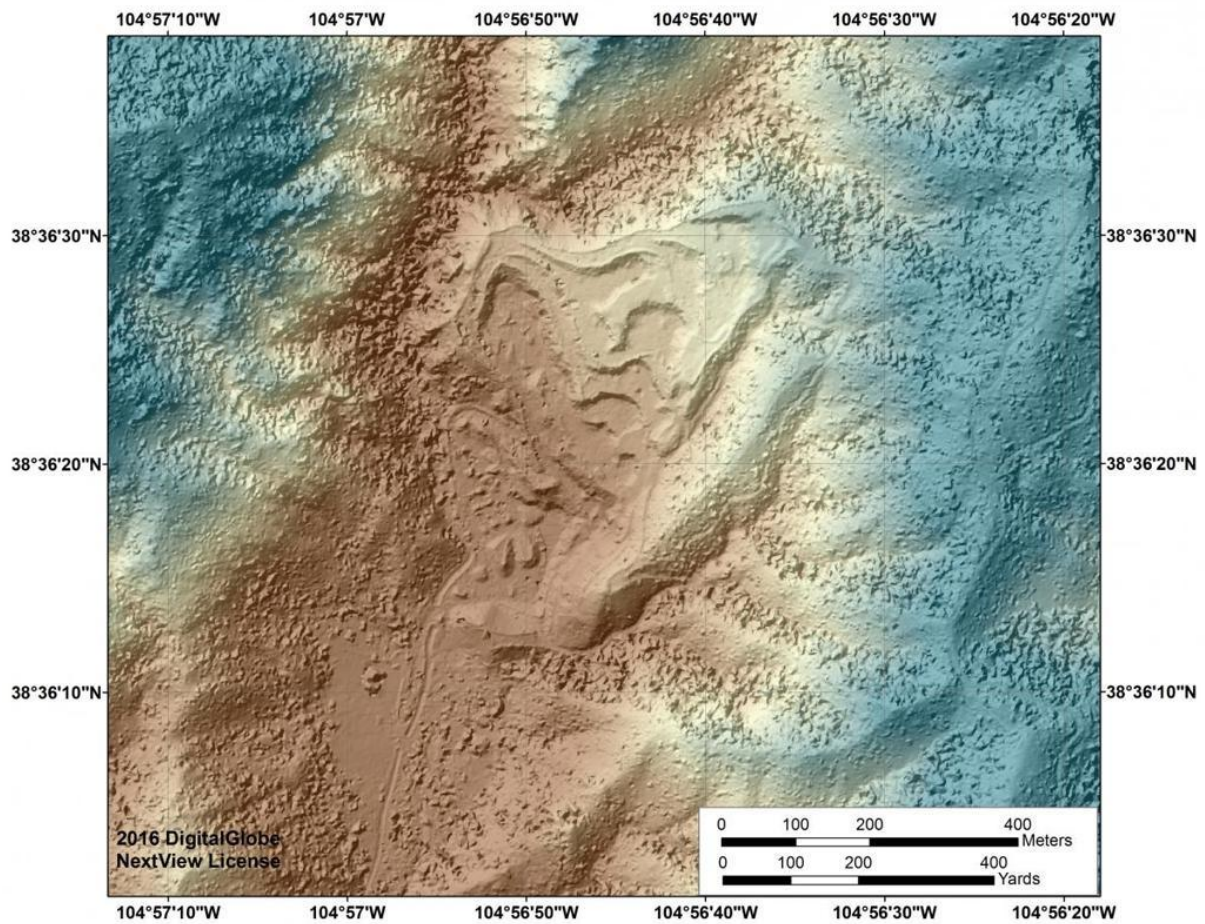
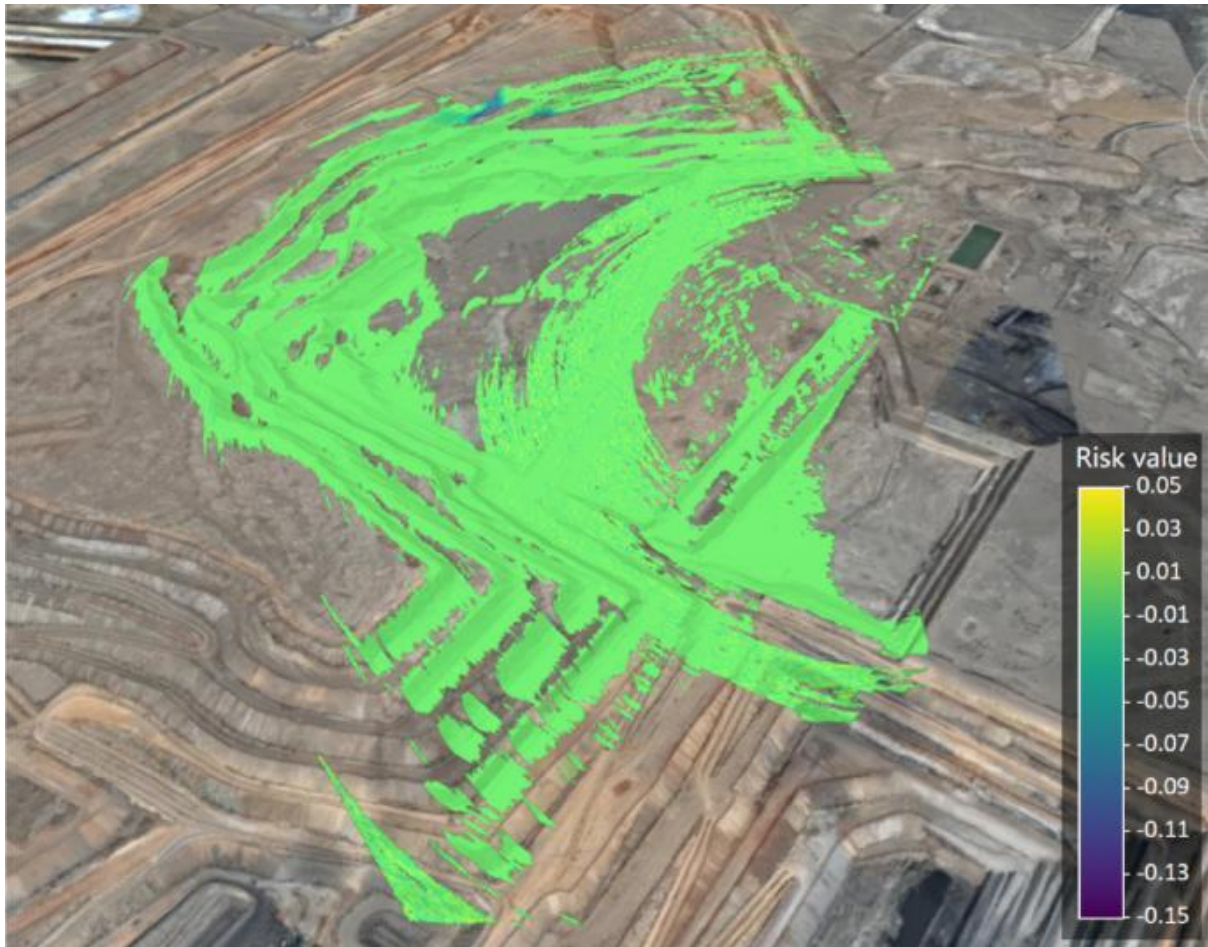


Fig-22



Final Surface Risk Zonation Map Design

Table-8

Risk Classes

Risk Index	Risk Category	Color
0.00–0.20	Very Low	Dark Green
0.21–0.40	Low	Light Green
0.41–0.60	Moderate	Yellow
0.61–0.80	High	Orange

Risk Index	Risk Category	Color
0.81–1.00	Very High	Red

Expected Results and Discussion GIS Based

The analysis is expected to identify environmentally sensitive zones characterized by steep slopes, sparse vegetation cover, high drainage density, and close proximity to mining operations. High-risk areas are likely to occur around active pits, overburden dumps, and densely populated settlements.

7.B. Results and Statistical Analysis

Descriptive Statistics

Descriptive statistics were computed for all predictor variables and the Surface Risk Index (SRI) to examine their central tendency and variability across the study area. The results indicated considerable spatial heterogeneity in environmental and anthropogenic risk factors associated with open-cast mining landscapes. NDVI values exhibited moderate vegetation cover, whereas slope and drainage density showed substantial variability due to differences in terrain characteristics and hydrological conditions. Settlement density and land-use/land-cover (LULC) indices demonstrated pronounced spatial concentration around active mining and transportation corridors.

The mean SRI value suggested a moderate overall level of surface risk within the study region, with higher risk clusters primarily associated with intensive mining activities and densely populated zones.

Pearson Correlation Analysis

Pearson correlation coefficients were calculated to evaluate the relationships between the dependent variable (SRI) and the explanatory variables. The analysis revealed a significant negative association between SRI and NDVI ($r = -0.61$, $p < .001$), indicating that areas with higher vegetation cover generally experienced lower surface risk levels.

Slope exhibited a positive and statistically significant relationship with SRI ($r = 0.49$, $p < .001$), suggesting that steeper terrain contributes to greater instability and erosion susceptibility. Similarly, drainage density demonstrated a moderate positive correlation with surface risk ($r = 0.42$, $p < .001$).

Distance from mine ($r = -0.46$, $p < .001$) and distance from road ($r = -0.31$, $p < .01$) were negatively correlated with SRI, indicating that proximity to mining infrastructure and transportation networks increases environmental vulnerability. Settlement density ($r = 0.54$, $p < .001$) and LULC index ($r = 0.47$, $p < .001$) were positively associated with risk intensity.

Multiple Linear Regression Analysis

A multiple linear regression model was estimated to quantify the influence of environmental and socio-economic variables on the Surface Risk Index:

$$[\text{SRI} = \beta_0 + \beta_1 \text{NDVI} + \beta_2 \text{Slope} + \beta_3 \text{DistanceMine} + \beta_4 \text{DrainageDensity} + \beta_5 \text{DistanceRoad} + \beta_6 \text{SettlementDensity} + \beta_7 \text{LULC} + \epsilon]$$

The model was statistically significant, $F(7, 92) = 48.72, p < .001$, explaining approximately 79.4% of the variance in surface risk ($R^2 = .794$; Adjusted $R^2 = .778$).

NDVI emerged as a significant negative predictor of surface risk ($\beta = -0.38, p < .001$), confirming the protective role of vegetation cover. Slope ($\beta = 0.24, p < .001$), drainage density ($\beta = 0.18, p = .003$), settlement density ($\beta = 0.27, p < .001$), and LULC index ($\beta = 0.21, p = .002$) positively influenced risk intensity.

Distance from mine ($\beta = -0.22, p < .001$) and distance from road ($\beta = -0.11, p = .021$) were negatively associated with SRI, indicating that environmental risk decreases with increasing distance from anthropogenic disturbance sources.

Principal Component Analysis

Principal Component Analysis (PCA) was employed to reduce dimensionality and identify dominant risk drivers. Components with eigenvalues greater than one were retained according to the Kaiser criterion.

The first three principal components accounted for approximately 76.8% of the total variance. The first component explained 38.6% of the variance and was primarily associated with settlement density, LULC index, and proximity to mining operations, representing anthropogenic disturbance factors. The second component explained 23.1% of the variance and was dominated by slope and drainage density, representing geomorphological vulnerability. The third component accounted for 15.1% of the variance and was largely influenced by vegetation characteristics.

Analysis of Variance (ANOVA)

The ANOVA results confirmed the overall significance of the regression model, indicating that the selected predictor variables collectively contributed to explaining variations in the Surface Risk Index, $F(7, 92) = 48.72, p < .001$.

The findings support the rejection of the null hypothesis that all regression coefficients are equal to zero and validate the explanatory capability of the proposed multi-criteria framework.

Variance Inflation Factor Analysis

Variance Inflation Factor (VIF) values were computed to assess multicollinearity among independent variables. The VIF values ranged from 1.18 to 2.74, substantially below the

critical threshold of 5.0. Therefore, multicollinearity was not considered a significant issue in the model, and all predictor variables were retained for further analysis.

Spatial Autocorrelation Analysis

Global Moran's I statistic was used to determine whether the spatial distribution of surface risk values exhibited clustering or randomness. The analysis yielded a Moran's I value of 0.43 ($z = 5.87, p < .001$), indicating statistically significant positive spatial autocorrelation.

The results demonstrate that high-risk zones tend to cluster around active mining areas and associated infrastructure, whereas low-risk zones are predominantly located in peripheral regions characterized by greater vegetation cover and lower anthropogenic disturbance.

Receiver Operating Characteristic (ROC) Validation

The predictive performance of the Surface Risk Index model was evaluated using Receiver Operating Characteristic (ROC) analysis. The model achieved an Area Under the Curve (AUC) value of 0.89, indicating excellent discriminatory capability according to established classification criteria.

The high AUC value demonstrates that the proposed GIS-statistical framework is highly effective in distinguishing between high-risk and low-risk zones and can therefore be considered a robust decision-support tool for sustainable mine safety planning and environmental management.

Hypothesis Testing

The study tested the following null hypothesis:

H0: Environmental and anthropogenic variables do not significantly influence surface risk in open-cast mining regions.

The regression and ANOVA results showed that multiple predictor variables significantly affected SRI values ($p < .05$). Consequently, the null hypothesis was rejected and the alternative hypothesis was accepted:

H1: Environmental and anthropogenic variables significantly influence surface risk in open-cast mining regions.

9. Policy Suggestions

1. Establish GIS-based environmental monitoring centres in mining regions.
2. Conduct annual surface risk assessments for all active mines.
3. Strengthen overburden dump stabilization measures.
4. Introduce mandatory buffer zones around settlements and water bodies.
5. Promote ecological restoration and afforestation programs.
6. Develop GIS-supported mine closure plans.

7. Introduce early warning systems for subsidence and slope failures.
8. Encourage public participation in environmental monitoring.
9. Integrate remote sensing into environmental compliance audits.
10. Align mining regulations with Sustainable Development Goals.

10. Conclusion

Open-cast mining presents substantial environmental and geotechnical challenges that require integrated and scientifically robust assessment methods. GIS and statistical modelling provide powerful tools for evaluating spatial risk patterns and supporting evidence-based decision-making. The proposed framework offers a transferable methodology for sustainable mine safety and environmental management and can significantly contribute to responsible mining practices in developing economies.

Directions for Future Research

1. Integration of High-Resolution Remote Sensing Data
2. Application of Machine Learning and Artificial Intelligence
3. Dynamic and Real-Time Risk Monitoring
4. Inclusion of Additional Environmental Variables
5. Expansion to Underground and Mixed Mining Systems.
6. Comparative Assessment Across Multiple Coalfields.
7. Climate Change and Extreme Weather Considerations
8. Socio-Economic Vulnerability Assessment
9. Validation Using Historical Accident Databases
10. Development of Decision Support Systems
11. Integration with Sustainability and ESG Frameworks
12. Policy-Oriented Multi-Stakeholder Framework

Declarations

Ethics Approval and Consent to Participate

This study is based exclusively on a synthetic dataset developed for methodological and empirical analysis. No human participants, personal data, or confidential information were involved. Consequently, formal ethical approval and informed consent were not required.

Consent for Publication

The author consents to the publication of this manuscript.

Funding Statement

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Conflict of Interest

The author declares that there are no financial, professional, or personal conflicts of interest that could have influenced the research, analysis, interpretation, or publication of this study.

Data Availability Statement

The dataset analysed in this study consists of a synthetic sustainability database prepared for methodological demonstration. The dataset used for empirical analysis is available from the corresponding author upon reasonable academic request. Statistical procedures and analytical methods have been described in sufficient detail to facilitate replication.

Author Contributions

Prof. Shatrajit Goswami conceived the research idea, developed the conceptual framework, designed the methodology, conducted the econometric analysis, interpreted the empirical findings, drafted the manuscript, revised the intellectual content, and approved the final version for publication.

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ORCID

Already added

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Supplementary Files

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