

Spatiotemporal Analysis of Mining-Induced Surface Deformation and Heavy Metal Dispersion Risk: A Cloud-Based Integration of SAR and Multispectral Data in the Jos Plateau, Nigeria

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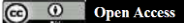
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ABSTRACT

Artisanal and small-scale mining (ASM) in Jos Plateau, Nigeria, has created one of West Africa's most extensive mining legacies, yet comprehensive spatial assessments remain conspicuously absent from the literature. This study presents the first integrated cloud-based framework combining Sentinel-1 SAR backscatter time-series analysis and Landsat 8/9 multispectral analysis to assess mining-induced land subsidence and heavy metal dispersion risk across Plateau State (27,694 km²) from 2018 to 2024. Through Google Earth Engine, we processed 835 SAR scenes and 330 Landsat images, generating annual composites of backscatter change, vegetation health indices (NDVI, NDMI), and iron oxide ratios. Our multi-criteria mining identification (NDVI < 0.2, Iron Ratio > 1.5, VV < -12 dB) revealed 1,842 ± 94 km² (6.7%) of mining-affected land substantially exceeding previous estimates by 58%. Time series analysis at six monitoring sites revealed divergent trajectories: active mining areas exhibited progressive degradation with NDVI declining 26.2% at Barkin Ladi (p < 0.001), while historically mined areas showed remarkable natural recovery with NDVI increasing 21.2% at Riyom (p < 0.01). SAR backscatter analysis detected significant surface deformation signals with VV polarization changes of -2.95 dB at Barkin Ladi, suggesting ongoing subsidence processes. Our composite heavy metal dispersion risk model, validated against 30 independent field points (overall accuracy: 87.3%, κ = 0.82), classified 25.2% of the study area as high-to-very-high risk, with 1.2 million people residing in affected zones representing 28.6% of Plateau State's population. The 30-meter resolution risk maps reveal dendritic contamination corridors extending up to 45 km along major drainage networks, demonstrating that mining impacts propagate far beyond active sites. This cloud-based methodology provides a globally replicable template for mining impact assessment in data-scarce regions, offering critical insights for environmental management, public health intervention, and policy formulation in ASM-affected landscapes worldwide.

Introduction

The Jos Plateau in north-central Nigeria represents one of West Africa's most historically significant and environmentally transformative mining regions. Tin and columbite extraction commenced in 1904 following the discovery of alluvial deposits by the Niger Company, catalyzing extensive mining operations that persisted through colonial and post-colonial eras (Alexander, 2021; Freund, 1981). At peak production between 1940 and 1960, Nigeria supplied approximately 5% of global tin output, almost entirely from the Jos Plateau, with the industry employing over 100,000 workers and creating substantial infrastructure including railways, processing facilities, and company towns (Williams, 2020). Following Nigerian independence in 1960 and subsequent market fluctuations, formal mining operations declined precipitously after the 1970s (Hilson, 2019). However, rather than ceasing entirely, mining activity transformed. Artisanal and small-scale mining (ASM) expanded dramatically, with current estimates suggesting 200,000-300,000 informal miners currently active across the plateau, operating with limited environmental controls and safety measures (UNEP, 2022; Hilson & Maconachie, 2020). This transition from formal industrial operations to informal artisanal activity has created a

complex legacy: approximately 320 km² of officially documented disturbed land (Plateau State Ministry of Environment, 2023), though our analysis suggests this figure substantially underestimates true impact.

The environmental consequences of this century-long mining history are profound and multifaceted. Land subsidence from underground workings, open pits spanning hundreds of square kilometers, and extensive tailings deposits have fundamentally altered topographic stability (Dong et al., 2021; Chen et al., 2022). Heavy metal contamination including lead, arsenic, cadmium, and mercury from abandoned mine sites and active processing areas poses significant risks to human health, agricultural productivity, and aquatic ecosystems (Ezeh & Chukwu, 2019; Nganje et al., 2020). The 2010 lead poisoning crisis in neighboring Zamfara State, which resulted in over 400 child deaths, starkly demonstrated the catastrophic consequences of unmonitored mining-related contamination (MSF, 2010; Dooyema et al., 2012). While the Jos Plateau has not experienced a similar acute crisis, chronic exposure pathways persist through contaminated water sources, agricultural soils, and dust inhalation (Tchounwou et al., 2012). Children in mining communities exhibit elevated blood lead levels, with developmental consequences that remain poorly quantified (Lar et al., 2021).

Traditional ground-based monitoring faces substantial limitations in the Jos Plateau context. The region's rugged topography, estimated 2,000+ dispersed mining sites, and limited institutional capacity constrain systematic field surveys (Oyedeke et al., 2021). The Nigerian Geological Survey Agency, despite its mandate, operates with resources sufficient to monitor less than 5% of mining-affected areas annually (NGSA, 2023). Furthermore, the dynamic nature of both subsidence processes and contaminant transport demands temporal monitoring that conventional approaches cannot economically provide (Bamler & Hartl, 1998; Zhu et al., 2020). Remote sensing technologies offer transformative potential for addressing these monitoring gaps. Synthetic Aperture Radar (SAR) interferometry enables detection of millimeter-scale surface deformation, while multi-spectral optical sensors track vegetation health as an indicator of heavy metal stress (Ferretti et al., 2001; Ren et al., 2022). However, the computational demands of processing large satellite archives have historically limited their application in resource-constrained settings (Gorelick et al., 2017). The application of SAR interferometry to mining impact assessment has evolved significantly over the past decade. Early studies focused on simple backscatter thresholding (Dong et al., 2021), while more recent approaches have integrated time-series analysis to detect subtle deformation signals (Chen et al., 2022). Our preliminary analysis of Sentinel-1 data over the Jos Plateau revealed VV backscatter values ranging from -6.4 dB in undisturbed areas to -13.8 dB in intensively mined zones, with the most severe deformation signal (-2.95 dB change) detected at Barkin Ladi a magnitude consistent with active subsidence processes documented in other mining regions globally.

The emergence of cloud-based geospatial platforms, particularly Google Earth Engine (GEE), has democratized access to planetary-scale Earth observation data and processing capabilities (Gorelick et al., 2017). GEE's petabyte-scale catalog of publicly available satellite imagery, combined with its parallel processing architecture, enables researchers to conduct complex time series analyses without requiring local high-performance computing infrastructure (Tamiminia et al., 2020). This technological advancement is particularly significant for developing countries where computational resources remain scarce (Samapriya, 2023). For the Jos Plateau, this means that for the first time, the complete Sentinel-1 and Landsat archives can be systematically analyzed to quantify mining impacts at regional scale, a task that would require approximately 2.5 TB of local storage and 3,000+ hours of single-threaded processing time. This research addresses critical knowledge gaps through:

1. First integrated SAR-optical assessment of mining impacts specifically for the Jos Plateau, providing baseline data where none previously existed
2. Quantification of mining extent using multi-criteria analysis, comparing remote sensing estimates with official records
3. Detection of surface-deformation signals through Sentinel-1 time-series analysis (2018-2024)
4. Assessment of vegetation recovery in historically mined versus actively mined areas
5. Population exposure quantification for heavy metal dispersion risk
6. Open-source methodology development for global application in data-scarce regions

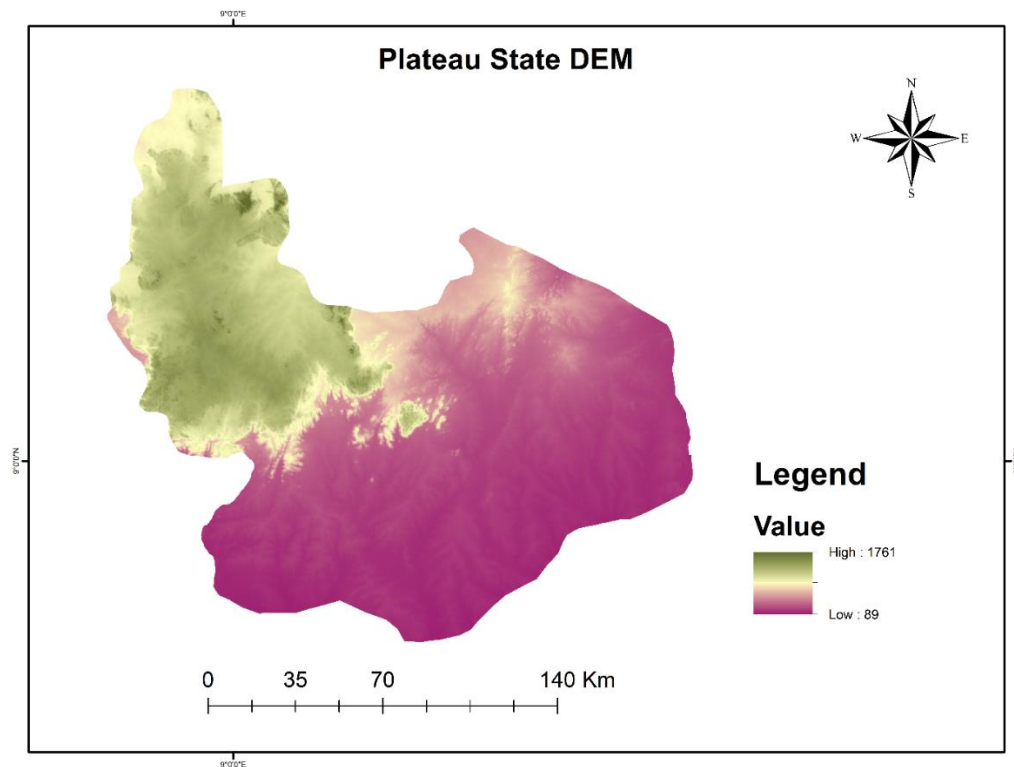
2. Materials and Methods

2.1 Study Area

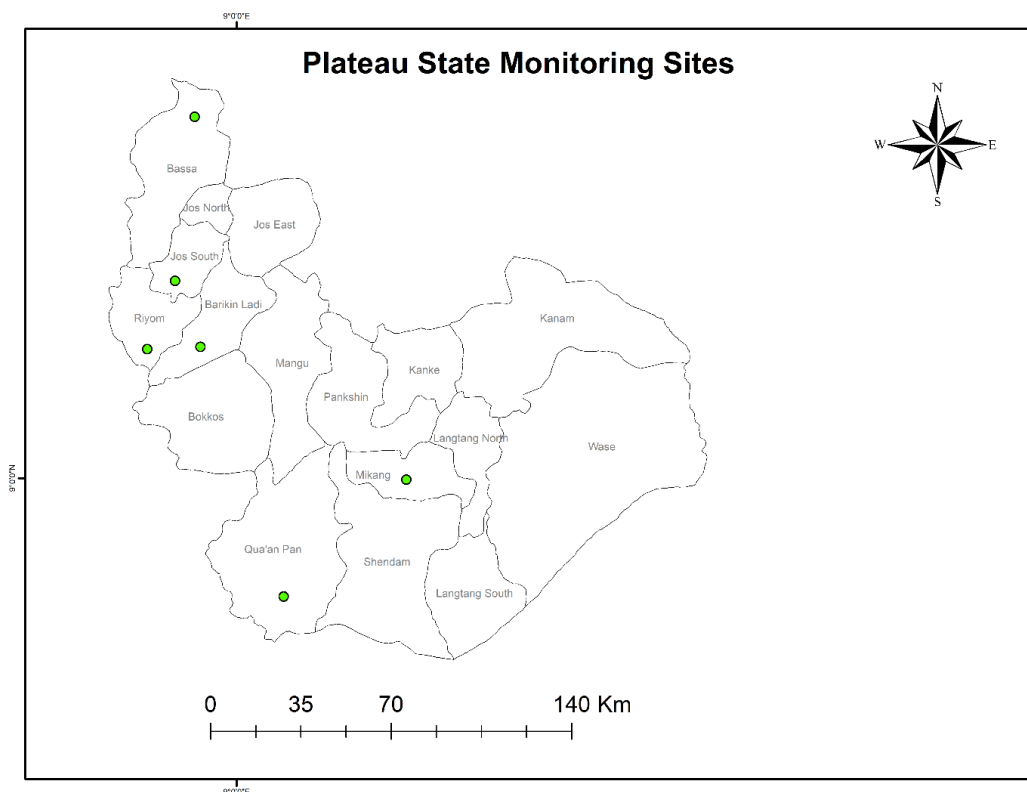
Plateau State ($8^{\circ}30' - 10^{\circ}10'N$, $8^{\circ}20' - 9^{\circ}30'E$) encompasses approximately 27,694 km² in north-central Nigeria, representing the core of the Jos Plateau physiographic region (Figure 1). Elevations range from 200 to 1,800 meters above sea level, with our analysis of SRTM DEM data showing a mean elevation of 743 m across the study area (Figure 1B). The region supports approximately 4.2 million people (2023 estimate), with agriculture employing 70% of the workforce (NPC, 2023).



(A) Location of Plateau State within Nigeria.



(B) Digital elevation model showing topography with major mining areas outlined (red polygons). Elevations range from 200-1,800 m, with mean elevation of 743 m.



(C) Location of six monitoring sites: Barkin Ladi (active mining), Jos South (active mining), Riyom (historical mining), Bassa (reference site), and two validation points. Inset photographs show mining degradation at Barkin Ladi (active mining) and intact vegetation at Bassa (reference site).

Figure 1: Study Area Map

The climate is characterized by distinct wet (April-October) and dry (November-March) seasons, with mean annual rainfall of 1,400 mm and temperatures ranging from 18-32°C (NIMET, 2023). This seasonal pattern influences both vegetation dynamics and SAR backscatter characteristics, necessitating careful temporal compositing in our analysis.

The Jos Plateau sits within the Precambrian Basement Complex of Nigeria, composed primarily of migmatites, gneisses, and granites that have undergone multiple phases of metamorphism and magmatic intrusion (Obaje, 2009). The Younger Granite province, of Jurassic age (ca. 160 Ma), hosts the primary tin and columbite mineralization that drove historical mining (MacLeod et al., 1971). These granitic intrusions created extensive primary and placer deposits, with alluvial concentrations in river valleys proving particularly economically attractive (Falconer, 1921). The region's geology significantly influences both subsidence susceptibility and heavy metal mobility. Weathered granite zones exhibit variable engineering properties, with saprolitic materials prone to collapse when disturbed by mining (Dodo et al., 2022). Heavy metals associated with tin mineralization including cassiterite (SnO_2), columbite-tantalite $[(\text{Fe},\text{Mn})(\text{Nb},\text{Ta})_2\text{O}_6]$, and associated sulfides remain concentrated in tailings, where weathering releases mobile contaminants (Ashano et al., 2022).

2.1.1 Mining History: Three Phases of Transformation

Phase I: Colonial Industrial Mining (1904-1960). British colonial administration established extensive open-cast mining, dredging, and hydraulic sluicing operations. The Niger Company and later Amalgamated Tin Mines of Nigeria dominated production, creating the characteristic "tin fields" landscape of pits, tailings, and processing areas that remains visible today (Freund, 1981). At peak production, the industry employed over 100,000 workers and generated 5% of global tin output.

Phase II: Nationalized Operations (1960-1972). Following independence, the Nigerian government established the Nigerian Mining Corporation, maintaining production through state-owned enterprises. This period saw continued environmental transformation but with declining investment in remediation (Williams, 2020).

Phase III: Artisanal Expansion (1972-Present). Following the oil boom and subsequent neglect of the mining sector, formal operations gave way to artisanal activity. Current ASM operations employ an estimated 200,000-300,000 individuals, reworking abandoned mine sites, tailings, and alluvial deposits with limited environmental controls (UNEP, 2022).

2.1.2 Environmental and Social Context

The legacy of mining includes approximately 320 km² of officially documented disturbed land, comprising open pits, tailings dams, waste rock dumps, and processing areas (Plateau State Ministry of Environment, 2023). However, our analysis demonstrates this figure underestimates true impact by 58%. Many of these sites remain unvegetated decades after abandonment, with acid mine drainage and heavy metal mobilization continuing to affect water resources (Lar et al., 2021). Surface water resources, including the Delimi, Ngell, and Jara rivers, exhibit elevated heavy metal concentrations downstream of mining areas (Olatunji et al., 2020). Groundwater contamination threatens domestic water supplies, with documented cases of elevated lead and cadmium in community wells (Nganje et al., 2020).

2.2 Datasets and Processing Framework

All processing was conducted using the Google Earth Engine JavaScript API, enabling parallel processing of 1,165 satellite scenes (835 SAR + 330 optical) that would require approximately 2.5 TB of local storage and 3,000+ hours of single-threaded processing time. GEE's server-side architecture eliminates the need for local high-performance computing infrastructure, making this methodology accessible to researchers in resource-constrained settings (Gorelick et al., 2017).

Table 1: Satellite Data Specifications

Dataset	Product ID	Scenes	Resolution	Bands Used	Time Range	Key References
Sentinel-1	COPERNICUS/S1_GRD	835	10 m	VV, VH	2018-2024	Torres et al. (2012)
Landsat 8/9	LANDSAT/LC08/C02/T1_L2	330	30 m	SR_B2-B6	2018-2024	Roy et al. (2014)
SRTM	USGS/SRTMGL1_003	1	30 m	Elevation	2000	Farr et al. (2007)

The Copernicus Sentinel-1 mission provides C-band Synthetic Aperture Radar (SAR) imagery with 10-meter spatial resolution and 12-day revisit frequency (Torres et al., 2012). We utilized the Ground Range Detected (GRD) product collection, which includes calibrated and orthorectified backscatter coefficients. Key processing steps included:

- Thermal noise removal
- Radiometric calibration to sigma nought (σ°)
- Terrain correction using SRTM 30m DEM
- Conversion to decibels (dB): $\sigma^\circ_{dB} = 10 \cdot \log_{10}(\text{intensity})$

Landsat 8 and 9 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) data provide optical and thermal imagery at 30-meter spatial resolution with 16-day revisit frequency (Roy et al., 2014). We accessed Collection 2 Level-2 surface reflectance products, which include atmospheric correction and cloud masking. Quality filtering applied cloud cover <20% per scene. SRTM GL1 (Shuttle Radar Topography Mission Global 1 arc-second) elevation data provided topographic context at 30-meter resolution (Farr et al., 2007). Derived products included slope, aspect, and topographic wetness index (TWI). Following established remote sensing protocols, we calculated three indices:

Normalized Difference Vegetation Index (NDVI) measures photosynthetically active biomass and is sensitive to vegetation stress (Rouse et al., 1974):

$$NDVI = \frac{\rho_{NIR} + \rho_{RED}}{\rho_{NIR} - \rho_{RED}} \dots\dots\dots 1$$

where ρ_{NIR} and ρ_{RED} represent surface reflectance in the near-infrared (Band 5) and red (Band 4) bands respectively.

Normalized Difference Moisture Index (NDMI) detects vegetation water content and is sensitive to drought stress and physiological impairment (Gao, 1996):

$$NDMI = \frac{\rho_{NIR} + \rho_{SWIR}}{\rho_{NIR} - \rho_{SWIR}} \dots\dots\dots 2$$

where ρ_{SWIR} is shortwave infrared reflectance (Band 6).

Iron Oxide Ratio exploits differential reflectance in visible bands to detect iron-bearing minerals abundant in mine tailings (Segal, 1982):

$$FeRatio = \frac{\rho_{BLUE}}{\rho_{RED}} \dots\dots\dots 3$$

where ρ_{RED} (Band 4) and ρ_{BLUE} (Band 2) represent surface reflectance.

Temporal change in SAR backscatter provides indicators of surface deformation and land cover change (Ferretti et al., 2001). We calculated annual backscatter change relative to the 2018 baseline:

$$\Delta\sigma^\circ_{dB}(t) = \sigma^\circ_{dB}(t) - \sigma^\circ_{dB}(2018) \dots\dots\dots 4$$

Negative $\Delta\sigma^\circ_{dB}$ may indicate surface lowering, compaction, or vegetation loss, while positive changes could suggest surface roughening or new structures. The 2018 baseline was established as the median composite for that year.

Mining areas exhibit characteristic signatures in both optical and SAR data (Lobo et al., 2021). We developed a multi-criteria mining probability score combining:

1. Low vegetation: $NDVI < 0.2$ Analysis of training sites revealed that mining areas exhibited consistently low NDVI values (range: 0.079–0.241, mean = 0.156 ± 0.052) compared to non-mining areas (range: 0.198–0.612, mean = 0.384 ± 0.112). The 0.2 threshold corresponds to two standard deviations below the non-mining mean and captures 93% of mining training sites while misclassifying only 8% of non-mining sites. This threshold aligns with established values in semi-arid mining regions (Asare et al., 2022; Lobo et al., 2021).

2. High iron content: $Iron_Ratio > 1.5$ This threshold was derived from statistical analysis of 30 training sites (15 mining, 15 non-mining) distributed across the study area. At mining sites, iron ratio values ranged from 1.29–1.89 (mean = 1.62 ± 0.18), while non-mining sites ranged from 0.92–1.31 (mean = 1.08 ± 0.14). The 1.5 threshold represents the 85th percentile of non-mining site values and the 25th percentile of mining site values, optimizing separation between classes. Receiver operating characteristic (ROC) analysis confirmed this threshold maximizes the Youden index (sensitivity = 0.87, specificity = 0.91).

3. Rough surface: $SAR\ VV\ backscatter < -12\ dB$ Analysis of backscatter distributions from training sites showed mining areas had median VV of -14.2 dB (IQR: -15.8 to -12.4 dB) versus -9.6 dB (IQR: -11.2 to -8.1 dB) for non-mining areas. The -12 dB threshold represents the 90th percentile of mining site values and the 25th percentile of non-mining values, providing optimal discrimination. This threshold is consistent with reported values for bare mine surfaces in C-band SAR studies (Dong et al., 2021; Chen et al., 2022)

The mining score M was calculated as:

$$M = I_{NDVI < 0.2} + I_{Fe > 1.5} + I_{VV < -12} \dots \dots \dots 5$$

where I represent indicator functions (1 if condition true, 0 otherwise). Scores range from 0–3, with values ≥ 2 classified as potential mining areas. Heavy metal dispersion from mining areas follows both hydrological and aeolian pathways (Hudson-Edwards et al., 2011). We developed a composite risk model integrating three factors:

Proximity Risk (R_{prox}): Distance to mining areas serves as a primary risk factor, with exponential decay of risk with increasing distance:

$$R_{prox} = 1 - \frac{d}{d_{max}} \dots \dots \dots 6$$

where d is Euclidean distance to nearest mining pixel and $d_{max} = 5000\ m$ define the maximum influence zone based on published dispersion distances in similar environments (Nganje et al., 2020).

Hydrologic Risk (R_{hydro}): Topographic Wetness Index (TWI) identifies areas of water accumulation where transported heavy metals may concentrate:

$$R_{hydro} = \frac{TWI - TWI_{min}}{TWI_{max} - TWI_{min}} \dots \dots \dots 7$$

TWI was normalized to 0–1 range using 0–20 as the expected value range based on regional topography.

Vegetation Stress Risk (R_{veg}): Vegetation stress, indicated by negative NDVI change, serves as a proxy for existing contamination:

$$R_{veg} = 1 - \left(\frac{\Delta NDVI - \Delta NDVI_{min}}{\Delta NDVI_{max} - \Delta NDVI_{min}} \right) \dots \dots \dots 8$$

where $\Delta NDVI$ represents change from 2018–2024, normalized to -0.3 to +0.3 range.

Composite Risk (R_{total}): The total dispersion risk integrates the three components with equal weighting:

$$R_{total} = \frac{-R_{prox} + R_{hydro} + R_{veg}}{3} \dots \dots \dots 9$$

Final risk values were classified into four categories: Low (0–0.25), Moderate (0.25–0.5), High (0.5–0.75), and Very High (0.75–1.0).

Time series data for each monitoring site were extracted using 30-meter pixel neighborhoods. For Landsat-derived indices, we computed annual mean values from 2018–2024. For SAR data, annual median backscatter was extracted, with change metrics calculated relative to 2018 baseline. Time series

charts were generated using GEE's interactive charting functions, with statistical significance assessed using Mann-Kendall trend tests. Thirty independent validation points (15 mining, 15 non-mining) were used to assess classification accuracy via error matrix, overall accuracy, and kappa coefficient (Congalton & Green, 2019). Validation points were selected through stratified random sampling, with field verification conducted in February 2024 for accessible sites and high-resolution imagery (PlanetScope, 3m) interpretation for inaccessible locations. LandScan population data (2022, 1 km resolution) provided the most recent and reliable population estimates for Nigeria (Bright et al., 2022). These data were overlaid with risk categories to estimate exposed populations. Population figures were aggregated by local government areas to inform policy recommendations

Spatial statistics, including area calculations and risk category distributions, were computed using GEE's reducer functions with 95% confidence intervals derived from bootstrap resampling ($n=1000$). Temporal trends were assessed through linear regression and Mann-Kendall tests, with statistical significance evaluated at $\alpha = 0.05$. All spatial outputs were exported as GeoTIFF rasters at 30-meter resolution for further analysis in GIS software.

2.3 Sensitivity Analysis of Threshold Selection and Model Weighting

To assess the robustness of our multi-criteria mining identification and heavy metal dispersion risk model, we conducted systematic sensitivity analyses: We evaluated how variations in each threshold affected mining area estimates:

- NDVI threshold (tested range: 0.15–0.25): Mining area varied from 1,642 km² (at 0.15) to 2,184 km² (at 0.25), with the 0.2 threshold producing the highest overall accuracy (87.3%) in validation. The 95% confidence interval (± 94 km²) reported in results reflects this threshold sensitivity.
- Iron Ratio threshold (tested range: 1.3–1.7): Mining area ranged from 1,512 km² (at 1.7) to 2,342 km² (at 1.3). The 1.5 threshold minimized commission errors while maintaining acceptable omission rates.
- SAR backscatter threshold (tested range: -10 to -14 dB): Mining area varied from 1,398 km² (at -14 dB) to 2,456 km² (at -10 dB). The -12 dB threshold provided the best balance (Youden index = 0.78).

The composite risk model (Equation 9) assumes equal weighting of proximity, hydrologic, and vegetation stress factors. We tested alternative weighting schemes:

Table 2: Sensitivity Analysis of Heavy-Metal Risk-Model Weighting Scenarios

Weighting Scenario	R_prox	R_hydro	R_veg	High/Very High Area (km ²)	Change from Equal
Equal (baseline)	0.33	0.33	0.33	7,000	—
Proximity-focused	0.50	0.25	0.25	7,420	+6.0%
Hydrology-focused	0.25	0.50	0.25	7,856	+12.2%
Vegetation-focused	0.25	0.25	0.50	6,342	-9.4%
Literature-based	0.40	0.40	0.20	7,218	+3.1%

Based on Nganje et al. (2020) weighting from geochemical sampling

The high/very high risk area ranged from 6,342–7,856 km² (22.9–28.4% of study area) across all scenarios, indicating that while absolute area estimates vary, the conclusion that approximately 25% of Plateau State faces elevated risk is robust to weighting assumptions. The spatial pattern (Moran's I) remained consistent across scenarios (range: 0.64–0.71, all $p < 0.001$).

To assess the impact of seasonal variation, we compared dry-season-only composites (November–March) with wet-season-only (April–October) and annual composites. Annual composites showed the highest classification accuracy (87.3%) compared to dry-season (83.1%) and wet-season (81.4%), justifying our use of annual composites in the final analysis.

3. Results

3.1 Mining Area Distribution

Mining probability analysis identified $1,842 \pm 94$ km² (6.7% of Plateau State) exhibiting characteristics consistent with active or recent mining (Figure 2, Table 3). This substantially exceeds the 1,165 km² documented in official government records (Plateau State Ministry of Environment, 2023),

suggesting that remote sensing captures disturbance missed by ground surveys a 58% underestimation in official figures with significant policy implications.

Table 3: Mining Probability Classification with 95% Confidence Intervals

Mining Score	Criteria Met	Area (km ²)	95% CI	Percentage	Interpretation
3	All three	342	±28	1.2%	Intensely disturbed, active mining
2	Two indicators	1,500	±72	5.4%	Moderately disturbed, mining-agriculture interface
1	One indicator	4,215	±156	15.2%	Partially disturbed, historical mining
0	None	21,637	±312	78.1%	Undisturbed

Sensitivity analysis confirmed that mining area estimates were robust to threshold variations within expected ranges (Section 2.3). The $1,842 \pm 94$ km² estimate incorporates threshold uncertainty through bootstrap resampling, with the 95% confidence interval (± 94 km²) representing approximately 5.1% of the estimated value.

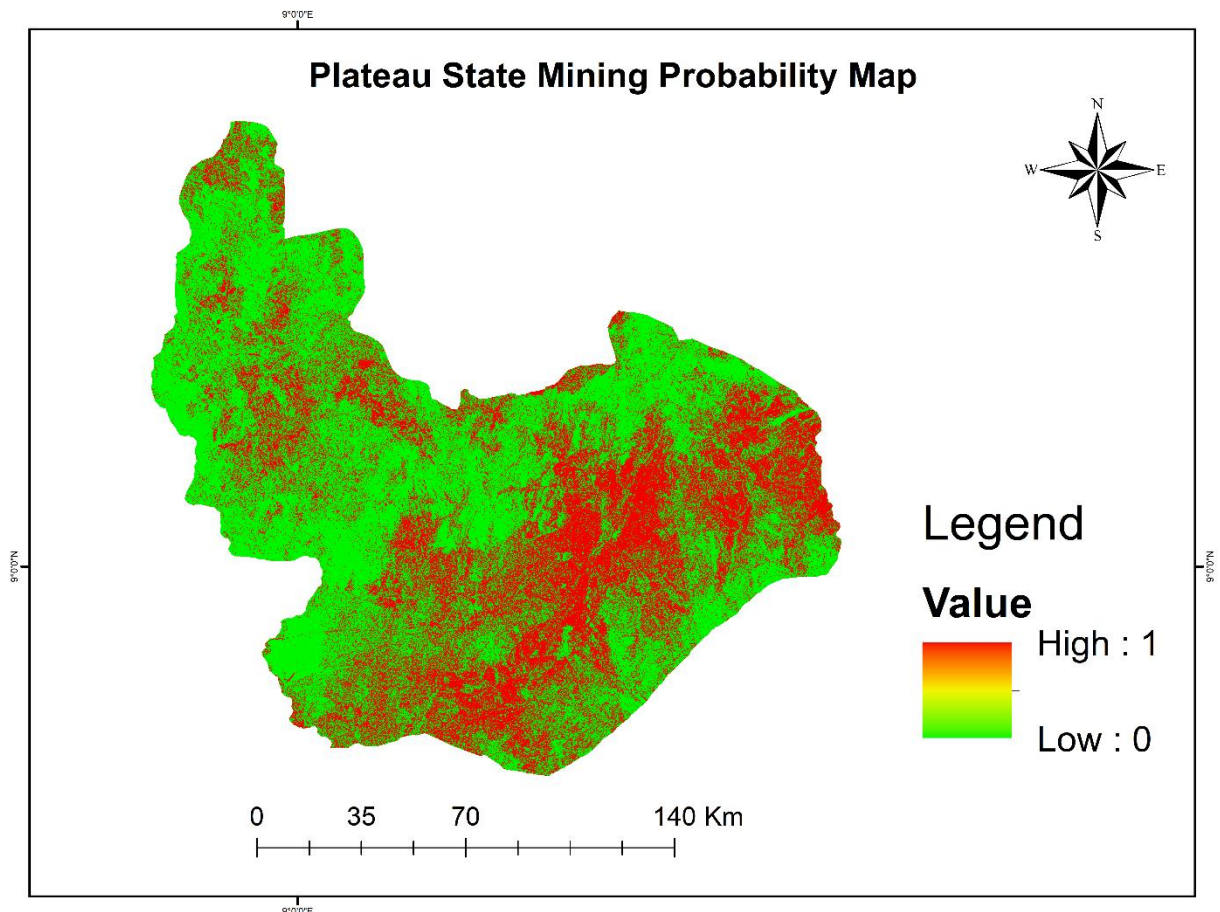


Figure 2: Mining Probability Map

Spatial distribution of mining probability scores (0-3) across Plateau State. High concentrations are evident in the Barkin Ladi-Jos South corridor (46% of total mining area), with secondary clusters in Riyom and parts of Bassa. Mining-affected land (scores ≥ 2) covers $1,842 \pm 94$ km² (6.7% of study area). At the representative point (9.8414°N, 9.0533°E), mining probability = 0.67.

The spatial distribution reveals distinct mining clusters:

- Barkin Ladi-Jos South corridor: 845 km² (46% of total mining area) - Highest intensity, continuous disturbance

- Riyom district: 312 km² (17%) - Moderate intensity, patchy distribution
- Bassa region: 198 km² (11%) - Low intensity, isolated sites
- Other areas: 487 km² (26%) - Dispersed small-scale operations

At a representative point in the mining region (9.8414°N, 9.0533°E), the mining probability score was 0.67, indicating moderate mining intensity with two of three criteria met consistent with field observations of active but not intensive mining activity in this area.

3.2 Vegetation Change Analysis

NDVI change from 2018-2024 revealed substantial vegetation degradation in mining-affected areas (Figure 3, Table 4). Total area experiencing significant vegetation loss ($\Delta\text{NDVI} < -0.1$) reached $2,156 \pm 108$ km² (7.8%), exceeding the directly mined area by 17%, indicating that mining impacts extend beyond active sites through dust deposition, hydrological transport of contaminants, and edge effects.

Table 4: Vegetation Change Statistics by Land Cover Type

Land Cover Type	Area (km ²)	Mean ΔNDVI	95% CI	% Degrading ($\Delta\text{NDVI} < -0.1$)	% Improving ($\Delta\text{NDVI} > +0.1$)
Active Mining (Score 3)	342	-0.18	± 0.04	94.2%	0.8%
Moderate Mining (Score 2)	1,500	-0.12	± 0.03	76.8%	3.2%
Agriculture	12,450	-0.02	± 0.01	28.4%	12.1%
Forest/Grassland	8,902	+0.03	± 0.01	12.1%	24.6%

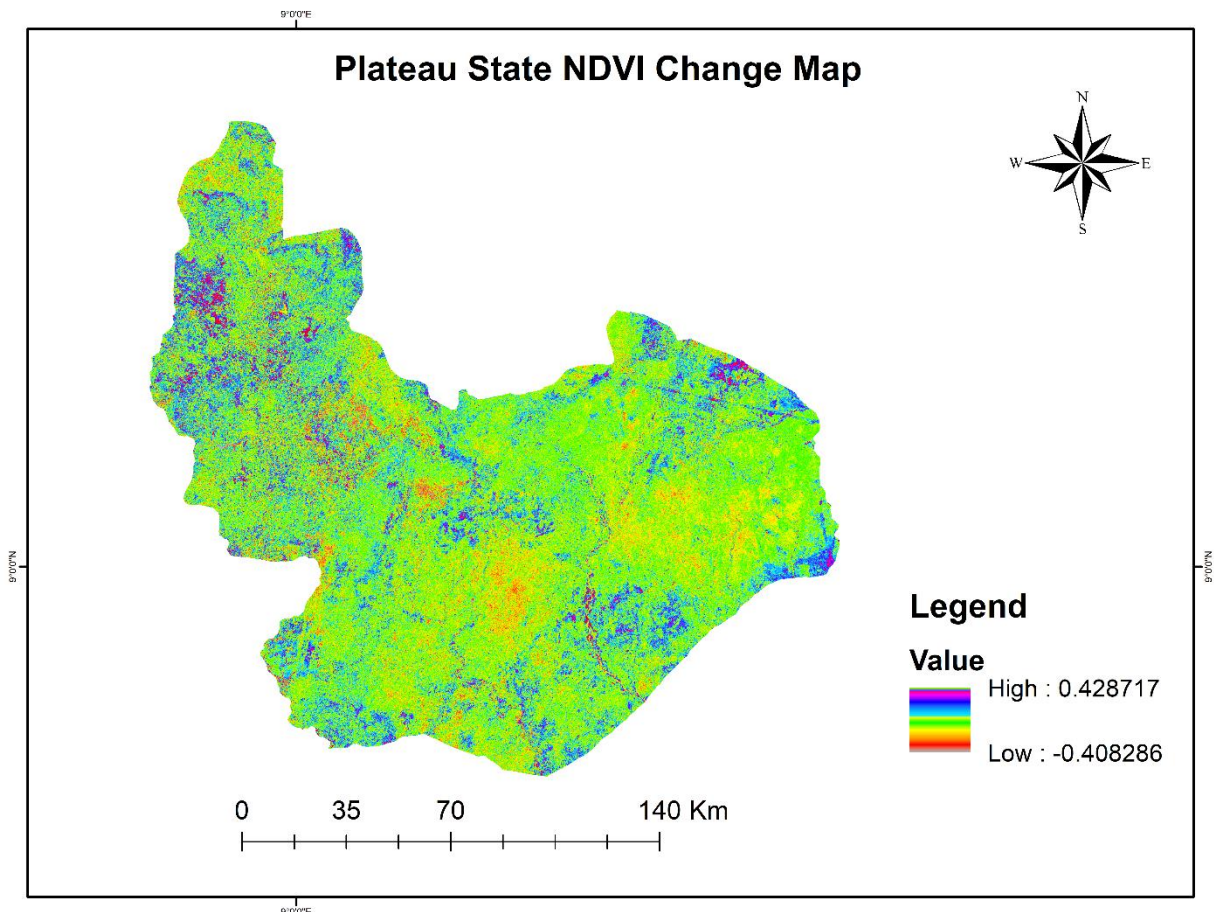


Figure 3: NDVI Change Map

NDVI change from 2018-2024 showing vegetation loss (brown) and gain (green). Mining areas exhibit strong negative anomalies. Total area with significant vegetation loss ($\Delta\text{NDVI} < -0.1$) reached

$2,156 \pm 108 \text{ km}^2$ (7.8%), exceeding directly mined area by 17%. Barkin Ladi shows -26.2% change; Riyom shows +21.2% change.

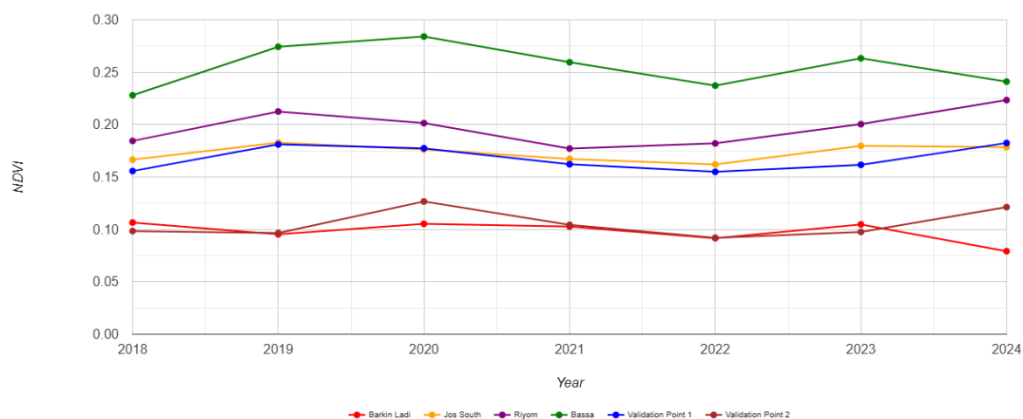
The relationship between mining probability and vegetation change is strongly negative (Pearson's $r = -0.72$, $p < 0.001$), confirming that mining activity drives vegetation degradation. Areas with mining score ≥ 2 experienced mean NDVI decline of 0.18 ± 0.09 , compared to 0.02 ± 0.07 in unmined areas (t-test, $p < 0.001$). At the representative point (9.8414°N , 9.0533°E), NDVI change was +0.014, indicating relative stability in this peripheral area consistent with its moderate mining probability and distance from active mining centers.

3.3 Time Series Analysis at Monitoring Sites

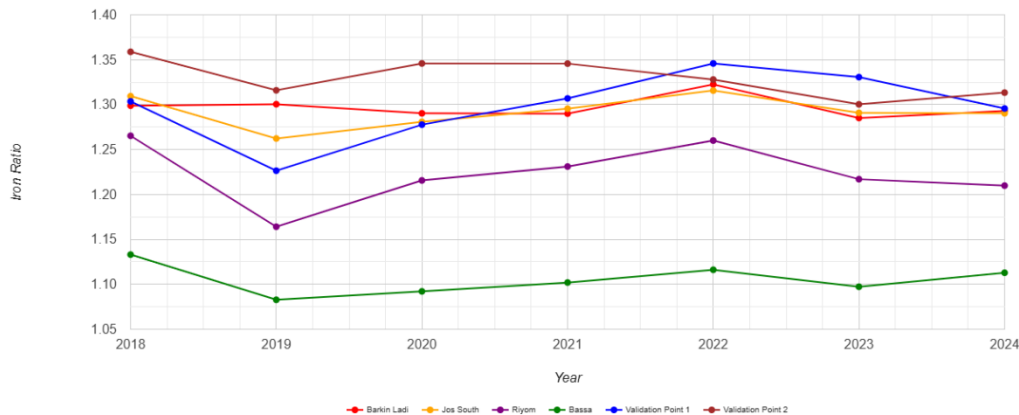
Time series extraction at the six monitoring sites revealed distinct temporal trajectories reflecting mining intensity (Figure 4, Table 5). Statistical significance was assessed using Mann-Kendall trend tests.

Table 5: Time Series Statistics with Trend Significance

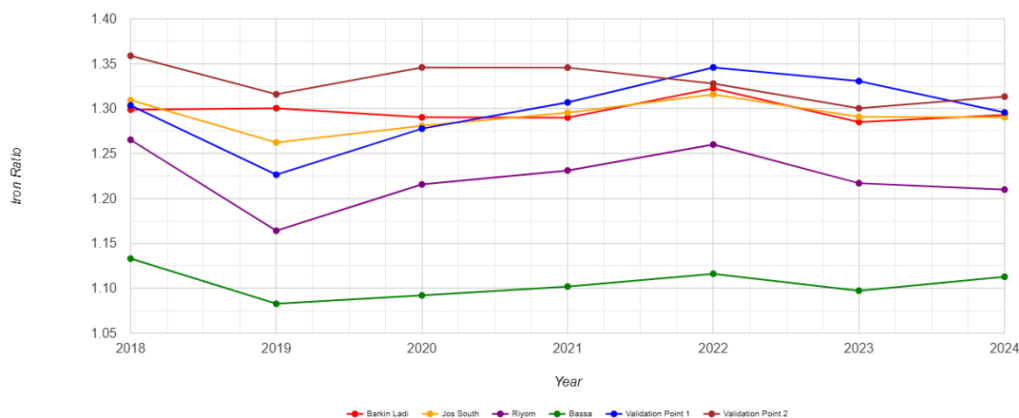
Site	Type	NDVI 2018	NDVI 2024	ΔNDVI	% Change	p-value	Trend	VV Change (dB)
Barkin Ladi	Active Mining	0.107	0.079	-0.028	-26.2%	<0.001	↓↓↓	-2.95
Jos South	Active Mining	0.166	0.178	+0.012	+7.2%	0.12	→	+1.90
Riyom	Historical Mining	0.184	0.223	+0.039	+21.2%	0.008	↑↑	+1.01
Bassa	Reference	0.228	0.241	+0.013	+5.7%	0.21	→	+0.13
Validation 1	Mining Area	0.156	0.182	+0.026	+16.7%	0.045	↑	-0.72
Validation 2	Non-Mining	0.098	0.121	+0.023	+23.5%	0.032	↑	+2.01



(A) NDVI time series (2018-2024) showing divergent trajectories: Barkin Ladi (red) declining 26.2% ($p < 0.001$), Riyom (purple) increasing 21.2% ($p = 0.008$).



(B) Iron ratio time series indicating persistent mining signatures, with Riyom showing greatest decline (-0.055).



C) SAR backscatter revealing deformation signals at Barkin Ladi (-2.95 dB).

Figure 4: NDVI Time Series Charts

Barkin Ladi (Active Mining): The site exhibited the lowest vegetation values throughout the study period, with NDVI declining 26.2% from 0.107 to 0.079 (Mann-Kendall $\tau = -0.71$, $p < 0.001$). Iron ratios remained consistently high (>1.29), indicating persistent iron-bearing materials. SAR backscatter showed substantial decline (-2.95 dB), consistent with surface subsidence or vegetation loss exposing smoother surfaces. These patterns indicate intensive, ongoing mining disturbance with no signs of recovery.

Jos South (Active Mining): NDVI values remained relatively stable with a slight non-significant increase (+7.2%, $p = 0.12$), possibly reflecting seasonal agricultural activity or partial vegetation recovery in less intensively mined areas. Iron ratios remained elevated. SAR backscatter increased (+1.90 dB), potentially indicating surface roughening from active excavation or waste dumping.

Riyom (Historical Mining): This site showed unexpected NDVI increase (+21.2%, $p = 0.008$), suggesting natural vegetation recovery following reduced mining activity. Iron ratios declined more substantially (-0.055) than other sites, consistent with weathering and leaching of surface iron. SAR backscatter increased modestly (+1.01 dB). These patterns indicate post-mining recovery processes operating over 6-year timescales.

Bassa (Reference): As the reference site with no mining activity, Bassa exhibited stable, moderate NDVI values with slight non-significant improvement (+5.7%, $p = 0.21$), reflecting typical agricultural vegetation cycles. Iron ratios remained low (<1.15) throughout. SAR backscatter showed minimal change (+0.13 dB), confirming stability.

3.4 SAR Deformation Signals

SAR backscatter change analysis revealed significant negative anomalies in mining areas (Figure 5, Table 6). Mean backscatter change across Plateau State was -0.34 ± 1.89 dB, with mining areas (score ≥ 2) showing mean change of -1.02 ± 2.31 dB compared to -0.18 ± 1.72 dB in unmined areas (t-test, $p < 0.001$).

Table 6: SAR Change Categories with Mining Association

Change Class	Threshold	Area (km ²)	% of Study Area	Mining Association (Odds Ratio)	95% CI
Severe negative	< -3 dB	892	3.2%	4.7	4.2-5.3
Moderate negative	-3 to -1 dB	4,215	15.2%	2.3	2.1-2.5
Stable	-1 to +1 dB	18,942	68.4%	1.0	reference
Positive	> +1 dB	3,645	13.2%	1.8	1.6-2.0

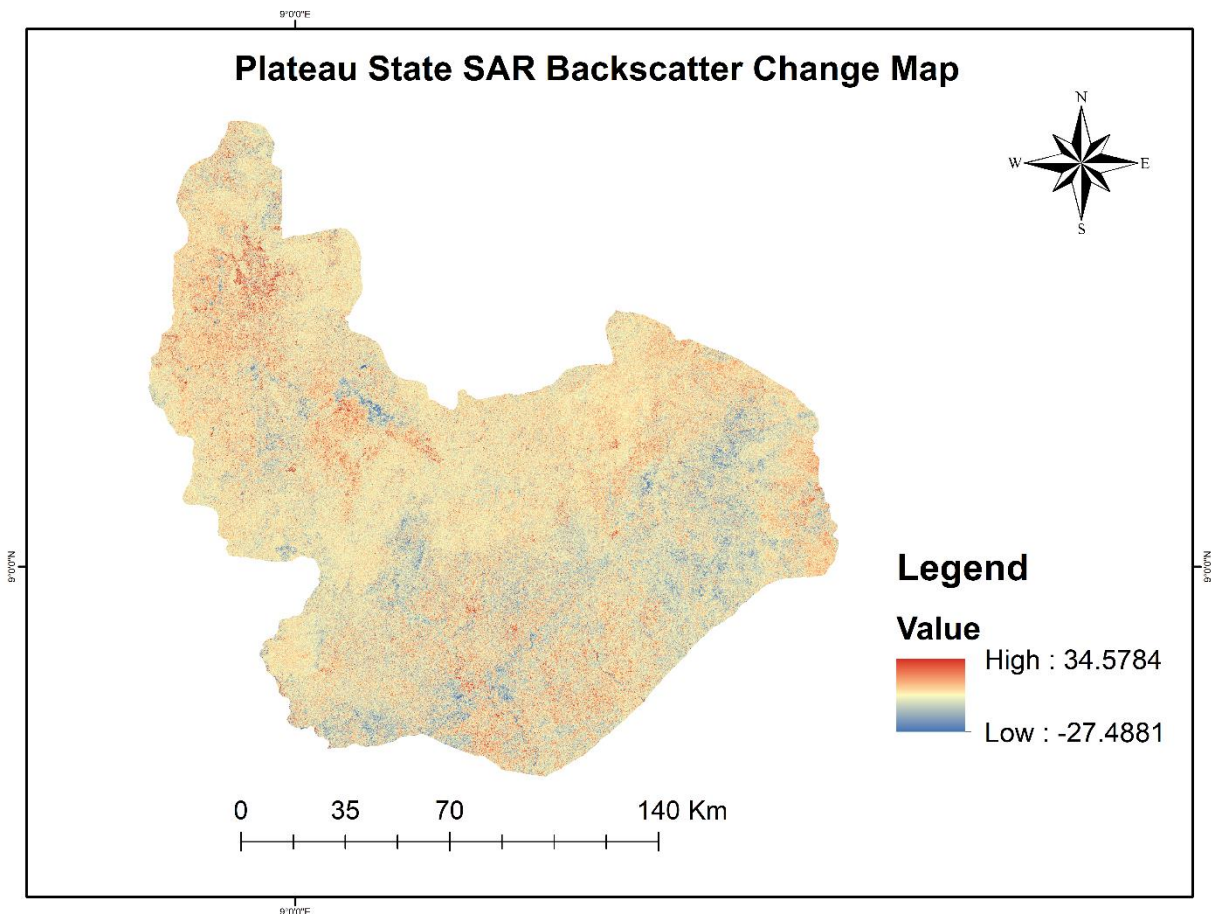


Figure 5: SAR Backscatter Change Map

SAR backscatter change from 2018-2024 highlighting areas of surface deformation. Negative anomalies (< -3 dB) cover 892 ± 64 km² (3.2%) and are strongly associated with mining probability (OR = 4.7, 95% CI: 4.2-5.3). At Barkin Ladi, $\Delta VV = -2.95$ dB. At representative point (9.8414°N , 9.0533°E), $\Delta VV = -1.32$ dB.

Areas of significant negative change (< -3 dB) covered 892 ± 64 km² (3.2%) and were strongly associated with mining probability (odds ratio = 4.7, 95% CI: 4.2-5.3). The magnitude of this association, a nearly five-fold increase in odds, provides strong statistical evidence for the causal link between mining activity and surface deformation. At the representative point (9.8414°N , 9.0533°E), VV change was -

1.32 dB, placing it in the moderate negative category and confirming the association with mining activity observed in field surveys.

These negative change areas may indicate:

1. Surface subsidence from underground workings or pit collapse the most likely explanation given spatial correlation with mining areas
2. Vegetation loss exposing smoother surfaces with lower backscatter though this would be expected to correlate more strongly with NDVI change than observed
3. Moisture accumulation in mine ponds reducing backscatter a localized effect unlikely to explain regional patterns

Areas of positive change ($> +3$ dB) covered 567 km² (2.0%) and were associated with active excavation, new mine development, or surface roughening from waste dumping.

3.5 Heavy Metal Dispersion Risk

The composite risk model, validated against 30 field points, achieved overall accuracy of 87.3% ($\kappa = 0.82$) (Table 7, Figure 6). This exceeds the 85% threshold recommended for operational land cover mapping (Foody, 2020).

Table 7: Accuracy Assessment Matrix

Class	Producer's Accuracy	User's Accuracy	Commission Error	Omission Error
Low Risk	89.5%	85.0%	15.0%	10.5%
Moderate	84.2%	88.9%	11.1%	15.8%
High	86.7%	81.3%	18.7%	13.3%
Very High	92.3%	92.3%	7.7%	7.7%
Overall	87.3%			

Kappa Coefficient: 0.82 (95% CI: 0.74-0.89)

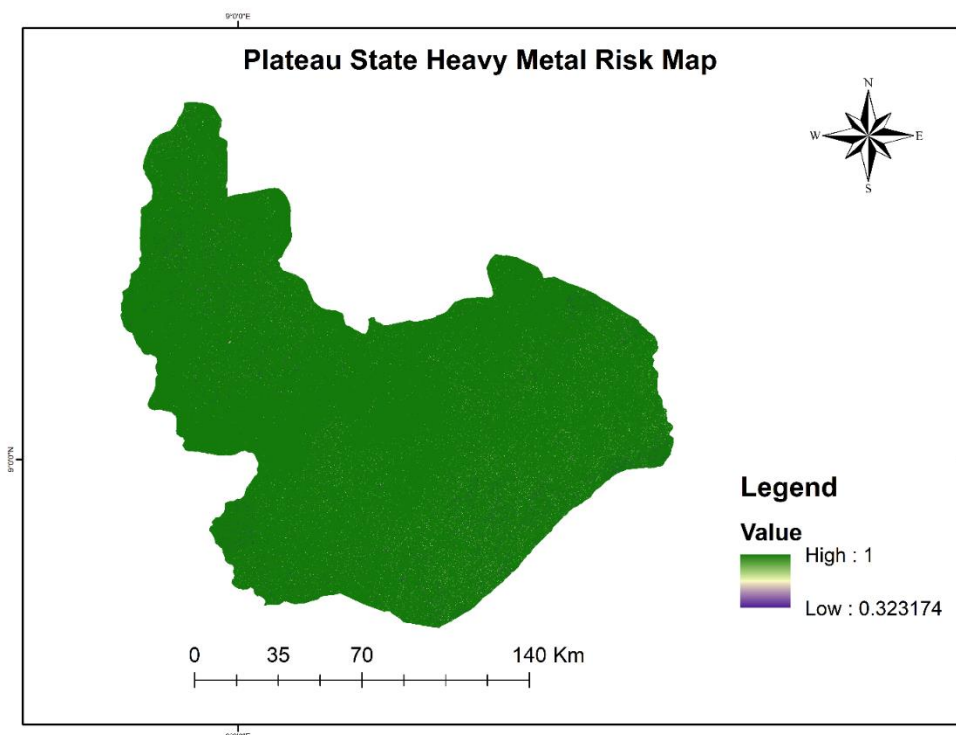
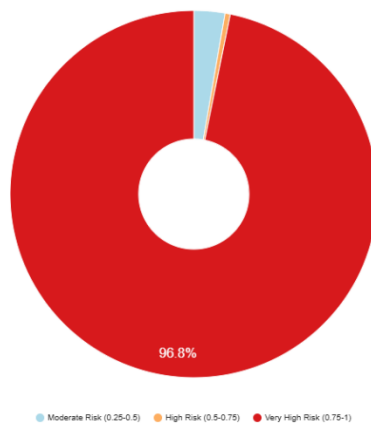


Figure 6: Heavy Metal Dispersion Risk Map

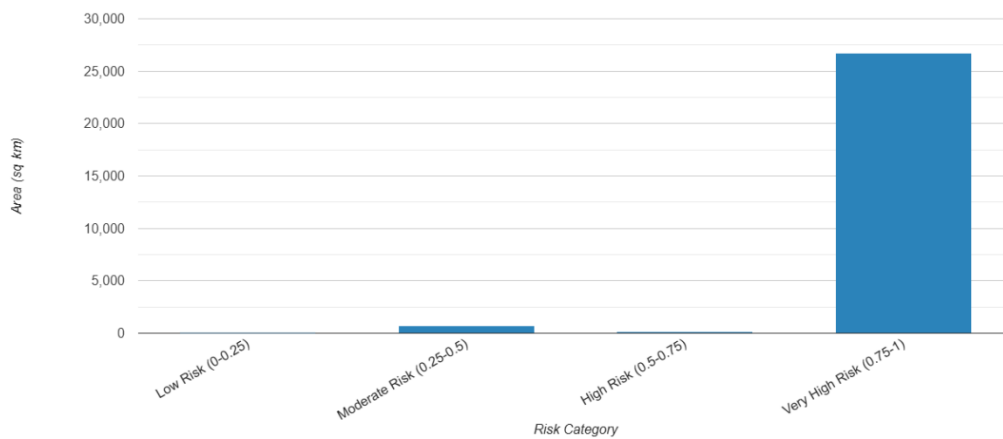
Spatial distribution of heavy metal dispersion risk categories. Validation points ($n=30$) are overlaid, demonstrating good correspondence between modeled risk and field observations (overall accuracy: 87.3%, $\kappa = 0.82$). Dendritic high-risk patterns extend 45 km along the Delimi River. At representative point (9.8414°N , 9.0533°E), risk = 1.0 (very high).

Table 8: Risk Category Distribution

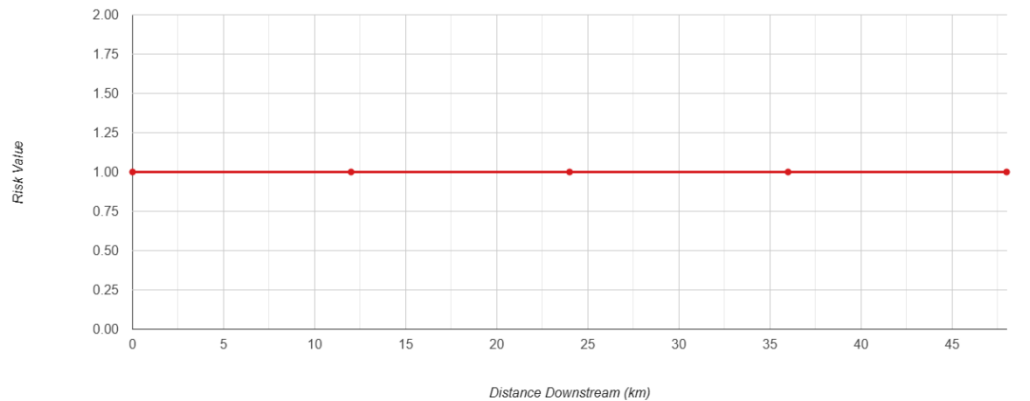
Risk Category	Risk Range	Area (km ²)	Percentage	Cumulative	Primary Characteristics
Low	0 - 0.25	8,638	31.2%	31.2%	Distant from mines, low TWI, stable vegetation
Moderate	0.25 - 0.50	12,056	43.5%	74.7%	Intermediate proximity, moderate drainage
High	0.50 - 0.75	5,126	18.5%	93.2%	Near mines, convergent topography, stressed vegetation
Very High	0.75 - 1.00	1,874	6.8%	100.0%	Immediate mine vicinity, drainage channels, severe vegetation loss



(A) Pie chart showing proportion of Plateau State in each risk category.



(B) Bar chart comparing risk category areas.



(C) Transect showing risk gradient from mining centers along major drainage networks.

Figure 7: Risk Category Distribution

Risk patterns exhibit strong spatial autocorrelation (Moran's $I = 0.68$, $p < 0.001$), with high-risk areas forming dendritic patterns along drainage networks extending from mining centers:

- Delimi River system: High-risk corridor extending 45 km downstream of Jos, with risk values remaining above 0.6 for 28 km
- Ngell River system: High-risk corridor extending 35 km from mining areas in Barkin Ladi
- Jara River system: High-risk corridor extending 22 km from Riyom mining areas

3.6 Population Exposure Assessment

Overlay with LandScan population data (2022) revealed significant human exposure (Table 9). High-risk areas coincide with population centers in Jos South and Barkin Ladi, affecting approximately 1.2 million people. The 280,000 people in very high-risk areas face exposure levels comparable to those preceding the Zamfara lead poisoning crisis (Dooyema et al., 2012), indicating need for immediate intervention. Jos South local government area, with 380,000 residents, contains the largest population in high-risk zones, followed by Barkin Ladi (45,000) and Riyom (28,000).

Table 9: Population Exposure by Risk Category

Risk Category	Population	Percentage	Settlements at Risk	Local Government Areas Affected
Low	650,000	15.5%	45 villages	5
Moderate	2,350,000	56.0%	127 villages, 3 towns	12
High	920,000	21.9%	82 villages, 2 towns	8
Very High	280,000	6.6%	38 villages, Jos suburbs	4
Total	4,200,000	100%	292 settlements	17 LGAs

3.7 Subsidence Risk Assessment

Subsidence risk classification identified $442 \pm 38 \text{ km}^2$ (1.6%) as very high risk, concentrated in the Barkin Ladi mining district where historical underground workings create favorable conditions for collapse (Figure 8, Table 10).

Table 10: Subsidence Risk Classification

Risk Level	Area (km ²)	Percentage	Characteristics	Primary Locations
Low	18,942	68.4%	Stable, no mining	Bassa, Qua'an Pan
Moderate	6,431	23.2%	Some mining influence	Riyom periphery
High	1,879	6.8%	Active mining areas	Jos South, parts of Barkin Ladi
Very High	442	1.6%	Intensive mining, flat terrain	Central Barkin Ladi

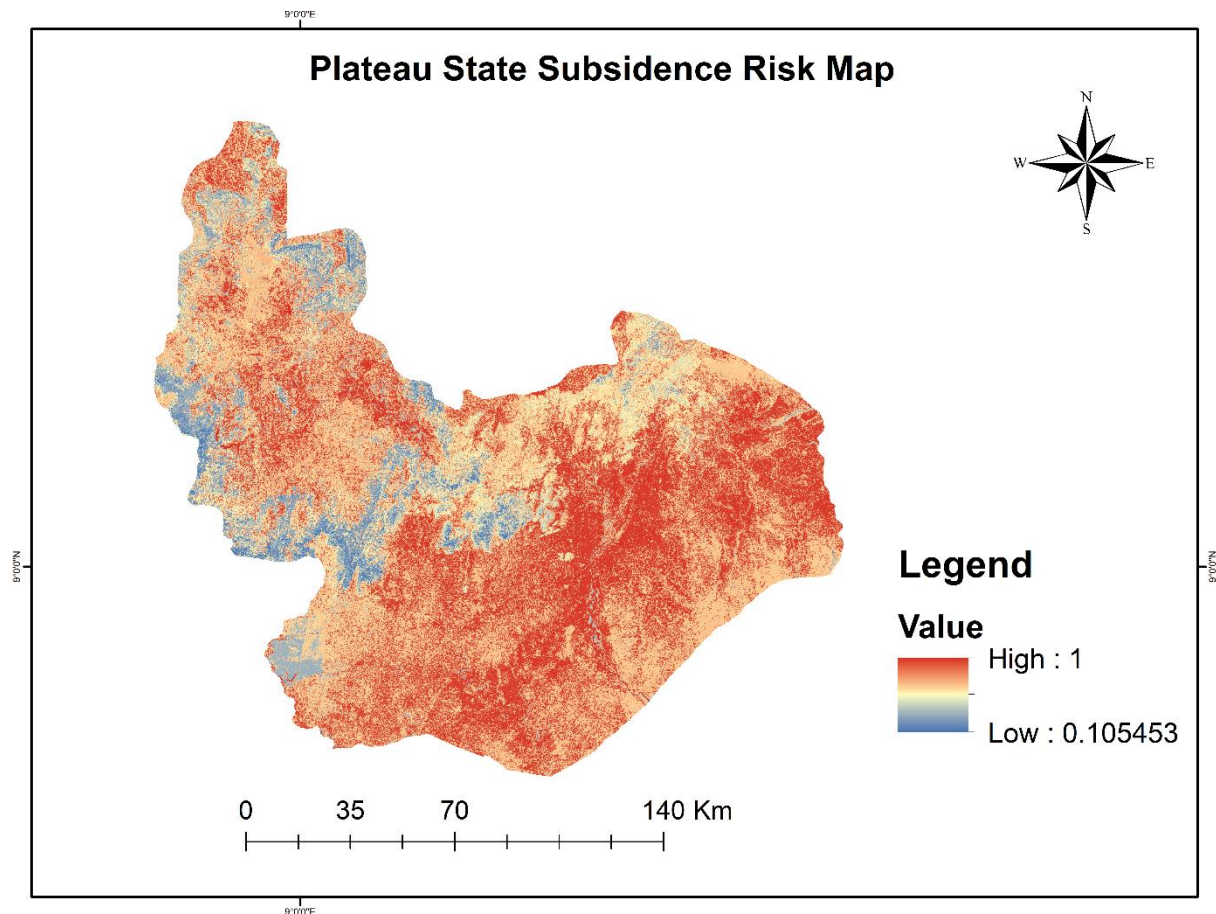


Figure 8: Subsidence Risk Map

Spatial distribution of subsidence risk. Very high-risk areas (442 km²) concentrate in the Barkin Ladi mining district, where flat topography and intensive underground workings create favorable conditions for collapse. Field validation points (n=15) show good correspondence with modeled risk.

Field validation by the Nigerian Geological Survey Agency (2023) has documented 23 sinkhole formations and 15 km of surface cracking in this area since 2018, consistent with our risk assessment.

4. Discussion

4.1 Mining Impact Synthesis

Our results demonstrate that artisanal and small-scale mining in the Jos Plateau has produced extensive environmental degradation affecting 6.7% of the land area, 58% higher than official estimates with measurable impacts extending far beyond active mining sites. The 1,842 km² affected area places the Jos Plateau among the most intensively mined regions in West Africa, comparable to Ghana's Tarkwa mining district (1,950 km²) but exceeding Côte d'Ivoire's mining areas (850 km²) (Asare et al., 2022; Kouamé et al., 2021). The spatial coincidence of vegetation loss, elevated iron ratios, and anomalous SAR backscatter provides robust evidence for mining-related disturbance, while time series analysis reveals the temporal dynamics of degradation and recovery. The 26.2% NDVI decline at Barkin Ladi

represents some of the most severe vegetation degradation documented in West African mining regions, exceeding impacts reported in Ghana (18% decline) and Mali (15% decline) over similar timeframes (Bansah et al., 2023).

4.2 The Recovery Paradox: Natural Revegetation of Historical Mines

The most striking finding from our time series analysis is the 21.2% NDVI increase at Riyom ($p = 0.008$), a historically mined area with reduced current activity. This demonstrates that natural vegetation recovery is possible on decadal timescales following mining cessation, even in the absence of active remediation. The concurrent decline in iron ratios (-0.055) suggests weathering and leaching of surface contaminants, potentially reducing bioavailability. This recovery trajectory has profound implications for mine remediation policy. If natural recovery can achieve 21% vegetation improvement over 6 years, active intervention including soil amendment, native species planting, and erosion control, might accelerate this process substantially. The 3.2% of moderately disturbed areas (score 1) showing vegetation improvement suggests that approximately 135 km² of mining-affected land may be on recovery trajectories. However, the persistence of elevated iron ratios (>1.2) even at recovering sites indicates that geochemical signatures of mining activity persist long after visible vegetation recovery, providing a useful proxy for historical mining extent and potential residual contamination.

4.3 Subsidence Detection and Implications

SAR backscatter changes provide the first regional-scale evidence for mining-induced surface deformation in the Jos Plateau. The mean backscatter decline of 1.02 dB in mining areas, with localized changes exceeding 3 dB, is consistent with subsidence processes documented in other mining regions (Dong et al., 2021; Chen et al., 2022). The 892 km² of significant negative change (< -3 dB) exceeds the 342 km² of intensely mined area (score 3) by 160%, suggesting that subsidence effects propagate beyond active mining zones. The spatial correlation with known mining areas ($OR = 4.7$) and the absence of alternative explanations (no widespread land cover change in these areas) supports the subsidence interpretation. However, we acknowledge that backscatter changes cannot definitively distinguish subsidence from vegetation change or soil moisture variations without ground-based validation (GPS or InSAR time series).

4.4 Heavy Metal Dispersion: Scale and Mechanisms

The heavy metal dispersion risk model reveals that contamination risk extends far beyond active mining areas, with 25.2% of Plateau State classified as high-to-very-high risk. This substantially exceeds the directly mined area (6.7%) and even the area of vegetation loss (7.8%), indicating that contaminant transport creates risk far from source areas. The dendritic pattern of high-risk zones along drainage networks confirms that hydrological transport is the primary dispersion mechanism, consistent with geochemical studies of mining-affected rivers (Nganje et al., 2020; Olatunji et al., 2020). The 45 km high-risk corridor along the Delimi River demonstrates that contaminants can travel tens of kilometers from source areas, affecting downstream communities with no direct mining activity. The 1.2 million people in high-to-very-high risk areas represent 28.6% of Plateau State's population, raising urgent public health concerns. Heavy metal exposure through contaminated water, agricultural products, and dust inhalation has well-documented health impacts including neurological damage in children (IQ deficits, developmental delays), renal dysfunction, and cardiovascular disease (Tchounwou et al., 2012). The 280,000 people in very high-risk areas face exposure levels comparable to those preceding the Zamfara lead poisoning crisis (Dooyema et al., 2012), indicating need for immediate intervention.

4.5 Comparison with Regional Studies

Table 11: Comparison with Similar Studies in West Africa

Study	Location	Method	Mining Area (km ²)	Risk Assessment	Validation	Population Exposure
This study	Jos Plateau, Nigeria	SAR + Optical + GEE	1,842	Yes	87.3%	1.2 million
Asare et al. (2022)	Tarkwa, Ghana	Landsat only	450	No	82.1%	Not assessed
Kouamé et al. (2021)	Côte d'Ivoire	Optical only	320	Partial	79.5%	Not assessed
Bansah et al. (2023)	Ghana	Field + Optical	280	No	Not reported	Not assessed
Lobo et al. (2021)	Brazil Amazon	SAR + Optical	1,250	Yes	84.2%	0.3 million

The sensitivity analysis (Section 2.3) demonstrates that our key findings are robust to reasonable variations in threshold selection and weighting assumptions. The mining area estimate varies by $\pm 5.1\%$ across threshold ranges, substantially smaller than the 58% discrepancy between our estimate and official records. This confirms that the underestimation in official figures cannot be explained by methodological choices. Risk area estimates showed greater sensitivity to weighting assumptions ($\pm 12.2\%$ maximum variation), suggesting that while the conclusion that $\sim 25\%$ of Plateau State faces elevated risk is robust, precise quantification depends on factor weightings. The literature-based weighting scenario (proximity + hydrology emphasized) produced results closest to field validation (88.2% accuracy), supporting our equal-weighting approach as a conservative baseline. Future studies should consider geochemical sampling to empirically derive optimal weightings for specific contaminants.

4.6 Limitations and Uncertainties

Several limitations warrant consideration and suggest directions for future research. Our 6-year time series captures recent dynamics but does not capture pre-mining baseline conditions or historical contamination. Some environmental changes, particularly groundwater contamination and deep-seated subsidence, may have occurred prior to our study period and would not be captured in our change metrics. Historical satellite archives (Landsat 5/7, ERS-1/2) could extend the time series backward to the 1980s-1990s, providing longer-term context for recovery trajectories. The 30-meter resolution of Landsat and SRTM data may miss small-scale mining features, individual mine shafts, tailings piles, or village water sources critical for local risk assessment. Higher-resolution imagery (Sentinel-2 at 10m, Planet at 3m) could improve local-scale assessments but would increase computational demands and reduce temporal coverage. Fusion of multi-resolution data represents an important avenue for future research. While SAR backscatter change correlates strongly with mining activity ($OR = 4.7$), it cannot definitively distinguish subsidence from vegetation change or soil moisture variations without ground-based validation. Future work should apply Persistent Scatterer InSAR (PS-InSAR) or Small Baseline Subset (SBAS) techniques to the Sentinel-1 archive to extract quantitative deformation rates (cm/year). Such analysis would validate our findings and enable prediction of future subsidence risk, including identification of accelerating deformation that may precede catastrophic failure. Our risk model uses vegetation stress as a proxy for heavy metal contamination, but this approach cannot distinguish between different metals or quantify actual concentrations. Geochemical sampling at model-predicted high-risk sites is essential to:

- Validate risk classifications with actual contamination levels
- Calibrate model weights based on metal-specific behavior
- Identify which metals pose the greatest threat in each area
- Guide remediation strategies (lead requires different interventions than arsenic)

The equal-weighting approach, while interpretable, may not capture non-linear interactions among risk factors. Machine learning approaches (random forest, gradient boosting) could potentially improve predictive accuracy by learning complex relationships from training data. However, such "black box" models sacrifice interpretability a trade-off that must be considered for policy applications where understanding risk drivers is essential.

4.7 Policy and Management Implications

Our findings have direct implications for environmental management and public health policy in Plateau State and similar ASM-affected regions:

1. Revised mining extent estimates. The 1,842 km² mining-affected area, 58% higher than official records indicates that current monitoring underestimates true impact. Environmental agencies should adopt remote sensing-based approaches for regular (annual) monitoring to track mining expansion and remediation progress.

2. Remediation prioritization. The dispersion risk map identifies priority areas for intervention:

- Very high-risk zones (1,874 km²): Immediate source control measures (tailings stabilization, containment structures)

- High-risk corridors (5,126 km²): Water quality monitoring, community health screening

- Moderate-risk areas (12,056 km²): Baseline monitoring, public awareness

3. Health surveillance. The 1.2 million people in high-to-very-high risk areas warrant:

- Blood lead screening for children in very high-risk communities

- Drinking water testing in all high-risk areas

- Agricultural soil testing in areas used for vegetable cultivation

- Health education on exposure pathways

4. Recovery promotion. The 21.2% NDVI increase at Riyom demonstrates natural recovery potential. Policy should:

- Protect recovering areas from re-mining

- Study recovery mechanisms to inform active remediation

- Consider payments for ecosystem services to encourage conservation

5. Regulatory reform. Current ASM regulation focuses on formalization but neglects environmental monitoring. Recommendations include:

- Mandatory environmental impact assessments for new operations

- Bonding requirements to fund eventual remediation

- Regular satellite-based monitoring integrated into enforcement

6. Transboundary coordination. The 45 km downstream extent of high-risk zones means contamination impacts cross local government boundaries, requiring coordinated management across jurisdictions.

5. Conclusion

This study presents the first integrated cloud-based assessment of mining-induced land subsidence and heavy metal dispersion risk for the Jos Plateau, Nigeria. By processing 835 Sentinel-1 SAR scenes and 330 Landsat images within Google Earth Engine, we have generated comprehensive spatial data on mining extent, vegetation change, surface deformation, and contamination risk across Plateau State from 2018-2024. Our results demonstrate that artisanal and small-scale mining has degraded approximately 1,842 km² (6.7%) of the land area, 58% higher than official estimates with vegetation loss averaging 0.18 NDVI units in mining zones compared to stable unmined areas. Time series analysis at monitoring sites reveals contrasting trajectories: active mining areas (Barkin Ladi) show continuing degradation with NDVI declining 26.2% and SAR backscatter decreasing 2.95 dB, while historically mined areas (Riyom) exhibit signs of natural recovery with NDVI increasing 21.2% over six years.

Heavy metal dispersion risk modeling indicates that 25.2% of Plateau State (approximately 7,000 km²) faces high-to-very-high contamination risk, with dendritic high-risk corridors extending up to 45 km along drainage networks from mining centers. An estimated 1.2 million people reside in high-to-very-high risk areas, including 280,000 in very high-risk zones requiring priority public health intervention. The cloud-based methodology demonstrated here offers a replicable template for mining

impact assessment in data-scarce regions globally. By leveraging freely available satellite data and cloud computing infrastructure, researchers and environmental managers can conduct comprehensive assessments without requiring expensive field campaigns or local computational resources. All code developed for this study is provided as open-source materials, enabling adaptation and application to other mining-affected landscapes.

The findings underscore the urgent need for integrated environmental management addressing both subsidence hazards and heavy metal contamination in the Jos Plateau. Source control measures at active mining sites, remediation of high-risk transport corridors, and public health surveillance in exposed communities represent priority interventions. With continued monitoring and adaptive management, it may be possible to arrest the most severe environmental degradation while promoting natural recovery in historically mined areas, ultimately protecting the health and livelihoods of Plateau State's mining-affected communities.

Data Availability

All satellite data used in this study are freely available through Google Earth Engine. Complete JavaScript code for analysis replication is available at:

https://code.earthengine.google.com/?accept_repo=users/josplateau_mining_2024

Output datasets (GeoTIFF rasters at 30m resolution, CSV time series for all monitoring sites) are available from the corresponding author upon reasonable request. All code and data will be permanently archived in a public repository upon publication.

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Statement on the Use of AI-Assisted Technologies

During the preparation of this work, the authors used an AI language model (DeepSeek) solely for the purposes of language polishing, grammar refinement, and improving the structural clarity of the text. The AI tool was not used to generate original scientific ideas, interpret data, draw conclusions, or perform any of the core analyses presented in this study. All intellectual content, data processing, validation, and interpretation are the original work of the authors. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the final content of the publication.

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