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Integrating Revised Universal Soil Loss Equation (RUSLE) Modeling and Random Forest-Based Feature Importance Ranking to Assess Soil Erosion Risk and Spatial Variability of Pb in a Tropical Post-Tin Mining Landscape

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Abstract

Open-pit tin mining transforms tropical landscapes into heterogeneous Technosols that are vulnerable to soil degradation and heavy-metal redistribution. This study integrated the Revised Universal Soil Loss Equation (RUSLE) and Random Forest-Based Feature Importance Ranking (RF) to assess spatial erosion patterns and identify key environmental predictors of Pb concentration in the Diniang Watershed, Bangka Island, Indonesia. Soil erosion was estimated using spatial layers of rainfall erosivity, soil erodibility, topography, vegetation cover, and support practices. Five predictors (erosion rate, soil pH, soil organic carbon (Corg), and distance to roads and rivers) were integrated with spatial Pb concentration data and analyzed using a Random Forest Regressor. The results revealed pronounced spatial heterogeneity in tropical technosol properties and Pb concentration. RUSLE indicated that 92.32% of the watershed experienced low potential soil loss (<15 t ha^{-1} yr^{-1}), while localized areas were classified as high to very severe erosion, forming potential erosion hotspots. Random Forest ranking identified soil pH and Corg as the dominant predictors of Pb concentration, with

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substantially higher importance than erosion rate, distance to roads, and distance to rivers. These findings suggest that Pb concentration in the study landscape is more strongly associated with soil chemical properties than with modeled erosion under the conditions examined. The integrated RUSLE-RF framework provides a spatially explicit diagnostic approach for identifying soil erosion risk and potential heavy-metal hotspots and can support targeted restoration and monitoring of tropical post-tin mining landscapes. Field-based validation and denser sampling are recommended to strengthen model reliability.

Keywords

Tropical Technosols; post-tin mining; soil erosion risk; RUSLE; Random Forest-Based Feature Importance Ranking; Pb concentration; soil pH; soil organic carbon; spatial heterogeneity.

1. Introduction

Global land-use change, particularly through extensive mining operations, serves as a primary driver of environmental degradation and the ongoing biodiversity crisis (Hutagaol et al. 2026, Pairon and Dufrêne 2026). Opencast mining is recognized as one of the most dramatic disturbances to terrestrial ecosystems, involving rapid and often irreversible changes to both soil physical properties and vegetation cover (Hamidi et al. 2024, Moreno-de las Heras 2009). This process, frequently defined as land-take, causes a durable alteration of soil characteristics that significantly reduces the capacity of landscapes to deliver essential ecosystem services, including nutrient cycling and water regulation (Pairon and Dufrêne 2026). The mechanical processes of land clearing and overburden removal can increase soil erosion rates to levels several hundred times greater than those found in undisturbed environments (Ramli et al. 2020, Singh et al. 2024). Furthermore, the creation of artificial topographic structures through dumping and grading often leads to severe soil compaction, which dramatically lowers infiltration rates and facilitates the discharge of eroded materials into surrounding watercourses (Moreno-de las Heras 2009, Singh et al. 2024, Sinha et al. 2017, Yellishetty et al. 2012). Consequently, these anthropogenic modifications transform stable natural systems into highly vulnerable landscapes prone to chronic siltation and heavy metal contamination (Moreno-de las Heras 2009, Yellishetty et al. 2012).

On Bangka Island, Indonesia, mining systematically converts naturally developed soils (such as Ultisols) into technogenic tailings, known as Tropical Technosols (Maftukhah et al. 2025). This process drastically removes vegetation cover, strips organic-rich topsoil, destroys biodiversity, and dismantles the aggregate stability that once protected organic matter from mineralization (Zhou et al. 2020). Mechanical separation during tin ore extraction leaves post-mining soils dominated by quartz sand (>80%) and very low clay and silt. These physicochemical characteristics result in Technosols with high bulk density in compacted layers, low porosity, poor water-holding capacity, and low Cation

Exchange Capacity (CEC) (Sari et al. 2017). Intensive leaching follows, depleting the nutrient stocks, raising soil temperatures, and increasing the risk of heavy metal pollution (such as arsenic, chromium, and lead), all of which reduce ecosystem functionality (Blenke et al. 2026, Irzon et al. 2018).

Quantifying the specific impacts of land-use transitions on erosion rates and soil quality is essential for assessing the agricultural potential of these reclaimed landscapes, which often suffer from shallow soil solums and low fertility that cannot sustain crop productivity (Hamidi et al. 2024, Pairon and Dufrêne 2026, Singh et al. 2024). Integrated modeling approaches, such as the Revised Universal Soil Loss Equation (RUSLE) combined with geographic information systems (GIS), enable spatial estimation of soil loss and sediment yield across the heterogeneous mosaic of mining heaps (Ramli et al. 2020, Singh et al. 2024). To navigate the non-linear complexities of these processes, the Random Forest (RF) algorithm has proven highly effective in ranking the relative importance of soil and landscape variables (Fathizad and Ardakani 2026, Nwobi 2026). Variable importance metrics, such as the mean decrease in Gini impurity or Increase in Node Purity, reveal that elevation, slope, and Topographic Wetness Index (TWI) serve as primary topographic drivers governing catchment-scale hydrological collapse and surface instability (Fathizad and Ardakani 2026). Simultaneously, edaphic factors, particularly sand-to-clay ratios and cation exchange capacity (CEC), act as critical pedological triggers that influence both erodibility and the distribution of heavy metals such as lead and zinc (Fathizad and Ardakani 2026, Nwobi 2026). These dynamics are inextricably linked to the accumulation of soil organic carbon and total nitrogen (C/N), which serve as the fundamental triggers for the development of soil physical structure and biological functionality (Moreno-de las Heras 2009, Nwobi 2026). Ultimately, understanding the spatial coincidence of anthropogenic pressures, such as proximity to mining infrastructure and roads, with natural soil-forming processes provides a diagnostic basis for restoring nutrient cycling and determining the long-term viability of future agricultural use (Fathizad and Ardakani 2026, Hamidi et al. 2024).

Despite the extensive application of erosion models in coal mining and arid environments, a significant research gap remains in the integrated assessment of tropical post-tin mining landscapes, where the complex interactions between microtopographic heterogeneity and heavy metal concentration are poorly understood (Bekova et al. 2026, Nwobi 2026). Most existing literature focuses on isolated components, such as static soil loss inventories or point-source metal concentrations, without analyzing how these drivers synergistically govern the evolution and biological functioning of tropical technosols over time (Fathizad and Ardakani 2026, Nwobi 2026). The novelty of this study lies in bridging this gap through a high-resolution, machine-learning-driven framework that integrates the Revised Universal Soil Loss Equation (RUSLE) with Random Forest (RF) variable ranking to isolate the specific pedological and topographic triggers of degradation (Fathizad and Ardakani 2026, Singh et al. 2024). By disentangling the relative importance of edaphic factors, such as C/N ratios and sand-to-clay fractions, alongside anthropogenic pressures, such as proximity to mining infrastructure, this research provides a robust diagnostic tool for quantifying the long-term agricultural

potential and ecological resilience of reclaimed tin tailings (Fathizad and Ardakani 2026). Ultimately, this multi-dimensional approach moves beyond purely surface-based land-take assessments to reveal the deep-seated chemical and physical shifts that define the success or failure of tropical land restoration (Fathizad and Ardakani 2026, Pairon and Dufrêne 2026).

Based on the knowledge gaps, this study aims to integrate the Revised Universal Soil Loss Equation (RUSLE) with Random Forest (RF) variable importance analysis to quantify soil degradation processes and identify the key environmental drivers controlling heavy metal concentrations in tropical post-tin-mining landscapes. Specifically, this study seeks to

1. estimate the spatial distribution of potential soil erosion across heterogeneous post-mining landforms using a GIS-based RUSLE framework;
2. evaluate the spatial patterns of heavy metal concentration in relation to erosion-prone areas and land-use transformation;
3. rank the relative importance of topographic, soil, land-cover, and anthropogenic variables governing degradation using the Random Forest algorithm; and
4. develop an integrated spatial assessment framework capable of identifying priority areas for ecological restoration and sustainable agricultural reclamation.

By combining physically based erosion modeling with machine-learning interpretation, this study provides a comprehensive approach for understanding the coupled processes of soil erosion and contaminant concentration, thereby supporting evidence-based restoration planning and long-term land management in tropical post-mining environments.

2. Description of The Study Area

The Diniang Watershed (Fig. 1) was selected as a representative tropical post-tin mining landscape because its catchment structure enables assessment of runoff, soil erosion, sediment transport, and heavy-metal redistribution within a single drainage system. Sentinel-2 imagery revealed extensive tin mining along the Diniang River and its tributaries, where vegetation has been converted to exposed tailings and mining ponds. Industrial mining reportedly ceased approximately 30 years ago, although intermittent artisanal re-mining has continued, creating a mosaic of legacy and recently disturbed mining areas.

Located on the east coast of Bangka Island, Indonesia (106°7′9.116″ E; 1°50′51.821″ S), the watershed covers approximately 7,762 ha and ranges from coastal lowlands to upstream hills (~200 m a.s.l.). Gentle slopes of 0–8% dominate the area (5,046 ha), followed by 8–15% slopes (1,401 ha). Geologically, the watershed comprises Klabat Granite (74%), Alluvium (26%), and the Pemali Complex (1%). Intensive tin mining has transformed naturally developed soils into heterogeneous Technosols characterized by

sandy texture, disrupted structure, low organic matter and cation exchange capacity, and variable acidity. Histosols and Nitisols also occur locally (Fig. 2).

The watershed has a humid tropical climate (Af), with annual rainfall of 2,288–2,989 mm and temperatures of 26.6–27°C. High rainfall and the porous nature of Technosols influence groundwater and hydrological dynamics (Cardozo et al. 2026, Maftukhah et al. 2025). The present landscape comprises agricultural land, secondary vegetation, and exposed post-mining areas, with bare Technosols covering approximately 32–40% of the watershed. Their coexistence with regenerating vegetation and agricultural land creates pronounced spatial heterogeneity relevant to erosion processes and Pb redistribution.

3. Materials and Method

3.1. Land-Use Map Development

Land-use dynamics play a pivotal role in governing the lithosphere's response to hydrological processes, directly dictating surface runoff, erosion dynamics, and nutrient or contaminant redistribution within a watershed. Quantifying these spatio-temporal shifts is therefore critical for understanding soil degradation and hydro-pedological behavior in post-mining landscapes. Due to the limited availability of historical spatial archives, land-use changes in the Diniang watershed were evaluated across two distinct time periods utilizing medium-resolution satellite imagery from Sentinel-2, accessed through the Google Earth Engine (GEE) cloud computing platform. To classify these multi-temporal datasets accurately, a Random Forest (RF) machine learning algorithm was implemented. Prior to classification, only imagery with low cloud cover was selected, and a cloud masking procedure was applied to all scenes to ensure optimal data quality. The filtered images were subsequently composited over defined time ranges to produce stable, spatially representative depictions of land-cover conditions across the study area for both observation periods.

To handle non-linear spectral signatures and minimize overfitting (Layeghi et al. 2020, Mborah et al. 2015), an ensemble Random Forest (RF) machine learning algorithm was applied to classify pixel-level spectral data into five key classes:

1. built-up land,
2. water bodies,
3. open land,
4. forests, and
5. seasonal agriculture.

Model training was guided by representative samples derived from high-resolution imagery and field knowledge.

Classification reliability was rigorously validated against 250 stratified random reference points (50 points per class) sourced from high-resolution ArcGIS basemaps. Accuracy

metrics including Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), and the Kappa Coefficient were extracted via a confusion matrix. Models were iteratively refined until meeting target thresholds of OA > 85% and Kappa > 0.80, ensuring a robust spatial baseline for subsequent RUSLE soil degradation modeling.

3.2. Soil Sampling Design

A stratified random sampling design was adopted to ensure representative sampling across contrasting land-use categories that reflect different stages of post-mining recovery. Stratification by land use improves the representation of heterogeneous environmental conditions and enables comparisons along ecological recovery gradients while reducing sampling bias associated with highly variable post-mining landscapes (Harries et al. 2024, Tang et al. 2025). In this study, four distinct land-use categories were established as sampling strata based on their reclamation status and management intensity: abandoned former mining sites (untreated sand tailings and settling ponds), reforested areas (revegetated/reclaimed forest plots), agricultural land (managed by local communities using organic amendments/biochar), and surrounding natural vegetation (serving as undisturbed reference sites).

Within each land-use stratum, three replicate 10 x 10 m sampling plots were established, yielding a total of 12 intensive plots across the study area. Soil samples were collected to characterize both soil physicochemical properties and Pb concentrations across the contrasting post-mining land-use conditions. The measured soil parameters included texture, bulk density, soil pH, total nitrogen, available phosphorus, exchangeable cations (Ca, Mg, K, and Na), soil organic carbon, carbon fractions, soil moisture, and Pb concentration. Pb was specifically selected as the target heavy metal because previous research in the study region identified Pb as the dominant heavy metal associated with post-tin mining soils and tailings (Maftukhah et al. 2025).

To evaluate soil properties and Pb concentration, composite disturbed soil samples were collected from the topsoil layer (0–20 cm) using a stainless-steel soil shovel. Within each 10 × 10 m plot, four subsamples were collected along a diagonal grid pattern and thoroughly mixed into a single composite sample to minimize microspatial heterogeneity. The composite samples were subsequently used for physicochemical characterization and Pb determination. Simultaneously, undisturbed soil core samples were collected from the center of each plot using standard stainless-steel ring samplers (5 cm diameter, 5 cm height) to determine soil bulk density. For Pb analysis, the soil samples were air-dried, gently disaggregated, and passed through a 2-mm sieve prior to laboratory digestion and determination by Atomic Absorption Spectrometry (AAS), as described in Section 3.3.

3.3. Soil Laboratory Analysis

Composite soil samples were prepared from three replicates within each land-use category. The three replicate samples were combined to obtain one composite sample

representing each land-use category and sampling depth. The composite samples were air-dried, gently crushed, and passed through a 2 mm sieve. Because previous research identified Pb as the dominant heavy metal in post-tin mining soils in the study region (Maftukhah et al. 2025), Pb was the primary target analyte. Pb concentration was determined after complete acid digestion using Atomic Absorption Spectrometry (AAS), and the resulting concentrations were used as the response variable in the spatial and Random Forest analyses.

Other soil properties included texture, bulk density, pH, total nitrogen, available phosphorus, exchangeable Ca, Mg, K, and Na, and soil organic carbon (SOC). Texture was determined using the hydrometer method, bulk density gravimetrically after oven-drying at 105ºC for 24 h, and pH using a soil-to-deionized water ratio of 1:2.5 (w/v). Total N was determined by micro-Kjeldahl digestion, available P using Bray I or Olsen extraction depending on pH, and exchangeable cations using 1 M NH_4OAc (pH 7.0) followed by flame photometry or AAS.

SOC was fractionated into particulate organic matter (POM, >53 µm) and mineral-associated organic matter (MAOC <53 µm). A 10 g soil aliquot was dispersed in 30 mL sodium hexametaphosphate (5 g L^{-1}), shaken for 15 h, and separated using a 53 µm sieve. The POM and MAOC fractions were oven-dried at 60ºC and analyzed for carbon using the Walkley–Black method.

3.4. Soil Erosion Assessment Using the RUSLE Model

Annual soil loss (A, t ha^{-1} yr^{-1}) was estimated using the Revised Universal Soil Loss Equation (A = R.K.LS.C.P) , with all raster layers projected, clipped, and aligned at a 10 spatial resolution. The rainfall erosivity factor (R) was derived from GPM IMERG mean annual precipitation (2001–2025) using a tropical empirical relationship. Soil erodibility (K) was calculated via the EPIC equation using depth-weighted averages (0-15) of SoilGrids v2.0 properties, converted to SI units (0.1317), with missing values replaced by the watershed mean. The topographic factor (LS) was computed from a hydrologically corrected DEMNAS DEM using the Moore and Burch (1986) formulation. Cover management (C) was derived from Sentinel-2 median composite NDVI following Van der Knijff et al. (2000), assigning C = 1 to pixels where NDVI <= 0. Due to unavailable spatial conservation data, the support practice factor (P) was set to 1. Finally, annual soil loss was mapped by multiplying the five factor rasters and classified into five erosion severity classes: very slight (<15), slight (15-60), moderate (60-180), severe (180-480), and very severe (>480 t ha^{-1} yr^{-1}).

Erosion modeling was not field-validated in this study due to limited ground-truth data. Although validation could be performed by relating predicted erosion hazard classes to observed erosion types, as demonstrated by Candra Dewi et al. (2024), the present study focuses on developing a method to identify key drivers of land degradation and heavy metal redistribution in post-tin mining landscapes. The analysis integrates erosion, distance from roads and rivers, soil pH, and soil organic carbon (Corg) to assess their relative contributions to degradation and heavy metal redistribution.

3.5. Machine Learning and Variable Importance

Five predictor variables were considered: erosion rate, soil pH, soil organic carbon (Corg), and distance to roads and rivers, with Pb concentration as the response variable. Spatial analysis was conducted in QGIS by preparing raster-based thematic maps of the predictor variables and converting the raster layers to point features to obtain pixel-level attribute values and build the spatial predictor database. Random Forest (RF) regression was then performed in Python using Visual Studio Code and the RandomForestRegressor class from the scikit-learn library. Soil pH, Corg, and Pb concentration were interpolated using ordinary Kriging, whereas road and river proximity were derived using Euclidean distance. All variables were represented as 10 × 10 m raster layers.

The RF model was configured with n_estimators=300, max_depth=None, min_samples_split=2, min_samples_leaf=1, max_features="sqrt", bootstrap=True, random_state=42, and n_jobs=-1. The dataset was divided into training and testing subsets at a ratio of 80:20. Five-fold cross-validation was performed on the training set using the predefined RF configuration, with R^2, RMSE, and MAE used as evaluation metrics. The RF model was subsequently fitted to the complete training set using the same configuration and evaluated on the independent test set. Impurity-based feature importance was extracted from the fitted RF model to quantify the relative contribution of the five predictor variables to Pb concentration.

4. Results

4.1. Land Cover Transformation Associated with Tin Mining Activities

Spatial analysis revealed extensive land-cover transformation in the Diniang watershed associated with long-term tin mining activities (Fig. 3). Historical and Sentinel-2 data showed a transition from vegetation-dominated areas toward bare land and artificial water bodies formed by mine excavation. Mine ponds were concentrated along the central valley and drainage network, indicating preferential extraction of accessible alluvial deposits and substantial modification of the original geomorphological setting. This pattern reflects the documented effects of open-pit mining, including soil-horizon removal, redistribution of geological materials, and formation of anthropogenic landscapes (Sukarman et al. 2020, Pratiwi et al. 2025).

Change detection further demonstrated spatially heterogeneous degradation and vegetation recovery (Fig. 4). The dominant degradation pathways were transitions from high-density vegetation (HDV) to medium- and low-density vegetation, covering approximately 525 and 131 ha, respectively. Conversely, recovery occurred through transitions from MDV to HDV (230 ha), LDV to HDV (93 ha), and LDV to MDV (62 ha), indicating contrasting post-mining trajectories (Fig. 5). Mining disturbance was

concentrated mainly on gently sloping terrain (0–8%), where bare surfaces replaced vegetated Histosols. The dominant LMUs comprised vegetated Histosols (2,589 ha; 33%) and bare mining surfaces (2,457 ha; 32%), together accounting with other major units for approximately 83% of the watershed (Fig. 6).

These transformations produced heterogeneous Technosols through topsoil removal, tailings exposure, overburden redistribution, and mine-pit formation. Such spatial heterogeneity provides the basis for assessing erosion-driven soil degradation and Pb redistribution using RUSLE and Random Forest, linking landscape transformation with the dominant environmental controls on post-mining soil degradation.

4.2. Spatial Heterogeneity of Soil Properties Tropical Technosols

The soil properties of the Tropical Technosols exhibited pronounced spatial heterogeneity across the four Land Mapping Units (LMUs) Table 1 and Suppl. material 1. Soil texture was dominated by sand, ranging from 67.3% in IIHTT to 85.1% in IHTT, while clay content varied from 10.9% to 23.2%. Bulk density also showed substantial variation (1.03–1.40 g cm^{-3}), indicating differences in soil structure and compaction among LMUs. Soil pH was relatively homogeneous and near neutral (6.80–7.06), whereas organic-C showed a much wider spatial variation, from 0.85% in IHTT to 5.79% in IIHTT. Similarly, soil moisture varied markedly (0.17–4.47%), reflecting differences in water-retention conditions.

Nutrient availability was also highly heterogeneous, particularly for P and K. Extractable P ranged from only 6.47 in IHTT to 206.86 in IIHTT, while K varied from 6.57 to 17.13. Most notably, Pb concentrations showed a clear spatial contrast, increasing from undetectable levels in IIHVG and IHVG to 4.12 in IIHTT and 13.79 in IHTT. Overall, these patterns demonstrate that Tropical Technosols in the post-tin mining landscape are spatially heterogeneous, with substantial variation in soil physical and chemical properties and a particularly pronounced spatial differentiation in Pb accumulation. This heterogeneity highlights the importance of spatially explicit approaches for assessing soil degradation and heavy-metal redistribution in post-mining landscapes.

4.3. Spatial Distribution of Soil Erosion Risk Based on RUSLE

The RUSLE assessment revealed a predominantly low but spatially heterogeneous erosion pattern across the tropical post-tin mining landscape Fig. 7. The lowest erosion class (0–15 t ha^{-1} yr^{-1}) covered 7,170.52 ha (92.32%) of the study area, whereas 475.39 ha (6.12%) was classified as moderate erosion (15–60 t ha^{-1} yr^{-1}). Higher erosion classes were spatially more limited, comprising 98.74 ha (1.27%) for 60–180 t ha^{-1} yr^{-1}, 17.39 ha (0.22%) for 180–480 t ha^{-1} yr^{-1}, and 4.74 ha (0.06%) for >480 t ha^{-1} yr^{-1}. Although the high-to-extreme erosion classes occupied only a small proportion of the landscape, their scattered and localized distribution indicates distinct erosion hotspots within the post-mining area. These spatially concentrated areas of elevated soil loss are particularly relevant to soil degradation and may facilitate the redistribution of soil-

associated heavy metals. Accordingly, the RUSLE-derived erosion rate was incorporated as a predictor in the subsequent Random Forest analysis to identify its relative contribution to heavy-metal redistribution.

4.4. Random Forest Model Performance

The spatial distributions of the five predictor variables (soil pH, Corg, erosion rate, distance to roads, and distance to rivers), together with Pb concentration, are presented in Fig. 7b**.** These spatial layers were converted into a point-based attribute dataset, with Pb concentration as the response variable and the five environmental variables as predictors. The dataset was then divided into 80% training and 20% testing subsets and used to train a Random Forest Regressor. Model performance was evaluated using five-fold cross-validation and an independent test set, while impurity-based feature importance was used to quantify the relative contribution of each predictor to the spatial variability of Pb concentration.

Fig. 8a shows a highly heterogeneous concentration of Pb, with the highest concentrations occurring in the western LMUs, particularly around IHHT and IHTT. These areas partly coincide with localized higher erosion and land-use transitions, suggesting potential enhanced mobilization of Pb-bearing materials under disturbed surface conditions. However, the highest Pb concentrations do not consistently coincide with the highest RUSLE-derived soil loss, indicating that erosion may contribute to Pb contamination but is unlikely to be the sole determinant of Pb enrichment. Land-use transitions toward lower vegetation density may further increase soil exposure and facilitate sediment transport.

The baseline Random Forest model revealed a clear hierarchy among the five predictors Fig. 9. Soil pH exhibited the highest impurity-based feature importance (approximately 0.59), followed by Corg (approximately 0.38), whereas distance to roads, erosion rate, and distance to rivers contributed marginally (<0.02). These results identify soil pH and Corg as the dominant predictors of Pb variability, while erosion and landscape-proximity variables showed limited contributions in the baseline model. Thus, the Random Forest analysis complements the RUSLE-based spatial assessment by distinguishing the relative importance of environmental predictors associated with Pb concentration.

5. Discussion

Long-term tin mining has transformed the Diniang Watershed from a vegetation-dominated landscape into a heterogeneous mosaic of bare mining surfaces, mine ponds, regenerating vegetation, and agricultural areas. The concentration of mining disturbance on gently sloping Histosols indicates that land transformation was strongly associated with terrain accessibility. More importantly, the removal of natural soil horizons, exposure of quartz-rich tailings, redistribution of overburden, and formation of excavation ponds have fundamentally altered the original pedogenic environment. These processes

explain the development of spatially heterogeneous Tropical Technosols, in which soil properties and recovery conditions vary substantially across the watershed. Thus, the observed LMUs represent not only land-cover differences but also contrasting stages of post-mining soil development, consistent with the anthropogenic nature of technosols described by Sukarman et al. (2020), Uzarowicz and Skiba (2011), Perlatti et al. (2025).

This landscape heterogeneity is also reflected in the erosion pattern. RUSLE estimated that 92.32% of the watershed has low potential soil loss (<15 t ha^{-1} yr^{-1}), while only a small proportion falls within moderate to very severe classes. Nevertheless, the spatial concentration of high-erosion areas identifies localized hotspots that may function as important sediment-source zones. In post-mining environments, such hotspots can be disproportionately important because exposed and weakly structured technosols are susceptible to runoff and sediment detachment. Therefore, the predominance of low modeled erosion should not obscure the management significance of localized high-risk areas. Rather, the RUSLE results provide a spatial screening of potential erosion pressure that can be used to identify priority areas for further field investigation and restoration.

The spatial concentration of Pb further demonstrates that heavy-metal enrichment does not simply follow the pattern of modeled erosion. Although some areas with elevated Pb coincide with disturbed land and localized erosion, the highest Pb concentrations do not consistently occur in areas with the greatest RUSLE-derived soil loss. This indicates that erosion may provide a physical pathway for Pb-bearing particle transport, but it does not adequately explain the spatial variability of Pb under the conditions examined. The Random Forest analysis provides stronger evidence for this interpretation: soil pH and Corg accounted for most of the predictor importance, whereas erosion rate, distance to roads, and distance to rivers contributed only marginally.

The dominance of pH and Corg is consistent with the role of soil chemical properties in controlling Pb retention and mobility. Soil pH can regulate metal adsorption–desorption processes and consequently influence Pb mobility, while organic carbon can provide binding sites and affect the retention and concentration of Pb within the soil matrix. In developing Technosols, where organic matter accumulation and soil structure remain spatially variable, these properties may exert stronger controls on Pb concentration than the modeled erosion rate. The results suggest a conceptual distinction between erosion as a potential transport pathway and soil chemical properties as important controls on Pb concentration. This explains why Pb hotspots may occur even where predicted erosion is relatively low.

The integration of RUSLE and Random Forest consequently provides a complementary diagnostic framework for post-mining degradation. RUSLE identifies where potential physical soil-loss pressure is concentrated, whereas Random Forest indicates which environmental variables are most strongly associated with Pb variability. The combined interpretation shows that soil degradation and heavy-metal concentration are coupled but not governed by a single process. Areas with both high erosion and elevated Pb represent potential priorities for erosion and contaminant management, whereas Pb-

enriched areas under relatively low erosion conditions require greater attention to soil chemical properties and contaminant retention. This spatial differentiation supports targeted rather than uniform restoration strategies.

The findings should, however, be interpreted as spatial associations rather than causal relationships. RUSLE was not field-validated, while Pb and predictor surfaces were derived from limited sampling, and the Random Forest model lacked independent field validation. Consequently, denser and more spatially representative sampling is required to confirm the identified relationships across different Technosol development stages and post-mining landforms. Despite these limitations, the integrated RUSLE–Random Forest approach demonstrates its value for screening degradation and Pb concentration hotspots and for guiding spatially targeted monitoring and restoration in tropical post-tin mining landscapes.

6. Conclusion

This study demonstrates that tropical post-tin mining landscapes are spatially heterogeneous in terms of soil properties, erosion risk, and Pb distribution. The integration of RUSLE and Random Forest provided a spatial framework for assessing soil erosion risk and identifying key predictors of Pb redistribution. RUSLE showed that erosion was predominantly low (92.32% of the area), but localized high-to-very-severe erosion hotspots were identified. Random Forest ranking identified soil pH and Corg as the dominant predictors of Pb concentration, whereas erosion, distance to roads, and distance to rivers had relatively minor contributions. These findings indicate that Pb concentration is more strongly associated with soil chemical properties than with the modeled erosion rate under the conditions of this study.

Overall, the integrated RUSLE–Random Forest approach provides a useful diagnostic basis for identifying degradation hotspots and supporting targeted restoration and monitoring of tropical post-tin mining landscapes. However, further field sampling and independent validation are required to strengthen the predictive reliability of the results.

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Conflicts of interest

The authors have declared that no competing interests exist.

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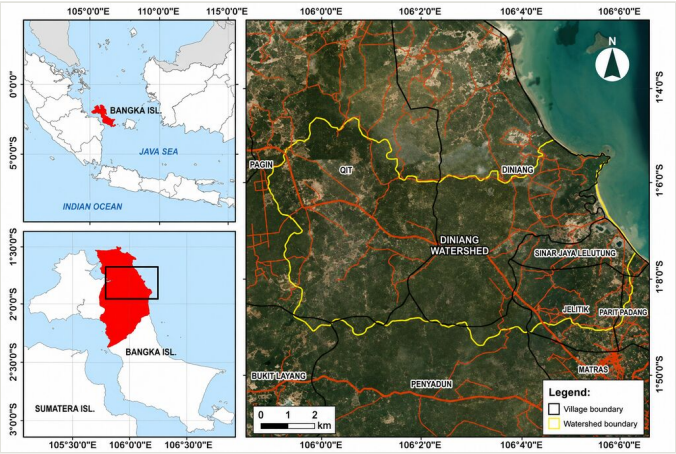

Figure 1.

Location of the Diniang Watershed, Bangka Island, Indonesia, showing the watershed boundary and surrounding administrative villages.

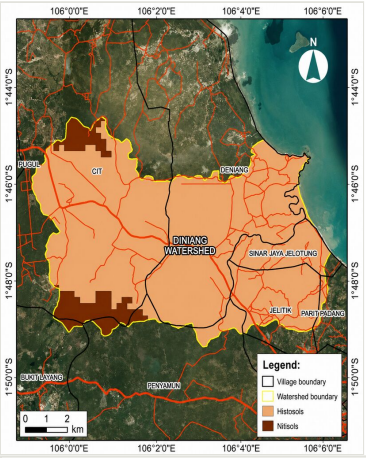

Figure 2.

Soil map of Diniang Watershed.

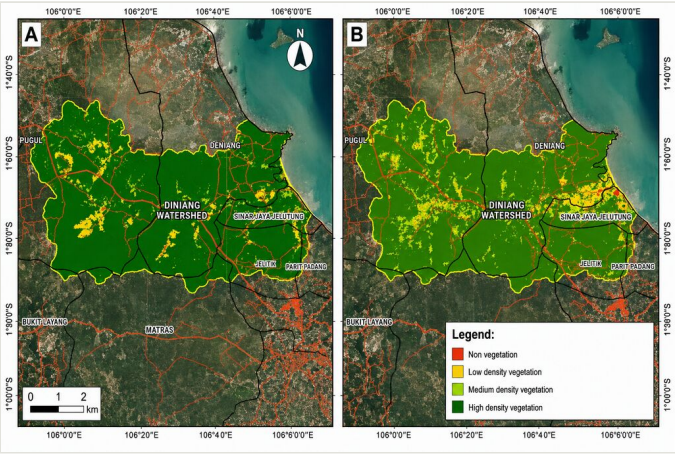

Figure 3.

(a) 2017 RTRW Map; (b) 2025 Sentinel II Imagery.

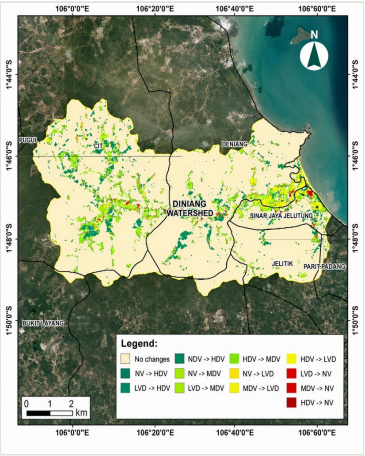

Figure 4.

Change detection from 1990 to 2026; NV (no vegetation), LDV (low density vegetation), MDV (medium density vegetation), and HDV (high density vegetation).

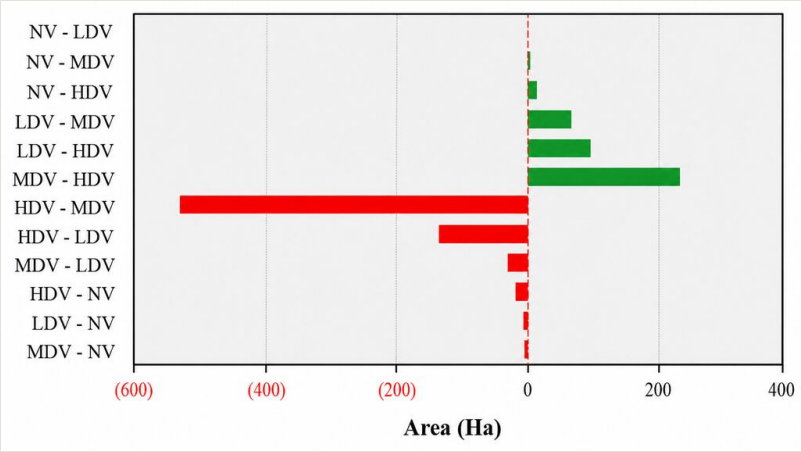

Figure 5.

Land use change balance between degradation (red) and vegetation recovery (green); NV (no vegetation), LDV (low density vegetation), MDV (medium density vegetation), and HDV (high density vegetation).

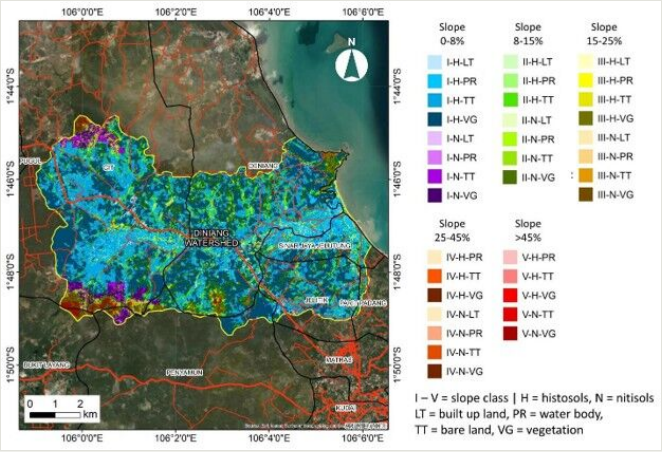

Figure 6.

Land Mapping Unit (LMU) Map.

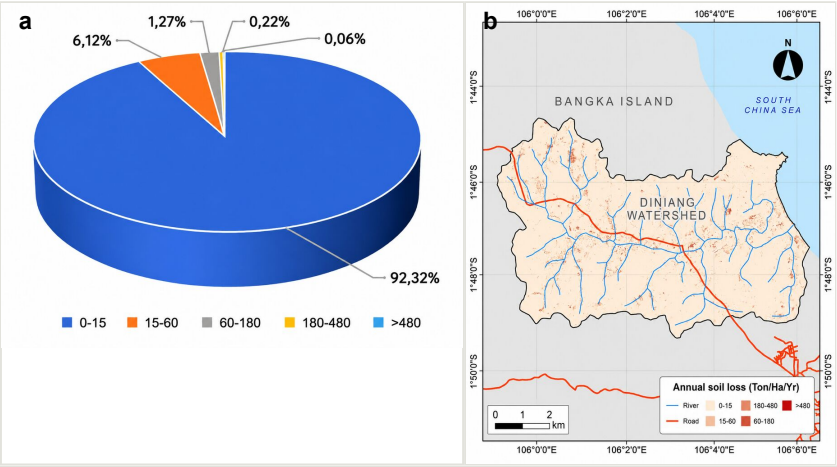

Figure 7.

a: Area distribution of RUSLE-based soil erosion classes.
b: Spatial distribution erosion classes.

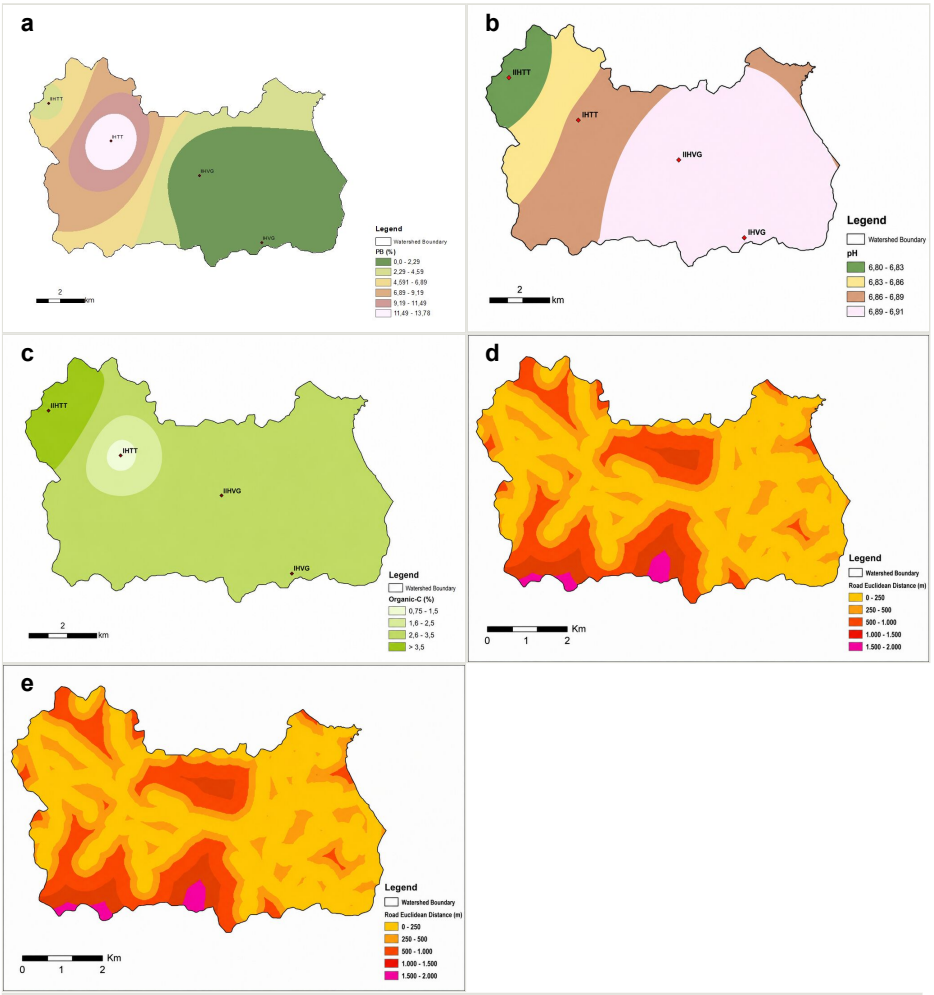

Figure 8.

a: Spatial concentration of Pb
b: soil pH
c: soil organic
d: distance to river
e: distance to road

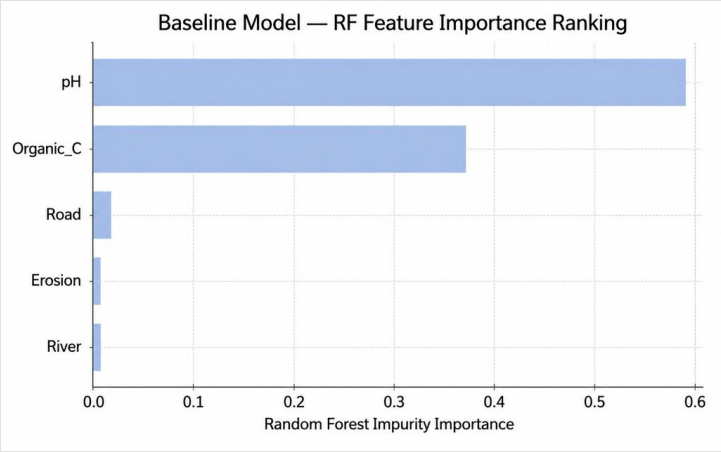

Figure 9.

Relative Importance of Environmental Predictors in Explaining Pb Redistribution.

Table 1.

Soil properties of tropical technosols Bangka.

Soil properties	IIHVG	IHVG	IIHTT	IHTT
Sand (%)	81.09	68.88	67.30	85.8
Clay (%)	14.91	19.02	23.21	10.91
Silt (%)	4.01	12.10	9.49	4.01
Bulk Density (g/cm3)	1.27	1.14	1.03	1.40
DOC (mg/l)	11.64	19.62	21.71	30.86
PH	6.91	6.92	6.80	7.06
Organic-C (%)	3.21	3.46	5.79	0.85
N (%)	0.13	0.15	0.25	0.04
Moisture (%)	1.49	4.47	3.06	0.17
Ash (%)	93.11	89.57	86.98	97.10
C/N	25.32	22.87	23.46	21.50
P (mg/kg)	168.69	125.88	206.86	6.47
K (mg/100)	9.32	11.76	17.13	6.57
PB (ppm)	0.00	0.00	4.12	13.79

Supplementary material

Suppl. material 1: Raw Data Soil Properties

Authors: Ngadisih, Shofi Azhari Fadhilah Minawati
Data type: Table
Download file (19.05 kb)