



Vegetation-Based Early Warning System for Post-Mining Reclamation to Reduce Disaster Risk and Achieve SDGs

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Abstract

Post-mining land reclamation in Indonesia faces critical operational challenges, particularly in continuously monitoring long-term vegetation recovery trajectories and proactively preventing slope failures and landslide disasters across expansive, remote concession areas. Traditional field-based monitoring protocols are often constrained by high labor costs, limited spatial coverage, and severe logistical difficulties, making the early detection of localized land degradation difficult. To address these limitations, this study develops and evaluates an operational vegetation-based early-warning framework designed to optimize post-mining land management and directly align with Indonesia's commitment to Sustainable Development Goals (SDGs)—specifically SDG 15 (Life on Land), SDG 13 (Climate Action), and SDG 12 (Responsible Consumption and Production). The proposed system utilizes multitemporal Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) time series derived from quarterly Sentinel-2 Level-2A satellite imagery. These remote sensing spectral indices were integrated with key contextual attributes, including detailed planting-age datasets and topographic parameters derived from Digital Elevation Models (DEMs), such as slope steepness and elevation profiles. This feature space was subsequently used to train a Multilayer Perceptron (MLP) neural network classifier using 462 ground-verified sample pixels collected from an active post-mining reclamation site in Central Sulawesi, Indonesia. The MLP classification model achieved a robust 76% overall predictive accuracy across all designated reclamation status categories. Crucially for disaster risk reduction applications, the model showed exceptional sensitivity to high-risk degradation zones, achieving 98% recall in identifying areas vulnerable to canopy loss, vegetation stress, and potential geotechnical slope instability. To translate these predictive outputs into actionable management tools, the trained model and decision-support pipeline were fully integrated into a web-based Geographic Information System (GIS) dashboard, enabling concession managers and regulatory authorities to visualize spatial risk zones interactively in near real time. The findings demonstrate that combining multitemporal satellite vegetation indices with machine learning classifiers provides a scalable, cost-effective methodology for monitoring post-mining land restoration. By facilitating early identification of site-specific vegetation decline before severe slope failure occurs, this early-warning framework strengthens evidence-based decision-making, mitigates environmental disaster risks, and advances regulatory compliance within Indonesia's national environmental governance and ecological restoration policy frameworks.

Keywords *Post-Mining Reclamation, Vegetation Indices, Landslide Risk Reduction, Multilayer Perceptron, Sustainable Development*

INTRODUCTION

Post-mining reclamation aims to restore the ecological integrity, hydrological function, and

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productivity of land disturbed by mining activity; it encompasses topsoil management, soil-property improvement, erosion control, and planned revegetation (Sheoran, 2009). In Indonesia, reclamation and post-mining obligations are regulated under a strict legal framework, including Law No. 3 of 2020, Minister of Energy and Mineral Resources (ESDM) Regulation No. 26 of 2018, and its technical guideline, ESDM Ministerial Decree No. 1827 K/30/MEM/2018, which require mining-license holders to carry out land restoration in a phased and measurable manner. In practice, implementation is constrained by topsoil damage, changes in soil physical and chemical properties, and disrupted nutrient cycling: overburden and mined soil tend to show increased bulk density and reduced essential nutrients, which limits vegetation recovery (Ahirwal, 2016).

As a result, revegetation plays a key role in rehabilitation by stabilizing soil structure, reducing erosion, protecting the soil from further degradation, and supporting the recovery of nutrient cycling and mycorrhizal associations (Sheoran, 2010; Ahirwal, 2021). Vegetation-cover development over time also reflects the progress of soil recovery, since sustained revegetation has been shown to correlate positively with increases in soil organic carbon, nitrogen availability, biomass, enzyme activity, and soil moisture (Maiti, 2017); canopy condition and land-cover closure can therefore serve as a practical indicator of restoration success, although a more comprehensive assessment still requires supporting biological parameters such as microflora, mycorrhizae, and soil enzyme activity (Sheoran, 2010).

Reclamation success, however, cannot be judged from planting activity alone, because reclaimed vegetation is a dynamic process that needs time to develop, stabilize, and mature, and the expected trajectory differs by vegetation type (Guan, 2021; Hiu, 2022). An increase in vegetation cover alone is not a sufficient endpoint, since evaluation must also consider the desired species composition, the absence of weeds, and the ecosystem-structure components needed to meet the reclamation or end-land-use target (McKenna, 2020). Revegetation is strongly constrained by site conditions, particularly water availability, soil retention, and slope topography (Shi, 2025), and the heterogeneity of mine-site conditions and disturbance-recovery pathways means that revegetation trajectories can differ substantially between locations (Vidal-Macua et al., 2020; Jiang, 2022), so that periodic field monitoring alone is difficult to scale across large post-mining areas and is often limited by cost, labor, and spatial coverage (Smith, 2024).

Mining activity also creates artificial slopes, such as mine slopes, waste dumps, and tailings slopes, whose stability is affected by the geological structure exposed during excavation (Wei, 2024), and landslides in mine areas can be triggered directly by excavation, reduced bearing capacity of the cover layer, subsidence, and repeated mining-induced surface deformation (Yang, 2022). Slope steepness is a consistent factor in landslide studies, but it acts together with lithology, soil, land cover, and rainfall (Segoni, 2024); rainfall and infiltration increase pore-water pressure, reduce matric suction and shear strength, and accelerate slope failure, particularly on steeper slopes or more susceptible material (Nasir, 2025). Vegetation supports slope stability through two mechanisms: root systems that increase soil cohesion and shear strength, and canopy cover that reduces rainfall impact energy and regulates infiltration, so a decline in vegetation cover on a reclaimed slope can also be an early indicator of elevated landslide and erosion risk.

Remote sensing offers an effective alternative to conventional field monitoring because it allows periodic, multitemporal observation of land-surface conditions over wide areas without direct measurement across the entire site, and its results can be combined with field data to improve interpretation accuracy (Gordon, 2023; Prasetya, 2025). Building on this rationale, this study proposes an early-warning monitoring framework for post-mining land reclamation that integrates multitemporal NDVI and SAVI, topographic parameters from a DEM, and an MLP classifier, with the aim of classifying reclamation blocks into operational risk levels so that changes in reclamation condition can be identified earlier and more accurately, supporting more effective

evaluation and decision-making in post-mining land management.

LITERATURE REVIEW

Post-Mining Reclamation and Disaster Risk in Indonesia

Post-mining land reclamation is a legal and environmental imperative in Indonesia, yet large areas remain inadequately restored. Poorly vegetated mining landscapes are vulnerable to erosion, landslides, and downstream flooding—hazards that directly threaten community safety and livelihoods. Landslide disasters triggered by inadequate vegetation recovery on mine-reclaimed slopes are well documented in the mining regions of Sumatra and Kalimantan. Vegetation recovery is therefore not merely an ecological goal but a critical mechanism for slope stabilization and disaster risk reduction, making early detection of vegetation stagnation operationally essential.

Remote Sensing and Vegetation Indices for Reclamation Monitoring

Normalized Difference Vegetation Index (NDVI) analysis has been applied to monitor vegetation change on coal-mine reclamation land, demonstrating sensitivity to vegetation-cover changes across reclaimed mining concessions over time. Related work using unmanned aerial vehicle (UAV) multispectral orthophoto data has shown that NDVI can evaluate vegetation health at high spatial resolution within specific reclamation areas, complementing satellite-based observations with fine-grained, site-level detail.

Comparative studies among vegetation indices—NDVI, Enhanced Vegetation Index (EVI), and Soil-Adjusted Vegetation Index (SAVI)—have shown that index performance varies with vegetation density and bare-soil exposure. Critically, SAVI is more stable than NDVI in areas where bare-soil reflectance dominates the pixel signal—a condition ubiquitous during early-stage reclamation. This stability advantage makes SAVI particularly valuable for detecting genuine vegetation degradation (high-risk signals) in landscapes where soil background reflectance can confound single-index analysis.

Machine Learning Integrations in Environmental

The integration of remote-sensing indices with artificial-intelligence methods has been explored for related environmental-prediction problems. For example, fusing remotely sensed fire-related indices for wildfire prediction shows that combining multiple spectral indices with a learning-based classifier improves the ability to capture nonlinear relationships between vegetation condition and underlying environmental processes. These studies collectively motivate the approach used in this research: rather than relying on a single vegetation index at a single point in time, this research integrates multitemporal vegetation indices with planting-age and topographic information as input features for a supervised MLP classifier.

This study addresses a significant gap identified in prior post-mining reclamation studies in Indonesia and the region, which have generally been limited to single-index or descriptive analysis and have not fully exploited multitemporal vegetation-index data for automated, operational classification of reclamation condition. Furthermore, existing literature has not deeply integrated reclamation monitoring with explicit disaster-risk frameworks, despite the clear connection between vegetation recovery and slope stability.

RESEARCH METHOD

Study Area and Data Sources

The study was conducted on the post-mining reclamation area of PT Citra Palu Minerals (PT CPM), located in Palu, Central Sulawesi, Indonesia. Three main data sources were utilized:

1. Sentinel-2 Level-2A satellite imagery (10 m spatial resolution), obtained through Google

- Earth Engine, serving as the primary source of multitemporal spectral information
- 2. UAV/drone imagery, used as a high-resolution reference source to support visual verification of field conditions
- 3. Shapefile of reclamation-area boundaries with planting-age attribute data provided by PT CPM

The Sentinel-2 dataset served as the primary input for model training, while drone imagery supported verification rather than serving as primary experimental data.

Data Pre-Processing

Raw satellite imagery cannot be used directly for classification and must first pass through several pre-processing stages:

1. Coordinate reference system alignment between the Sentinel-2 raster data and the reclamation boundary vector data, performed using the Rasterio and GeoPandas libraries.
2. Image clipping to the reclamation area boundary using the rasterio.mask function, so that pixels outside the area of interest do not affect the vegetation-index calculation.
3. Selection of the spectral bands required for vegetation-index computation, namely Band 4 (Red) and Band 8 (Near-Infrared), both at 10 m spatial resolution.
4. Cloud and cloud-shadow masking using the Scene Classification Layer (SCL), so that only valid pixels are retained for analysis. Because imagery was collected quarterly, a median composite was generated for each quarter to reduce noise and anomalies introduced by atmospheric variation or sensor artifacts.

Vegetation Indices

Two vegetation indices were computed from the pre-processed imagery. The Normalized Difference Vegetation Index (NDVI) was calculated as:

$$NDVI = (NIR - Red) / (NIR + Red)$$

where NIR corresponds to Sentinel-2 Band 8, and Red corresponds to Band 4. NDVI values theoretically range from -1 to $+1$, with higher values indicating denser, healthier vegetation. Because reclamation areas at an early stage still have substantial bare-soil exposure, the Soil-Adjusted Vegetation Index (SAVI) was also computed as a supporting index to reduce the influence of soil background reflectance:

$$SAVI = [(NIR - Red) / (NIR + Red + L)] \times (1 + L)$$

where L represents the soil-brightness correction factor, set to 0.5 to balance soil influence across varying vegetation densities. Both NDVI and SAVI were computed independently for each of the four quarters (Q1-Q4) using their corresponding median composites. This multi-temporal framework produced an eight-feature time-series dataset (NDVI Q1-Q4 and SAVI Q1-Q4) per pixel, enabling the system to capture seasonal variations, track growth trajectories, and identify early signals of land degradation.

Feature Engineering and Data Labeling

The final feature dataset integrates the multi-temporal vegetation indices, reclamation age (in months), cyclical seasonal metrics (sine and cosine transformations of the planting month), elevation, and slope. For model training under a supervised learning framework, ground-truth target labels were derived by combining high-resolution Unmanned Aerial Vehicle (UAV) imagery with historical slope stability assessment data. Land conditions were categorized into a three-tier risk framework (Table 1).

Table 1. Class Early Warning

Class Code	Risk Level	Description
0	Low risk	Healthy Vegetation cover and stable slope
1	Medium risk	Moderate vegetation stress or minor slope variation
2	High risk	Severe vegetation degradation or high erosion potential

This three-class scheme serves as an operational decision support tool tailored for automated monitoring and predictive modeling. It flags prioritized areas requiring intervention rather than replacing comprehensive, field-based ecological audits.

Model Development and System Architecture

The final tabular dataset containing 13 temporal and spatial features (NDVI Q1-Q4, SAVI Q1-Q4, planting age, sine/cosine transformation of month, elevation, and slope) was used for predictive modeling. To prevent spatial data leakage across temporal observations, we used a grouped splitting strategy with GroupShuffleSplit based on unique polygon identifiers (polygon_id). The data was partitioned into training (64%), validation (16%), and test (20%) sets. Feature standardization was performed using StandardScaler, fitted exclusively on the training set.

To address class imbalance without over-degrading majority-class performance, manual class weights were assigned during training (1.0 for Low Risk, 2.0 for Medium Risk, and 1.5 for High Risk). A Multilayer Perceptron (MLP) architecture was constructed using TensorFlow/Keras:

1. Input Layer: 13 input features.
2. Hidden Layer: Three fully connected layers with 128, 64, and 32 units, respectively. Rectified Linear Unit (ReLU) activations, L2 weight regularization ($\lambda = 0.01$), and Dropout layers (0.40) were integrated into the deeper layers to mitigate overfitting.
3. Output Layer: 3-unit Dense layer with Softmax activation to compute multi-class probability distributions.

The network was compiled with Sparse Categorical Cross-Entropy loss and optimized using Adam (initial learning rate = 0.0005). Training was conducted over up to 150 epochs with a batch size of 64. Early stopping (patience = 30) and learning-rate reduction on plateau (factor = 0.5, patience = 10) were monitored against validation loss. During inference, a custom decision-threshold rule was applied to predicted probabilities to prioritize high-risk detection sensitivity.

The trained model was deployed behind a React.js (Vite) web application integrated with a Leaflet WebGIS interface, featuring Role-Based Access Control (RBAC) across Admin, Staff HSE (Health, Safety, and Environment), and Executive Leadership roles. This deployment architecture ensures that monitoring results are accessible to decision-makers without requiring specialist geospatial or data-science expertise, supporting institutional capacity building within PT CPM and providing a model for broader adoption across Indonesian mining operators.

FINDINGS AND DISCUSSION

Model Accuracy

The MLP model was evaluated on an unseen test dataset ($n = 462$ pixels) using confusion matrix analysis and per-class performance metrics. Table 2 summarizes the classification performance.

Table 2. Model Classification Performance

Risk Class	Precision	Recall	F1-score	Support
Low Risk	0.79	0.73	0.76	159
Medium Risk	0.63	0.55	0.59	140
High Risk	0.83	0.98	0.90	163
Overall accuracy			76%	462

The model achieved an overall classification accuracy of 76%. Critically, the classifier demonstrated exceptional sensitivity for the High-Risk category, achieving a Recall of 0.98 (98%) and an F1-score of 0.90. This performance indicates that the system rarely misses critical land-degradation or severe-risk signals—a capacity essential for disaster-risk reduction and early intervention.

The Low-Risk class also demonstrated strong performance with an F1-score of 0.76, reliably identifying areas where vegetation recovery is progressing normally and no immediate intervention is needed. Performance was moderate for the Medium-Risk class (F1-score of 0.59) due to spectral overlap during transitional vegetation states. From an operational early-warning perspective, this performance trade-off is highly desirable: prioritizing high recall for critical risk zones minimizes false negatives, ensuring vulnerable areas are reliably flagged for field inspection. False positives (areas flagged as high-risk but requiring verification) are operationally acceptable, as they trigger field investigation that may identify undetected problems or validate model confidence. This sensitivity-focused architecture directly supports the study's disaster-risk-reduction objective.

Interpretation and Operational Implications

The overlap observed between the medium-risk and stagnant classifications reflects a genuine characteristic of vegetation-index data: vegetation in a transitional growth phase can exhibit spectral characteristics similar to vegetation that has stalled, since both may show modest or inconsistent change in NDVI between periods. This ambiguity motivates a multitemporal rather than single-period approach—a core methodological strength of this research.

The system's deployment as an operational web-based GIS dashboard with role-based access control marks a significant advance in Indonesia's institutional capacity for environmental monitoring. Users with minimal geospatial expertise can access quarterly monitoring results, visualize reclamation progress, and prioritize field inspections. The admin role enables model retraining as new field data accumulate; the Staff HSE role supports inspection and reporting; and Executive Leadership has access to summary dashboards for decision support. This architecture ensures that science-based, data-driven decision-making is accessible to mining operators and government agencies without requiring specialized technical capacity.

From a disaster-risk-reduction perspective, the high recall (0.98) for high-risk areas means that the system identifies nearly all pixels exhibiting severe vegetation degradation or slope instability, providing an early signal for intervention before catastrophic failure. In contrast, field-based monitoring alone would likely detect such conditions only after visual confirmation, potentially allowing progression to more hazardous states. The 30–60 day lag between satellite overpasses (Sentinel-2 revisit frequency) provides sufficient temporal resolution for detecting vegetation stress trends over quarterly intervals, while operational costs remain far below those of conventional field surveys covering equivalent spatial areas.

Alignment with SDG Targets

This system directly contributes to Indonesia's progress toward SDG targets:

1. SDG 15.2 (Promote sustainable forest and land management): The quarterly monitoring system enables tracking of vegetation recovery in post-mining landscapes, supporting data-driven decision-making to ensure restored lands achieve target vegetation densities and structural diversity.
2. SDG 13.1 (Strengthen resilience to climate-related hazards): By detecting early signs of vegetation degradation that increase slope-failure risk, the system enables proactive intervention before landslide disasters occur, reducing casualty risk and economic losses in mining-affected communities.
3. SDG 12.2 (Achieve sustainable management of natural resources): The system operationalizes science-based monitoring of mining-related land restoration, ensuring extractive industries meet legal environmental-restoration obligations and operate within planetary ecological boundaries.

By providing Indonesian mining companies and government agencies with cost-effective, spatially explicit, data-driven tools to monitor reclamation progress, this study strengthens institutional capacity for environmental governance and sustainable resource management—capacity that is fundamental to achieving Indonesia's sustainable development commitments.

CONCLUSIONS

This study developed and evaluated a multitemporal, remote-sensing-based early-warning system for post-mining land reclamation, designed to support disaster-risk reduction and sustainable land management in Indonesia. By integrating quarterly Sentinel-2 Level-2A imagery into multitemporal NDVI and SAVI features, combined with planting-age and topographic information, an MLP classifier was trained to categorize reclamation conditions into three operational risk classes (Low, Medium, High). The model achieved 76% overall accuracy with exceptional performance for high-risk detection (Recall = 0.98), demonstrating practical utility for early identification of vegetation degradation and slope-instability risk.

Deployment of the system as an operational web-based GIS dashboard with role-based access control confirmed its usability as a decision-support tool for prioritizing field verification and intervention. Functional testing with PT Citra Palu Minerals users across Admin, Staff HSE, and Executive Leadership roles confirmed that the system is operationally effective without requiring advanced technical expertise.

LIMITATIONS & FURTHER RESEARCH

The study's scope is limited to vegetation-growth dynamics as an indicator of reclamation progress; it does not constitute a comprehensive ecological assessment nor a direct geotechnical landslide-prediction system. Instead, vegetation decline serves as an early indicator that an area may warrant closer inspection, consistent with operational disaster-risk frameworks. The system is designed to complement, not replace, comprehensive field-based ecological audits and professional slope-stability assessments.

This research contributes directly to Indonesia's institutional capacity for environmental monitoring and advances progress toward SDG targets 15.2, 13.1, and 12.2. By providing mining operators and government agencies with science-based, data-driven tools for vegetation monitoring, the system supports more effective post-mining land management, reduces disaster risk to communities, and ensures that extractive industries meet environmental restoration obligations aligned with Indonesia's development commitments. Future work should pursue the following directions:

1. Integration of climatic covariates: Incorporation of rainfall, temperature, and drought indices to improve model discrimination between transitional (developing) and stagnant vegetation, reducing spectral ambiguity.
2. Texture and multispectral feature engineering: Development of image-texture metrics (e.g., Haralick features) and additional spectral indices (e.g., Lignin Cellulose Absorption Index) to capture vegetation structure and composition beyond NDVI/SAVI.
3. Geotechnical integration: Partnership with slope-stability modelers to integrate vegetation-based early warnings with hydrological and geotechnical slope-failure models, enabling quantitative landslide-risk assessment.
4. Multi-site validation: Retraining and testing the model on additional post-mining reclamation sites across diverse geological and climatic regions in Indonesia to assess generalizability and develop national-scale monitoring capacity.
5. Integration of UAV time-series data: Systematic collection of drone-based multispectral imagery at quarterly intervals to establish high-resolution ground-truth datasets for model refinement and local-scale validation.
6. Policy uptake and institutional adoption: Engagement with the Indonesian Ministry of Energy and Mineral Resources and provincial mining agencies to establish national standards for reclamation monitoring, ensuring system adoption across mining operators.

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