Mapping Landslide Susceptibility Using the Random Forest and Land Use Correlation in Northern Bandung

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Abstract *Landslides are among the most damaging geomorphic hazards in tropical volcanic regions, where steep slopes, intense rainfall, and extensive land-use modification frequently interact to trigger slope failures. Northern Bandung, West Java, represents one of Indonesia's most landslide-prone areas due to its volcanic lithology, active tectonics, and rapid agricultural and infrastructural expansion. The cumulative impacts of deforestation, drainage alteration, and soil disturbance have accelerated instability processes, threatening both environmental sustainability and human safety. This study aims to develop a high-resolution landslide susceptibility model and quantify the influence of land-use dynamics on slope instability using the Random Forest algorithm integrated with multi-source geospatial data. A total of 3,056 verified landslide occurrences were compiled from field surveys, government archives, and multi-temporal satellite imagery. Fourteen conditioning factors, encompassing topographic, hydrological, geological, vegetation, and anthropogenic variables, were analyzed to capture the spatial variability of slope failure. The dataset was randomly split into 70% for training and 30% for validation. Model evaluation yielded an accuracy of 0.98, demonstrating the robustness and high predictive performance of the Random Forest classifier. Spatial interpretation reveals that steep volcanic slopes under dryland agriculture and plantation systems exhibit the highest landslide density, particularly near roads, faults, and river corridors where slope cutting and erosion are prevalent. The susceptibility map classifies approximately 30% of the study area as very high risk and 10% as high risk, predominantly within highly dissected volcanic ridges composed of tuff and weathered andesites. These findings confirm that land-use modification plays a critical role in amplifying natural geomorphological instability. The integration of land-use parameters with topographic and hydrological indicators enhances both model interpretability and practical relevance for policy formulation. The resulting model provides a robust geospatial framework for local governments to support disaster mitigation, spatial planning, and sustainable land management, and can be applied to other volcanic mountainous regions across Indonesia for climate-resilient development.*

Keywords: Landslide Susceptibility, Random Forest, Land Use, Northern Bandung,

Introduction

Landslides are among the most destructive geomorphic processes in tropical mountainous regions, particularly in Indonesia, where high-intensity rainfall, steep slopes, and anthropogenic land-use changes frequently converge (Fell et al., 2008). In West Java, the combined influence of volcanic lithology, tectonic structures, and rapid agricultural expansion has increased the frequency and magnitude of slope failures, especially in densely populated upland areas. Local-scale studies have shown that shallow regolith, structural discontinuities, and vegetation loss are key factors accelerating slope instability (Lumban Raja, 2023; Sulastri et al., 2024). These interactions pose severe environmental and socio-economic threats in volcanic highlands such as Northern Bandung, where land pressure and topographic fragility are pronounced.

Despite the growing number of landslide susceptibility studies in Indonesia, a critical limitation persists: many models focus predominantly on topographic, geological, and hydrological parameters while underestimating the direct influence of land-use dynamics. Land-use modification—including deforestation, plantation expansion, and urban development—significantly alters natural drainage and vegetation cohesion, thereby amplifying slope instability (Alcántara-Ayala, 2025). While vegetation indices such as NDVI are frequently used as proxies for land cover, explicit quantification of the relationship between land-use categories and landslide occurrence in tropical volcanic terrains remains insufficient (Niraj et al., 2023; Riestu & Hidayat, 2023). This gap highlights the need for a more integrative modeling framework that captures both environmental and anthropogenic dimensions of slope instability.

Therefore, this study aims to model landslide susceptibility in Northern Bandung using a machine learning approach—specifically the Random Forest (RF) algorithm—integrated with multi-source geospatial datasets. The primary objectives are: (1) to identify key conditioning factors influencing slope instability, (2) to assess the correlation between land-use classes and landslide distribution, and (3) to produce a high-resolution susceptibility map for disaster risk reduction and spatial planning.

A total of 3,056 verified landslide points were compiled from field surveys, government archives, and multi-temporal satellite imagery. Fourteen conditioning factors—encompassing topographic, hydrological, geological, vegetation, and anthropogenic variables—were analyzed. The dataset was divided into 70% for training and 30% for validation using the Random Forest algorithm implemented in Python. This methodological framework enables robust prediction, minimizes overfitting, and provides interpretable outputs through variable importance analysis (Breiman, 2001; Taalab et al., 2018). The integrated approach offers actionable insights for sustainable land management, spatial planning, and landslide mitigation in tropical volcanic mountain regions.

Literature Review

Landslides are complex geomorphic processes influenced by the interaction of geological, topographic, hydrological, and anthropogenic factors (Zaruba & Mencl, 2014). In tropical mountainous regions, rainfall acts as the dominant triggering factor, where prolonged infiltration elevates pore-water pressure and reduces soil shear strength, leading to slope failures (Rahardjo et al., 2008; Cho, 2016). Climate change further intensifies these processes by increasing the frequency of extreme rainfall events and extending wet seasons (Jakob, 2022).

Topographic parameters such as slope gradient, aspect, curvature, and terrain ruggedness are primary determinants of slope instability (Liu et al., 1994; Romstad & Etzelmüller, 2012). Morphometric attributes, including drainage density and basin form, regulate runoff concentration and sediment transport, thereby influencing erosion and slope deformation (Lumban Raja et al., 2020). Among these, slope gradient plays a decisive role as it directly affects shear stress and erosion rates (Liu et al., 2001).

Geological conditions, particularly lithological variability and structural discontinuities such as faults and joints, create zones of mechanical weakness that often serve as failure planes (Segoni et al., 2020; Arifianti & Agustin, 2017). Vegetation provides mechanical reinforcement through root cohesion and hydrological regulation, while its removal substantially increases the probability of mass movement (Dahigamuwa et al., 2016).

Human activities have become an increasingly critical factor influencing slope instability. Deforestation, agricultural expansion, and road construction alter natural drainage patterns and decrease surface cohesion, thereby enhancing landslide susceptibility (Alcántara-Ayala, 2025). Recent research highlights that land-use change should not be regarded as a secondary factor but as a direct driver of slope instability in tropical volcanic terrains (Niraj et al., 2023; Riestu & Hidayat, 2023). Remote sensing has long been employed in landslide hazard studies, offering efficient mapping of landslide scars and geomorphic features (McKean et al., 1991). However, despite the availability of high-resolution land-cover data, explicit quantification of land-use categories in relation to susceptibility modeling remains limited in Indonesia and other tropical regions.

The advent of machine learning (ML) has significantly enhanced landslide susceptibility mapping by enabling the analysis of nonlinear relationships and high-dimensional geospatial datasets (Tehrani et al., 2022; Sreelakshmi et al., 2022). Among various ML algorithms, the Random Forest (RF) model has gained prominence for its robustness, interpretability, and resistance to overfitting (Breiman, 2001; Park & Kim, 2019). Numerous studies employing RF for landslide prediction across diverse landscapes have reported high classification accuracy (Rahmati et al., 2020; Purwanto et al., 2022).

Nevertheless, most RF-based susceptibility models primarily emphasize physical and geomorphological parameters—such as slope, lithology, and rainfall—while considering land-use effects only indirectly through vegetation indices like NDVI or coarse land-cover proxies. This creates a critical research gap in understanding the explicit contribution of anthropogenic drivers to slope instability, especially in tropical volcanic environments characterized by intensive land-use pressure (Niraj et al., 2023; Riestu & Hidayat, 2023).

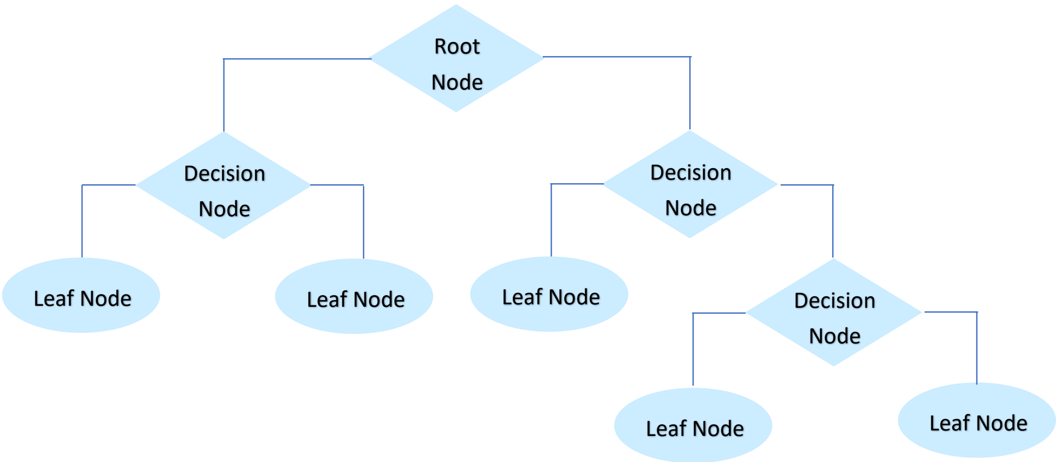

Figure 1: Decision Tree Ilustration

Building upon these findings, the present study situates itself at the intersection of geospatial machine learning and land-use dynamics. It extends the application of the Random Forest algorithm by explicitly integrating land-use classification as a conditioning factor, alongside traditional topographic, hydrological, and geological variables. This approach aims to quantitatively assess the correlation between land-use patterns and landslide occurrence in Northern Bandung—an area distinguished by steep volcanic slopes, high rainfall, and intensive agricultural activity. Through this integration, the study seeks to enhance model interpretability, improve predictive performance, and provide actionable insights for disaster risk reduction, sustainable land management, and spatial planning in tropical mountainous regions.

Methodology

a. Study Area

This study focuses on Northern Bandung, West Java Province, Indonesia, encompassing the subdistricts of Lembang, Cilengkrang, and Cimenyan (Figure 2). The area represents one of the most landslide-prone regions in the province due to its steep volcanic topography, high rainfall intensity, and extensive land-use modification. Elevations range between 600 and 2,302 meters above sea level, characterized by steep slopes (>30°) and volcanic lithologies dominated by tuffs, andesites, and pyroclastic deposits. The combination of high relief, fractured volcanic bedrock, and intensive dryland agriculture creates a geomorphologically unstable environment that makes the region highly suitable for susceptibility modeling.

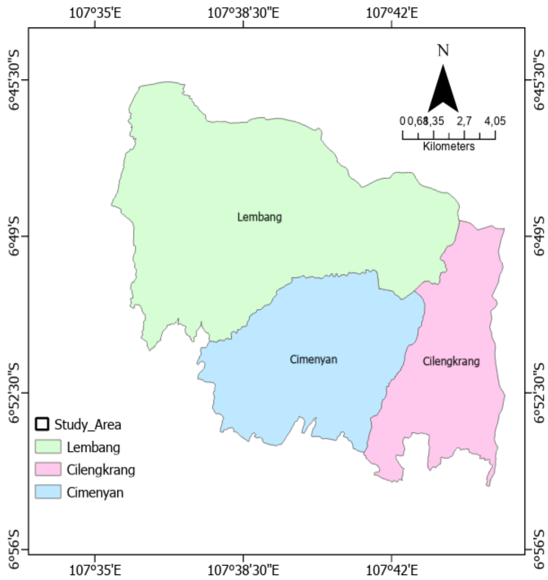

Figure 2: Research Study Area

b. Data Sources and Conditioning Factors

A total of 3,056 verified landslide points were compiled from multi-source datasets, including field surveys, government archives, and multi-temporal satellite imagery. Fourteen conditioning factors were employed to represent topographic, hydrological, geological, vegetation, and anthropogenic influences. These factors include slope gradient, elevation, aspect, curvature, Terrain Ruggedness Index (TRI), Topographic Wetness Index (TWI), flow direction, NDVI, land use, rainfall, lithology, and distances to roads, rivers, and geological lineaments (Beven & Kirkby, 1979; Rahmati et al., 2020; Niraj et al., 2023).

Topographic and hydrological parameters were derived from a 10 m Digital Elevation

Model (DEM) provided by the Indonesian Geospatial Agency. NDVI was calculated from Landsat 8 imagery to represent vegetation density, while land-use maps were generated through supervised classification in ArcGIS Pro. Vector datasets of roads, rivers, and geological faults were converted into proximity rasters to quantify their spatial influence on slope stability. Rainfall data were obtained from regional climatological stations managed by the Indonesian Meteorological Agency.

c. Random Forest Modeling and Validation

The Random Forest (RF) algorithm was selected for landslide susceptibility modeling due to its ability to handle nonlinear relationships, multicollinearity among predictors, and high-dimensional geospatial data (Breiman, 2001; Park & Kim, 2019). The dataset was randomly divided into 70% for training and 30% for validation to ensure balanced model generalization. Model development was implemented in Python using the scikit-learn library.

RF operates as an ensemble of decision trees, each trained on bootstrapped subsets of the data. The final classification is determined by majority voting across all trees, enhancing stability and reducing overfitting. This approach is well suited for complex geomorphological environments, as it can manage mixed data types and capture intricate variable interactions (Taalab et al., 2018).

Model performance was assessed through precision, recall, F1-score, and overall accuracy metrics. The results indicated excellent predictive capability, achieving 0.98 accuracy and balanced performance for both landslide and non-landslide classes. The feature importance output from the RF model was further analyzed to evaluate the relative influence of each conditioning factor on slope instability, allowing for a more interpretable and physically meaningful model.

d. Validation and Field Verification

Field validation was conducted in Lembang and Cimenyan subdistricts to verify the correspondence between predicted high-susceptibility zones and observed landslide features. The validation confirmed that areas classified as “Very High” and “High” susceptibility in the model corresponded well with actual landslide scars, slope failures, and erosion zones. This verification reinforces the robustness of the Random Forest approach in replicating real-world conditions.

The methodological workflow, as illustrated in Figure 3, integrates data acquisition, preprocessing, model training, and validation into a concise and replicable framework. This approach demonstrates the practicality of combining open-access geospatial datasets with ensemble learning algorithms for large-scale landslide susceptibility assessment in tropical volcanic terrains.

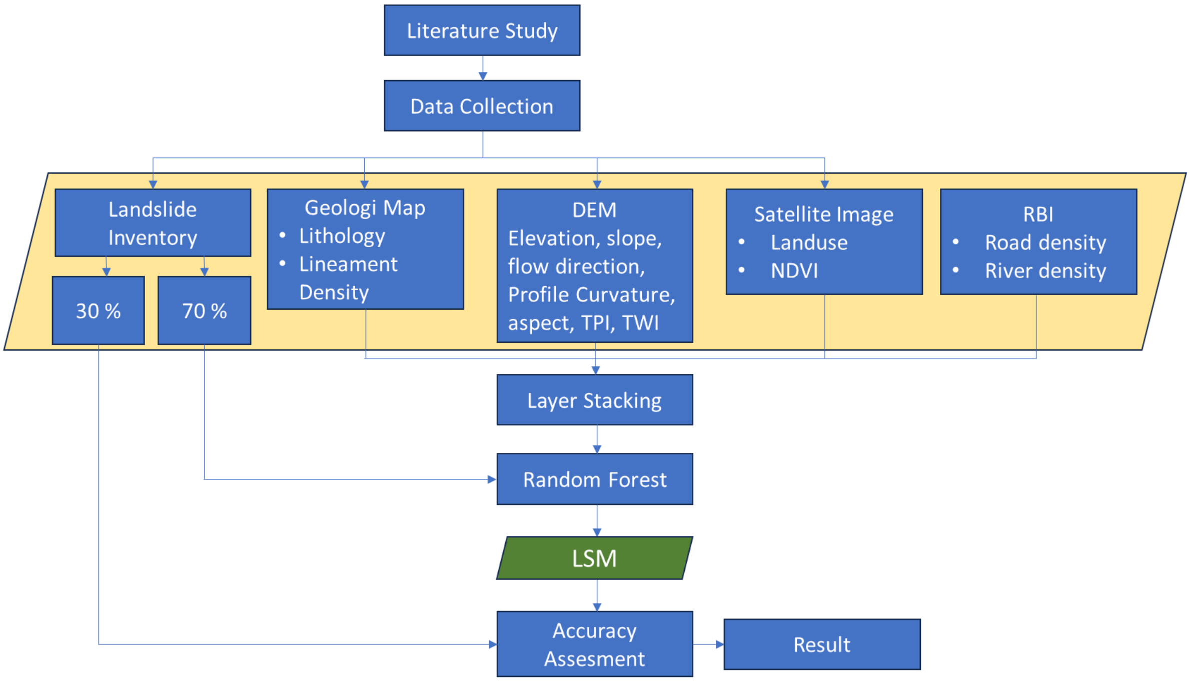

Figure 3: Workflow of Landslide Susceptibility Mapping Using Random Forest and Geospatial Data Inputs

Results and Discussion

This study produced a high-resolution landslide susceptibility map for Northern Bandung using the Random Forest (RF) algorithm, integrating fourteen conditioning factors representing topographic, hydrological, geological, vegetation, and anthropogenic influences. The spatial modeling process followed the workflow illustrated in Figure 3, while Figure 4 displays the distribution of 3,056 verified landslide points across the study area. These landslides are concentrated mainly along steep volcanic ridges and valley margins, where topographic gradients and human-induced modifications interact to generate slope instability.

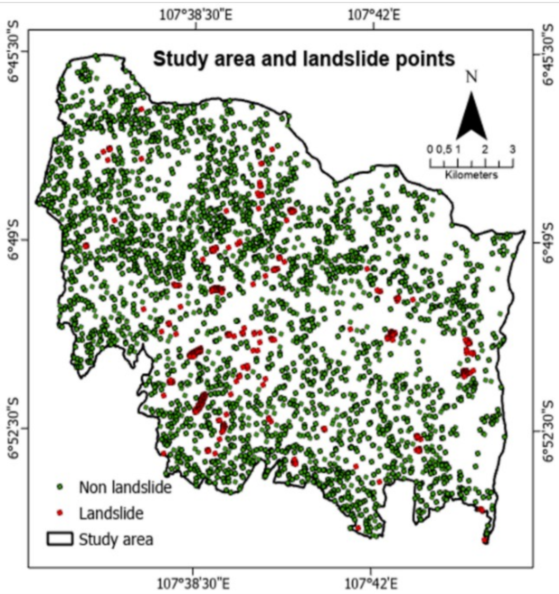

Figure 4: Study area and landslide points

a. Topographical and Hydrological Contributions

Topographic parameters are fundamental in determining slope stability. The slope gradient map (Figure 5a) reveals that areas with gradients exceeding 30°—primarily in Lembang, Cimenyan, and Cilengkrang—coincide with the majority of recorded landslides. These slopes are composed predominantly of tuffs and weathered andesites, whose low shear strength and high porosity increase susceptibility to failure.

The elevation map (Figure 5b) shows altitudes ranging between 600 and 2,302 m a.s.l. Higher elevations in the eastern region are more prone to mass movements due to orographic rainfall and persistent weathering processes. The aspect map (Figure 5c) indicates that southeast- and west-facing slopes are more vulnerable, possibly due to differential sunlight exposure affecting soil moisture and vegetation density. The curvature map (Figure 5d) further highlights the predominance of concave slopes, which tend to accumulate water and enhance pore pressure during intense rainfall events.

Hydrological controls, represented by flow direction (Figure 5e) and lithology (Figure 5f), play an equally important role. Flow accumulation channels act as drainage pathways where runoff convergence increases subsurface saturation. Areas underlain by volcanic tuff and pyroclastic breccia exhibit low permeability, leading to perched groundwater conditions that exacerbate shallow landslide initiation. These spatial relationships confirm the hydrological–geomorphological coupling that drives slope instability in tropical volcanic terrains.

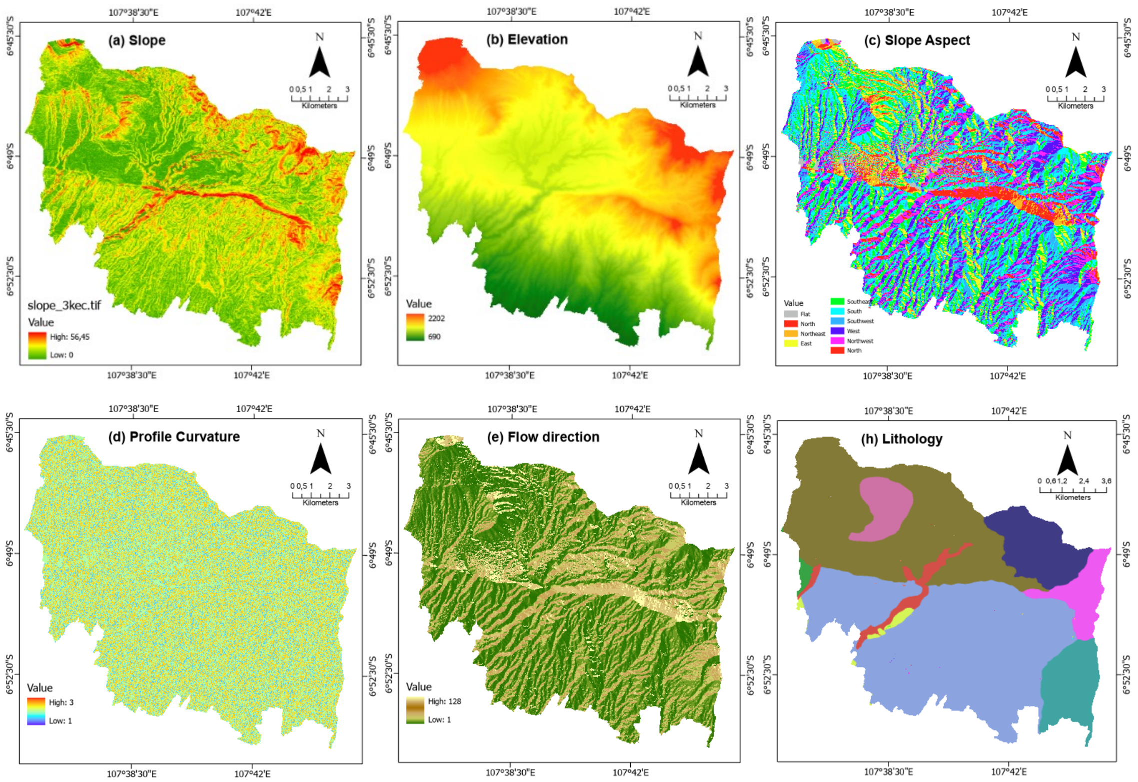

Figure 5: Maps of slope (a), elevation (b), slope aspect (c), profile curvature (d), flow direction (e), and lithology (h), illustrating terrain and subsurface variability relevant to landslide susceptibility.

b. Terrain Ruggedness and Wetness Indicators

The Terrain Ruggedness Index (TRI) in Figure 6 (left) reflects the degree of slope dissection and surface roughness. High TRI zones correspond to faulted volcanic escarpments and deeply incised valleys, especially in the northern and eastern sectors of the study area. These rugged terrains exhibit steep microrelief transitions that promote localized instability through slope undercutting and gravitational stress concentration.

The Topographic Wetness Index (TWI) in Figure 6 (right) identifies zones of hydrological convergence. Areas with high TWI values correspond to valleys and concave depressions where infiltration exceeds drainage, resulting in increased soil saturation. The correlation between high TRI and high TWI indicates compound hazard zones—areas both structurally fragile and hydrologically active—making them critical targets for slope management. This integrated approach demonstrates how geomorphometric indicators can effectively capture complex spatial feedbacks that traditional linear models often overlook.

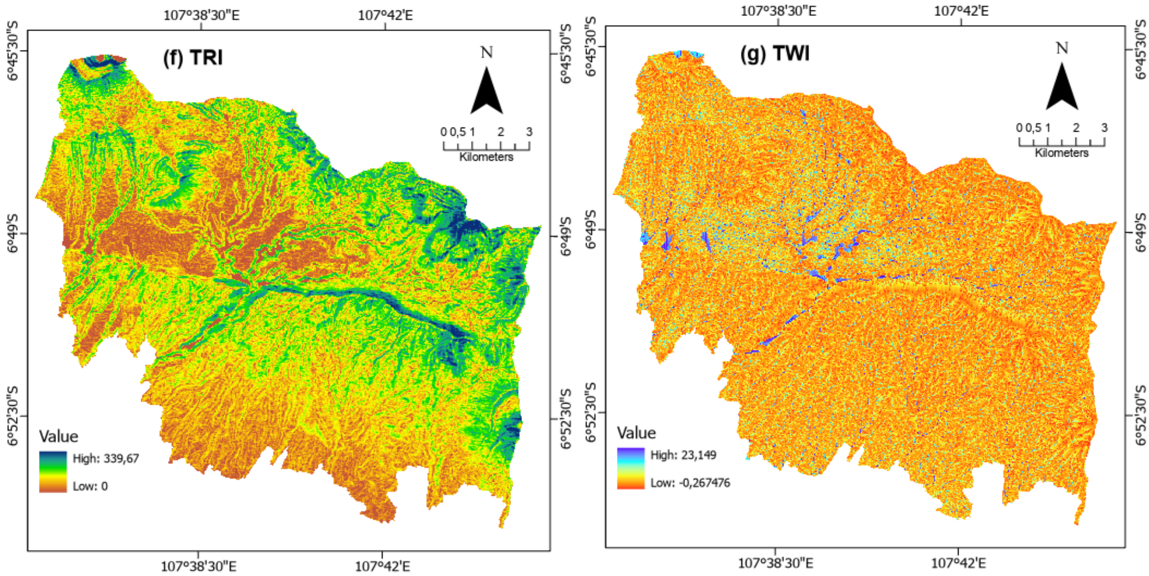

Figure 6: Maps of TRI and TWI, showing the spatial distribution of morphological complexity and hydrological concentration zones in Northern Bandung.

c. Land Use and Anthropogenic Influence

Human-induced land modifications substantially influence slope stability in Northern Bandung. The land-use map (Figure 7, left) reveals that dryland agriculture and plantations dominate approximately 46% of the landscape, replacing natural forest cover. Field verification confirms that many shallow landslides occur within these cultivated zones, where vegetation removal and ploughing reduce root reinforcement and alter infiltration capacity.

Proximity to roads, depicted in Figure 7 (right), further elevates hazard potential. Approximately 45% of landslides were recorded within 300 m of road networks. Road cuts, embankments, and inadequate drainage systems concentrate surface runoff, initiating shallow debris slides. These findings underscore that infrastructure expansion without slope stabilization measures significantly aggravates natural instability, transforming geomorphically sensitive terrain into disaster-prone zones.

The combined effect of agricultural pressure and infrastructure development highlights the critical role of land-use planning in slope hazard management. Reforestation and bioengineering interventions should be prioritized along high-susceptibility corridors, especially in the Cimenyan–Lembang transition zone.

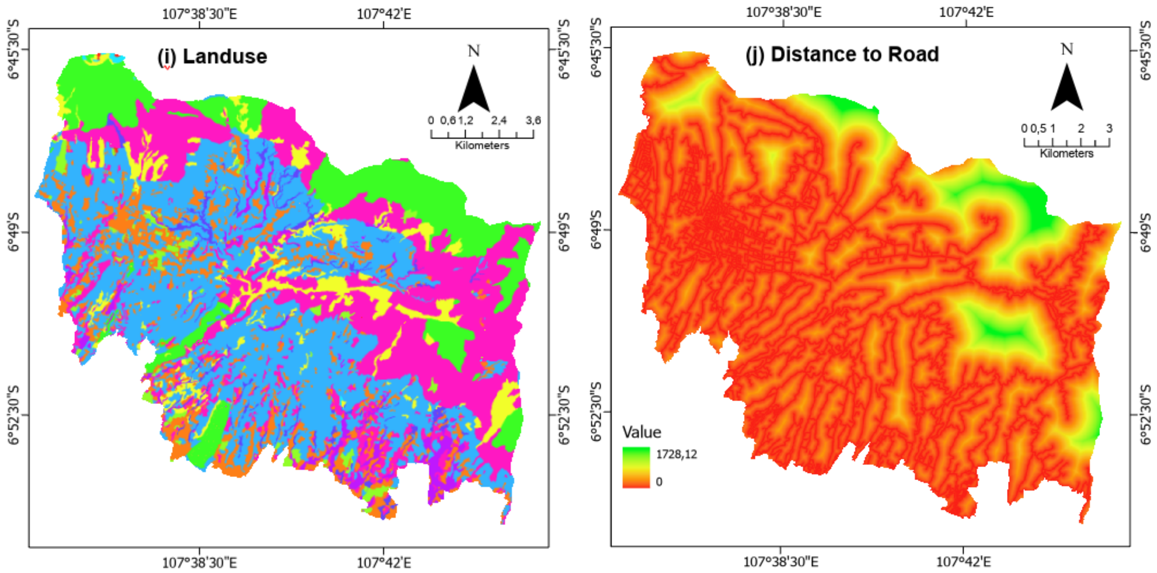

Figure 7: Maps of (i) Land Use and (j) Distance to Road, showing areas affected by vegetation conversion and infrastructure-induced destabilization.

d. Geological and Hydrometeorological Triggers

The proximity to fault lines (Figure 8a) indicates that many landslides cluster within 200–500 m of structural discontinuities. Fault zones weaken bedrock integrity and enhance water infiltration, leading to deep-seated failures along weathered tuffaceous strata. Similarly, the distance to rivers (Figure 8b) demonstrates that slope undercutting and channel migration contribute to toe erosion, further reducing slope stability.

The rainfall distribution map (Figure 8c) shows annual precipitation exceeding 2,400 mm in upper catchments. High rainfall intensities and prolonged wet periods lead to elevated pore pressure and reduced effective stress, triggering multiple shallow slides. These findings confirm that rainfall acts as both a preparatory and triggering factor, operating synergistically with geological and land-use variables. For hazard mitigation, coupling susceptibility maps with rainfall threshold analysis could provide a more dynamic early warning framework.

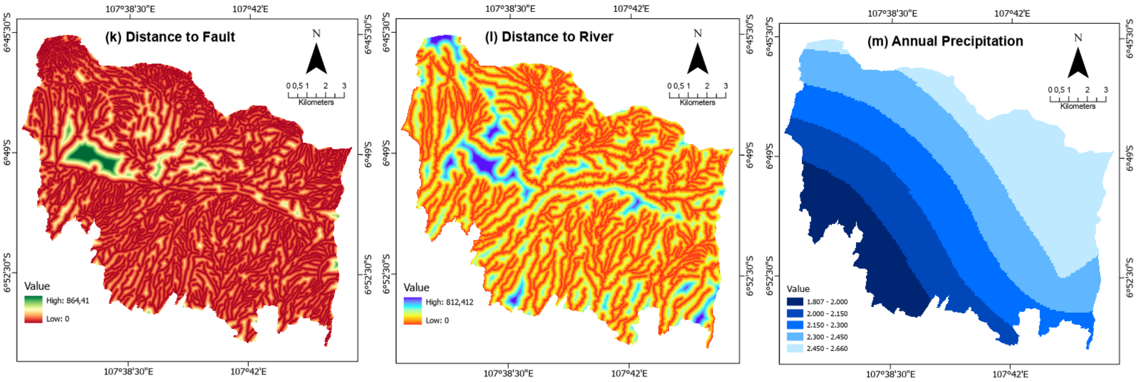

Figure 8: Maps of (k) Distance to Fault, (l) Distance to River, and (m) Annual Precipitation, representing structural, fluvial, and climatic factors in landslide triggering.

e. Vegetation Density and NDVI Analysis

The Normalized Difference Vegetation Index (NDVI) (Figure 9) exhibits a strong inverse correlation with landslide occurrence. Areas with NDVI < 0.25 correspond to degraded agricultural land and plantations where root cohesion is minimal. Conversely, dense forest areas with NDVI > 0.35 display greater stability. However, NDVI alone cannot fully represent slope resilience because root structure, soil type, and rainfall infiltration interact in complex ways.

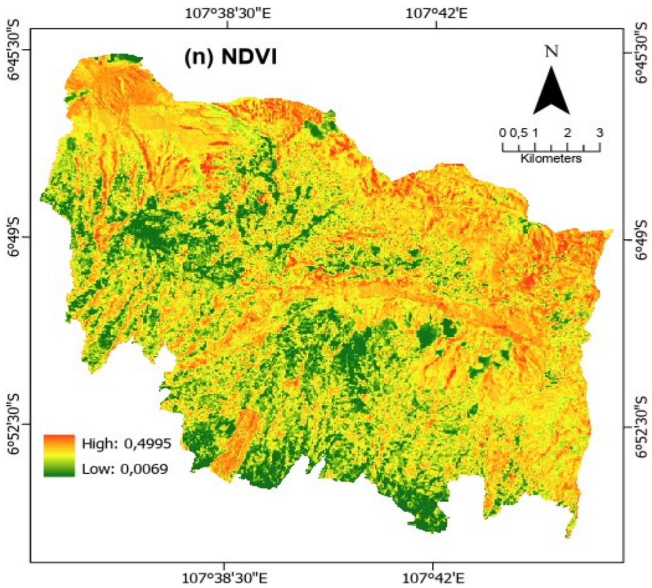

Figure 9: NDVI map showing spatial variations in vegetation density, where lower values indicate areas with degraded cover associated with increased landslide risk.

Temporal NDVI monitoring could enhance predictive capability by detecting vegetation disturbance before slope failure occurs. Integrating Sentinel-2 NDVI time series with rainfall data can enable near-real-time detection of hazard evolution, offering a cost-effective addition to Indonesia's disaster early warning system.

f. Landslide Susceptibility Map and Model Evaluation

The final RF-based susceptibility map (Figure 10) classifies the study area into five categories: Very Low, Low, Moderate, High, and Very High susceptibility. According to Table 1, approximately 30.40% of the total area falls under the Very High category, predominantly concentrated in steep volcanic ridges and mid-slope agricultural zones. Meanwhile, 48.38% of the area is categorized as Very Low, corresponding mainly to forested and gently sloping terrain.

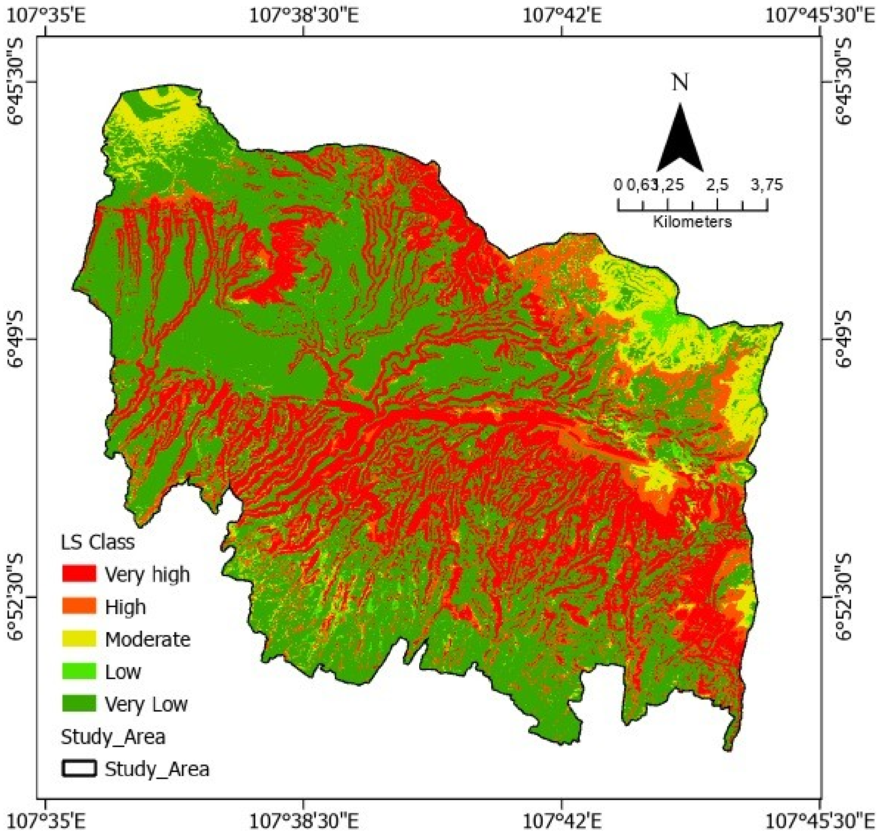

Figure 10: Random Forest-based Land Use Area Calculation in Northern Bandung.

Table 1 summarizes the areal distribution of susceptibility classes, while Table 2 presents the model's classification performance metrics used to evaluate prediction reliability. The Random Forest model achieved 98% accuracy, with balanced precision, recall, and F1-scores (Table 2). These metrics confirm the reliability of the model in discriminating between landslide and non-landslide zones. Variable importance analysis identified slope, TWI, land use, and NDVI as the four most influential predictors, accounting for more than 70% of the model's explanatory power.

Table 1: Areal distribution of Random Forest-based landslide susceptibility classes in Northern Bandung

Class	**Area (ha)**	**Percentage (%)**
Very Low	8,818	48.38283
Low	751	4.118637
Moderate	1,195	6.557431
High	1,920	10.53739
Very high	5,541	30.40371
Total	18,225	100

Compared to conventional logistic regression or support vector machine methods, the RF model demonstrates superior adaptability in handling multicollinearity and nonlinear interactions among conditioning factors. This advantage results in improved generalization and interpretability, particularly in geologically complex regions such as Northern Bandung. The feature importance output also provides practical insights for prioritizing slope stabilization measures.

Table 2: Classification report of the Random Forest model showing precision, recall, F1-score, and support for each class in landslide susceptibility prediction.

Score		Precision	Recall	F1-score	Support
Min	0	0.97	0.99	0.98	917
Max	1	0.99	0.97	0.98	917
Accutacy				0.98	1834

Macro avg	0.98	0.98	0.98	1834
	0.98	0.98	0.98	1834

g. Interpretation and Implications

Beyond the technical accuracy of the Random Forest model, the broader significance of this study lies in demonstrating how geospatial intelligence can directly support disaster risk management in volcanic mountain regions. The susceptibility maps generated from this research are not only academic outputs but also practical decision-support tools that can guide provincial and district authorities in planning safer and more sustainable land use. Integrating these results into spatial development plans would allow the delineation of protected slope zones and the restriction of settlement or agricultural expansion in areas classified as “High” and “Very High” susceptibility. Such policy alignment between scientific evidence and spatial regulation could substantially reduce future exposure to slope-related hazards.

The Random Forest–based framework also offers great potential for dynamic monitoring when coupled with near-real-time environmental data. Combining susceptibility maps with satellite-derived rainfall, vegetation, and soil-moisture indicators can produce an adaptive early-warning system. This would enable local disaster management agencies to anticipate slope failures and prioritize preventive actions, such as temporary evacuation, slope reinforcement, or drainage improvement, before critical thresholds are reached. The integration of machine learning and remote-sensing observations thus establishes a foundation for proactive, data-driven resilience planning in Indonesia’s mountainous landscapes.

At the community level, the translation of scientific outputs into local awareness is equally crucial. Many villages in Northern Bandung experience recurring shallow landslides yet lack sufficient understanding of their underlying causes. By converting susceptibility maps into accessible communication tools—posters, digital dashboards, and participatory mapping workshops—communities can visualize local risks and learn to identify early signs of slope instability. Collaboration between universities, local governments, and non-governmental organizations is essential to transform these scientific insights into community-based adaptation practices. Training programs focusing on simple slope monitoring, vegetation maintenance, and household-level mitigation can strengthen local preparedness and embed disaster awareness into everyday decision-making.

From a broader perspective, the methodological framework developed in this study can serve as a reference for regional applications across Indonesia's volcanic belts. Applying a consistent Random Forest modeling approach to other areas such as Dieng, Merapi, and Batur would enhance interregional comparability and accelerate the production of reliable hazard maps. The approach also promotes transparency and reproducibility in susceptibility assessment, ensuring that future studies can refine model parameters while maintaining methodological coherence. In addition, integrating local field validation with continuous satellite observation will provide the temporal depth required to track changes in land use, vegetation cover, and slope behavior over time.

Scientifically, this research highlights the importance of combining data-driven modeling with geomorphological interpretation. While the Random Forest algorithm effectively captures nonlinear relationships among conditioning factors, its explanatory power increases when contextualized with field-based understanding of lithology, hydrology, and land-use processes. This hybrid perspective enhances both the interpretability and policy relevance of the model. Ultimately, the study demonstrates how machine learning can bridge the gap between scientific research and spatial governance. As rainfall extremes and land-use pressures continue to intensify, adopting such integrated frameworks will be essential for safeguarding lives, infrastructure, and ecosystems in Indonesia's volcanic highlands.

Conclusion and Recommendation

This study successfully developed a high-resolution landslide susceptibility model for Northern Bandung using the Random Forest algorithm integrated with multi-source geospatial datasets. A total of 3,056 verified landslide points and fourteen conditioning factors—representing topographic, hydrological, geological, vegetation, and anthropogenic variables—were analyzed to determine the key spatial drivers of slope instability. The Random Forest classifier demonstrated strong predictive capability, achieving 98% overall accuracy with balanced precision and recall, confirming its robustness in managing complex nonlinear relationships among conditioning variables.

The analysis revealed that slope gradient, topographic wetness index (TWI), land use, and NDVI are the dominant parameters controlling landslide occurrence. High-susceptibility zones are primarily distributed on steep volcanic slopes where dryland farming, plantation expansion, and road construction are most intense. These findings demonstrate that anthropogenic pressures, when combined with natural geological and hydrological factors, significantly amplify slope instability. The susceptibility map derived from this study provides a valuable reference for local authorities to delineate high-risk areas and formulate spatially informed mitigation strategies.

Recommendations derived from this research emphasize the importance of integrating geospatial modeling into land management and policy planning. Slope rehabilitation through vegetative measures, such as reforestation and bioengineering, should be prioritized in degraded agricultural zones to restore hydrological balance and soil cohesion. Infrastructure development must adopt slope-protection standards and incorporate proper drainage systems to minimize surface runoff concentration. Furthermore, land-use zoning should strictly regulate agricultural and residential expansion in highly susceptible zones identified in this study. Integrating the Random Forest-based susceptibility model with near-real-time rainfall and NDVI monitoring can enhance early warning systems and reduce potential disaster impacts.

Overall, this research confirms that combining machine learning with multi-source spatial data provides a robust, transparent, and replicable framework for landslide susceptibility mapping. The methodological approach and findings can be applied to other volcanic mountainous regions across Indonesia, supporting national efforts toward disaster risk reduction, spatial resilience, and sustainable land management.

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