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Random forest modeling for landslide susceptibility assessment in the complex terrain of Tinggimoncong, South Sulawesi, Indonesia

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ABSTRACT

Landslides are among the most frequent and destructive geological hazards in Indonesia, particularly in mountainous regions with steep slopes, complex geomorphology, and high rainfall. In addition to their role as natural hazards, landslides act as significant drivers of environmental disturbance and land degradation, highlighting the need for reliable susceptibility assessment as part of environmental monitoring and sustainable land-use planning. This study applies a random forest (RF) machine learning model integrated with geographic information systems (GIS) to support environmental monitoring of landslide-prone landscapes in the Tinggimoncong District, Gowa Regency, South Sulawesi, Indonesia. A balanced dataset of 440 sample points (220 landslide and 220 non-landslide locations) was constructed using high-resolution imagery, field verification, and official records, and combined with twelve conditioning factors representing topography, geology, hydrology, land cover, and human activities. Model performance was evaluated using accuracy, F1-score, ROC–AUC, and PR–AUC. The RF model demonstrated high predictive performance (AUC = 0.971; F1-score = 0.95). Feature importance analysis indicates that slope aspect, elevation, slope gradient, and distance to roads are the dominant factors controlling environmentally driven slope instability. The resulting probabilistic and classified susceptibility maps identify zones of high environmental instability that spatially correspond with areas prone to land degradation due to recurrent landslides. The proposed RF-based framework provides a robust basis for environmental monitoring, land degradation management, and sustainable spatial planning in complex tropical terrains.

Keywords: environmental monitoring, landslide susceptibility, random forest, geographic information systems, land degradation, tropical mountainous environment.

INTRODUCTION

Landslides are among the most frequent and destructive geological hazards in Indonesia, particularly in regions characterized by steep slopes, complex geomorphology, and high rainfall intensity (Noviyanto et al., 2020; Shao et al., 2022). Slope failure results from the interaction of geological, geomorphological, hydrological, and anthropogenic factors when driving forces exceed the resisting strength of slope materials. Beyond their immediate role as geological hazards, landslides also represent major environmental disturbances that accelerate soil erosion, modify land cover patterns, disrupt hydrological processes, and contribute to long-term land degradation. Such events often lead to extensive damage to infrastructure and agricultural land, loss of human lives, and long-term socio-economic disruption (Keller, 2017; Sam et al., 2025). Consequently, reliable landslide susceptibility assessment is essential not only for disaster risk reduction but also as part of environmental monitoring systems supporting sustainable land-use planning (Galve et al., 2014; Roccati et al., 2021). Advances in geographic information systems (GIS) and data-driven modeling have substantially enhanced landslide susceptibility analysis and the capacity to monitor environmentally driven slope instability at regional scales (Laode et al., 2025). Conventional approaches, including weighted overlay and index-based methods, rely heavily on expert judgment and predefined weighting schemes, which may introduce subjectivity and limit their ability to represent complex, nonlinear interactions among landslide conditioning factors. These limitations reduce their effectiveness as objective and repeatable tools for environmental monitoring, particularly in heterogeneous tropical landscapes. In contrast, machine learning–based models provide a more flexible framework for capturing multivariate and nonlinear relationships among topographic, geological, environmental, and anthropogenic variables (Haghighi et al., 2021; Wang et al., 2023). Among these models, Random Forest has been widely adopted due to its robustness in handling high-dimensional data, resistance to overfitting, strong predictive performance through ensemble learning, and its ability to quantify the relative importance of conditioning factors for environmental monitoring and evidence-based decision support (Arif et al., 2025; Karurung et al., 2025; Salam et al., 2021).

The Tinggimoncong District in Gowa Regency, South Sulawesi, Indonesia, is characterized by complex terrain and high landslide susceptibility. Steep slopes, pronounced elevation variability, high annual rainfall, and intensive land-use activities associated with agriculture and tourism development, particularly in the Malino highland area, collectively increase slope instability. These interacting natural and anthropogenic drivers have transformed landslides into a recurrent environmental process contributing to ongoing land degradation and landscape change, making Tinggimoncong a critical area for environmental monitoring–oriented landslide susceptibility assessment, especially under intense or prolonged rainfall conditions.

Previous landslide studies in Tinggimoncong and its surrounding areas have predominantly employed conventional susceptibility assessment methods, such as weighted overlay and the Storie Index. While these methods provide an initial depiction of landslide-prone zones, they are limited by subjective weighting schemes, limited capacity to capture nonlinear factor interactions, and the absence of rigorous quantitative model validation. As a result, their contribution to long-term environmental monitoring and land degradation assessment remains limited. Although Random Forest–based landslide susceptibility assessments have demonstrated strong performance in regions with complex geomorphological settings elsewhere (Chen et al., 2018; Dou et al., 2019; Sahin et al., 2020; Sun et al., 2020, 2021), their systematic application as part of an integrated environmental monitoring framework in the Tinggimoncong region remains lacking.

This gap underscores the need for a data-driven, objective, and quantitatively validated landslide susceptibility assessment capable of addressing terrain complexity in Tinggimoncong. Accordingly, the primary objective of this study is to develop and evaluate a Random Forest–based landslide susceptibility model integrated with GIS-derived environmental conditioning factors in the Tinggimoncong highlands, South Sulawesi. Beyond producing a susceptibility map, this study aims to identify the dominant landslide-controlling factors and to quantify their relative importance and interactions, thereby generating new scientific insight into the mechanisms governing environmentally driven slope instability in a tropical mountainous setting. The specific scientific contribution lies in moving from subjective, index-based mapping toward an evidence-based framework suitable for environmental monitoring and land degradation assessment. It is hypothesized that morphometric factors, particularly slope gradient and elevation, combined with proximity to anthropogenic disturbances such as roads, exert a stronger control on landslide occurrence than lithological variability alone, and that the Random Forest model will demonstrate robust predictive performance validated through multiple quantitative metrics. The results are expected to provide a reproducible and reliable basis for integrating landslide susceptibility into environmental monitoring systems and sustainable land-use planning in Tinggimoncong and geomorphologically comparable regions.

MATERIAL AND METHODS

This study follows a systematic and reproducible workflow integrating landslide inventory preparation, conditioning factor analysis, Random Forest modeling, quantitative validation, and spatial susceptibility mapping to support environmental monitoring of slope instability and land degradation. The overall technical workflow for landslide susceptibility assessment within an environmental monitoring framework is summarized in Figure 1.

Study area

The study was conducted in the Tinggimoncong District, Gowa Regency, South Sulawesi, Indonesia, a mountainous region characterized by complex terrain and high landslide susceptibility (Figure 2). The area exhibits steep slopes, significant elevation variability, and high annual rainfall. In addition, intensive land-use activities related to agriculture and tourism development, particularly in the Malino highlands, have altered natural slope conditions and increased terrain instability (Dariati et al., 2021). These interacting natural and anthropogenic pressures have made landslides a recurrent environmental process contributing to ongoing land degradation, making Tinggimoncong an appropriate case study for environmental monitoring–oriented landslide susceptibility assessment in complex tropical environments.

Landslide inventory and dataset preparation

A landslide inventory was compiled by integrating historical landslide records from Gowa Regency with visual interpretation of high-resolution Google Earth imagery and systematic field verification. Landslide locations were initially identified from documented landslide occurrence histories provided by the Gowa Regency Disaster Management Agency (BPBD) and subsequently confirmed through geomorphological interpretation of satellite imagery, including the presence of head scarps, disrupted vegetation patterns, and debris accumulation. The spatial distribution of landslide and non-landslide inventory points, together with representative satellite imagery illustrating geomorphological evidence of landslide features, is presented in Figure 3. Field surveys were conducted to verify the location and extent of selected landslide sites, ensuring that only confirmed landslide events with clear geomorphological evidence were included in the inventory. In total, 220 landslide sample points (label = 1) were established based on the convergence of historical records, image interpretation, and field validation, thereby ensuring the reliability of the landslide dataset for environmental monitoring purposes.

An equal number of 220 non-landslide sample points (label = 0) were selected from areas with no recorded history of landslides and no observable geomorphological evidence of slope failure on satellite imagery or during field verification. Non-landslide points were sampled from geomorphologically stable zones and were spatially constrained to maintain a sufficient distance from mapped landslide locations, thereby reducing spatial ambiguity and potential autocorrelation effects. Figure 3 also provides satellite imagery examples from selected landslide locations, highlighting diagnostic geomorphological indicators such as head scarps, displaced material, and

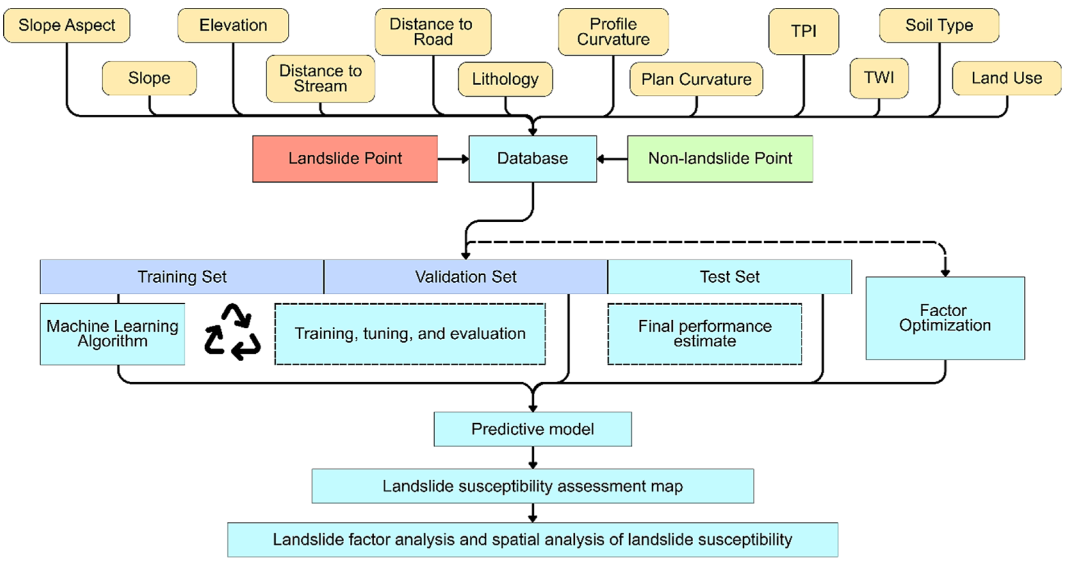

Figure 1. Research workflow for landslide susceptibility assessment (modified from Li et al., 2024)

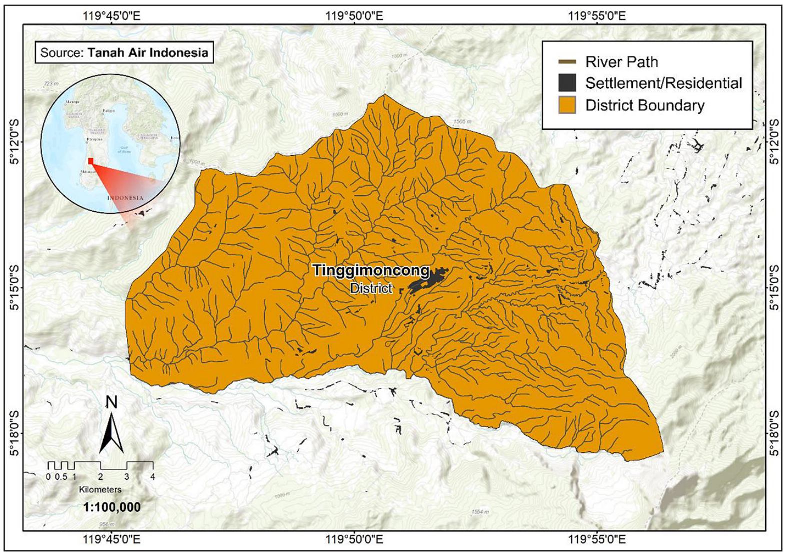

Figure 2. Location of the study area

Table 1. Landslide conditioning factors used in this study

Category	Conditioning factor	Description	Data source	Derivation method/Tools
Topography	Slope gradient	Steepness of terrain	DEMNAS (Badan Informasi Geospasial, Indonesia)	Derived from DEM using *Slope* function in ArcGIS 10.8 (Horn algorithm)
	Elevation	Absolute height above sea level	DEMNAS (Badan Informasi Geospasial, Indonesia)	Directly extracted from DEM raster
	Aspect	Slope orientation	DEMNAS (Badan Informasi Geospasial, Indonesia)	Derived from DEM using *Aspect* function in ArcGIS 10.8
	Plan curvature	Surface curvature perpendicular to slope	DEMNAS (Badan Informasi Geospasial, Indonesia)	Derived from DEM using *Curvature* tool (plan curvature option)
	Profile curvature	Curvature parallel to slope direction	DEMNAS (Badan Informasi Geospasial, Indonesia)	Derived from DEM using *Curvature* tool (profile curvature option)
	Topographic position index (TPI)	Relative position within terrain	DEMNAS (Badan Informasi Geospasial, Indonesia)	Calculated as the difference between cell elevation and mean elevation of a surrounding neighborhood (TPI), using raster neighborhood analysis
	Topographic wetness index (TWI)	Potential soil moisture accumulation	DEMNAS (Badan Informasi Geospasial, Indonesia)	Calculated as TWI = ln (As / tanβ), where *As* is specific catchment area and *β* is slope angle, derived using flow accumulation and slope rasters
Geology and soil	Lithology	Bedrock type	Geological Map (ESDM – Geological Agency of Indonesia)	Vector geology map reclassified and converted to raster format
	Soil type	Engineering soil characteristics	FAO Soil Map	Soil units extracted and reclassified based on engineering soil properties
Land cover	Land use/land cover	Vegetation and anthropogenic cover	KLHK (Ministry of Environment and Forestry, Indonesia)	Land use classes reclassified into dominant land cover categories
Distance-based	Distance to streams	Proximity to fluvial erosion zones	RBI (Badan Informasi Geospasial, Indonesia)	Euclidean distance calculated from stream network using *Distance* tool
	Distance to roads	Proximity to anthropogenic disturbances	RBI (Badan Informasi Geospasial, Indonesia)	Euclidean distance calculated from road network using *Distance* tool

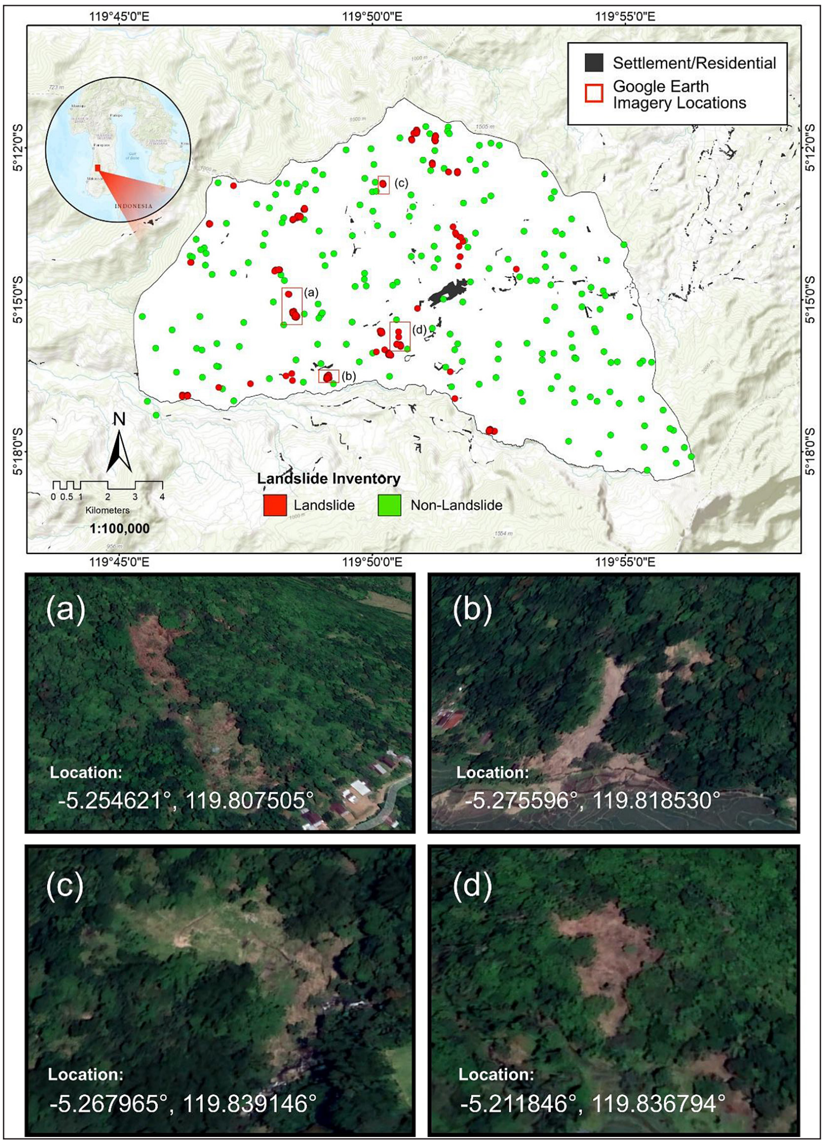

Figure 3. Spatial distribution of landslide and non-landslide inventory points in the research area. Landslide locations are shown as red points and non-landslide locations as blue points. (a–d) present representative Google Earth satellite imagery locations illustrating geomorphological evidence of landslide occurrence, including head scarps, debris accumulation, and disturbed vegetation patterns used for inventory validation

disturbed vegetation patterns used to validate landslide occurrence. The resulting balanced dataset, comprising 440 sample points, provided equal representation of landslide and non-landslide classes and formed a robust basis for Random Forest model training, validation, and repeatable landslide susceptibility assessment.

Landslide conditioning factors

Twelve landslide conditioning factors were selected to represent the combined influence of topography, geology, hydrology, land cover, and human activities on slope stability and associated environmental change processes (see Table 1). These factors capture the spatial variability of terrain morphology, subsurface conditions, surface processes, and anthropogenic disturbances that control landslide occurrence and landscape degradation in the study area. The spatial distribution of the selected conditioning factors is illustrated in Figure 4 and Figure 5. All raster layers were standardized to a spatial resolution of 30 m and projected to UTM Zone 50S (WGS84) to ensure spatial consistency. Factor values were extracted at landslide and non-landslide sample locations to construct a multivariate dataset suitable for environmental monitoring–oriented Random Forest modeling.

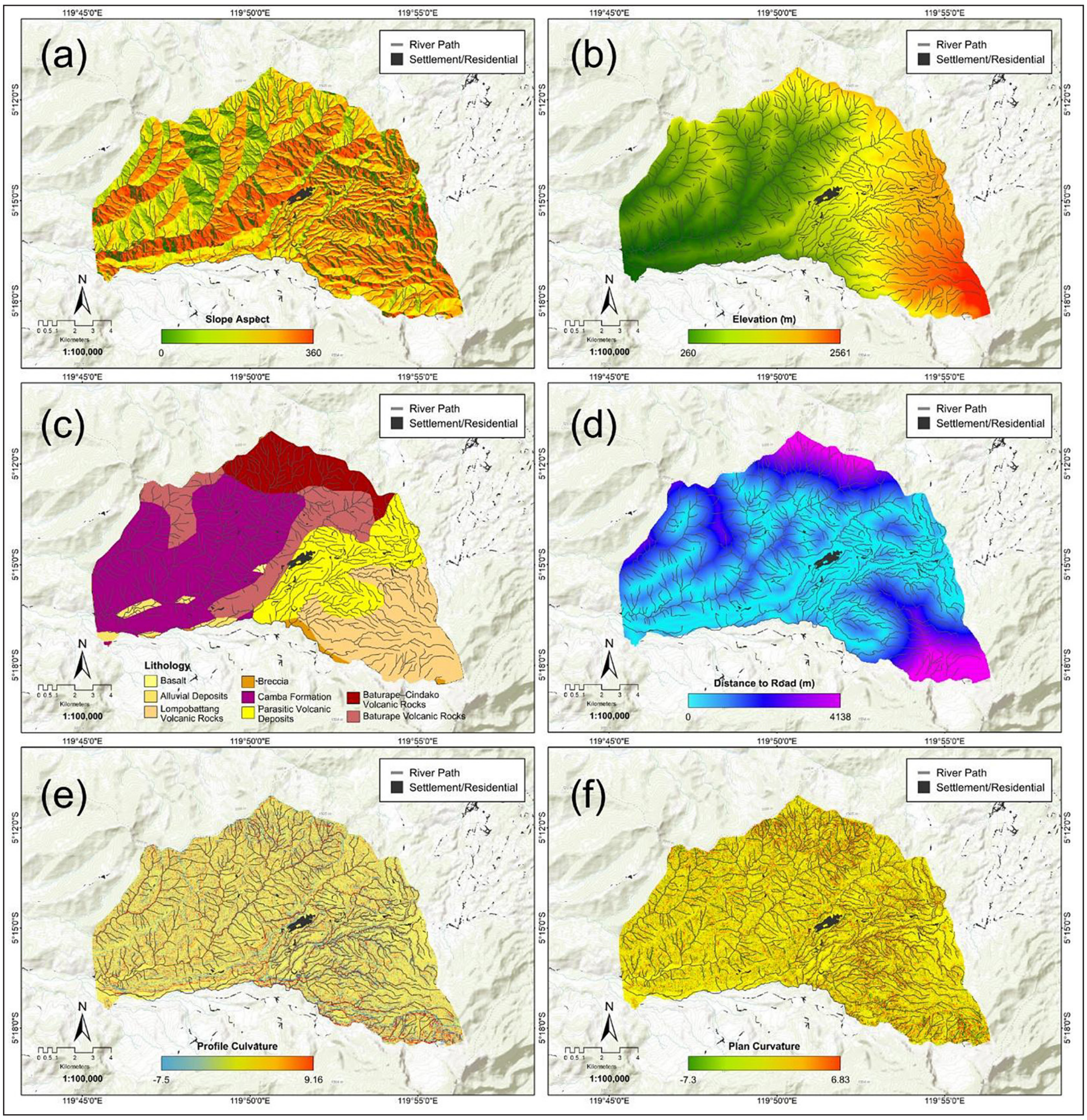

Figure 4. Landslide conditioning factors used in this study: (a) slope aspect, (b) elevation, (c) lithology, (d) distance to road, (e) profile curvature, (f) plan curvature

Random forest modeling

Landslide susceptibility modeling was performed using the RF algorithm, an ensemble learning method that constructs multiple decision trees based on bootstrapped samples and randomly selected subsets of predictor variables. The final prediction is obtained by aggregating the outputs of all trees, which enhances predictive stability and reduces overfitting in environmental monitoring applications involving complex multivariate data. Model implementation was conducted using the Python programming language with the Scikit-learn library. The dataset was divided into training (80%) and testing (20%) subsets using stratified sampling to preserve class distribution. Hyperparameter optimization was performed using RandomizedSearchCV combined with five-fold cross-validation. Key hyperparameters optimized in this study include the number of trees (n_estimators), maximum tree depth (max_depth), and class weights to account for potential class imbalance in monitoring landslide-prone environments.

Model evaluation

Model performance was evaluated using multiple quantitative metrics to comprehensively assess predictive accuracy and classification reliability for environmental monitoring and decision-support purposes. These metrics include accuracy, precision, recall, F1-score, the area under the receiver operating characteristic curve

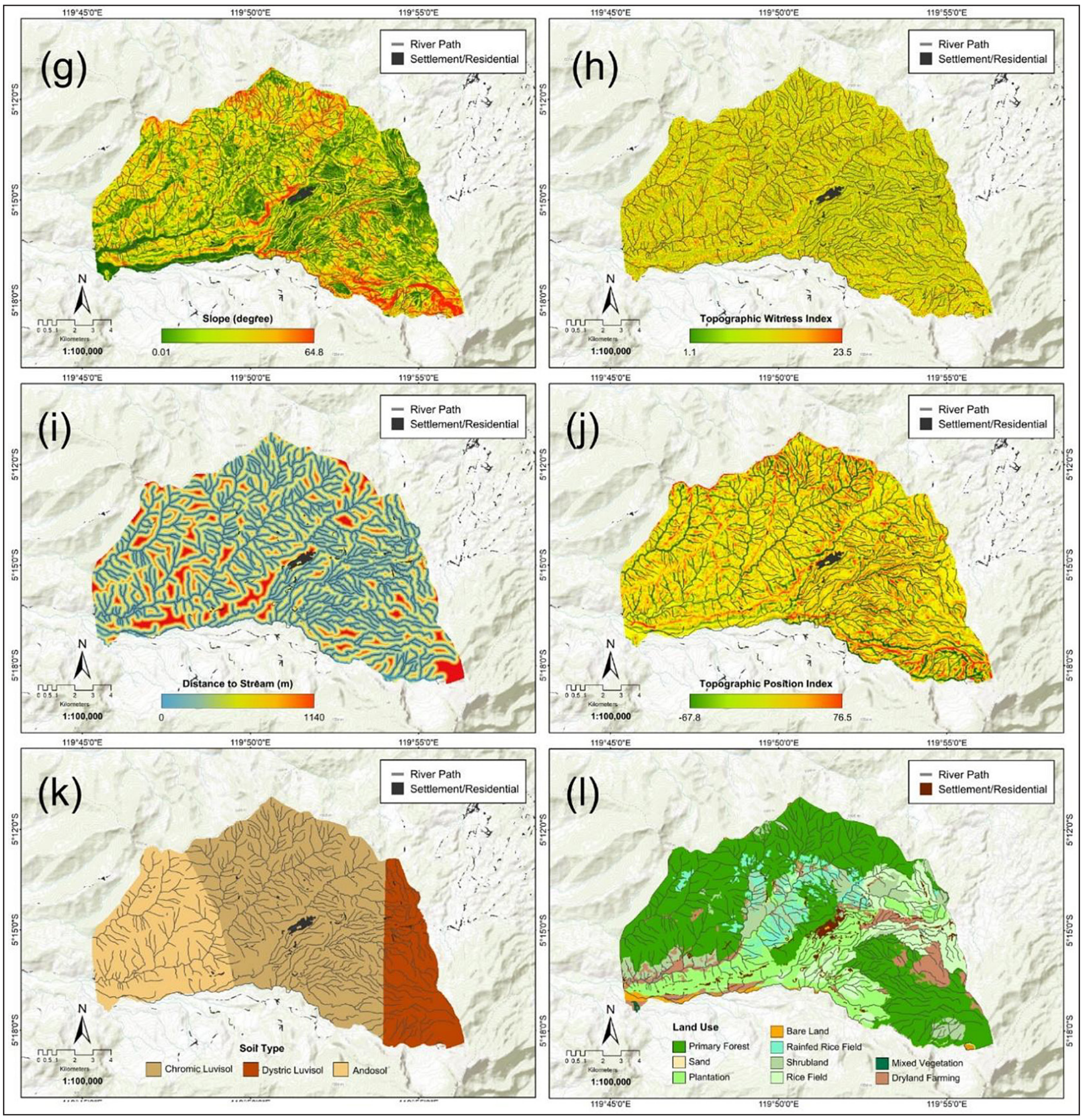

Figure 5. Landslide conditioning factors used in this study: (g) slope, (h) topographic wetness index (TWI), (i) distance to stream, (j) topographic position index (TPI), (k) soil type, and (l) land use/land cover

(ROC–AUC), and the precision–recall area under the curve (PR–AUC) (Krkač et al., 2017; Lagomarsino et al., 2017; Miao and Zhu, 2022; Park et al., 2019). The confusion matrix was generated by comparing the predicted class labels obtained from the trained Random Forest model with the observed landslide and non-landslide labels in the independent testing dataset using the confusion_matrix function implemented in the scikit-learn library. The primary performance metrics were calculated as follows (Agboola et al., 2024; Nugroho et al., 2025):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

where: TP – true positive, TN – true negative, FP – false positive, and FN – false negative.

ROC–AUC was used to evaluate the discriminative capability of the model across classification thresholds, while PR–AUC was employed to assess model performance under potential class imbalance. The ROC curve was constructed by plotting the true positive rate against the false positive rate at various threshold settings, and the AUC was used to quantify overall discrimination performance. All modeling and performance evaluation were conducted using Python in the scikit-learn library.

Feature importance

After evaluating the model using the RF model obtained, the feature importance was quantified by calculating the total reduction in node impurity attributed to each conditioning factor, which was then averaged over all trees in the ensemble. This can explain why the model made those decisions by identifying the most influential variables in the model. The higher mean decrease value indicates that the variable has a more significant role in the classification process in the dataset (Li, 2024).

Feature importance values were extracted directly from the trained Random Forest model using the *feature_importances* attribute of the scikit-learn implementation, which represents the normalized mean decrease in Gini impurity contributed by each conditioning factor across all decision trees in the ensemble.

Landslide susceptibility mapping

The probabilistic output of the Random Forest model was exported in raster format (GeoTIFF) to generate the landslide susceptibility map. Susceptibility values were classified into two levels using the Equal Interval method: low (0.0–0.5 and high (0.5–1.0). All spatial processing and visualization were performed using ArcGIS 10.8.

RESULTS AND DISCUSSION

Relationship between landslide conditioning factors and landslide occurrence

The relationship between landslide conditioning factors and historical landslide occurrence was examined using feature importance derived from the RF model. Model performance in Table 2 was evaluated using a confusion-matrix-based approach that illustrated in Figure 6. Accuracy, precision, recall, and F1-score were computed using formula (1) to (4).

The results indicate that slope aspect is the most influential factor controlling landslide susceptibility in the Tinggimoncong District, followed by elevation and slope gradient (see Table 3 and Figure 7). The high importance of slope aspect suggests that slope orientation strongly affects hydrological and microclimatic conditions, particularly rainfall exposure, soil moisture retention, and vegetation distribution, which collectively influence slope stability and related environmental processes (Capitani et al., 2013; Cellek, 2022; Zhu et al., 2025). Elevation and slope gradient further emphasize the dominant role of terrain morphology, as steeper and higher areas are more susceptible to gravitational failure under intense rainfall conditions.

Anthropogenic influence is clearly reflected by the relatively high importance of distance to road. Road construction and associated slope cutting, excavation, and modification of natural drainage patterns can significantly reduce slope stability, particularly in mountainous environments. This finding highlights the critical role of infrastructure development in amplifying

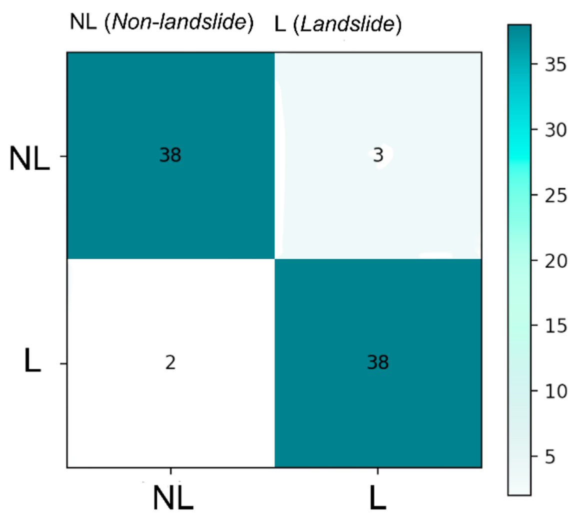

Figure 6. Confusion matrix for landslide and non-landslide classes

Table 2. Performance metrics of the random forest model

RF model		True condition		Summation
		Landslide (L)	Non-landslide (NL)	
Prediction condition	Landslide (L)	38 (TP)	3 (FP)	Precision: 0.927
	Non-landslide (NL)	2 (FN)	38 (TN)	Precision: 0.950
Summation		Recall: 0.950	Recall: 0.927	Accuracy: 0.938

Table 3. Feature importance of conditioning factors derived from the random forest model

No	Conditioning factor	Feature importance
1	Slope aspect	0.1761
2	Elevation	0.1515
3	Slope gradient	0.1300
4	Distance to road	0.0780
5	TPI	0.0778
6	Profile curvature	0.0700
7	Lithology	0.0658
8	Plan curvature	0.0600
9	Land use	0.0562
10	Distance to stream	0.0486
11	TWI	0.0446
12	Soil type	0.0413

landslide susceptibility in the study area. Land use also shows a notable contribution, indicating that agricultural expansion and land-cover modification contribute to surface instability through vegetation removal and soil disturbance.

Geomorphometric indices, including the topographic position index (TPI), profile curvature, and plan curvature, exhibit moderate importance, reflecting the influence of local terrain configuration on water convergence and stress redistribution along slopes. Hydrological factors such as distance to stream and the topographic wetness index (TWI) show comparatively lower importance but still contribute to landslide initiation by enhancing pore-water pressure and reducing soil shear strength at localized scales. Soil type and lithology display lower relative importance, suggesting that while material properties affect slope behavior, landslide occurrence in Tinggimoncong is primarily controlled by topographic and anthropogenic factors rather than lithological variability alone.

Overall, the feature importance analysis reveals that landslide occurrence in the study area is governed by a combination of dominant morphometric controls and significant human-induced disturbances, with hydrological and geological factors acting as secondary modifier.

Model performance assessment and validation

The predictive performance of the Random Forest model was evaluated using multiple quantitative metrics to assess classification accuracy, robustness, and generalization capability for environmental monitoring and decision-support applications. Model performance statistics are reported in Table 2, while classification outcomes are illustrated by the confusion matrix shown in Figure 6.

The RF model demonstrates excellent predictive performance, achieving a high area under the curve (AUC) value of 0.971 (Figure 8a) and an average precision (PR–AUC) of 0.956 (Figure 8b), indicating strong discriminative capability between landslide and non-landslide classes in

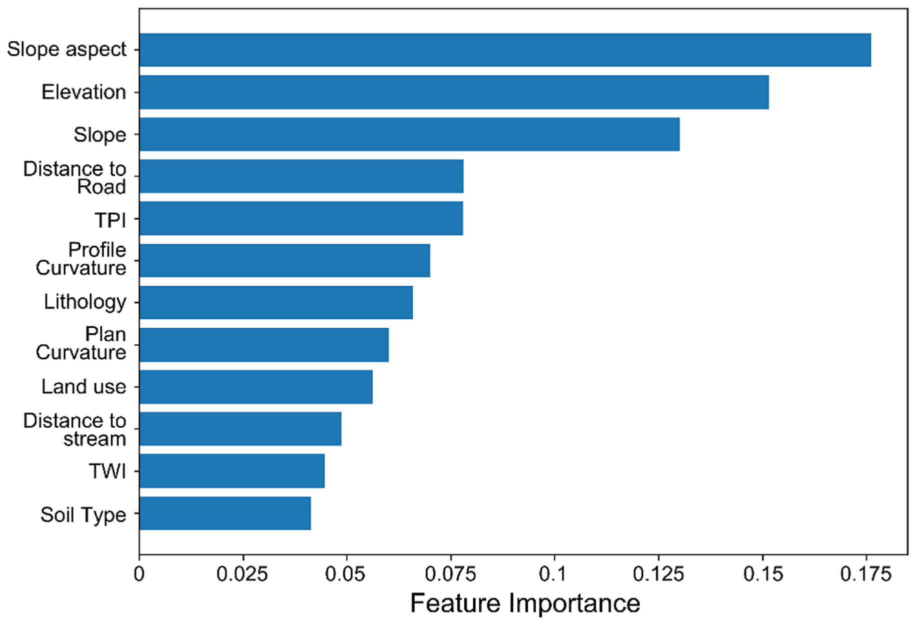

Figure 7. Feature importance of landslide conditioning factors

monitoring environmentally driven slope instability. The overall accuracy reaches approximately 0.95, and the F1-score of 0.95 confirms a well-balanced trade-off between precision and recall. These results indicate that the model is able to identify landslide-prone areas with a low rate of misclassification relevant for reliable environmental monitoring. Analysis of the confusion matrix reveals that the model correctly classified 38 landslide locations and 38 non-landslide locations, with only a small number of misclassifications. The low number of false negatives is particularly important for environmental monitoring and risk-informed land management, as it reduces the likelihood of overlooking environmentally vulnerable zones.

The strong balance between precision and recall demonstrates that the RF model generalizes well to unseen data and is not biased toward either class. These findings confirm the suitability of Random Forest for modeling landslide susceptibility as part of environmental monitoring systems in complex tropical terrain, where nonlinear relationships and interactions among environmental variables are common.

Spatial analysis of landslide susceptibility and land degradation implications

The spatial distribution of landslide susceptibility derived from the Random Forest model is presented in Figure 9, which illustrates continuous probabilistic susceptibility values ranging from 0.00 to 1.00 across the Tinggimoncong District. This probabilistic map represents the direct output of the model and captures spatial variations in the likelihood of landslide occurrence as an indicator of environmental instability. Areas with high probabilistic values are predominantly concentrated in the eastern, northern, and southern parts of the study area. These zones are characterized by steep slopes, higher elevations, and intensive land-use activities, particularly along road corridors and cultivated hillslopes. The spatial concentration of high-probability values in these regions reflects the combined influence of terrain morphology and anthropogenic disturbances on slope instability that drive ongoing land degradation processes, consistent with previous studies (Akinci et al., 2020; Kim et al., 2018; Liu et al., 2022). In contrast, areas with low probabilistic values are mainly distributed in the western and southeastern parts of the district, where gentler terrain and relatively stable land cover prevail indicating lower environmental stress.

For decision-support purposes, the probabilistic susceptibility map was further reclassified into two susceptibility levels; low and high, as illustrated in Figure 10. The classified susceptibility map clearly delineates zones with elevated landslide potential and provides a simplified representation suitable for environmental monitoring, land degradation assessment, and spatial planning. The high-susceptibility class corresponds spatially with areas experiencing recurrent slope failures and intensive land modification, indicating zones of active land degradation. In these areas, repeated landslide events contribute to accelerated soil erosion, vegetation loss, and long-term deterioration of land productivity. Conversely, low-susceptibility zones generally coincide with more stable geomorphological conditions and

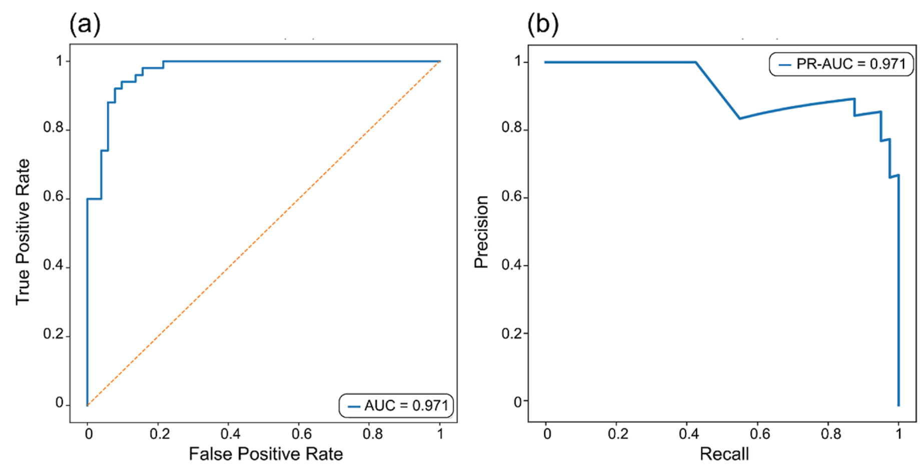

Figure 8. (a) Receiver operating characteristic (ROC) curve showing the trade-off between true positive rate and false positive rate, with an area under the curve (AUC) of 0.971; (b) precision–recall (PR) curve illustrating the relationship between precision and recall, with an average precision (PR–AUC) of 0.956

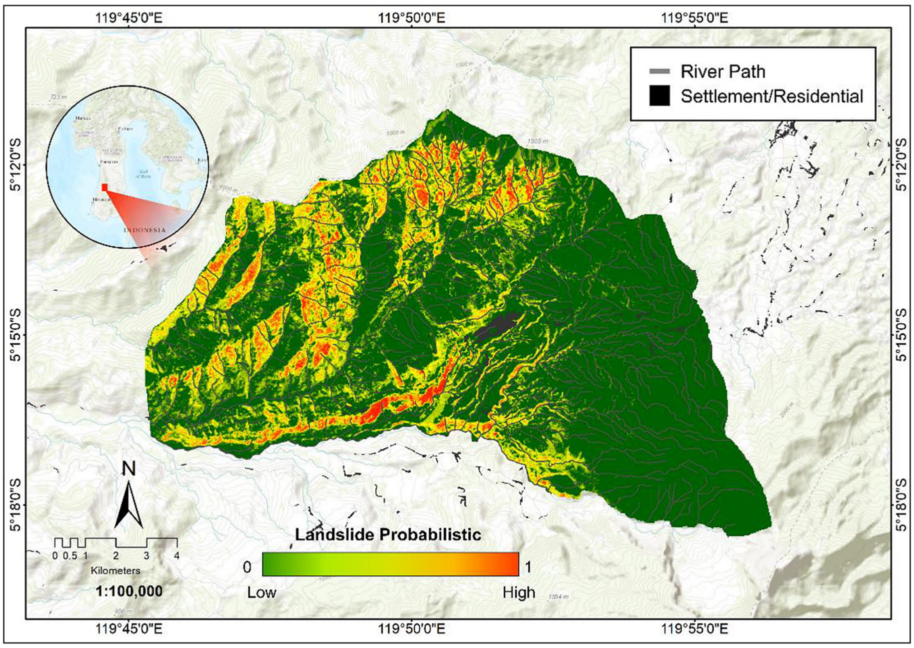

Figure 9. Probabilistic landslide susceptibility map of the Tinggimoncong District, south Sulawesi, Indonesia. The map shows continuous landslide susceptibility values ranging from 0.00 to 1.00 derived from the Random Forest model, representing the spatial probability of landslide occurrence across the study area

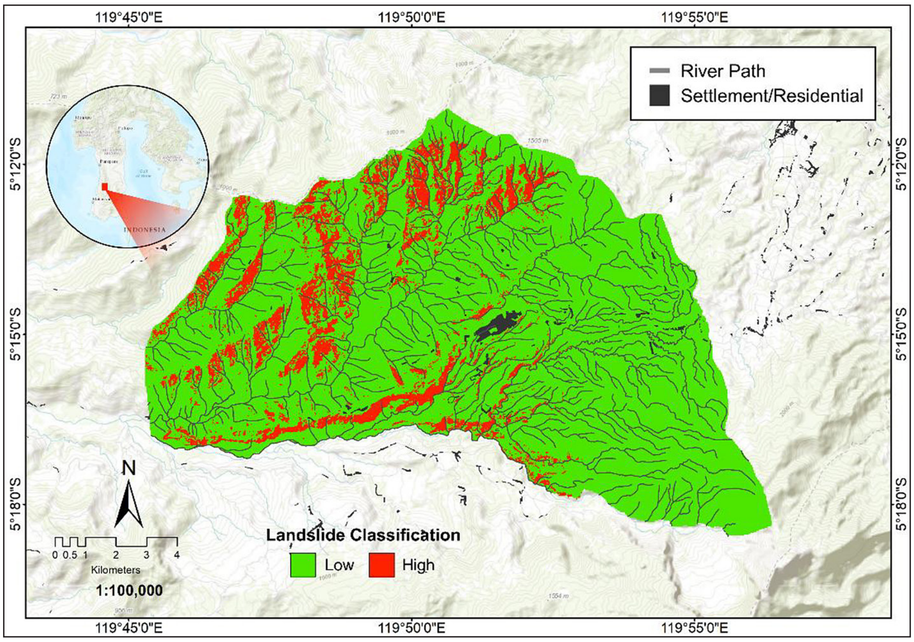

Figure 10. Classified landslide susceptibility map of the Tinggimoncong District, south Sulawesi, Indonesia. The probabilistic susceptibility values were reclassified into two classes; low and high susceptibility to support landslide hazard interpretation, land degradation assessment, and decision-making for disaster risk mitigation and spatial planning

lower levels of human disturbance, reflecting reduced landslide risk and limited land degradation.

The strong spatial consistency between the probabilistic and classified susceptibility maps demonstrates the robustness of the Random Forest model in capturing landslide-prone environments in complex terrain. Together, these outputs provide an environmental monitoring framework for understanding landslide processes and their contribution to land degradation, supporting data-driven land management and sustainable spatial planning in the Tinggimoncong highlands.

CONCLUSIONS

This study successfully applied the RF algorithm to assess landslide susceptibility in the Tinggimoncong District, Gowa Regency, South Sulawesi, achieving high predictive performance and model stability (AUC = 0.971; F1-score = 0.95). Within an environmental monitoring context, the RF approach proved effective in capturing nonlinear relationships among spatial variables and produced statistically and spatially consistent susceptibility patterns that reflect spatial variations in environmental instability in a complex tropical terrain. One of the main strengths of the RF model lies in its ability to process multivariate datasets with heterogeneous variable types without requiring linearity assumptions, while simultaneously providing feature importance information relevant for interpreting key environmental controls. The results indicate that morphometric factors, particularly slope aspect, slope gradient, and elevation, together with anthropogenic influences such as proximity to road networks, are the dominant controls on landslide susceptibility and associated land degradation processes in the study area. These findings highlight the critical role of both terrain morphology and human activities in shaping environmentally vulnerable landscapes.

Despite the strong performance of the model, several limitations should be acknowledged. The landslide inventory used in this study is limited in terms of temporal coverage and the number of documented landslide events. In addition, the model does not incorporate dynamic triggering factors such as daily rainfall intensity or soil moisture conditions, which are important variables for continuous environmental monitoring of slope processes. Future research should integrate time-dependent variables and multi-temporal landslide inventories to strengthen the applicability of landslide susceptibility modeling within long-term environmental monitoring frameworks.

The findings of this study provide a robust scientific basis for environmental monitoring–informed land management and spatial planning in the Tinggimoncong highlands. The probabilistic and classified susceptibility maps can support local authorities, including disaster management and regional planning agencies, as spatial indicators for monitoring environmental stress and land degradation, in identifying high-risk zones and prioritizing mitigation measures. Moreover, the proposed RF-based framework is transferable and can be readily applied to other regions with similar geomorphological and geological settings, offering a reliable and efficient machine learning approach for environmental monitoring of landslide-prone landscapes and land degradation management.

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