

Landslide Susceptibility Mapping Using the Weight of Evidence Model: A Case Study on A Tropical Volcanic Region

Dimas Hastama Nugraha, Wahyu Wilopo*, and Teuku Faisal Fathani

Received : January 20, 2025

Revised : September 23, 2025

Accepted : October 8, 2025

Online : January 17, 2026

Abstract

Landslides are one of the major hazards in volcanic areas, causing loss of life, property damage, and degradation of the environment. The western slopes of Mount Lawu, a stratovolcano in Central Java Province, Indonesia, are especially prone to landslides because of steep topography and increasing human activities. The rapid population growth and land use changes, driven by tourism and agricultural expansion, have increased the vulnerability of the area. This study examines the performance of the weight of evidence (WoE) method in mapping landslide susceptibility over the western slopes of Mount Lawu, with a focus on the interaction between environmental factors and land use. The parameters considered in this research include slope, lithology, distance from lineaments, roads, and rivers, rainfall, and land use. The spatial datasets used included a digital elevation model (DEM) at a scale of 1:16,000, as well as slope, river, lineament, and land-use data at a scale of 1:25,000, and lithology data at a scale of 1:50,000. All of these datasets were processed and analyzed using ArcGIS Pro. The WoE analysis resulted in the landslide susceptibility map, which divided susceptibility into four classes: high, moderate, low, and very low. The model achieved an accuracy of 0.81, demonstrating strong predictive capability. The landslide susceptibility map showed high-risk zones along steep slopes, near rivers, and close to roads, particularly in northern Ngargoyoso and western-southern Tawangmangu Districts. These results highlight the utility of the WoE method for developing the landslide susceptibility map with good accuracy. A landslide susceptibility map can be used to evaluate existing land use and to create spatial planning-based landslide disaster risk reduction.

Keywords: landslide susceptibility map, land use, volcano, weight of evidence

1. INTRODUCTION

The world's regional geology shows that the most significant geological activity occurs along tectonic plate boundaries, particularly in the Pacific Ring of Fire. Indonesia is located at the center of intense geological activity, where interactions between the Eurasian, Indo-Australian, and Pacific plates create conditions that favor the occurrence of earthquakes and volcanic eruptions [1][2]. Java Island is part of a volcanic arc formed by the subduction of the Indo-Australian plate beneath the Eurasian plate. This process not only produces active volcanoes but also triggers landslides, especially in steep and weathered materials.

Land use change and urbanization in mountainous areas can increase the risk of landslides [3][4]. In addition, the geological

characteristics of Java Island, consisting of volcanic and sedimentary rocks, as well as the presence of unstable soil layers, contribute to the high landslide risk in the area [5][6]. Moreover, its position on the equator allows Indonesia to have high rainfall intensity. This condition triggers numerous landslides in Indonesia [7], resulting in significant losses of life and property [8]. Data from the National Disaster Management Agency (BNPB) states that during 2020–2022, more than 500 people died, and 10,000 were injured due to landslides [9].

Mount Lawu, a strato-type volcano dominated by andesite lava, lies on the border of Central and East Java [10]. Its steep slopes, high rainfall, and intensive land use make the western flank of Karanganyar Regency prone to landslides [11][12]. Urbanization and tourism development, while providing economic benefits, exacerbate slope instability through land conversion, erosion, and poorly managed drainage [4][6][10][11]. Areas with slopes steeper than 30%, combined with heavy rainfall and agricultural use, are particularly vulnerable to landslides [12][13]. In 2022, the Karanganyar Local Disaster Agency (BPBD) recorded 210 landslide events on the western slope, concentrated in high-risk zones with steep terrain and intensive human activity [14][15]. Some of the landslide occurrences documented during field surveys are shown in Figure 1.

Publisher's Note:

Pandawa Institute stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright:

© 2026 by the author(s).

Licensee Pandawa Institute, Metro, Indonesia. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).



Figure 1. Landslide occurrences in the western slope of mount Lawu.

Based on data from Indonesia's Statistical Center Agency, land use changes in Karanganyar Regency in 2013 and 2022 were significant. Land change from 2013 to 2022 is dominated by the type of residential land use, with as much as 11,946 ha [16]. While the use of rice fields, water bodies, and vegetation experienced a reduction in area. Spatially, land use changes occurred in all sub-districts. The sub-districts with the highest land use change are Jatiyoso sub-district with an area of 7,536 ha, Tawangmangu sub-district with 6,235 ha, and Gondangrejo sub-district with 6,111 ha [17]. The area of agricultural land has also shrunk, from 719 ha in 2018 to 55 ha in 2022. On the other hand, dryland has increased, from 6284 ha in 2018 to 6947 ha in 2022 [18].

Despite the frequent landslide occurrences and substantial risks to communities, comprehensive landslide susceptibility mapping specific to the western slope of Mount Lawu remains scarce. Existing research has often been fragmented, focusing on general assessments that may overlook critical environmental and anthropogenic factors contributing to landslides in this region. This gap highlights the need for conducting detailed, region-specific analyses to identify areas most vulnerable. Accurate landslide susceptibility maps are crucial for guiding disaster risk reduction strategies, enhancing land use management, and mitigating the adverse impacts of landslides on both property and human life [19]-[21].

A critical research gap is the limited integration of anthropogenic drivers into susceptibility models, particularly land-use changes driven by agricultural expansion, tourism development, and settlement growth. Risks of landslides on settlements are assessed using a combination of statistical and spatial approaches. These models primarily focus on physical parameters (slope, lithology, soil type, and rainfall) and vulnerability assessment, with relatively limited attention to the dynamic role of land-use change and spatial planning [22]. Previous studies rely on medium-scale maps (1:100,000 or broader), which often generalize local geomorphological and geological conditions. This limits the accuracy of susceptibility and risk models, especially in heterogeneous volcanic regions such as Karanganyar. Higher-resolution datasets and detailed scale maps (e.g., 1:50,000 or better) are needed to capture localized topography, geological, and fragmented land-use patterns that critically influence landslide occurrence.

There is a gap in evaluating the integration of susceptibility models with spatial and land-use planning frameworks. Although existing studies have produced susceptibility and risk maps, limited effort has been made to explicitly connect these outputs with the development of land use and their evaluation. This creates a mismatch between scientific evidence and policy application, reducing the effectiveness of disaster risk reduction strategies. Therefore, this research aims to utilize

higher-resolution datasets to enhance the detail and accuracy of landslide susceptibility maps, and to link the findings with spatial planning evaluations, particularly in identifying settlement areas and agricultural expansion zones that overlap with moderate- to high-risk classes. Investigation of landslide potential can be done through various methods. There are three main categories of landslide hazard mapping methods, namely heuristic methods, statistical methods, and deterministic approaches. Statistical method is considered the most feasible [23]-[25] because the heuristic method relies on expert knowledge in preparing landslide hazard maps, which inherently has limitations due to subjectivity. In comparison, the deterministic approach requires detailed geotechnical and hydrological data. Statistical methods are ensured to have low subjectivity and are easier to apply to an area with unique regional characteristics [26].

Statistical methods such as the weight of evidence (WoE) method are widely used for landslide hazard mapping [27][28]. The WoE method is based on information from the relationship between parameters and event data so that areas with potential landslides can be predicted [25]. It has been applied to landslide susceptibility

mapping in various parts of the world with high accuracy [19]. WoE is the most used weighting for landslide susceptibility mapping because it is simple, easy to use, and not time-consuming [29]. The WoE results determine whether a variable increases or decreases the likelihood of a landslide. A positive WoE indicates variables favoring the event, while a negative WoE indicates variables that may reduce it. WoE is inseparable from logistic regression models, where WoE variables are often the main predictors in building accurate models to forecast landslide susceptibility [30][31].

Several other methods have been applied in volcanic and mountainous regions of Indonesia to assess landslide susceptibility. Earlier study on the slopes of Mount Lawu employed the analytic hierarchy process (AHP) method in combination with weighted overlay analysis to delineate risk zones, highlighting the roles of land use and slope steepness in triggering landslides [7][14][21]. Several volcano-related case studies in Indonesia and abroad have explored diverse statistical approaches, such as the frequency ratio, logistic regression, statistical index, and index of entropy, to compare predictive performances and reduce subjectivity [20][23]-[25]. Applications of WoE in tropical volcanic environments remain scarce, as

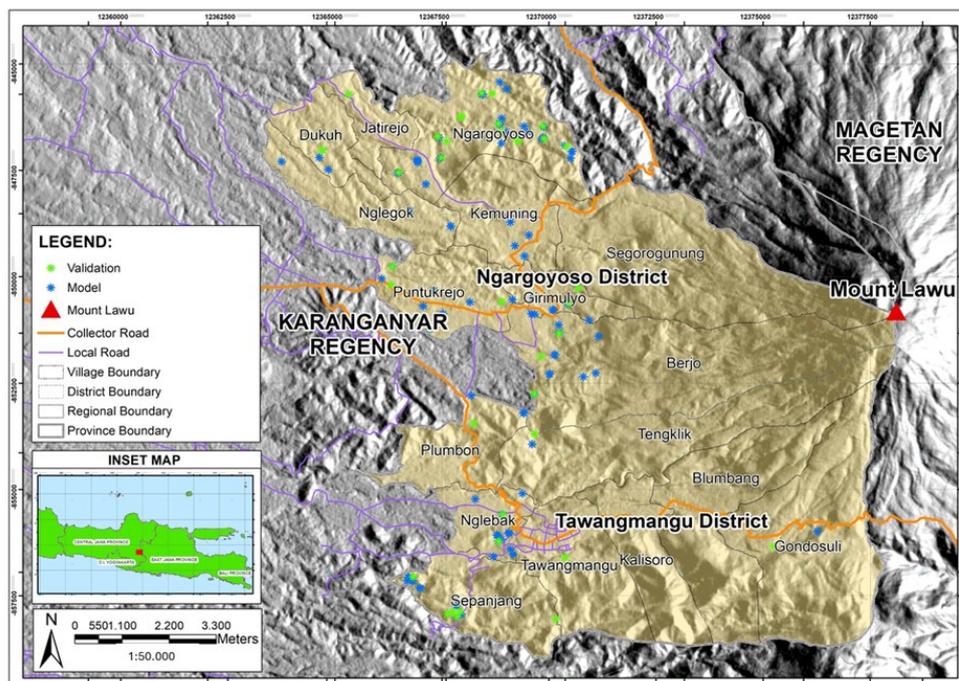


Figure 2. Landslide points location, green dots represent points for validation, blue dots represent points for the model.

most existing works still focus on sedimentary or tectonically stable regions [16][25]. Recent research combined WoE and logistic regression to strengthen predictive capability in highly landslide-prone volcanic terrains [26]. However, volcanic regions such as Mount Lawu present unique challenges due to their steep slopes, unconsolidated pyroclastic lithology, and high levels of human pressure on the landscape [19][25]-[31]. Therefore, this research contributes to the existing body of knowledge by demonstrating the adaptability of WoE in volcanic environments and addressing a significant gap in the literature on landslide susceptibility modeling.

The application of WoE also plays an important role in decision-making. Variables with high WoE can be the focus of landslide susceptibility prevention or mitigation efforts. By incorporating WoE in vulnerability evaluations, research can identify and prioritize the most significant factors. In addition, WoE can be used in multivariate analyses, allowing researchers to evaluate combinations of variables that have a synergistic or complementary influence on landslide susceptibility. Thus, proper understanding and application of WoE can improve the accuracy of landslide vulnerability analyses [32].

The WoE method for landslide susceptibility mapping presents a very important framework through which the impacts of one of the most common natural disasters – landslides – can be preliminarily forecast and possibly mitigated. Therefore, it brings the question "Can WoE be applied in volcanoes, especially in Mount Lawu, Central Java, Indonesia?". Previous studies have demonstrated the applicability of the Weight of Evidence (WoE) method for landslide and hazard risk assessment in various geomorphological settings [33]-[36]. However, its application in volcanic environments remains relatively limited. Building upon these existing studies, the results of this research are expected to contribute to the refinement of a more comprehensive and adaptable WoE-based framework for risk assessment across different environmental contexts, including volcanic regions. In addition, earlier research has emphasized the importance of understanding local communities' perceptions of volcanic hazards in supporting effective risk mitigation and management strategies [37][38]. Consistent with these findings, this study

provides further insights that may support the development of more context-specific and socially informed risk reduction approaches.

2. MATERIALS AND METHODS

2.1. Study Area

The research location, located in the western slope of Mount Lawu, encompasses a range of elevations, from relatively low-lying areas to higher mountainous terrain, with a total area of 118.61 km². The landscape is characterized by lush forests, fertile valleys, and cascading rivers, contributing to its scenic beauty and ecological significance. The research location also intersects with several rivers and streams, which contribute to its diverse and dynamic geomorphology. The study area features diverse landforms formed by volcanic processes. The volcanic activity in the area has led to the formation of volcanic cones, lava flows, and ash deposits, which contribute to the region's rugged terrain.

The study area is also situated within the Sunda Arc, a tectonically active region characterized by subduction-related volcanism. The area is underlain by a complex assemblage of volcanic rocks, including basalts, andesites, and dacites, which are associated with the activity of Mount Lawu and other nearby volcanic centers. These volcanic rocks are often overlain by layers of volcanic ash, tuff, and pyroclastic deposits, reflecting the region's volcanic history. The interplay of volcanic and fluvial processes has shaped the landscape over millions of years, creating a unique and complex terrain that offers valuable insights into the Earth's geological history and processes. In general, the geological structure is dominated by faults and straight lines from west to east and northwest to southeast, caused by the tectonic forces of Java Island [39].

2.2. Data Collection

The secondary data used include the National Digital Elevation Modelling (DEMNAS), topography map (*Rupa Bumi Indonesia*), and the Geological Map. Spatial data for all factors causing landslide (slope, alignment, lithology, distance from road, distance from river, land use, and lineaments) were prepared in raster format and processed with

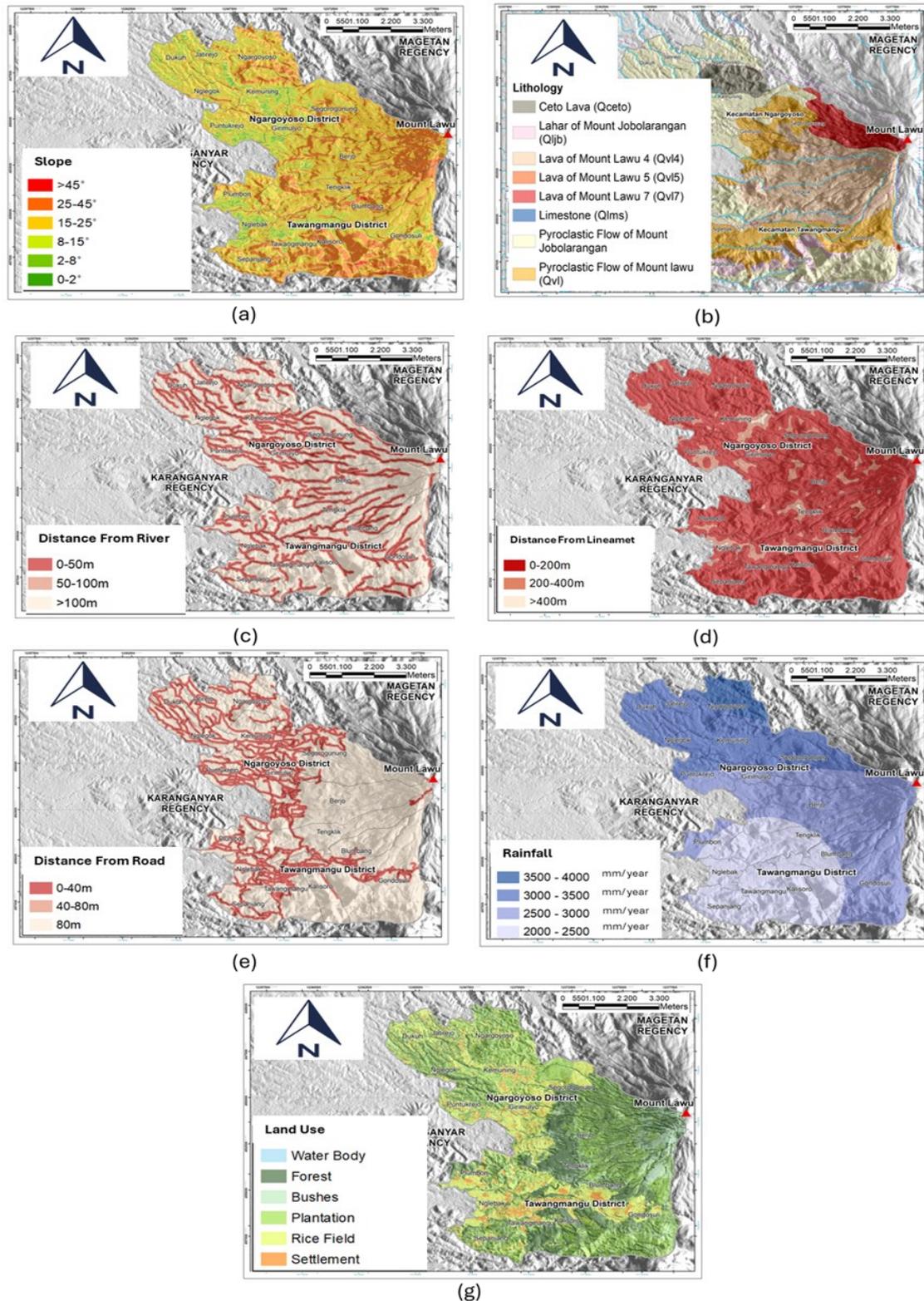


Figure 3. Parameters of the landslide susceptibility map, i.e., (a) slope, (b) lithology, (c) distance from river, (d) distance from lineaments, (e) distance from road, (f) rainfall, and (g) land use.

the UTM Zone 49S projection system, with the same pixel size. Data processing was conducted in ArcGIS Pro licensed by Universitas Gadjah Mada, Indonesia.

Topographic parameters such as slope, rivers, and lineaments are extracted from the digital elevation model (DEM) with a scale of 1:16,000 from Indonesia's Geospatial Information Agency.

Table 1. Weight of evidence calculation.

Factors	Class	C
Lithology	Pyroclastic Flow of Mount Jobolarangan	0.39
	Pyroclastic Flow of Mount Lawu	0.81
	Limestone	3.50
	Lahar of Mount Jobolarangan	-0.21
	Ceto Lava	-0.26
	Lava of Mount Lawu 4	-1.88
	Lava of Mount Lawu 5	-14.37
	Lava of Mount Lawu 7	-18.11
Distance from road (m)	>80	-2.03
	40–80	0.67
	0–40	1.68
Distance from lineaments (m)	>400	1.07
	200–400	-0.39
	0–200	0.28
	2,000–2,500	-0.05
Rainfall (mm/year)	2,500-3,000	-0.42
	3,000-3,500	-0.24
	3,500-4,000	1.69
	0–2°	0.71
Slope	2–8°	0.58
	8–15°	0.52
	15–25°	0.07
	25–45°	-1.10
	>45°	-0.99
Distance from the river (m)	>100 m	0.23
	50–100 m	-0.09
Land use	0–50	-0.25
	Forest	-0.73
	Shrubland/ Dryland Farming	-0.57
	Plantation	-1.14
	Rice Field	1.52
	Settlement	0.37

Lithology is developed based on previous research, utilizing a scale of 1:50,000 and field verification. Field validation was conducted by collecting representative rock samples, which provided additional support for the lithological classification. Land use parameters are taken from data from the Karanganyar Regency Public Works and Spatial Planning Office with a scale of 1: 25,000, and

verified with an identification from Google images. To address the variability in dataset scales, all inputs were adjusted, and the final map was set at a scale 1 of 50,000. In detail, the parameters used in this study have the following class divisions.

2.2.1. Slope

Slope degrees represent the angle of inclination

of a slope relative to the horizontal plane to provide a standardized and easily interpretable way to quantify the steepness of terrain [40][41]. The slope map was generated from DEMNAS (DEM scale 1:16,000) using ArcGIS Pro. To enhance geomorphological interpretation, a hillshade derived from the DEM was overlaid to provide a clearer visualization of terrain morphology. The DEM raster was first projected into UTM Zone 49S and clipped to the study boundary. The slope tool (spatial analyst > surface > slope) was then applied to calculate slope values in degrees. The slope class is divided into 6 slope classes, namely 0–3°, 3–5°, 5–8.5°, 8.5–24°, 24–45°, >45° [40][42].

2.2.2. Lithology

Lithology data were obtained from a previous geological map [43]–[49], conducted at a scale of 1:50,000, and verified through field checking. The map was georeferenced, digitized, and polygonized in ArcGIS Pro. Field validation was also conducted by recording rock types and structures with GPS points, and adjustments were made to polygon boundaries accordingly.

2.2.3. Distance from Rivers

River networks were delineated from the DEM using the hydrology toolset (spatial analyst >

hydrology > flow accumulation and stream definition). The resulting river polyline shapefile was buffered at 0–50, 50–100, and >100 m using the Buffer tool [50].

2.2.4. Lineaments

Lineament features that are assumed to represent structural weaknesses in the rock mass. These features can facilitate processes such as weathering and groundwater infiltration, ultimately increasing the likelihood of slope failure [50]. Lineaments were digitized from DEM-derived hillshade and geological maps, then converted into vector polylines. The Buffer tool (analysis > proximity > buffer) was applied with distances of 0–200, 200–400, and >400 m to represent zones of structural influence, assuming that the closer to the lineament, the rock/soil will disintegrate and be more weathered [50][51].

2.2.5. Distance from Road

Road data were obtained from Indonesia's Geospatial Information Agency, then digitized and projected into UTM Zone 49S. Buffer zones were generated in ArcGIS Pro using the Buffer tool at distances of 0–40, 40–80, and >80 m. The classification reflects the assumption that slopes closer to roads experience greater disturbance from

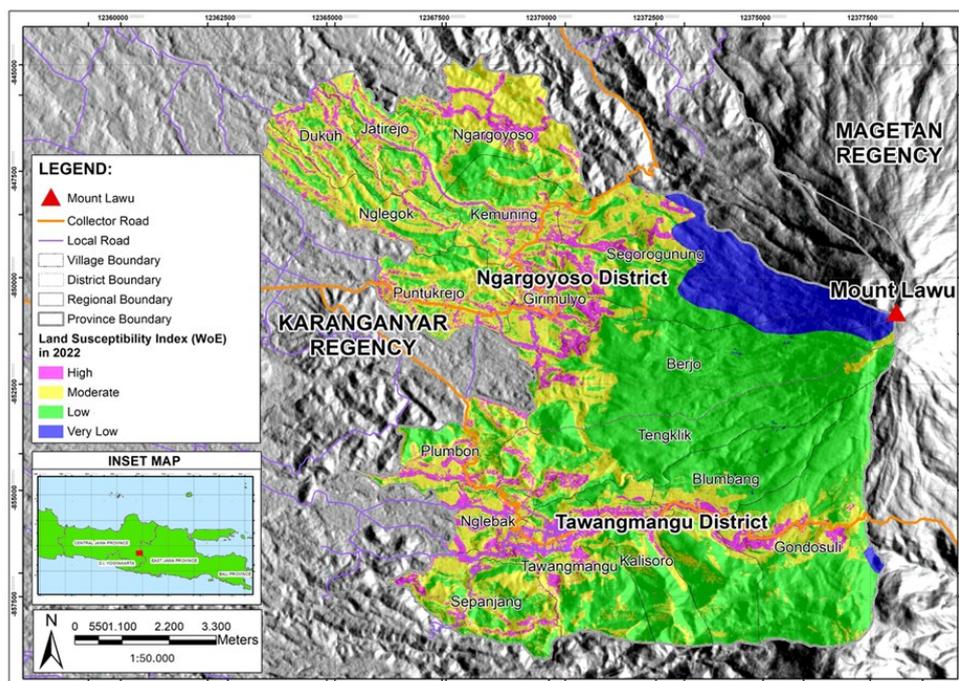


Figure 4. Landslide susceptibility (LS) map.

cut-and-fill construction, drainage alteration, and vibration [50].

2.2.6. Rainfall

The classification of rainfall in this study is based on the interpolation of 2022 rainfall data collected from the Meteorology, Climatology, and Geophysics Agency (BMKG) weather stations in Karanganyar Regency. Rainfall data from meteorological stations were compiled in Excel with latitude and longitude coordinates. The table was imported into ArcGIS Pro and converted into a point shapefile (XY table to point). Rainfall values were interpolated using the inverse distance weighting (IDW) tool (spatial analyst > interpolation > IDW). The interpolation raster was clipped to the study area and reclassified. The classification class of rainfall refers to the weather station data around the study area, namely, with 2,000–2,500, 2,500–3,000, 3,000–3,500, and 3,500–4,000 mm/year.

2.2.7. Land Use

Sentinel-2 imagery was preprocessed in Google Earth Engine (GEE), including atmospheric correction and image clipping to the study boundary from the images in 2022. The classified land use raster was exported into ArcGIS Pro. The raster was resampled and reclassified into five categories: forest, shrubland/dryland farming, plantation, rice field, and settlement. Accuracy assessment was conducted using random stratified sampling and confusion matrix calculation, confirming an overall accuracy of 96%. The land use classification class refers to the classification made from the data source of the Karanganyar Regency Public Works and Spatial Planning Office.

The landslide data was collected from the Local Disaster Management Agency of Karanganyar and field observation. There are 210 landslide data points in 2022, as shown in Figure 2. This data was used to evaluate the accuracy and predictive performance of the landslide susceptibility model. The landslide inventory dataset was randomly partitioned using the ArcGIS Geostatistical Analyst “Subset Features” tool, which allows for stratified random selection of spatial point features. In this process, 70% of the landslide points were allocated for model training, while the remaining 30% were

set aside for validation. This ratio (70:30) follows common practice in landslide susceptibility studies [52][53].

2.3. Analysis Method

The analysis method used is WoE. The WoE method is a statistical model that calculates the weight of predictive factors (trigger factors) based on the presence or absence of landslides in the study area, assuming that the factors allegedly triggering landslides are unrelated. This model requires spatial data on landslide occurrence points and triggering factors [26][54]. The WoE compares the distribution of existing landslide occurrence points with various landslide-triggering factors. The model is applied to evaluate the relationship between each variable predicted to be a landslide trigger factor and landslide occurrence, using both prior (unconditional) and posterior (conditional) probabilities. Prior probability is the probability of an event derived from the same event in the past within a period [19][54].

The probability of change due to additional information is called posterior probability. The conditional probability of landslide existence considering additional factors can be formulated as shown in Equation (1) [55].

$$W_{ji}^+ = \ln \left(\frac{P\{F_{ji}|L\}}{P\{F_{ji}|\bar{L}\}} \right) = \frac{P\{F_{ji} \cap L\}}{P\{L\}} \frac{P\{\bar{L}\}}{P\{F_{ji} \cap \bar{L}\}} \quad (1)$$

Meanwhile, the conditional probability of a landslide without a factor can be formulated as shown in Equation (2) [56].

$$W_{ji}^- = \ln \left(\frac{P\{\bar{F}_{ji}|L\}}{P\{\bar{F}_{ji}|\bar{L}\}} \right) = \frac{P\{\bar{F}_{ji} \cap L\}}{P\{L\}} \frac{P\{\bar{L}\}}{P\{\bar{F}_{ji} \cap \bar{L}\}} \quad (2)$$

where P : Probability, F_{ji} : the presence of factor j of class i , \bar{F}_{ji} : absence of factor j of class i , \bar{L} : no landslide, L : the presence of landslide, W_{ji}^+ : likelihood ratio stating that the ratio in the case of presence, of factor F_{ji} then a landslide L occurs or does not occur, and W_{ji}^- : likelihood ratio stating that the ratio in the case of absence of factor F_{ji} then a landslide L occurs or does not occur. Correlation measurements can also be measured by contrasting

weights, as shown in Equation (3) [55].

$$W_{contrast\ ji} = W_{ji}^+ - W_{ji}^- \quad (3)$$

The number of pixels for each parameter class is calculated using those equations. The number of pixels in each class can be defined in Equations (4) – (7) [57].

$$N_{pix1} = N_{slclass} \quad (4)$$

$$N_{pix2} = N_{slide} - N_{slclass} \quad (5)$$

$$N_{pix3} = N_{class} - N_{slclass} \quad (6)$$

$$N_{pix4} = N_{map} - N_{slide} - N_{class} + n_{slclass} \quad (7)$$

where: N_{slide} = the Number of pixels with a landslide in the map, N_{class} = the Number of pixels in the class, $N_{slclass}$ = the Number of pixels with a landslide in the class, and N_{map} = the Total number of pixels in the map.

From these results, the contrast weight (C) value is calculated, where the contrast weight is the difference between the positive and negative weights. The magnitude of this contrast value reflects the overall spatial association between each causal factor class and landslide. A positive contrast value indicates a positive spatial association, while a negative value indicates a negative spatial association. The formula is shown in Equations (8) and (9) [19].

$$C = W_{ji}^+ - W_{ji}^- \quad (8)$$

$$W_{map} = \sum C \quad (9)$$

$$LSI = \sum W_{map} \quad (10)$$

The landslide susceptibility (LS) is generated by combining each factor's weighted maps (W_{map}) through a spatial summation process (Equation (10)). The LS values were reclassified by the natural breaks method [19]. This approach was selected because it minimizes variance within classes while maximizing variance between classes, thereby producing categories that better represent the natural distribution of susceptibility values. In contrast, alternative approaches, such as the quartile method, divide the data into equal-sized groups regardless of the underlying distribution, which may oversimplify variations in heterogeneous volcanic terrains, such as Mount Lawu. The use of natural breaks thus ensures that the classification

reflects meaningful thresholds in the data rather than arbitrary intervals. The classification of landslide susceptibility into four categories (very low, low, moderate, high, and very high) according to the Indonesian National Standard of Landslide Susceptibility Zonation (SNI 8291:2024). This classification system provides a standardized framework for assessing the susceptibility of areas to landslides based on various factors.

The area under the curve (AUC) was calculated to evaluate the model's performance. For the success rate curve (SRC), the AUC is determined by plotting the ratio of successful predictions against the total actual data. Mathematically, the AUC can be computed using the trapezoidal method, where the area under the curve is approximated by summing the areas of trapezoids formed between consecutive points, as shown in Equation (11).

$$AUC = \sum_{i=1}^{n-1} \frac{(y_i + y_{i+1})}{2} \cdot (x_{i+1} - x_i) \quad (11)$$

Here, x_i and $x_i + 1$ represent the cumulative proportion of samples, while y_i and $y_i + 1$ are the success rates at each point. For the prediction rate curve (PRC), the AUC is calculated similarly, but the y-axis represents the ratio of correct predictions to all predictions made by the model. The trapezoidal method is applied to integrate the area under the curve, providing a numerical measure of overall model performance [58].

Alongside the WoE analysis, the Information value (IV) method was also applied to provide a comparative statistical perspective. While WoE emphasizes the weight of spatial associations, the IV method offers a straightforward measure of how strongly each factor contributes to landslide occurrence. The IV value for each factor is calculated using conditional and prior probabilities. Conditional probability is obtained by dividing the number of landslide pixels in each subclass by the total pixels of that subclass, while prior probability is derived from the ratio of total landslide pixels to the total pixels of the entire study area. The value for IV calculation can be obtained through Equation (12) as follows [59].

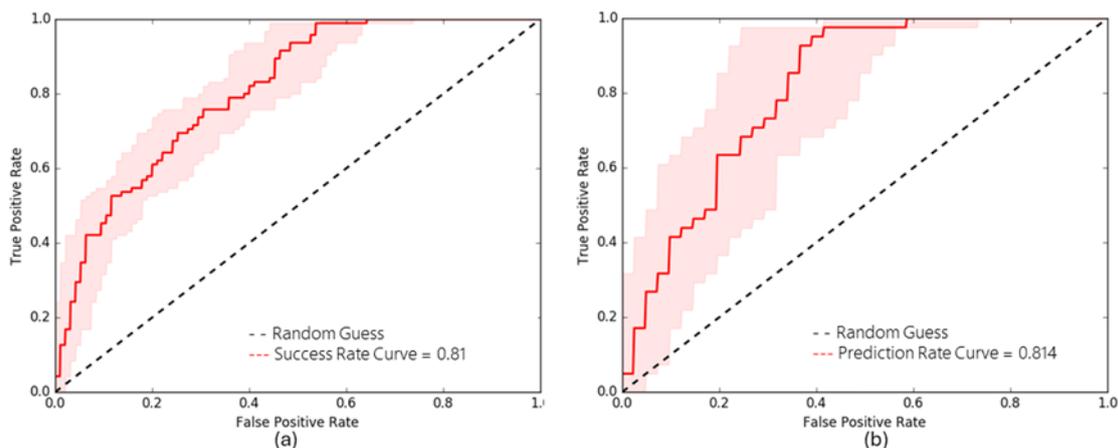


Figure 5. Success rate curve (a) and prediction rate curve (b).

$$IV = \Sigma\{(\% \text{ of non events} - \% \text{ of events})\} \times \text{WoE} \quad (12)$$

An Information Value (IV) of less than 0.02 is categorized as unpredictable. If the IV falls within the range of 0.02 to 0.10, its predictive power is considered weak. An IV between 0.1 and 0.3 indicates a medium predictive strength, while an IV greater than 0.3 reflects strong predictive power [60].

3. RESULTS AND DISCUSSIONS

Slope is a critical factor influencing landslide occurrence, and the western slope of Mount Lawu is predominantly characterized by steep gradients ranging from 24–45° to >45°. These steep slopes are particularly susceptible to various types of landslides due to the instability caused by the weight of overlying soil and material. Slopes within the 24–45° range experience increased pressure and shearing potential, while slopes >45° are subject to even higher instability due to the significant load exerted at the base of the slope. These conditions are further exacerbated by groundwater flow, where infiltrating water reduces shear strength, alters soil properties, and increases landslide risks, particularly during intense rainfall. The slope parameter map (Figure 3(a)) highlights the distribution of these steep gradients across the study area. The study area is dominated by diverse volcanic lithologies associated with Mount Lawu's eruptive history [43]–[49]. The lithology in the study area consists of Pyroclastic Flow of Mount Jobolarangan (Qvpfj), Pyroclastic Flow of Mount

Lawu (Qvl), Limestone (Qlms), Lahar of Mount Jobolarangan (Qljb), Ceto Lava (Qceto), Lava of Mount Lawu 4 (Qvl4), Lava of Mount Lawu 5 (Qvl5), Lava of Mount Lawu 7 (Qvl7), as shown in Figure 3(b).

Rivers intersecting the western slope also play a significant role in landslide occurrence. Rapid water flow can erode riverbanks, destabilize adjacent slopes, and increase the likelihood of landslides. Proximity to rivers affects groundwater levels, with rising groundwater saturation decreasing slope stability. Rivers that flow through or near steep slopes create conditions conducive to slope failure due to erosion and changes in hydrological patterns (Figure 3(c)). Lineaments further influence landslide susceptibility on the western slope of Mount Lawu. These features act as zones of structural weakness, intersecting slopes and reducing their stability. Lineaments also serve as pathways for groundwater flow, concentrating stress and altering the mechanical properties of soil and rock. When these structural features intersect volcanic formations such as pyroclastic deposits or weathered volcanic rocks, they create areas of heightened landslide risk, particularly during heavy rainfall or seismic activity (Figure 3(d)). Road networks constructed on the western slopes also contribute to landslide susceptibility. Roads built in steep areas can disrupt slope stability, especially when poorly designed drainage systems allow rainwater to seep into the surrounding soil, increasing moisture and reducing soil strength. Additionally, frequent traffic, particularly from heavy vehicles, can compact soil and alter its

physical properties, further heightening the risk of landslides. The mountainous terrain of Mount Lawu's western slope limits road network expansion, leaving many areas with slopes $>45^\circ$ and $24\text{--}45^\circ$ more prone to landslide hazards (Figure 3(e)).

Rainfall is another significant factor influencing landslides on the western slope of Mount Lawu. With annual rainfall ranging from 2,000 to 4,000 mm/year, the area experiences frequent high-intensity rainfall events that can saturate slopes and increase pore water pressure, reducing soil strength. Prolonged rainfall weakens slope materials over time, amplifying landslide risks (Figure 3(f)). The land use map of Ngargoyoso and Tawangmangu districts in Karanganyar Regency illustrates the spatial distribution of major land use types (Figure 3(g)). Forest areas dominate the eastern and southeastern parts of the region, particularly around Berjo, Tengklik, and Blumbang villages, reflecting the steep mountainous terrain. Plantations are widely distributed across mid-slope zones such as Kemuning, Puntukrejo, and Plumbon, where agricultural activities are intensive. Bushes and mixed vegetation are scattered across transitional landscapes between forested and cultivated areas. Rice fields are concentrated in relatively flat valley bottoms and lower slopes, particularly in Dukuh, Jatirejo, and Nglegok villages. Settlements appear as dense clusters, especially in Tawangmangu, Kalisoro, Gondosuli, and parts of Ngargoyoso villages, where human activities are most concentrated.

The WoE analysis provides insights into how various environmental factors, and their specific classes, contribute to landslide susceptibility in the vicinity of Mount Lawu. The inventory data were

carefully georeferenced to ensure spatial accuracy, with each landslide polygon delineated based on scarp boundaries and depositional areas. The WoE analysis reveals contrast (C) values that correspond to diverse susceptibility levels associated with predictor variables, which can be used to understand their impact on landslide hazard. The results of the C-value calculation were used in the creation of the landslide susceptibility map, as shown in Table 1.

The results indicate that three parameters exert the strongest influence on landslide susceptibility. Lithology emerges as the most decisive factor, with limestone showing the highest positive contrast ($C = 3.50$) due to its fractured and highly weathered structure, while massive lava flows of Mount Lawu ($C = -14.37$ to -18.11) provide strong natural resistance. Land use also plays a critical role, where rice fields ($C = 1.52$) markedly increased risk through soil saturation, whereas forests and plantations show stabilizing effects ($C = -0.73$ to -1.14). Rainfall exerts a decisive role, with areas receiving 3500–4000 mm/year showing a high positive association ($C = 1.69$), confirming that extreme precipitation is a critical trigger of slope failure in the study area. Interestingly, gentle to moderate slopes ($0\text{--}15^\circ$) show higher positive contrast values ($C = 0.52\text{--}0.71$), while steeper slopes ($>25^\circ$) exhibit negative associations. This contrast can be explained by the accumulation of thick weathered soil and colluvium on gentler slopes, which become highly unstable when saturated by rainfall. In contrast, very steep slopes are often dominated by thin soil cover or exposed bedrock, reducing the likelihood of shallow landslides despite stronger gravitational forces.

The LS map generated from the WoE analysis integrates these weighted factors, producing a zonation of susceptibility classes ranging from very low to high, as presented in Figure 4. High susceptibility zones are concentrated in the eastern part of Ngargoyoso and Tawangmangu districts, particularly around Segorogunung, Girimulyo, and parts of Tawangmangu villages. These areas are characterized by steep slopes, dense settlement patterns, and intensive land use, which amplify slope instability. Moderate susceptibility zones are distributed across mid-slope areas such as Kemuning, Plumbon, and Kalisoro villages, where

Table 2. Information value (IV) result.

Factors	IV
Lithology	1.63
Distance to road	0.98
Land use	0.59
Rainfall	0.26
Slope	0.20
Distance to lineament	0.02
Distance to river	0.01

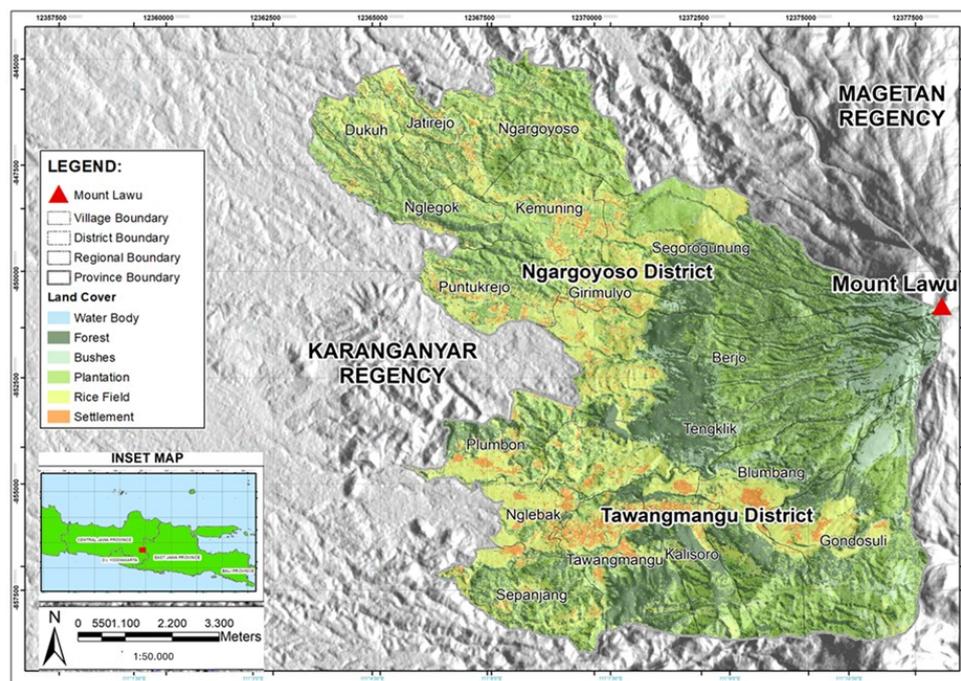


Figure 6. Land use map.

terrain gradients remain significant but slightly more stable. Low susceptibility zones dominate broader hilly landscapes, including Berjo, Tengklík, and Blumbang villages, where slope inclination is moderate and geomorphological conditions reduce the likelihood of landslides. Very low susceptibility areas are mainly found in flatter terrain and valley bottoms, such as Puntukrejo, Nglegok, and Dukuh villages, where geomorphological controls on slope failure are minimal.

The two receiver operating characteristic (ROC) curves (Figure 5) show the model's updated performance metrics. Figure 5(a) shows the success rate curve with an AUC value of 0.81, while Figure 5(b) shows the prediction rate curve with an AUC value of 0.814. These values are classified as a good model of landslide susceptibility map performance and reliability in distinguishing between landslide-prone and non-prone areas [26][29][34][36]. These results are consistent with other WoE-based susceptibility models, such as Ethiopia (AUC = 0.79) and Vietnam (AUC = 0.83) [16][17], situating our model within a reliable performance range. However, while the AUC values confirm the robustness of the model, they also highlight an inherent limitation: ROC analysis primarily measures the model's ability to discriminate between landslide and non-landslide areas, but does

not fully capture spatial prediction errors or the balance between omission and commission errors. This suggests that although the model achieves comparably high discrimination power, further validation using field-based inventories and alternative statistical indices (e.g., precision, recall, or Kappa coefficient) would provide a more comprehensive assessment of its predictive reliability. The slightly improved AUC value for the prediction rate suggests that the model has benefited from calibration or additional refinements.

The IV can explain the high predictive performance. The IV results confirm lithology as the dominant controlling factor, followed by distance to roads (IV = 0.98) and land use (IV = 0.59). Rainfall (IV = 0.26) and slope (IV = 0.20) contribute moderately, while distance to lineaments and rivers show only minor influence, as shown in Table 2. This indicates that geological conditions, infrastructure development, and land use are the primary drivers of landslide susceptibility in the study area.

The comparison between the landslide susceptibility map (Figure 4) and the land use map (Figure 6) underscores the role of vegetation and land management in slope stability. High susceptibility areas (red zones) overlap extensively

with settlements, plantations, and rice fields, highlighting the contribution of land conversion and cultivation on steep slopes to slope instability. In contrast, areas dominated by natural forests, particularly on the upper slopes of Mount Lawu and eastern Ngargoyoso, generally correspond to low or very low susceptibility. Forest cover provides critical protection by stabilizing soil and reducing runoff, while fragmented forest patches near settlements and road networks exhibit localized increases in susceptibility, reflecting the influence of anthropogenic disturbance.

The observed spatial correspondence between high-susceptibility zones and areas of intensive land use in Mount Lawu is consistent with previous studies that emphasized the effectiveness of statistical models in capturing the role of geomorphological and anthropogenic factors in slope instability [61][62]. The cross-tabulation of land use with landslide susceptibility classes (Table 3) shows strong spatial patterns. In the high

susceptibility zone, rice fields dominate (1,039.84 ha, $\approx 80\%$), followed by settlements ($\approx 14\%$), underscoring the vulnerability of irrigated agriculture and built-up areas on steep slopes. In the moderate class, rice fields (34%), forests (27%), and plantations (25%) share almost equal proportions, with settlements (312 ha) and shrubs (319 ha) reflecting additional exposure. The low susceptibility zone is the most extensive, dominated by forests (41%) and plantations (40%), highlighting their stabilizing role, though shrubs (778 ha) remain less stable. The very low susceptibility class ($\approx 3\%$ of the total area) is mainly forest (37%) and plantations (22%), reinforcing the protective effect of natural and managed vegetation on gentler slopes.

Settlement areas are predominantly located within zones of moderate and high landslide susceptibility. Out of a total 505.15 ha of settlements, approximately 498.61 ha (98.7%) are situated in these two classes, highlighting the

Table 3. Cross-tabulation of land use with landslide susceptibility classes.

Landslide susceptibility classes	Land use	Area (ha)
High	Forest	22.06
	Plantation	18.56
	Settlement	186.97
	Rice-Field	1,039.84
	Bushes	4.79
Moderate	Forest	1,148.37
	Plantation	1,065.72
	Settlement	311.64
	Rice-Field	1,445.02
	Bushes	318.84
Low	Forest	2,389.45
	Plantation	2,296.20
	Settlement	4.63
	Rice-Field	104.30
	Bushes	777.63
Very Low	Forest	346.88
	Plantation	202.28
	Settlement	1.91
	Rice-Field	43.32
	Bushes	120.00
Grand Total		11,849.43

considerable exposure of human habitation to landslide hazards. Specifically, 186.97 ha (37% of the total settlement area) fall within the high-susceptibility zone. Within this class, settlements occupy 14.7% of the total high-risk area (1272.22 ha), underscoring the concentration of population centers in terrain highly prone to slope instability. The results confirm that rice fields and settlements are disproportionately concentrated in high susceptibility zones, while forests and plantations dominate low and very low categories. This contrast highlights the substantial impact of anthropogenic land use on slope instability, underscoring the importance of land management strategies that limit agricultural expansion and settlement development on steep terrain.

It is important to compare the WoE approach with other commonly used methods in landslide susceptibility mapping to contextualize the performance of the model. Although various statistical and machine learning approaches, such as logistic regression, random forest (RF), and support vector machine (SVM), have been widely applied in landslide susceptibility mapping, this study employed the WoE method due to its transparency, ability to manage categorical predictors, and proven applicability in data-limited contexts. While ML-based models may achieve higher predictive accuracy, they often require larger, more homogeneous datasets and involve complex parameter tuning. In contrast, WoE provides straightforward interpretability of factor contributions and performs reliably in volcanic tropical regions characterized by heterogeneous geospatial data, thereby offering practical advantages for local-scale disaster management. Compared with machine learning approaches such as RF or SVM, which often achieve higher predictive accuracy, WoE provides greater interpretability and lower data requirements, making it more suitable for volcanic tropical regions characterized by heterogeneous datasets.

Furthermore, landslide occurrence in the Mount Lawu area is not solely governed by a single factor, but is influenced by multiple factors, both controlling and triggering. For instance, the steepest slopes on the volcanic edifice are predominantly underlain by compact lava and massive volcanic rock, which impart relative stability and account for

fewer landslide events. Conversely, mid- and lower slopes, where thick weathered deposits coincide with intensive agricultural and settlement activities, show higher susceptibility. This emphasizes the necessity of adopting a multi-parameter approach to better capture the interplay between geological and human factors. This predictive capability is essential for creating effective landslide susceptibility maps, which are crucial tools for disaster risk management and land-use planning. The model's ability to approach perfection in classification ensures that it can be confidently used to prioritize areas for landslide mitigation measures, infrastructure development, and community safety planning.

Despite the satisfactory performance of the WoE model in predicting landslide susceptibility, several limitations need to be acknowledged. First, the variability in data resolution may affect the accuracy of spatial relationships, particularly when integrating datasets of different scales, such as a DEM (1:16,000) and a lithology map (1:50,000). Second, the WoE approach assumes conditional independence among causative factors, whereas in reality, interactions such as between slope, lithology, and rainfall may introduce correlations that influence the weight calculation. Third, the completeness of the landslide inventory remains a potential source of bias, as unrecorded events could lead to underestimation or overestimation of susceptibility in certain areas. To address these limitations, future studies should consider employing higher-resolution DEM data, refining thematic maps, and constructing multi-temporal landslide inventories that better capture the dynamic nature of slope failures. Such improvements would enhance the reliability and policy relevance of susceptibility maps for disaster risk reduction in mountainous regions.

4. CONCLUSIONS

High-risk zones are concentrated in the northern part of Ngargoyoso District, particularly Segorogunung, Berjo, and Girimulyo villages, and in the western-southern areas of Tawangmangu District, including Tengklik, Blumbang, and Gondosuli villages. These locations are underlain mainly by pyroclastic deposits and lahar units of

Mount Lawu, which are unconsolidated and highly weathered, and in addition, land use dominated by rice fields and settlements, which intensify susceptibility due to slope modification, soil saturation, and construction pressures. By contrast, more stable areas with extensive forest and plantation cover are predominantly found in the low and very low susceptibility classes. The model achieved an AUC of 0.81, indicating strong predictive accuracy and confirming that the landslide susceptibility map reliably captures both geomorphological, geological, hydrological, and anthropogenic factors that influence landslide occurrence in the study area. WoE-based landslide susceptibility maps inform zoning regulations by restricting settlements in high susceptibility areas and support infrastructure planning and development. Importantly, integrating these susceptibility maps into local disaster risk reduction and spatial planning frameworks offers a practical strategy to mitigate future landslide risks in Mount Lawu. Analysis of land use in the study area shows that high-susceptibility areas are often settled or cultivated, indicating a mismatch between current land use and landslide risk. This highlights the need for risk-informed spatial planning, in which settlement already aligns with very low to low susceptibility zones, current practices are appropriate. However, when the settlement area is located in a moderate to high susceptibility zone, mitigation measures such as restricting development, improving slope stabilization, reforestation, and community empowerment are recommended.

AUTHOR INFORMATION

Corresponding Author

Wahyu Wilopo — Department of Geological Engineering, Universitas Gadjah Mada, Yogyakarta-55281 (Indonesia);
orcid.org/0000-0001-6059-6318

 Email: wilopo_w@ugm.ac.id

Authors

Dimas Hastama Nugraha — Department of Geological Engineering, Universitas Gadjah Mada, Yogyakarta-55281 (Indonesia);
orcid.org/0009-0007-5076-1771

 **Teuku Faisal Fathani** — Department of Civil and Environmental Engineering, Universitas Gadjah Mada, Yogyakarta-55281 (Indonesia);
orcid.org/0000-0001-5114-7879



Author Contributions

Conceptualization, Methodology, Data Curation, and Writing – Original Draft Preparation, D. H. N. and W. W.; Software, Visualization, Formal Analysis, Investigation, Resources, Project Administration, and Funding Acquisition, D. H. N.; Supervision, and Validation, Writing – Review & Editing, W. W. and T. F. F.

Conflicts of Interest

The authors declare no conflict of interest.

ACKNOWLEDGEMENT

The author thanks the Indonesia Endowment Fund for Education Agency (LPDP) for funding the research process and the Universitas Gadjah Mada for the support and assistance. Their contributions have been invaluable in making this study possible.

DECLARATION OF GENERATIVE AI

The authors declare that no generative artificial intelligence (AI) or AI-assisted technologies were used to generate the scientific content, analyze data, interpret results, or draw conclusions in this manuscript. Generative AI tools were only used to assist with language editing and grammatical refinement to improve clarity and readability. All scientific interpretations, analyses, and conclusions remain the sole responsibility of the authors.

REFERENCES

- [1] F. Isola, S. Lai, F. Leone, and C. Zoppi. (2023). "Land Take and Landslide Hazard: Spatial Assessment and Policy Implications from a Study Concerning Sardinia". *Land*. **12** (2): 359. [10.3390/land12020359](https://doi.org/10.3390/land12020359).
- [2] N. Astawa and W. Luga. (2016). "Underwater Geology of the Seabed Based on the Interpretation of Shallow Reflective Seismic Records of Single Channels in the Waters of the Sunda Strait". *Jurnal Geologi*

- Kelautan*. **12** (2): 103. [10.32693/jgk.12.2.2014.250](https://doi.org/10.32693/jgk.12.2.2014.250).
- [3] K. S. M. Thein, M. Nagai, T. Nakamura, N. Phienweij, and I. Pal. (2023). "Assessment of the Impacts of Urbanization on Landslide Susceptibility in Hakha City, a Mountainous Region of Western Myanmar". *Land*. **12** (5): 1036. [10.3390/land12051036](https://doi.org/10.3390/land12051036).
- [4] D. Giordan, A. Wrzesniak, and P. Allasia. (2019). "The Importance of a Dedicated Monitoring Solution and Communication Strategy for an Effective Management of Complex Active Landslides in Urbanized Areas". *Sustainability*. **11** (4): 946. [10.3390/su11040946](https://doi.org/10.3390/su11040946).
- [5] D. Kubwimana, L. Brahim, P. Nkurunziza, A. Dille, A. Depicker, L. Nahimana, A. Abdleouafi, and O. Dewitte. (2021). "Characteristics and Distribution of Landslides in the Populated Hillslopes of Bujumbura, Burundi". *Geosciences*. **11** (6): 259. [10.3390/geosciences11060259](https://doi.org/10.3390/geosciences11060259).
- [6] K. D. Priyono and W. Budiati. (2023). "Community Capacity Analysis and Coping Strategies in Facing the Volcanic Disaster of Mount Kelud, Modangan Village, Nglegok Subdistrict, Blitar Regency". **2727** (1). [10.1063/5.0141755](https://doi.org/10.1063/5.0141755)
- [7] A. N. Umaterate, R. C. Tarore, and H. H. Karongkong. (2021). "Identification of Landslide Vulnerability Levels in North Kawangkoan District, Minahasa Regency". *Jurnal Spasial*. **8** (1): 126-132.
- [8] K. B. Sim, M. L. Lee, and S. Y. Wong. (2022). "A Review of Landslide Acceptable Risk and Tolerable Risk". *Geoenvironmental Disasters*. **9** (1): 1-17. [10.1186/s40677-022-00201-3](https://doi.org/10.1186/s40677-022-00201-3).
- [9] B. BNPB. (2024). *Indonesia Disaster Risk Index (IRBI) 2024*.
- [10] N. Rendy, H. Suzuki, S. Chiyonobu, T. Sato, D. Syavitri, E. Widiyanto, M. Burhannudinnur, T. E. Putra, and R. Raguwanti. (2021). "Cenozoic Basin History of the Cepu Area Based on Calcareous Nannofossil Biostratigraphy in Eastern Java, Indonesia". *International Journal on Advanced Science, Engineering and Information Technology*. **11** (5): 2071. [10.18517/ijaseit.11.5.14225](https://doi.org/10.18517/ijaseit.11.5.14225).
- [11] Y. Rabby, Y. Li, J. Abedin, and S. Sabrina. (2022). "Impact of Land Use/Land Cover Change on Landslide Susceptibility in Rangamati Municipality of Rangamati District, Bangladesh". *ISPRS International Journal of Geo-Information*. **11** (2): 89. [10.3390/ijgi11020089](https://doi.org/10.3390/ijgi11020089).
- [12] T. König, H. Kux, and A. Corsi. (2022). "Landslide Risk Management Using the Mathematical Model TRIGRS". *Geosciences (Geociências)*. **41** (1): 243-254. [10.5016/geociencias.v41i1.16290](https://doi.org/10.5016/geociencias.v41i1.16290).
- [13] W. Winarti. (2022). "Distribution Patterns and Groundwater Depth on the Slopes of Mount Lawu in the Western Part of Central Java". *National Seminar on Research and Technology Innovation*. 282-291.
- [14] O. Heru and S. Naryanto. (2011). "Analysis of Landslide Disaster Risk in Karanganyar Regency". *Jurnal Penanggulangan Bencana*. **2** (1): 21-32.
- [15] B. BNPB. (2024). *Disaster Report of Karanganyar Regency 2024*.
- [16] B. BPS. (2024). *Karanganyar in Numbers 2024*.
- [17] Z. M. Jannah and T. Taryono. (2024). "Analysis of Land Cover Change in Karanganyar District in 2013 and 2022 Based on Story Maps". **1357** : 012006. [10.1088/1755-1315/1357/1/012006](https://doi.org/10.1088/1755-1315/1357/1/012006)
- [18] R. P. Divanti. (2025). "Analysis of the Conversion of Agricultural Land to Non-Agricultural Land in the Lereng Gunung Lawu Karanganyar Tourism Area (Case Study on Culinary Business)". *Law and Society Review*. **5** (1): 389-417. [10.15294/lsr.v5i1.24678](https://doi.org/10.15294/lsr.v5i1.24678).
- [19] N. Getachew and M. Meten. (2021). "Weights of Evidence Modeling for Landslide Susceptibility Mapping of Kabi-Gebro Locality, Gundomeskel Area, Central Ethiopia". *Geoenvironmental Disasters*. **8** (1): 1-22. [10.1186/s40677-021-00173-4](https://doi.org/10.1186/s40677-021-00173-4).
- [20] H. T. Hang, P. D. Hoa, V. N. Tru, and N. V. Phuong. (2021). "Landslide Susceptibility Mapping along National Highway 6, Hoa Binh Province, Vietnam, Using Frequency

- Ratio Model and GIS". *International Journal of GEOMATE*. **21** (85): 84-90. [10.21660/2021.85.j2222](https://doi.org/10.21660/2021.85.j2222).
- [21] I. W. Diara, R. Suyarto, and M. Saifulloh. (2022). "Spatial Distribution of Landslide Susceptibility in New Road Construction Mengwitani–Singaraja, Bali, Indonesia, Based on Geospatial Data". *International Journal of GEOMATE*. **23** (96): 95-103. [10.21660/2022.96.3320](https://doi.org/10.21660/2022.96.3320).
- [22] K. D. Priyono, Jumadi, A. Saputra, and V. N. Fikriyah. (2020). "Risk Analysis of Landslide Impacts on Settlements in Karanganyar, Central Java, Indonesia". *Geotechnical Engineering, Construction Materials and Environment*. **73** : 128-134. [10.21660/2020.73.34128](https://doi.org/10.21660/2020.73.34128).
- [23] F. Girma, T. K. Raghuvansi, T. Ayenew, and T. Hailemariam. (2015). "Landslide Hazard Zonation in Ada Berga District, Central Ethiopia: A GIS-Based Statistical Approach". *Journal of Geomatics*. **9** (1): 25-38.
- [24] M. Sinčić, S. B. Gazibara, M. Krkač, and S. M. Arbanas. (2022). "Landslide Susceptibility Assessment of the City of Karlovac Using Bivariate Statistical Analysis". *Rudarsko-Geološko-Naftni Zbornik*. **37** (2): 149-170. [10.17794/rgn.2022.2.13](https://doi.org/10.17794/rgn.2022.2.13).
- [25] E. Putriani, Y. M. Wu, C. W. Chen, A. Ismulhadi, and D. I. Fadli. (2023). "Development of Landslide Susceptibility Mapping with a Multivariate Statistical Method Approach in Kepahiang, Indonesia". *Terrestrial, Atmospheric and Oceanic Sciences*. **34** (1): 1-22. [10.3319/TAO.2023.01.20](https://doi.org/10.3319/TAO.2023.01.20).
- [26] S. Kusmajaya, B. Tjahjono, and B. Barus. (2022). "Landslide Hazards in Sukabumi Regency Based on the Weight of Evidence, Logistic Regression, and WoE–LR Combination Methods". *Jurnal Ilmu Tanah dan Lingkungan*. **22** (2): 101-106. [10.29244/jitl.22.2.101-106](https://doi.org/10.29244/jitl.22.2.101-106).
- [27] V. E. Nwazelibé, C. O. Unigwe, and J. C. Egbueri. (2023). "Integration and Comparison of Algorithmic Weight of Evidence and Logistic Regression in Landslide Susceptibility Mapping of the Orumba North Erosion-Prone Region, Nigeria". *Modeling Earth Systems and Environment*. **9** (1): 967-986. [10.1007/s40808-022-01549-6](https://doi.org/10.1007/s40808-022-01549-6).
- [28] L. Bopche and P. P. Rege. (2022). "Landslide Susceptibility Mapping: An Integrated Approach Using Geographic Information Value, Remote Sensing, and Weight of Evidence Method". *Geotechnical and Geological Engineering*. **40** (6): 2935-2947. [10.1007/s10706-022-02070-4](https://doi.org/10.1007/s10706-022-02070-4).
- [29] A. K. Batar and T. Watanabe. (2021). "Landslide Susceptibility Mapping and Assessment Using Geospatial Platforms and Weights of Evidence Method in the Indian Himalayan Region: Recent Developments, Gaps, and Future Directions". *ISPRS International Journal of Geo-Information*. **10** (3): 69. [10.3390/ijgi10030114](https://doi.org/10.3390/ijgi10030114).
- [30] J. Torizin, N. Schübler, and M. Fuchs. (2022). "Landslide Susceptibility Assessment Tools v1.0.0b–Project Manager Suite: A New Modular Toolkit for Landslide Susceptibility Assessment". *Geoscientific Model Development*. **15** : 2791-2812. [10.5194/gmd-15-2791-2022](https://doi.org/10.5194/gmd-15-2791-2022).
- [31] G. Wang, X. Chen, and W. Chen. (2020). "Spatial Prediction of Landslide Susceptibility Based on GIS and Discriminant Functions". *ISPRS International Journal of Geo-Information*. **9** (3): 162. [10.3390/ijgi9030162](https://doi.org/10.3390/ijgi9030162).
- [32] Misbahudin. (2020). "Landslide Susceptibility Analysis in Kabandungan District and Salak Geothermal Field, West Java". *Jurnal Geografi Lingkungan Tropik*. **4** (2): 68-79. [10.7454/jglitrop.v4i2.75](https://doi.org/10.7454/jglitrop.v4i2.75).
- [33] S. More, V. Bampidis, D. Benford, C. Bragard, A. Hernández-Jerez, S. Bennekou, T. I. Halldorsson, K. Koutsoumanis, C. Lambré, H. Naegeli, J. R. Schlatter, V. Silano, S. Saxmose, D. Schrenk, D. Turck, and M. Younes. (2021). "Guidance Document on Scientific Criteria for Grouping Chemicals into Assessment Groups for Human Risk Assessment of Combined Exposure to Multiple Chemicals". *EFSA Journal*. **19** (12): e07033. [10.2903/j.efsa.2021.7033](https://doi.org/10.2903/j.efsa.2021.7033).

- [34] P. Martin, C. Bladier, B. Meek, O. Bruyère, E. Feinblatt, M. Touvier, L. Watier, and D. Makowski. (2018). "Weight of Evidence for Hazard Identification: A Critical Review of the Literature". *Environmental Health Perspectives*. **126** (7): 076001. [10.1289/EHP3067](https://doi.org/10.1289/EHP3067).
- [35] A. Canavez, G. Corrêa, V. Isaac, D. Schuck, and M. Lorencini. (2021). "Integrated Approaches to Testing and Assessment as a Tool for the Hazard Assessment and Risk Characterization of Cosmetic Preservatives". *Journal of Applied Toxicology*. **41** (10): 1687-1699. [10.1002/jat.4156](https://doi.org/10.1002/jat.4156).
- [36] J. Arnot, L. Toose, J. Armitage, M. Embry, A. Sangion, and L. Hughes. (2022). "A Weight of Evidence Approach for Bioaccumulation Assessment". *Integrated Environmental Assessment and Management*. **19** (5): 1235-1253. [10.1002/ieam.4583](https://doi.org/10.1002/ieam.4583).
- [37] J. Barclay, R. Few, M. Armijos, J. Phillips, D. Pyle, A. Hicks, S. K. Brown, and R. Robertson. (2019). "Livelihoods, Wellbeing and the Risk to Life during Volcanic Eruptions". *Frontiers in Earth Science*. **7** : 205. [10.3389/feart.2019.00205](https://doi.org/10.3389/feart.2019.00205).
- [38] B. Nyandwi, M. Kervyn, F. Habiaryemye, F. Kervyn, and C. Michellier. (2023). "Differences in Volcanic Risk Perception among Goma's Population before the Nyiragongo Eruption of May 2021, Virunga Volcanic Province (DR Congo)". *Natural Hazards and Earth System Sciences*. **23** (2): 933-953. [10.5194/nhess-23-933-2023](https://doi.org/10.5194/nhess-23-933-2023).
- [39] D. Y. W. S. Pambudi, M. Sakur, K. Ismail, I. F. Dwiyono, and L. D. Setijadji. (2014). "Delineation of Geothermal Prospect Areas Based on the Straightness of Landsat and Digital Elevation Model (DEM) Imagery in the Mount Lawu Area, Central Java and East Java Provinces". *Proceedings of the 7th National Seminar on Earth*. 438-446.
- [40] S. I. Elmahdy, M. M. Mohamed, and M. M. Marghany. (2015). "Mapping and Classification of Hydrological Parameters from Digital Terrain Data in the Musandam Peninsula, UAE and Oman". *Geocarto International*. **30** (3): 330-345. [10.1080/10106049.2014.883439](https://doi.org/10.1080/10106049.2014.883439).
- [41] V. Balabathina, R. P. Raju, and W. Mulualem. (2019). "Integrated Remote Sensing and GIS-Based Universal Soil Loss Equation for Soil Erosion Estimation in the Megech River Catchment, Tana Lake Sub-Basin, Northwestern Ethiopia". *American Journal of Geographic Information System*. **2019** (4): 141-157.
- [42] V. W. P. Van Engelen and J. A. Dijkshoorn. (2012). "Global and National Soils and Terrain Digital Databases (SOTER) Procedures Manual Version 2.0: Draft for Comments". ISRIC – World Soil Information.
- [43] D. Hermawan and L. Permana. (2018). "Geothermal Prospects of Mount Lawu Based on Volcanostratigraphic Studies". *Buletin Sumber Daya Geologi*. **13** (3): 199-213. [10.47599/bsdg.v13i3.232](https://doi.org/10.47599/bsdg.v13i3.232).
- [44] B. Legowo, S. Putra, M. K. I. Mufti, H. Purwanto, H. Rifai, W. Suryanto, and B. Purnama. (2023). "Identification of Pyroclastic Flow of Magnetic Minerals (Holocene Volcano): A Case Study of Paleo-Volcano Lawu on the South Side, Central Java, Indonesia". *Kuwait Journal of Science*. **50** (4): 724-730. [10.1016/j.kjs.2023.04.011](https://doi.org/10.1016/j.kjs.2023.04.011).
- [45] S. Koesuma, M. B. Septianingsih, and B. Legowo. (2020). "Identification of Subsurface Structures of Geothermal Potential Area in the East of Mount Lawu Using the Gravity Method". *Indonesian Journal of Applied Physics*. **10** (1): 65-72. [10.13057/ijap.v10i01.34217](https://doi.org/10.13057/ijap.v10i01.34217).
- [46] M. Nurcholis, D. F. Yudiantoro, D. Haryanto, A. B. Dianputra, and K. Aji. (2019). "Process and Mineralogy of Volcanic Materials on the South Side of the Old Lawu Volcano in Java Island". *Sains Tanah - Journal of Soil Science and Agroclimatology*. **16** (2): 127-138. [10.20961/stjssa.v16i2.27118](https://doi.org/10.20961/stjssa.v16i2.27118).
- [47] Sampurno and H. Samodra. (1997). "Geology of Ponorogo". Geological Research and Development Centre, Indonesia.
- [48] A. Setyawan, L. Khusna, J. Suseno, D. Rina, T. Yulianto, and Y. Aribowo. (2021). "Detecting Hot Spring Manifestations Based on Gravity Satellite Data on Mount Lawu".

- 1943** : 012034. [10.1088/1742-6596/1943/1/012034](https://doi.org/10.1088/1742-6596/1943/1/012034)
- [49] H. Helmi, H. Kurniawan, and W. Adam. (2020). "Geological Control of the Occurrence of Geothermal Manifestations in the Mount Lawu Area". *Kurvatek*. **5** (1): 1-9. [10.33579/krvtk.v5i1.1790](https://doi.org/10.33579/krvtk.v5i1.1790).
- [50] N. Sekarlangit, T. F. Fathani, and W. Wilopo. (2022). "Landslide Susceptibility Mapping of Menoreh Mountain Using Logistic Regression". *Journal of Applied Geology*. **7** (1): 51-63. [10.22146/jag.72067](https://doi.org/10.22146/jag.72067).
- [51] L. Ayalew and H. Yamagishi. (2005). "The Application of GIS-Based Logistic Regression for Landslide Susceptibility Mapping in the Kakuda-Yahiko Mountains, Central Japan". *Geomorphology*. **65** (1-2): 15-31. [10.1016/j.geomorph.2004.06.010](https://doi.org/10.1016/j.geomorph.2004.06.010).
- [52] S. Segoni, R. S. Ajin, N. Nocentini, and R. Fanti. (2024). "Insights Gained from the Review of Landslide Susceptibility Assessment Studies in Italy". *Remote Sensing*. **16** (23): 4491. [10.3390/rs16234491](https://doi.org/10.3390/rs16234491).
- [53] K. Halder, A. K. Srivastava, A. Ghosh, S. Das, S. Banerjee, S. C. Pal, U. Chatterjee, D. Bisai, F. Ewert, and T. Gaiser. (2025). "Improving Landslide Susceptibility Prediction through Ensemble Recursive Feature Elimination and Meta-Learning Framework". *Scientific Reports*. [10.1038/s41598-025-87587-3](https://doi.org/10.1038/s41598-025-87587-3).
- [54] W. Wilopo, D. P. E. Putra, T. F. Fathani, A. Pramaditya, R. Tandirerung, and E. Erzagian. (2023). "Comparison of Two Landslide Hazard Zonation Methods in the Volcanic Terrain of Temanggung Regency, Central Java, Indonesia". *Journal of Degraded and Mining Lands Management*. **10** (3): 4537-4546. [10.15243/jdmlm.2023.103.4537](https://doi.org/10.15243/jdmlm.2023.103.4537).
- [55] G. Samodra. (2014). "Development of Risk Analysis Technique and Its Application to Geo-Disaster Management in Indonesia"; Kyushu University. [10.15017/1470585](https://doi.org/10.15017/1470585)
- [56] G. F. Bonham-Carter.(1994)." Geographic Information Systems for Geoscientists". Pergamon. 267-302. [10.1016/B978-0-08-041867-4.50014-X](https://doi.org/10.1016/B978-0-08-041867-4.50014-X).
- [57] T. Mersha and M. Meten. (2020). "GIS-Based Landslide Susceptibility Mapping and Assessment Using Bivariate Statistical Methods in Simada Area, Northwestern Ethiopia". *Geoenvironmental Disasters*. **7** (1): 1-22. [10.1186/s40677-020-00155-x](https://doi.org/10.1186/s40677-020-00155-x).
- [58] J. N. Mandrekar. (2010). "Receiver Operating Characteristic Curve in Diagnostic Test Assessment". *Journal of Thoracic Oncology*. **5** (9): 1315-1316. [10.1097/JTO.0b013e3181f9f3e8](https://doi.org/10.1097/JTO.0b013e3181f9f3e8).
- [59] B. P. Bhandari, S. Dhakal, and C. Y. Tsou. (2024). "Assessing the Prediction Accuracy of Frequency Ratio, Weight of Evidence, Shannon Entropy, and Information Value Methods for Landslide Susceptibility in the Siwalik Hills of Nepal". *Sustainability*. **16** (5): 2092. [10.3390/su16052092](https://doi.org/10.3390/su16052092).
- [60] G. Zeng. (2013). "Metric Divergence Measures and Information Value in Credit Scoring". *Journal of Mathematics*. **2013** : 848271. [10.1155/2013/848271](https://doi.org/10.1155/2013/848271).
- [61] B. Youssef, I. Bouskri, B. Brahim, S. Kader, B. Igmoullan, B. Abdelkrim, and V. Spalević. (2023). "The Contribution of the Frequency Ratio Model and the Prediction Rate for the Analysis of Landslide Risk in the Tizi N'tichka Area on the National Road (RN9) Linking Marrakech and Ouarzazate". *Catena*. **232** : 107464. [10.1016/j.catena.2023.107464](https://doi.org/10.1016/j.catena.2023.107464).
- [62] D. Thapa and B. P. Bhandari. (2019). "GIS-Based Frequency Ratio Method for Identification of Potential Landslide Susceptible Areas in the Siwalik Zone of Chatara–Barahakshetra Section, Nepal". *Open Journal of Geology*. **9** (12): 873-896. [10.4236/ojg.2019.912096](https://doi.org/10.4236/ojg.2019.912096).