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Landslide susceptibility modelling using the weight of evidence and logistic regression approaches in the Balease watershed, Indonesia

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ABSTRACT

North Luwu Regency exhibits a high susceptibility to landslides; ten major landslides in South Sulawesi occurred in the Balease watershed of North Luwu Regency over a ten-year period. We aimed to inventory landslide occurrences, identify the controlling factors of landslides, generate landslide hazard maps, and determine the most reliable method for landslide susceptibility modeling in the Balease watershed. Spatial statistical analyses using the weight of evidence (WoE) and logistic regression (LR) models were performed. Landslide inventory mapping was conducted through visual interpretation of SPOT-6 satellite imagery (2020) and WorldView-3 imagery (2024). The parameters included topographic, hydrological, geological, climatic, soil, and anthropogenic factors. Model validation was performed using the area under the curve (AUC) approach. The results indicate that approximately 1.832 mapped landslide locations occurred during 2020–2024. Notable differences in area coverage between the LR and WoE methods across landslide susceptibility classes, particularly, the LR classified a larger proportion of the study area as low susceptibility (99,932.95 ha) compared to WoE (79,055.12 ha). In contrast, WoE allocated a substantially larger area to the high susceptibility class (34,073.73 ha) than LR (7,780.50 ha), indicating that WoE is more sensitive in identifying areas with a higher likelihood of landslide occurrence. The prominent factors controlling landslide occurrence in Balease watershed were rainfall with 0.91 AUC value, slope gradient (0.89), elevation (0.86), and stream power index (SPI) (0.85). The WoE model achieved an AUC value of 0.88, classified as good, while the LR model yielded an AUC value of 0.77, classified as fair. The study's finding, the WoE of the evidence model driven mainly by rainfall and topographic factors, provides the most accurate landslide susceptibility assessment for the Balease watershed, supporting effective disaster mitigation and spatial planning. The resulting landslide hazard maps are expected to support spatial planning, disaster mitigation strategies, and conservation planning in landslide-prone areas of North Luwu Regency.

Keywords: landslides, Balease watershed, weight of evidence, logistic regression, landslide hazard, AUC.

INTRODUCTION

Indonesia's extreme topography, coupled with climate change, urbanization, and environmental degradation, has led to increased landslide activity, resulting in loss of life and property (Tirsyayu et al., 2025). Therefore, increased disaster management preparedness is essential to mitigate the impact of disasters (Khalil et al., 2020). In the area of South Sulawesi, particularly in North Luwu Regency, landslides are frequently reported. North Luwu Regency is characterized by steep terrain, complex geological structures, and a tropical climate with intense and prolonged tropical rainfall throughout the year, which increases soil moisture, reduces slope stability, and all of which contribute to high landslide susceptibility (Zulfahmi et al., 2025). The landslide in North Luwu occurred as a result of excessive rainfall (3.822 mm/year), a wide slope area, and land conversion, which reduced the soil's ability to retain water and caused mass shifts during heavy rain (Thamsi et al., 2019). Due to its lack of vegetation to reduce erosion and steep slopes, North Luwu Regency is particularly vulnerable to landslides (Pazzi et al., 2019). Moreover, rapid land use changes and the expansion of settlements into hillside areas have further increased landslide risk, leading to greater potential damage to infrastructure (Fell et al., 2008). A total of 116 landslides occurred in South Sulawesi during 2014–2023, causing 15,601 fatalities, and ten major disasters were recorded in North Luwu (BNPB, 2024). These disasters are often intensified by secondary risks such as flash flooding, which results in more severe damage and increased numbers of fatalities.

Spatially identifying high-risk zones, such as through landslide susceptibility mapping, is a non-structural mitigation solution that offers an objective spatial basis for spatial planning, identifying secure zones, infrastructure development, and expanding early warning systems to reduce landslide risks (Xiong et al., 2017). The identification of a vulnerable landslide area aimed to mitigate or prevent landslide risks (Ahmad et al., 2023). Recent disaster events, like the flash floods and debris flows in 2020 caused by landslides in Masamba Sub-districts, which resulted in significant infrastructure damage and substantial financial loss, highlighting the significance of improved landslide susceptibility mapping in North Luwu. Recent disasters, such as the flash floods and debris flows in 2020 caused by landslides in Masamba Sub-districts, which resulted in significant infrastructure damage and substantial financial loss, highlight the significance of improved landslide susceptibility mapping in North Luwu (Ma'mur et al., 2024). In addition, different modeling approaches used in Indonesia, including statistical and machine-learning methods, offer varying strengths to identify the most reliable method for specific regions (Melati et al., 2024). High-accuracy susceptibility maps derived from such approaches are essential for supporting hazard mitigation, spatial planning, and community protection in landslide-prone areas of Indonesia.

Weight of evidence and LR are two statistical methods commonly used in landslide susceptibility mapping. These methods can identify relationships betwen environmental factors and landslide occurrences (Batar and Watanabe, 2021; Hong et al., 2017). LR models the combined influence of multiple variables (Misbahudin, 2020) and demonstrates high predictive accuracy for landslide occurrences (Małka, 2021). LR method was applied within a GIS framework to relate historical landslide occurrence records with multiple environmental and conditioning factors, estimate the statistical influence of each factor on landslide probability, and produce validated landslide susceptibility maps by converting the LR-derived probabilities into spatial hazard zones (Waiyasusri et al., 2023, 2025; Waiyasusri and Wetchayont, 2025).

Recent advances in landslide susceptibility mapping have introduced various statistical methods to improve prediction accuracy. Although landslide susceptibility mapping using machine learning approaches has not been widely applied in Indonesia, watershed-scale studies in North Luwu remain limited. Moreover, few studies have systematically compared different landslide susceptibility mapping methods, such as LR and WoE, using the same dataset within this region (e.g., Nwazelibe et al., 2023; Polykretis and Chalkias, 2018; Xie et al., 2017). Therefore, we hypothesize that (1) landslide occurrences in the Balease watershed are influenced by topographical, hydrological, geological, climatic, soil, and human activity factors; (2) landslide susceptibility in the Balease watershed can be predicted using spatial statistical methods based on the relationship between landslide occurrences and their conditioning factors; (3) higher predictive accuracy in landslide hazard mapping is expected to be achieved using the WoE method compared to the LR method. We aimed to assess the landslide susceptibility area using the WoE and LR method based on selected conditioning factors. The objectives of this were to (1) inventory landslide occurrence locations based on satellite imagery data; (2) identify and determine the factors contributing to landslide occurrence; (3) produce a landslide susceptibility map using the WoE method and the LR method and determine the most accurate method between the two. The outputs of this study include a validated landslide inventory map, thematic conditioning factor maps, landslide susceptibility maps generated using the WoE and LR methods, and a comparative accuracy assessment to identify the best-performing method in North Luwu Regency

MATERIAL AND METHODS

Research area

This study was conducted in the Balease Watershed (DAS Balease), North Luwu Regency, South Sulawesi, Indonesia (approximately 2°30′–2°55′ S and 120°20′–120°40′ E), covering an area of about 1.000 km² (Figure 1). The Balease watershed consists of lowland areas in the downstream region and steep mountainous terrain in the upstream zone, with elevations generally increasing toward the headwaters. The Balease River represents the main river system, supported by several tributaries that form the watershed drainage network. Geologically, the area is dominated by volcanic and sedimentary formations with varying degrees of weathering and structural complexity, including the presence of the Kambuno Granite. The elevation zone of 900–1.200 m above sea level represents a prominent topographic unit within the watershed. The study period spanned from January 2004 to December 2025. The landslide conditioning factors used in this study, along with their data sources and applied spatial analysis techniques, were represented in Table 1.

Inventory of landslide events

An extensive catalog of landslide occurrences was created to record the spatial distribution of landslides throughout the research region. This inventory was created using high-resolution satellite images and on-screen digitization methods with ArcGIS software (version 10.8.2; ESRI 2021). To improve the accuracy and reliability of the susceptibility analysis, the landslide inventory data were methodically partitioned into two subsets: 70% of the identified landslide points were assigned for model training and parameter optimization. In contrast, the remaining 30% were reserved for model validation.

Weight of evidence method

The weight of evidence method is a rigorous statistical approach utilized to evaluate the correlation between environmental variables and landslide events. This method, based on Bayes' theorem, integrates information from several

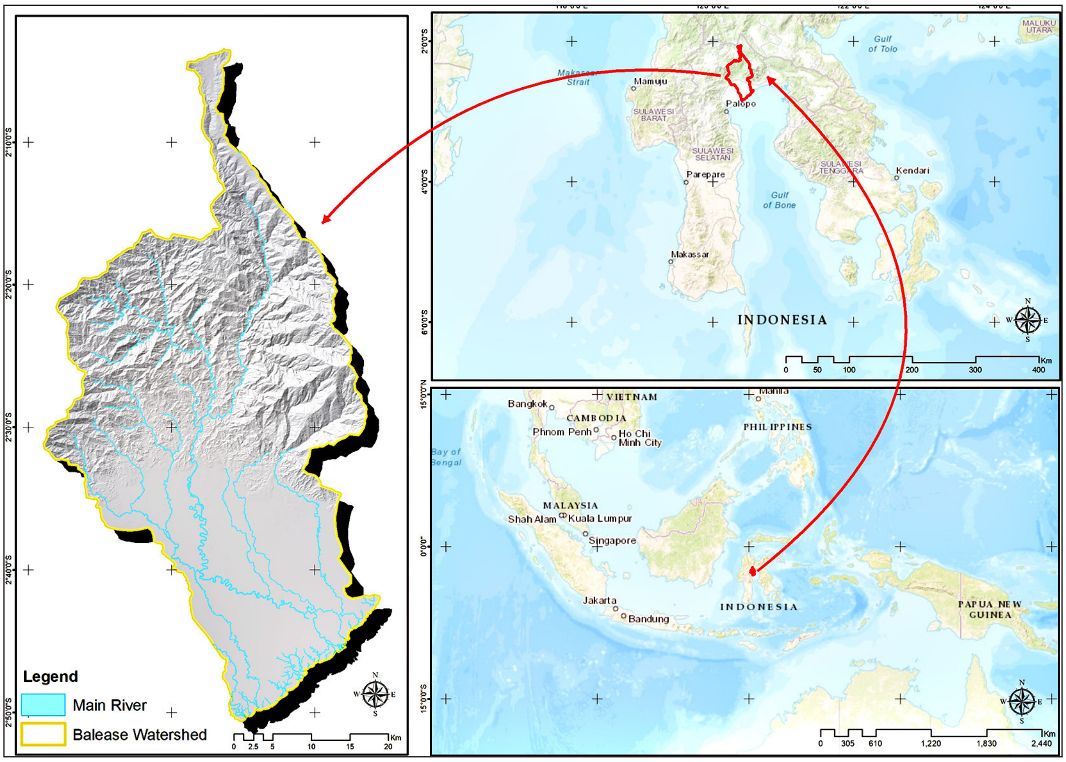


Figure 1. Research location in Balease watershed, North Luwu Regency, South Sulawesi, Indonesia

Table 1. Landslide parameters and analysis techniques

Data type	Parameter	Scale	Sources	Analysis technique	Data type
Topography	Elevation	30 meters	FABDEM (University of Bristol), 2022	Surface analysis	Secondary data
	Slope		FABDEM (University of Bristol), 2022	Surface analysis	Secondary data
	Aspect		FABDEM (University of Bristol), 2022	Surface analysis	Secondary data
	Plan curvature		FABDEM (University of Bristol), 2022	Surface analysis	Secondary data
	Profile curvature		FABDEM (University of Bristol), 2022	Surface analysis	Secondary data
Hydrology	Stream power index (SPI)	30 meters	FABDEM (University of Bristol), 2022	Surface analysis	Secondary data
	Terrain wetness index (TWI)		FABDEM (University of Bristol), 2022	Surface analysis	Secondary data
	Distance from river	1:50.000	Topographic Map of Indonesia, BIG 2018	Distance of Euclidean	Secondary data
Geology	Lithology	1:50.000	Interpretive Geological Map, Geological Agency 2010	-	Secondary data
	Distance from fault	1:100.000	Geological Map, Geological Agency 2009	Distance of Euclidean	Secondary data
	Landform	1:50.000	Land System, BIG 2022	-	Secondary data
Human	Distance from road	1:50.000	Topographic Map of Indonesia, BIG 2018	Distance of Euclidean	Secondary data
	Land use	1:50.000	Topographic Map of Indonesia, BIG 2018	-	Secondary data
Climate	Pecipitation	-	Precipitation, BMKG, One Map Policy	-	Secondary data
Soil	Soil type	1:50.000	Soil Map, Center for Agricultural Land Resources 2018	-	Secondary data
Landslide event	Point of landslide event	-	Spot 6 Satellite Imagery acquired in 2020, and image collection from Esri Wayback in the form of WorldView-3 imagery acquired in 2024 and survey	Object interpretation and segmentation	Secondary and primary data

aspects to assess the likelihood of a landslide occurrence. The posterior probability indicates the possibility of a landslide occurring after integrating additional knowledge from specific factors (Bui et al., 2022). The conditional probability of a landslide event, contingent upon the presence of influencing factors, is expressed as follows: The weight of evidence method is a robust statistical technique that measures the impact of several environmental variables on landslide incidence. This technique utilizes Bayes' theorem to enable researchers to combine multiple data sources and assess their collective impact on landslide probability. The posterior probability, a fundamental concept in WoE, represents the revised likelihood of a landslide occurrence after incorporating additional data from specific environmental variables. This method enhances the comprehension of landslide vulnerability by considering the intricate interactions among various geological, topographical, and hydrological factors (Batar and Watanabe, 2021).

The utilization of the WoE methodology in landslide susceptibility mapping has numerous benefits. It provides a systematic framework for evaluating the relative importance of different factors leading to landslide events. This technique accepts both continuous and categorical data, hence augmenting its adaptability in assessing various environmental variables. Moreover, the WoE methodology enables the creation of landslide susceptibility maps that are easily interpretable and applicable for decision-makers in land-use planning and risk management. By measuring the correlation between environmental variables and landslide occurrences, WoE improves the precision of forecasts concerning landslide-prone regions. It facilitates the formulation of efficient mitigation plans (Bui et al., 2022), utilizing equations:

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

$$W_{ji}{}^{+} = Ln\left(\frac{P\{L\}}{P\{\underline{L}\}}\right) = \frac{\left(\frac{P\{F_{ji} \cap L\}}{P\{L\}}\right)}{\left(\frac{P\{F_{ji} \cap \underline{L}\}}{P\{\underline{L}\}}\right)} \quad (2)$$

The conditional probability of the existence of a landslide that does not present any factors can be formulated as follows:

$$W_{ji}^{-} = Ln\left(\frac{P\{L\}}{P\{\underline{L}\}}\right) = \frac{\left(\frac{P\{\underline{F}_{ji} \cap L\}}{P\{L\}}\right)}{\left(\frac{P\{\underline{F}_{ji} \cap \underline{L}\}}{P\{\underline{L}\}}\right)} \tag{3}$$

where: W_{ji}^{+} – the likelihood ratio for landslide occurrence when the factor F_{ji} is present; W_{ji}^{-} – the likelihood ratio for landslide occurrence when the factor F_{ji} is present. Correlation: positive – W_{ji}^{+} is positive and W_{ji}^{-} is negative; negative – W_{ji}^{+} is negative and W_{ji}^{-} is positive. No correlation if W_{ji}^{+} = W_{ji}^{-} = 0. Weight contrast – to measure the contrast between the triggering factors and landslide occurrence, the following formula was used:

$$W_{contrast\,ji} = W_{ji}^{+} - W_{ji}^{-} \tag{4}$$

Logistic regression methods

Logistic regression (LR) is a multivariate statistical analysis used to correlate landslide occurrences with various triggering conditions simultaneously. This method analyzes the distribution of landslide occurrences in relation to triggering factors to determine the impact of each element on the likelihood of a landslide occurring. Landslide analysis using LR can examine the complex relationship between various triggering factors and landslide occurrences. This method examines the distribution of landslide events in relation to the triggering factors to determine the impact of each element on the likelihood of landslide occurrence. In landslide analysis, LR surpasses mere correlation by examining the intricate relationships among multiple triggering factors and landslide occurrences. It measures the impact of each element on overall landslide susceptibility, enabling researchers to identify which variables are most critical in predicting landslide events. The approach calculates odds ratios of each component, illustrating how changes in that factor affect the likelihood of a landslide occurrence.

A primary advantage of LR in landslide research is its ability to handle both continuous and categorical variables, making it suitable for analyzing various environmental and geological data. This versatility enables researchers to incorporate a wide range of parameters, such as slope angle, lithology, land use, rainfall intensity, and proximity to faults or roadways. Moreover, LR may generate probability maps that visually represent landslide susceptibility within a designated region, thereby providing essential resources for land-use planning and risk management. It is crucial to recognize that LR assumes a linear relationship between the independent variables and the log-odds of the outcome. This condition may not always hold in intricate natural systems. The logistic regression model is represented by a logit equation as follows (Southerland and Zhou, 2021):

$$In\left(\frac{P}{1-P}\right) = \beta_0 + \sum_{i=1}^{n} \beta_i X_i \tag{5}$$

where: P – probability of landslide occurrence, β_0 – intercept of the logistic regression model, β_i – regression coefficient associated with the i-th landslide conditioning factor, X_i – value of the i-th conditioning factor, n – number of conditioning factors.

The regression coefficient (β) measures the degree to which each causal element affects landslide likelihood. A positive coefficient indicates that an increase in the factor's value is associated with a heightened risk of landslides, whereas a negative coefficient denotes a decrease in risk (Akbari et al. 2014). Logistic Regression analysis enables a quantitative assessment of the impact of each factor on landslide susceptibility, thereby acting as an essential tool for vulnerability mapping and disaster mitigation planning. The validation of the WoE and LR models enhances the credibility of the analysis (Rahman et al. 2020).

Receiver operating characteristics (ROC)

The area under the curve (AUC) serves as a specific metric for testing the accuracy of probability-based prediction models, particularly in analyzing landslide susceptibility (Qiu et al., 2024). A good AUC value ranges from below 0.6 to 1, with values closer to 1 indicating superior model predictive performance. Models with an AUC value greater than 0.9 are categorized as excellent, those between 0.8 and 0.9 are categorized as good, values between 0.7 and 0.8 are categorized as fair, and values below 0.7 indicate inadequate model performance (Yu et al., 2023). This evaluation was conducted to verify the reliability and accuracy of the model in mapping landslide susceptibility. Table 2 presents the AUC Index values.

Table 2. AUC index value adopted by Yu et al. (2023)

AUC value	Explanation
> 0.9	Very good
0.8–0.9	Good
0.7–0.8	Quite good
<0.6	Bad

Figure 2 illustrates the methodological flowchart adopted in this study. The workflow consists of data acquisition and preprocessing, selection and classification of landslide conditioning factors, application of the WoE and LR models, and subsequent generation and validation of the landslide susceptibility map.

RESULTS AND DISCUSSION

Inventory and parameter selection influence the landslide historical distribution patterns

An inventory of landslide events in the Balease Watershed was performed by analyzing satellite images. This investigation utilized SPOT 6 imagery and the ESRI Wayback image collection, in conjunction with WorldView-3 imagery (Lin et al., 2022). This research detected 1.832 instances of landslides from 2020 to 2024, indicating a high level of vulnerability to land mass movement. Figure 2 clearly illustrates the distribution of landslide events. These results underscore the importance of ongoing monitoring activities to support disaster risk mitigation efforts in the region. The examination of landslide events in the Balease Watershed provides significant insights into the region's geomorphological processes.

The spatial distribution of landslide events, as shown in Figure 3, reveals certain patterns and trends that are of significant relevance for future land-use planning and disaster mitigation strategies. This distribution pattern indicates that most landslide events occur in areas with steep slopes and land cover conditions that have undergone significant changes due to human activity. This detailed data collection provides an important basis for understanding the characteristics and spatial dynamics of landslide events in the Balease watershed. Through in-depth analysis of this data, key triggering factors can be identified, such as rainfall intensity, seismic vibrations, and land use changes. This information can then be used in the development of more accurate prediction models to improve the effectiveness of early warning systems, thereby sustainably minimizing the risk and impact of landslides in the study area. This information can assist decision-makers in executing targeted slope stabilization actions and developing regulations to govern activities in high-risk areas (Masruroh et al., 2023).

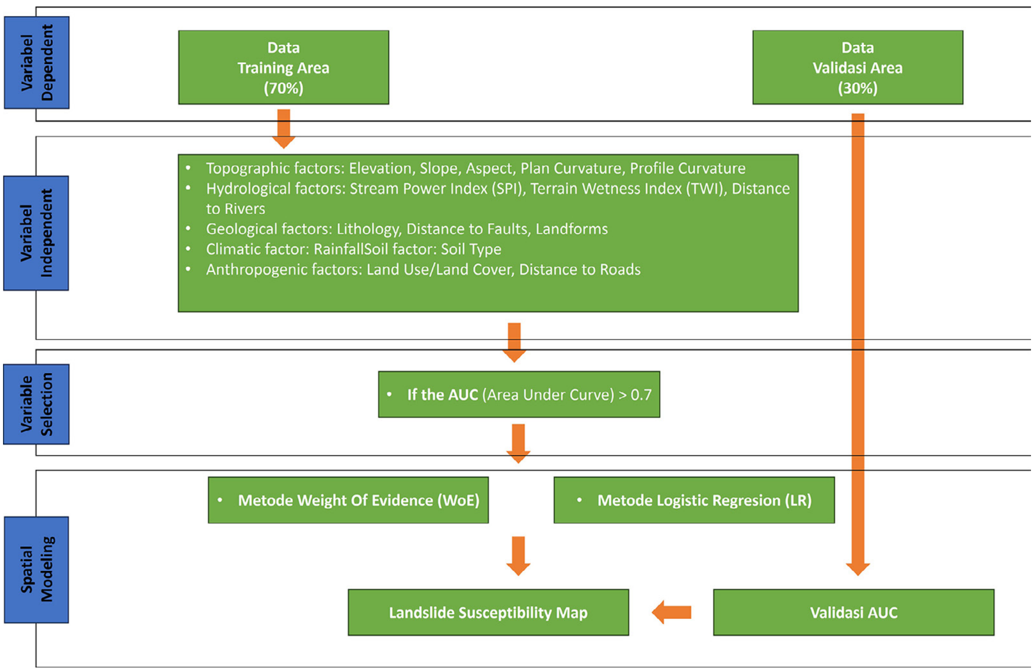


Figure 2. Methodological flowchart

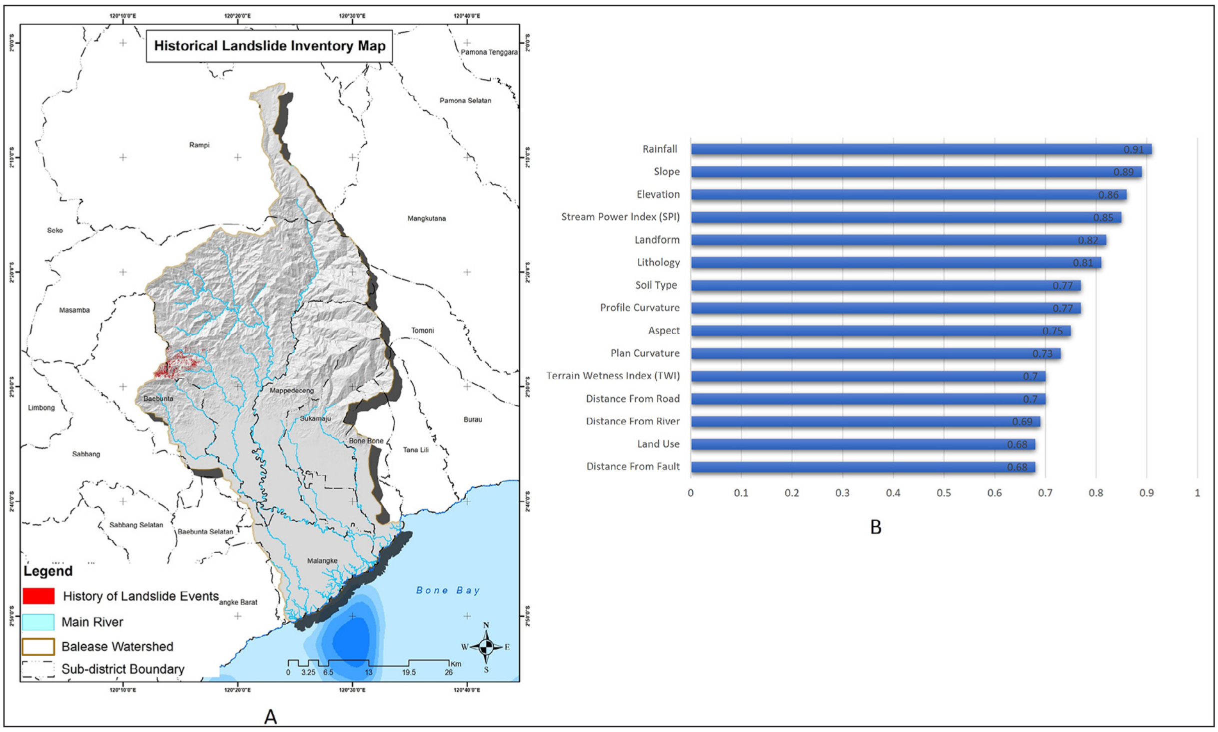


Figure 3. Landslide inventory (A), and factors causing landslides (B)

Logistic regression

The logistic regression analysis in this study was conducted using Python programming, which leveraged a variety of comprehensive tools and frameworks to facilitate machine learning and statistical analysis. This approach yielded an effective LR model for assessing factors influencing landslide susceptibility in the study area. Twelve variables were used in the analysis to determine their respective contributions to the level of susceptibility.

The results showed that the aspect parameter had a negative coefficient of –139.6557, while the slope had a positive coefficient of 123.5101 (Table 3 and Figure 4). These findings align with previous research by Ayalew and Yamagishi (2005), which showed that positive coefficient values reflect increased landslide risk as the parameter value increases. These two variables were shown to have the most dominant influence on the model, with the aspect with a significant negative coefficient indicating that a particular topographic orientation can reduce landslide potential (Lee et al., 2002). Conversely, slope with a significant positive coefficient indicates that steeper slopes increase the likelihood of landslides. These findings reinforce the important role of land morphometric conditions in determining slope stability in the study area.

The results of this study reveal a complex relationship between various environmental factors and the level of vulnerability to landslides. The negative coefficient value for the aspect parameter indicates that certain slope orientations can contribute to increased slope stability, possibly due to lower exposure to direct rainfall intensity and solar radiation. Conversely, the positive coefficient value obtained for slope gradient is consistent with the general understanding that steeper terrain has a higher tendency to landslides due to increased gravitational forces and decreased soil stability. The significant influence of these two parameters confirms the dominant role of aspect and slope in determining landslide vulnerability patterns in the study area, while also highlighting the importance of considering morphometric factors in mitigation efforts and land use planning in disaster-prone areas.

The results of the LR analysis, which include the coefficient values of the twelve triggering factors, are presented in Table 3 and visualised in Figure 4. This representation provides a comprehensive picture of the relative contribution of each factor to the level of landslide vulnerability in the research area, while also showing the relationship between environmental conditions and the spatial pattern of identified landslide events. Slope gradient parameters, stream power index

Table 3. Logistic regression (LR) value calculation results

Parameter	Coefficient
Aspect	-139.6557
Terrain wetness index (TWI)	-29.0746
Soil type	-0.644
Elevation	-0.6221
Plan curvature	-0.1124
Profil curvature	-0.0028
Lithology	0.1427
Landform	0.2748
Precipitation	1.8351
Distance from road	4.0303
Sream power indeks (SPI)	44.8582
Slope	123.5101

(SPI), proximity to road networks, rainfall patterns, landforms, and lithological composition were identified as the main factors contributing to landslide occurrence in the study area. All these characteristics showed positive coefficient values, indicating a significant influence on increasing the probability of landslide occurrence. This finding is consistent with the results of research by Ayalew and Yamagishi (2005), which confirmed that the combination of morphometric, hydrological, and geological conditions plays a significant role in controlling slope stability and the potential for land mass movement. The positive correlation among these factors and landslide occurrences suggests that regions with steeper slopes, elevated flow power indices, proximity to roads,

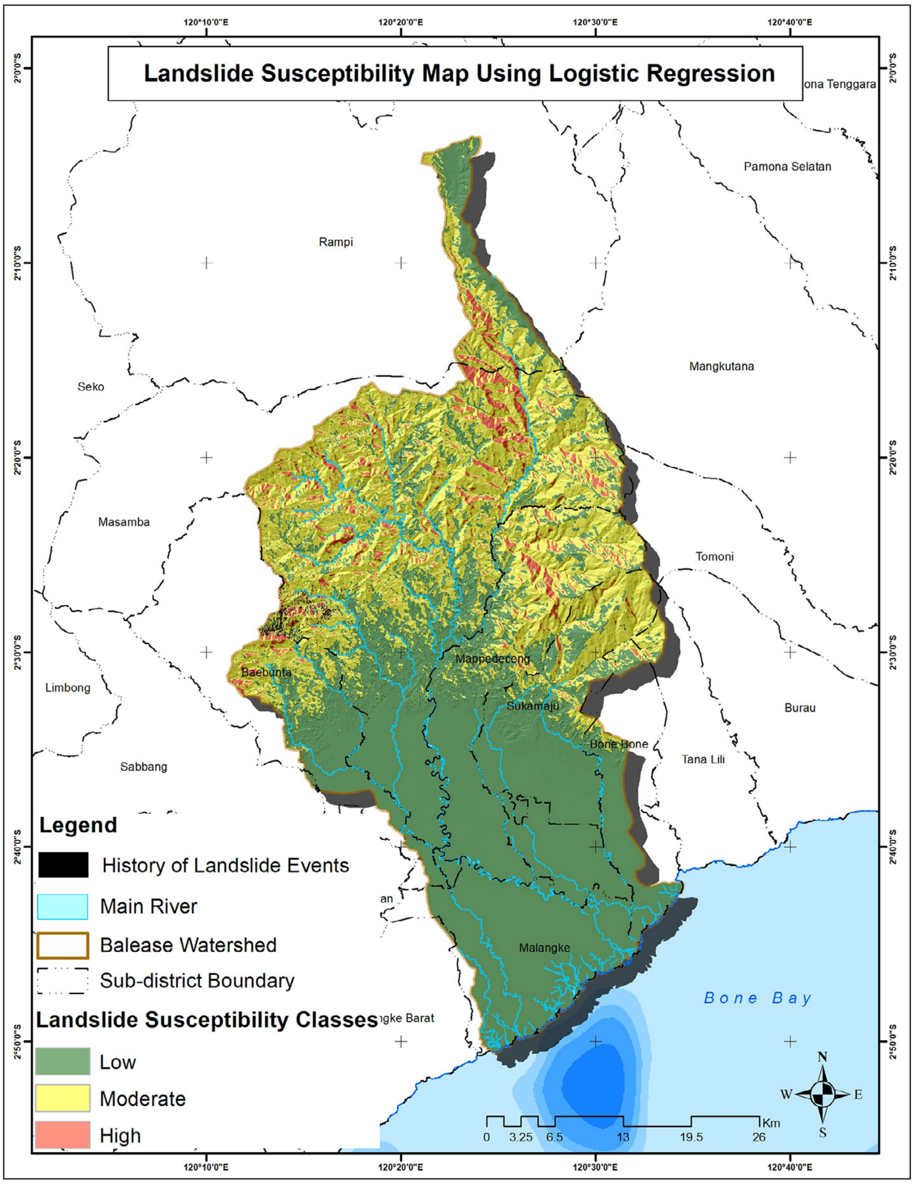


Figure 4. Landslide hazard map using logistic regression method

increased rainfall, specific landform characteristics, and particular lithological compositions are more susceptible to landslides.

Weight of evidence

The Weight of Evidence analysis was conducted using the Python programming language, which allows for systematic and efficient application of the method to identify the relationship between the distribution of landslide events and the environmental factors that influence them. The analysis results indicate that the spatial pattern of landslide point distribution has a substantial influence on the effectiveness of the WoE model in mapping vulnerability levels. This finding aligns with the statement by Bhandari et al. (2024), who emphasised that landslide location distribution is a key component in risk analysis and spatial modelling of landslide disasters. The results shown in Table 4 and Figure 3 indicate that the WoE analysis conducted using Python is an effective method for assessing landslide susceptibility. The distribution pattern of landslide locations has a significant impact on the accuracy and reliability of risk analysis outcomes. The weight of evidence methodology is used to quantify the spatial relationship between landslide occurrences and the various predisposing factors that influence them. This approach allows for a deeper understanding of the level of landslide vulnerability in an area by assessing the extent to which each factor contributes to the likelihood of landslide movement.

Parameters with positive W^+ and negative W^- values significantly influence landslide occurrence, indicating that these parameter classes increase the likelihood of such events. In contrast, when W^+ values are negative and W^- values are positive, the related parameters are considered to be of lesser significance or possibly inversely correlated with landslide susceptibility. This relationship supports the findings of Kusmajaya et al. (2022), which demonstrated that the WoE approach effectively quantifies the relationship between environmental variables and landslide risk levels. The differences in W^+ and W^- values provide a deeper understanding of how certain predisposing factors can contribute to or hinder slope instability, depending on the underlying geomorphological conditions.

The analysis results indicate that parameter classes with low predictive weight values, such as elevations below 600 m and slopes less than 2°, describe relatively stable terrain conditions. These areas generally have low gravitational pressure and limited surface runoff accumulation, thus minimizing the probability of landslide occurrence. Conversely, parameter classes with higher positive weights, particularly in the slope range of 24°–33° and elevations of 900–1200 m, showed a stronger correlation with the identified landslide locations. This condition confirms that the combination of steep slopes and medium elevations is a major factor contributing to increased slope vulnerability in the study area. Such conditions are generally associated with steeper topographies, heightened gravitational potential energy, and enhanced weathering processes that undermine soil cohesion and slope stability. The quantitative assessment presented in Table 4 and the spatial distribution patterns visualized in Figure 5 clearly illustrate how variations in the WoE values can be used to identify the terrain factors most influential in landslide occurrence. This information played a crucial role in improving the accuracy of vulnerability mapping and serves as a basis for prioritizing areas for land-use planning and implementing more effective disaster risk mitigation strategies.

Comparative method between the weight of evidence and logistic regression

The methods chosen for landslide susceptibility mapping were determined through a comparative analysis of the AUC values obtained from two statistical models: WoE and LR. The AUC value is used as the primary metric for assessing model performance, as it indicates the model's ability to distinguish between areas prone to and not prone to landslides (Figure 6). An AUC value close to 1.0 indicates excellent model performance with a high level of predictive accuracy, while a value close to 0.5 indicates classification ability equivalent to random chance, thus reflecting low model reliability. The model with the highest AUC value was identified as the most suitable for defining the spatial probability of landslide occurrence in the study area.

Figure 6 shows that both modelling approaches demonstrated excellent predictive ability; however, one method produced a higher AUC value, indicating superior model efficacy and accuracy. The difference in AUC values between the WoE and LR models reflects variations

Table 4. Weight of evidence value calculation results

Parameter	Class	Explanation	Pixel	Landslide	W+	W-	WoE
Elevation	1	600	1,159,049	439	-2	0.794	-2.679
	2	900	193,031	2,168.00	1.399	-0.392	1.907
	3	1200	213,502	2,075.00	1.253	-0.354	1.722
	4	>1200	425,475	884	-0.297	0.068	-0.25
Slope	1	2	684,396	-	-8.626	0.425	-9.237
	2	5	55,739	-	-8.626	0.029	-8.841
	3	8	13,358	-	-8.626	0.007	-8.819
	4	17	294,369	274	-1.103	0.11	-1.401
	5	24	309,296	1,194.00	0.322	-0.073	0.207
	6	33	500,266	3,235.00	0.84	-0.583	1.237
	7	>33	125,754	853	0.888	-0.101	0.803
Aspect	1	Flat	384,501	-	-8.626	0.216	-8.878
	2	North	146,763	671	0.491	-0.052	0.507
	3	Northeast	151,843	975	0.833	-0.114	0.91
	4	East	176,78	920	0.622	-0.088	0.673
	5	Southeast	248,439	1,450.00	0.737	-0.169	0.87
	6	South	293,46	1,056.00	0.251	-0.051	0.266
	7	Southwest	242,005	318	-0.758	0.071	-0.866
	8	West	191,635	62	-2.16	0.091	-2.287
	9	Northwest	147,752	104	-1.383	0.059	-1.478
Terrain wetness indeks (TWI)	1	5	395,996	1,815.00	0.494	-0.173	0.509
	2	10	1,022,350	3,506.00	0.203	-0.273	0.318
	3	15	542,167	234	-1.872	0.277	-2.307
	4	20	20,021	1	-4.02	0.01	-4.188
	5	>20	2,644	-	-8.626	0.001	-8.785
Sream power indeks (SPI)	1	1	902,97	919	-1.014	0.428	-2.065
	2	5	86,971	1	-5.456	0.045	-6.123
	3	10	72,72	49	-1.427	0.029	-2.078
	4	>10	920,517	4,587.00	0.578	-1.124	1.08
Plan curvature	1	Concave	532,283	2,866.00	0.658	-0.413	0.96
	2	Flat	657,277	342	-1.683	0.338	-2.132
	3	Convex	801,497	2,358.00	0.051	-0.036	-0.024
Profil curvature	1	Convex	565,938	2,173.00	0.318	-0.161	0.358
	2	Flat	572,854	337	-1.56	0.278	-1.959
	3	Concave	852,265	3,056.00	0.25	-0.238	0.366
Distance from road	1	100	245,225	2	-5.78	0.131	-10.778
	2	200	157,53	-	-8.627	0.083	-13.576
	3	300	132,149	-	-8.627	0.069	-13.562
	4	400	83,123	2	-4.737	0.042	-9.646
	5	500	67,455	6	-3.445	0.033	-8.344
	6	>500	1,305,575	5,556.00	0.422	-5.225	0.78
Landform	1	Bar (deposits of sand or gravel in rivers)	501	-	-8.627	-	-16.783
	2	Alluvial plain	418,519	-	-8.627	0.237	-17.019
	3	Small hilly plain	193,583	-	-8.627	0.103	-16.885
	4	Wavy plains	7,022	-	-8.627	0.004	-16.786
	5	Plain	39,419	-	-8.627	0.02	-16.803
	6	Delta	1,893	-	-8.627	0.001	-16.784
	7	slope	1,118,713	5,566.00	0.579	-8.627	1.051
	8	Upper slope	21,442	-	-8.627	0.011	-16.794
	9	lower slope	1,922	-	-8.627	0.001	-16.784
	10	Gentle slope	83,135	-	-8.627	0.043	-16.826
	11	Middle slope	4,724	-	-8.627	0.002	-16.785
	12	Hilltop	5,544	-	-8.627	0.003	-16.786
	13	Tidal swamp	60,149	-	-8.627	0.031	-16.814
	14	Highland side	15,131	-	-8.627	0.008	-16.79
	15	River	19,36	-	-8.627	0.01	-16.793

Parameter	Class	Explanation	Pixel	Landslide	W+	W-	WoE
Soil type	1	Endoaquepts	445,674	-	-8.627	0.254	-13.97
	2	Endoaquents	9,518	-	-8.627	0.005	-13.721
	3	Dystrudepts	1,111,497	5,557.00	0.583	- 5.565	1.06
	4	Eutrodox	155,857	8	-3.991	0.08	-9.16
	5	Eutrudepts	65,409	-	-8.627	0.033	-13.75
	6	Fluvaquents	82,995	1	-5.409	0.043	-10.54
	7	Hapludox	52,305	-	-8.627	0.027	-13.743
	8	Hapludults	12,9	-	-8.627	0.007	-13.723
	9	Sulfaquents	52,534	-	-8.627	0.027	-13.743
	10	Udipsamments	2,368	-	-8.627	0.001	-13.717
Lithology	1	Alluvium	670,027	-	-8.627	0.412	-12.208
	2	Endapan Danau	48,821	-	-8.627	0.025	-11.821
	3	Formasi Bongka	96,449	-	-8.627	0.05	-11.846
	4	Formasi Larona	44,711	6	-3.036	0.022	-6.226
	5	Kambuno granite	611,239	5,492.00	1.174	- 3.947	1.952
	6	Pompangeo complex	358,915	46	-3.081	0.191	-6.442
	7	Latimojong formation	114,652	22	-2.679	0.055	-5.904
	8	Ultramafic complex	46,243	-	-8.627	0.024	-11.82
Precipitation	1	3000	117,667	25	-3.809	0.056	-3.838
	2	3200	737,764	355	-1.761	0.398	-2.146
	3	3500	1,086,356	2,617.00	-0.149	0.154	-0.29
	4	>3500	49,27	2,569.00	2.977	-0.595	3.585

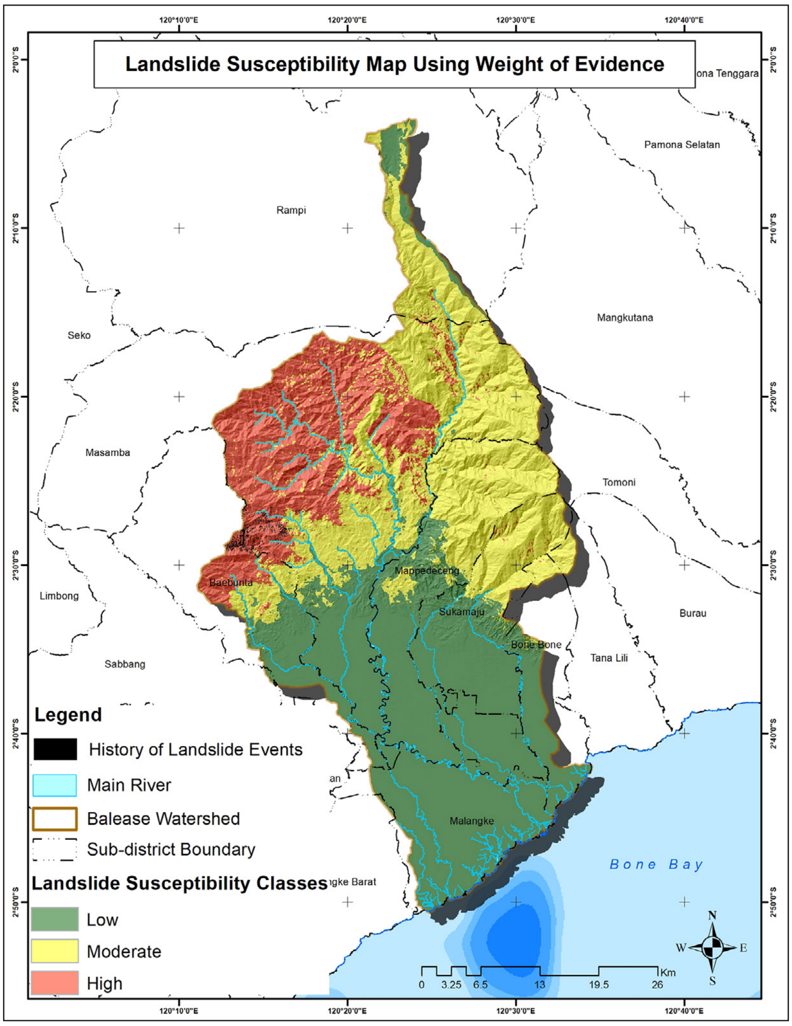
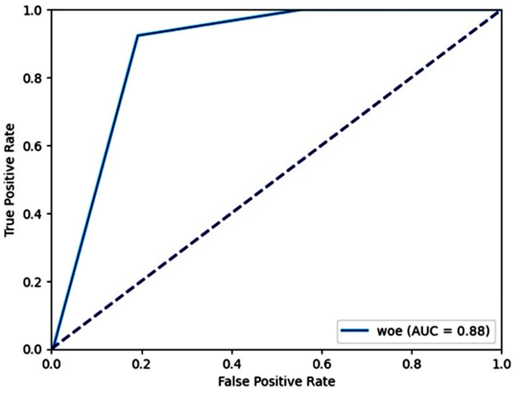


Figure 5. Landslide hazard map using WOE method



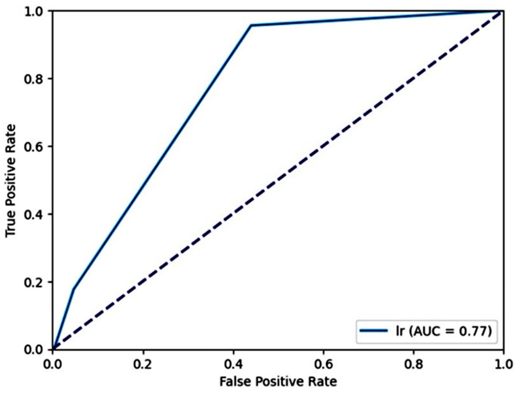


Figure 6. AUC accuracy test

in their respective methodological approaches, particularly in how they measure and interpret the relationship between conditioning factors and landslide occurrence in the study area. This comparison provides a quantitative basis for selecting the most suitable modelling approach for the Balease watershed, ensuring that the chosen method accurately reflects the spatial variability of landslide susceptibility affected by geological, geomorphological, and climatic factors.

This study was convinced that landslide occurrence was strongly controlled by topographic and hydrometeorological factors, particularly slope gradient, elevation, and rainfall-related variables. Waiyasusri et al. (2023) reported that steep slopes combined with high rainfall intensity significantly increased landslide probability, which was related to the annual mean of precipitation, slope gradient, elevation, and SPI as the dominant controlling factors. However, the LR-based susceptibility modeling demonstrated that WoE identified substantially larger high-susceptibility zones, highlighting localized hazard concentrations that LR tended to underrepresent. In line with the findings of Waiyasusri and Wetchayont (2025), revealed that the LR method resulting conservative and statistically robust susceptibility maps by integrating multiple controlling factors simultaneously. The LR method classified a larger area as low susceptibility because it only identified high-risk zones where rainfall, slope gradient, elevation, and hydrological effects jointly exerted a strong influence. Therefore, the LR method is appropriate for regional-scale landslide assessment and long-term spatial planning, although it may underestimate localized high-risk areas compared to the WoE method.

Inventory and selection of parameters that influence the historical distribution pattern of landslides

This study examines the factors contributing to the occurrence of landslides in the study area, utilising the AUC value as a basis for evaluating the relative importance and predictive ability of each conditioning parameter that influences landslide occurrences. The AUC value provides a quantitative assessment of the capacity of each factor to differentiate between landslide and non-landslide regions. Parameters with AUC values below 0.7 are categorized as less effective in predicting the spatial distribution of inventoried landslide points. This value indicates that the parameter's contribution to model accuracy is relatively low and has the potential to cause uncertainty in the analysis results. Parameters with an AUC value exceeding 0.7 demonstrate strong predictive power, suggesting that these variables significantly influence landslide susceptibility and effectively represent spatial variations in slope instability (Ado et al., 2022). Figure 2 displays the evaluation results for each parameter, sorted by the highest AUC values. This accuracy assessment plays a crucial role in identifying the most significant parameters influencing the historical distribution of landslide events, as explained by Reichenbach et al. (2018). They emphasized that AUC-based quantitative evaluation can enhance the understanding of the relative contributions of each conditioning factor in landslide susceptibility modeling. Parameters highlighted in red exhibit an AUC value below 0.7, signifying inadequate predictive accuracy, while those with an AUC value exceeding 0.7 are deemed reliable and pertinent for subsequent analyses.

Evaluating the AUC value of each factor was essential for optimising and validating the model. The analysis identified the most influential parameters, ensuring that only variables with high discriminative performance were included in the landslide susceptibility model. This process contributes to reducing data redundancy, increasing model efficiency, and improving the overall accuracy of the susceptibility map. High-performing parameters typically include slope gradient, lithology, land use, and rainfall intensity, as these factors directly influence soil shear strength, water infiltration rates, and slope surface stability. Therefore, parameter selection based on AUC thresholds not only enhances the reliability of the statistical model but also provides a robust scientific framework for understanding the key environmental factors that influence landslide occurrence in the study area. Analysis of the AUC values obtained from the WoE and LR methods provides an objective basis for determining the most appropriate approach for modeling geomorphological and environmental attributes in the study area. The WoE method, as a bivariate statistical tool, independently evaluates the relationship between each conditioning factor and landslide occurrence, demonstrating high effectiveness in areas with distinctive factor interrelationship patterns. In contrast, the multivariate LR method considers the cumulative influence of multiple parameters simultaneously, thus enabling the analysis of complex interactions between variables. The comparison of these two approaches reveals that the strategy with the higher AUC value, confirming the statistical validity of the resulting susceptibility map and its ability to represent the spatial dynamics of landslide processes in the study area.

The weight of evidence and logistic regression techniques were used to classify landslide vulnerability into three categories: low, medium, and high (Table 5). The analysis results showed that the AUC value for the WoE method reached 0.88, indicating excellent predictive performance. In contrast, the LR method yielded an AUC value of 0.77, indicating moderate predictive ability, as illustrated in Figure 5. These validation results confirm that the WoE method has a higher level of accuracy compared to LR, thus being considered more effective in mapping landslide vulnerability in the study area, supporting the conclusions of Bhandari et al. (2024), which assert that the WoE method is the most accurate technique for predicting landslide susceptibility, especially in the Siwalik Hills of Nepal. Kusmajaya et al. (2022) argue that combining the WoE and LR approaches can enhance the precision and effectiveness of landslide hazard mapping by considering the spatial distribution of landslide events. The integration of the WoE and LR approaches offers a viable approach to enhance the predictive accuracy of landslide risk evaluations.

The logistic regression method classified a much larger proportion of the study area as low susceptibility (99,932.95 ha), followed by moderate susceptibility (70,643.76 ha), with only 7,780.50 ha categorized as high susceptibility. In

Table 5. Comparison of landslide susceptibility area (ha) classified using logistic regression and weight of evidence methods across sub-districts of North Luwu

Sub-district boundary	Logistic regression method				Weight of evidence method			
	Low	Moderate	High	Total (ha)	Low	Moderate	High	Total (ha)
Baebunta	8.291,36	4.153,49	480,51	12.925,36	6.752,46	2.732,91	3.439,98	12.925,36
Baebunta Selatan	469,88	-	-	469,88	469,88	-	-	469,88
Bone Bone	5.733,86	602,97	43,83	6.380,66	5.539,21	832,73	8,72	6.380,66
Malangke	19.806,80	-	-	19.806,80	19.806,71	-	-	19.806,71
Malangke Barat	90,69	-	-	90,69	90,69	-	-	90,69
Mappedeceng	15.489,47	10.617,78	1.092,77	27.200,02	13.239,20	13.919,32	41,49	27.200,02
Masamba	25.608,27	44.192,53	5.257,29	75.058,08	12.061,43	32.607,13	30.389,53	75.058,08
Rampi	4.123,98	4.410,49	690,00	9.224,47	2.276,93	6.857,66	89,87	9.224,47
Sabbang	65,86	-	-	65,86	65,86	-	-	65,86
Sukamaju	13.622,25	6.010,37	203,50	19.836,12	12.277,56	7.455,06	103,50	19.836,12
Sukamaju Selatan	6.475,18	-	-	6.475,18	6.475,18	-	-	6.475,18
Tana Lili	155,36	656,14	12,60	824,09	-	823,46	0,64	824,18
Total	99.932,95	70.643,76	7.780,50	178.357,21	79.055,12	65.228,27	34.073,73	178.357,21

contrast, the WoE method assigned a smaller area to low susceptibility (79,055.12 ha) and a comparable area to moderate susceptibility (65,228.27 ha) but identified a substantially larger high-susceptibility area of 34,073.73 ha, which was more than four times that of the LR result.

At the sub-district scale, this contrast was particularly evident in Masamba, where WoE delineated 30,389.53 ha as high susceptibility compared to only 5,257.29 ha under LR, indicating that WoE was more sensitive in capturing high-risk zones in this area. Similar patterns were observed in Baebunta and Rampi, where WoE consistently allocated larger areas to the high-susceptibility class than LR. Conversely, in sub-districts such as Malangke, Malangke Barat, Baebunta Selatan, Sabbang, and Sukamaju Selatan, both methods predominantly classified the area as low susceptibility, suggesting agreement in relatively stable zones.

Approximately 1.832 landslide occurrences during the 2020–2024 period are consistent with previous landslide susceptibility studies in tropical and mountainous regions of Indonesia. The contrasting spatial patterns produced by the LR and WoE methods align with findings reported in earlier research, where LR typically classified larger areas as low susceptibility due to its conservative, probability-based modeling framework, while WoE delineated broader high-susceptibility zones by emphasizing strong spatial associations between landslide events and conditioning factor classes (Dimyati et al., 2022; Shitov et al., 2022; Shitov et al., 2025). In summary, LR tended to produce a more conservative susceptibility map by concentrating most areas into low and moderate classes, whereas WoE provided a more precautionary assessment by identifying broader high-susceptibility zones. This difference highlighted the importance of method selection in landslide hazard assessment, as WoE appeared to be more suitable for risk-averse planning and mitigation, while LR was preferable for more generalized regional assessments.

CONCLUSIONS

Twelve of the fifteen parameters evaluated had area under the curve (AUC) values over 0.7, including the final analysis. The results showed approximately 1.832 landslide locations during the 2020–2024 period. Furthermore, the WoE method outperformed the LR model, with AUC values of 0.88 and 0.77, respectively. These results indicated that the WoE method provided more accurate landslide risk predictions in the Balease watershed with superior performance compared to the LR method. The WoE approach is recommended as a more effective technique for landslide susceptibility mapping in this study area. These findings confirm the relevance of the bivariate statistical approach in analyzing the relationship between conditioning factors and landslide occurrence, especially in areas with complex geomorphological characteristics.

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