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Research Article

Landslide Potential Analysis in East Lombok District, West Nusa Tenggara Province Using the Weight of Evidence (Woe) Method

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ABSTRACT

Landslides are one of the most common geological disasters worldwide and can cause various losses to communities in terms of economic aspects, infrastructure, environment, and even loss of life (Grahn & Jaldell, 2017). Based on the Indonesian Disaster Risk Index (IRBI) data published by the National Disaster Management Agency (BNPB) in 2022, East Lombok Regency has a high-risk index with a score of 20.36 (Anonymous, 2023).

Identification, processing, and development of landslide vulnerability zoning are currently more focused on a data-driven approach through statistical analysis using Geographic Information System (GIS) technology. Weight of Evidence (WoE) is a quantitative data-based method used to combine datasets. This method employs the log-linear form of the Bayesian probability model, and each factor can be linearly stacked in data processing in ArcGIS (Ozdemir, 2011).

The main parameter influencing landslides in East Lombok Regency based on the Weight of Evidence (WoE) method is slope with an AUC value of 0.849. The distribution of very low vulnerability levels covers an area of 1,119,617 km² or approximately 69.55% of the research area, low vulnerability levels cover an area of 126,375 km² or approximately 7.85% of the research area, moderate vulnerability levels cover an area of 108,767 km² or approximately 6.76% of the research area, and high vulnerability levels cover an area of 255,008 km² or approximately 15.84% of the research area.

Keywords: Landslides, GIS, ArcGIS, WoE

INTRODUCTION

Landslides are one of the most common geological disasters worldwide and can damage the economy, infrastructure, environment, and even result in loss of life (Grahn & Jaldell, 2017) and caused by various factors, including geology (Agostini et al., 2014), rainfall (Peng et al., 2018), land use (Persichillo et al., 2017), earthquake (Wang et al., 2018), and climate change (Alvioli et al., 2018; Gariano & Guzzetti, 2016; Peres & Cancelliere, 2018). Nandi (2007) also argues that rainfall, slope gradient, soil conditions, vibrations, and human activities are the causes of landslides. To minimize casualties due to landslides, it is very important to mitigate landslide vulnerability.

Definition of landslide vulnerability according to Varnes (1984) can be described based on the probability of landslides occurring in a certain area over a specific period. However, mapping landslide vulnerability presents a significant challenge due to the detailed knowledge about

Landslide inventory and triggering process are still limited. Several methods have been successfully applied previously in the field of landslide vulnerability assessment, usually consisting of empirical methods, statistical methods, and deterministic methods (Anonim, 2016).

Data-based methods, particularly bivariate and multivariate statistical methods, have been widely regarded as efficient and accurate methods for quantitatively describing statistical relationships among various geological factors

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and the spatial distribution patterns of landslides on a regional scale. These methods are compared to knowledge-based methods that rely on specialized expertise. (Bordoni et al., 2019; Marin & Velásquez, 2020). Statistical data that includes past landslide events and related geological factors in a specific area can be used to measure the quantitative impact of each landslide trigger.
The independent characteristics of each landslide factor variable are another reason to use the WoE method. Thus, the effects of each causal factor can be considered independently, and the reduced number of variables can be determined in the landslide vulnerability analysis. Compared to other statistical methods, the WoE method avoids the possibility of correlated factors, which can lead to unpredicTable results (Cao et al., 2021).

The objective of this research is to create a reliable landslide vulnerability map for East Lombok Regency, West Nusa Tenggara Province, Indonesia, in order to reduce the potential landslide hazards faced by the local community.

LOCATION OF RESEARCH AND LANDSLIDE INVENTORY

East Lombok Regency is a regency located at the eastern tip of Lombok Island with an astronomical position between 116°46'-117°20' East Longitude and 8°-9° South Latitude, bordered to the west by North Lombok and Central Lombok Regencies, to the east by the Alas Strait, to the north by the Java Sea, and to the south by the Indian Ocean. The area of East Lombok Regency is 2,684.097 km², consisting of 1,609.767 km² of land and 1,074.33 km² of sea. The land area of East Lombok Regency covers 33.88 percent of the area of Lombok Island or 7.97 percent of the land area of West Nusa Tenggara Province. East Lombok Regency has a high mountain, namely Mount Rinjani. With an elevation reaching 3,726 meters above sea level, Mount Rinjani is the third highest active volcano in Indonesia. This condition makes the area prone to frequent landslides. Based on sources from the West Nusa Tenggara Provincial Disaster Management Agency (BPBD) and the East Lombok District Disaster Management Agency (BPBD), visual interpretation of remote sensing imagery, and field investigations, a total of 1,850 landslide points were recorded from 2013 to 2023. The Research Area and landslide points can be seen in the following **Figure 1.**

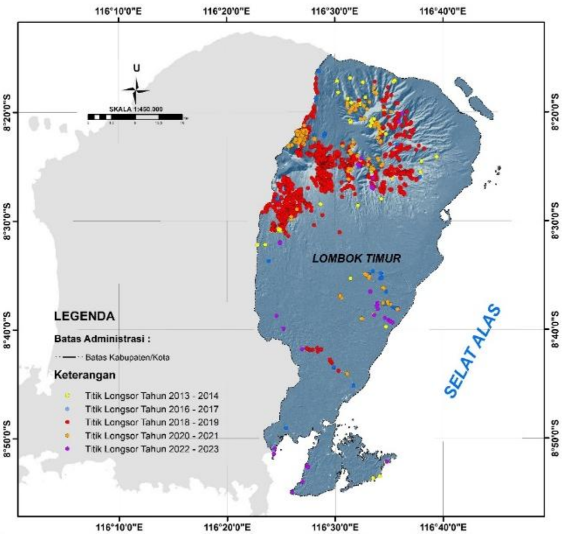

Figure 1. Research Area and Landslide Point

Materials and Methods

Weight of Evidence (WoE) is a method based on quantitative data used to combine datasets. This method uses the log-linear form of the Bayesian probability model, and each factor can be linearly stacked in data processing in ArcGIS (Ozdemir, 2011). Geographic Information System (GIS) is a computer-based system to assist in the collection, maintenance, storage, analysis, output, and distribution of spatial data and information. GIS is designed to collect, store, and analyze objects and phenomena where geographic location is an important or critical characteristic to be analyzed (Santoso, 2021).
The WoE method has been widely used in the field of landslide vulnerability zoning. The flow of the WoE method can be seen in **Figure 2.**

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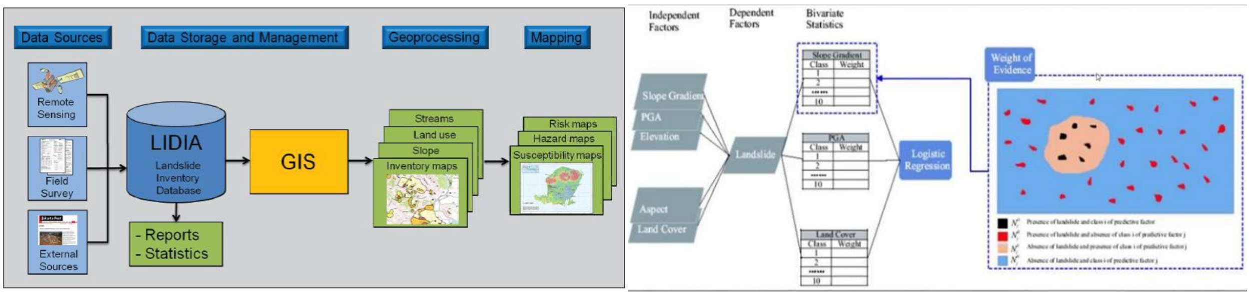

Figure 2. Illustration of class weighting calculations using the Weight of Evidence (WoE) method SNI 8291:2016.

Compared to deterministic methods such as field observation, this method is considered reliable and cost-effective (Armas, 2012; Felicísimo, 2003; Roering, 2012). In general, the working method of the WoE (Weight of Evidence) consists of two main assessments: the probability distribution of events for a specific class of a factor and the overall probability for the distribution of events (Cao et al., 2021). In statistical analysis for landslide vulnerability zoning, there are two main assumptions that are most important underlying it. First, the prediction of landslides in the future will occur under the same conditions as the landslides that have occurred previously. Second, the factors causing the landslide vulnerability zoning remain the same throughout the analysis period, due to geological factors and other factors that cause slope instability over a long period. Therefore, the landslide distribution mentioned above can be used to determine the prior probability and conditional probability of landslide events (i.e., posterior probability) in this Bayesian method (Cao et al., 2021). The posterior probability based on the contribution of landslides can be described in **Equation 1.**

$$P(E|Fi) = \frac{P(E).P(Fi|E)}{P(Fi)}$$

With:
$P(E|Fi)$ = The probability of event E occurring given that Fi has occurred (called the posterior probability).
$P(E)$ = The initial or unconditional probability of an event E (prior probability);
$P(Fi|E)$ = The probability that Fi happens on the condition that E has occurred;
$P(Fi)$ = Initial probability (without conditions) from Fi.
The potential for landslides in the future will be considered with or without the presence of a class of causal factors using a pair of odds ratios, as shown in **Equation 2.**

$$W_i{}^+ = In\left|\frac{P(Fi|I)}{P(Ei|I)}\right| = In\left|\frac{\frac{P(N_j \cap I)}{P(SI)}}{\frac{P(N_j \cap I)}{P(I)}}\right| = In\left|\frac{\frac{Npix\ Landsslide\ in\ class}{NPix\ total\ lansslide\ area}}{\frac{Npix\ stable\ in\ class}{NPix\ total\ stable\ area}}\right|$$

$$W_i{}^- = In\left|\frac{P(\bar{N}_j|I)}{P(\bar{N}_j|\bar{I})}\right| = In\left|\frac{\frac{P(\bar{N}_j \cap I)}{P(I)}}{\frac{P(\bar{N}_j \cap \bar{I})}{P(I)}}\right| = In\left|\frac{\frac{Npix\ Landsslide\ outside\ class}{NPix\ total\ lansslide\ area}}{\frac{Npix\ stable\ area\ outside\ class}{NPix\ total\ stable\ area}}\right|$$

With:

W^+ = The probability weight of landslide occurrence in a geofactor class (positive weight).

W^- = Weight of the impossibility of land movement in a certain geofactor class (negative weight)

Nj = The number of pixels in the parameter class

S = The total number of pixels containing ground movement across the entire area

P = Probability value

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Parameter C is introduced as the sum of W^+ and W^- considering the influence of the i-th class of the causal factor E, as well as the impact of the absence of other causal factors on the subclass, which will be used to identify the overall weight assigned to the raster unit, as explained in **Equation 3**.

$$C = W_i^+ + \left[\sum_{j=1}^{n} W_j^-\right] - W_i^-$$

With:

C = The total value or combined score of a unit (for example, a raster cell or subclass in a vulnerability map);

W_i^+ = A positive weight for factor i indicates a positive contribution of factor i to the occurrence;

W_j^- = A negative weight for factor j indicates a negative contribution (which reduces risk) from factor j;

$\sum_{j=1}^{n} W_j$ = The sum of all negative weights from all factors j (from 1 to n)

W_i^- = The negative weight of factor i, which is subtracted at the end to neutralize the calculation from the previous step (because factor i may have already been counted in the total amount Wj).

In the WoE method, which is based on Bayesian principles, the optimal landslide causative factors must be precisely selected to reflect the significant impact that landslides have on the spatial distribution of an area. Before starting the landslide vulnerability analysis, as mentioned above, the assumption of conditional independence of the factors must be determined. The likelihood of conditional dependence increases with a greater number of predictive variables, but the results are unreliable (Teerarungsigul et al., 2016).

One important step in quantitative statistical modeling is the evaluation (validation) of the model and the prediction result map. Without validation, the results of the analysis do not have clear scientific weight. To evaluate the magnitude of the parameter's influence on ground movement, a threshold-independent method is used, in the form of a ROC (receiver operating characteristic) curve. The basis for evaluating the ROC curve is by plotting the different accuracy values against the inferred threshold values. (Chung & Fabbri, 2003). Validation is divided into two (Chung & Fabbri, 2003) namely success rate and prediction rate. Success rate is the calculation of a model's success assessment. This shows how well the model aligns with past events (prior). The prediction rate is the validation of the prediction assessment calculation. It indicates how well the model can predict unknown or future events (posterior).

Calculation formulation *Area Under Curve* (AUC) (Pimiento, 2010) can be seen in **Equation 4**.

$$AUC = \sum_{i=0}^{n} (x_i - x_{i-1}) y_i - \frac{(x_i - x_{i-1}) - (y_i - y_{i-1})}{2}$$

With:

x_i = Percentage area

y_i = Percentage of landslide area

The AUC value of the parameters causing landslides that influence the occurrence of landslides is >0.6 (Pourghasemi et al., 2013). The higher the AUC value of a parameter, the greater its influence.

Table 1. AUC Value Classification

AUC Value	Description
0,9 – 1	Model Very Accurate
0,8 – 0,9	Model Very Good
0,7 – 0,8	Model Good
06 – 0,7	Model Fair/Good Enough
0,5 – 06	Model Poor/Weak

Source: Pourghasemi et al., (2013)

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The landslide susceptibility zone is an area or region that has a relative susceptibility degree for landslides to occur (SNI 8291, 2016).

Classification of landslide vulnerability zones using statistical methods is divided into four (SNI 8291, 2016), that is:

1. The high landslide vulnerability zone is an area that has a landslide occurrence proportion greater than 25% of the total occurrence population;
2. The medium landslide vulnerability zone is an area that has a landslide occurrence proportion greater than 10% up to 25% of the total occurrence population;
3. The low landslide vulnerability zone is an area that has a landslide occurrence proportion greater than 5% to 10% of the total occurrence population;
4. The zone of very low landslide susceptibility is an area that has a landslide occurrence proportion of 0% to 5% of the total occurrence population.

RESULTS AND DISCUSSION

The parameters used are limited to rainfall, slope gradient, slope direction, soil type, geology, and land use. These six data points are then overlaid with landslide points (training set) for subsequent calculations. The map of the six parameters, which have been overlaid with the training set landslide points, can be seen in **Figure 3-8**.

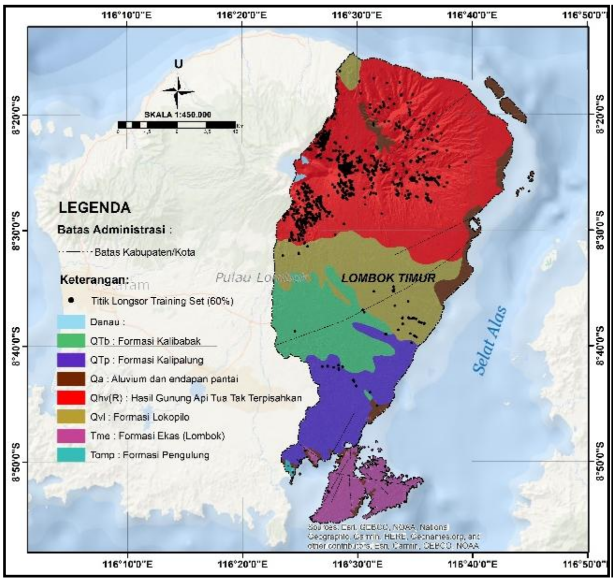

Figure 3. Geology Map

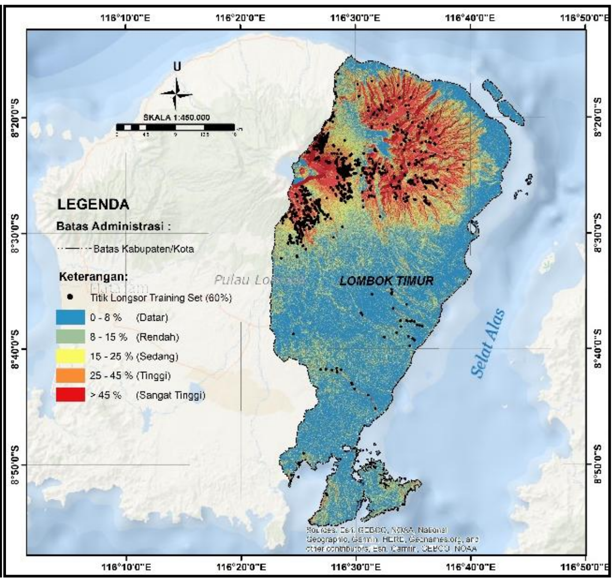

Figure 4. Slope Map

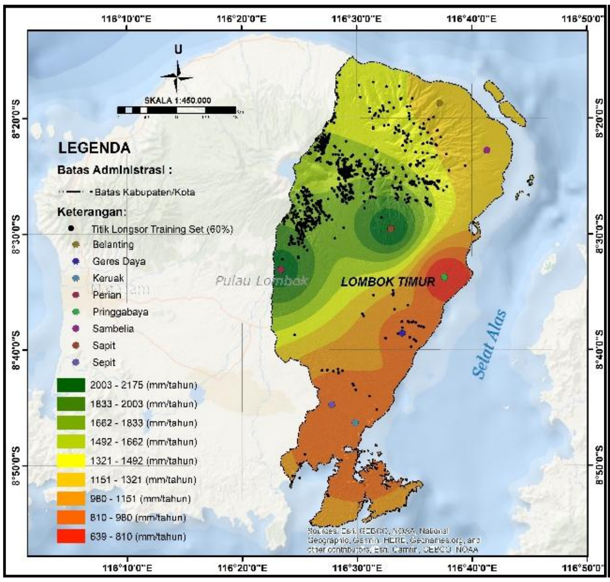

Figure 5. Rainfall Map

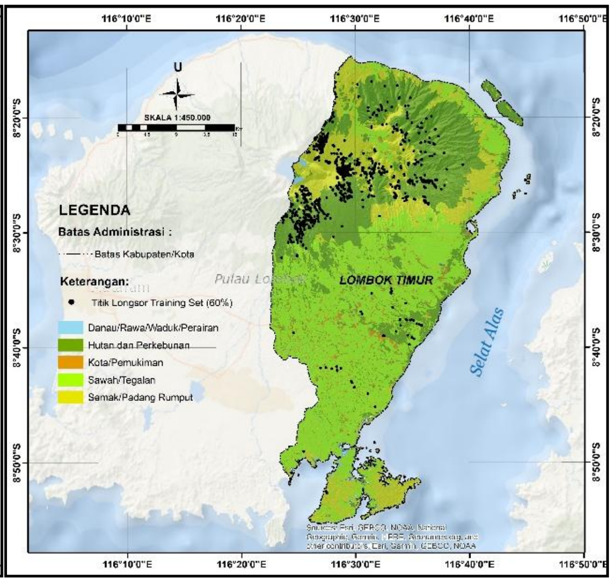

Figure 6. Land Use Map

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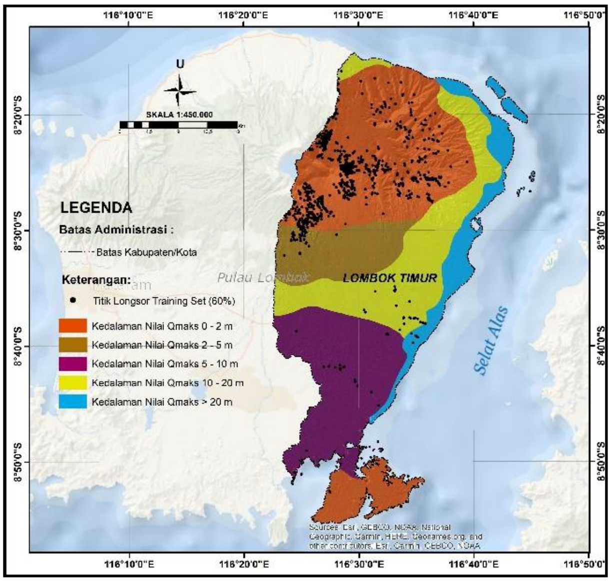

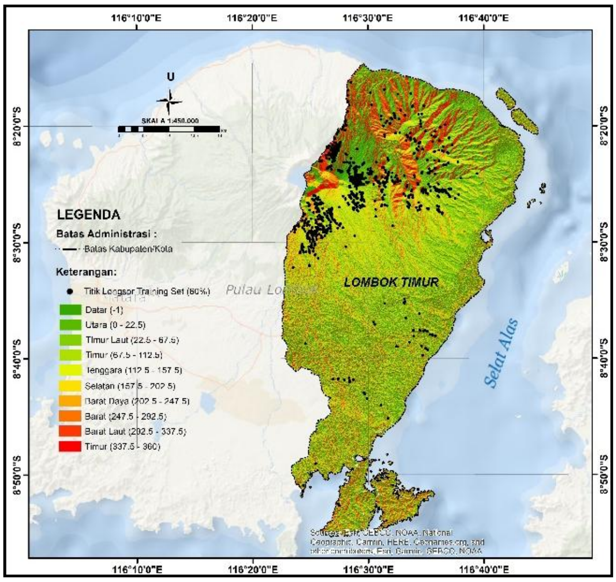

Figure 7. Soil Layer Type Map **Figure 8.** Slope Direction Map

The next step in the Weight of Evidence method is to weight each parameter and test the level of influence on landslide occurrence by calculating the Area Under Curve (AUC) value. The results of the AUC value calculations for each parameter are presented in **Table 2**.

Table 2. The Area Under Curve (AUC) value for each parameter

No	Parameter	Value *Area Under Curve* (AUC)
1.	Geology	0,734
2.	Slope	0,842
3.	Rainfall	0,825
4.	Land Use	0,753
5.	Soil Layer Type	0,766
6.	Slope Direction	0,604

The table above shows that the parameter with the highest AUC value is the slope gradient parameter at 0.842, and the parameter with the lowest AUC value is the slope direction parameter at 0.604. The AUC value indicates the level of influence a parameter has on landslide occurrences. The next step is to calculate the total WoE from the selected parameters with an AUC value > 0.6. The total WoE calculation is done by summing the selected parameters. The summation of the selected parameters is performed by overlaying the selected parameters statistically or using statistical assistance in ArcGIS through the raster calculator tool.

Based on the total weight of evidence (WoE) calculation data, the next step will be to test/validate the level of influence on landslide occurrence. The level of influence testing is conducted by validating the total WoE with the test set landslide occurrence data until an AUC value is obtained, where the model validation process is the same as the parameter verification process. This validation is carried out to ensure that the landslide vulnerability model (parameter selection and landslide occurrence) can be justified in its accuracy. The WoE calculation results for the level of influence on landslides at the research location yielded an AUC value of 0.883. The AUC graph of the selected parameters can be seen in **Figure 9**.

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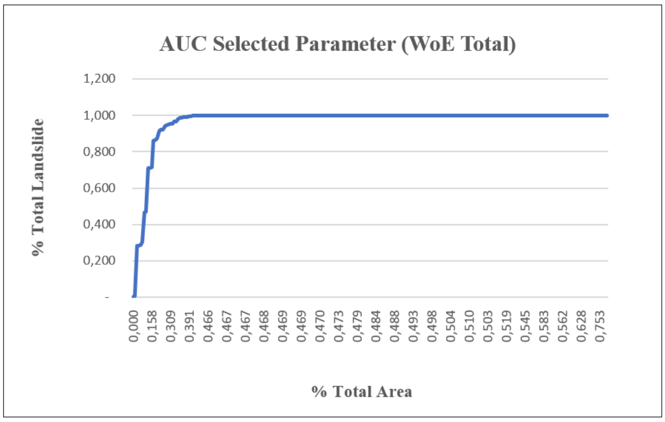

Figure 9. Graphic Area Under Curve (AUC) on the selected parameter (WoE Total)

Next, landslide classification and mapping of the total WoE value, expressed in percentages according to the landslide vulnerability zones in SNI 8291:2016, were carried out. The results of the landslide vulnerability classification and landslide points can be seen at **Figure 10-11.**

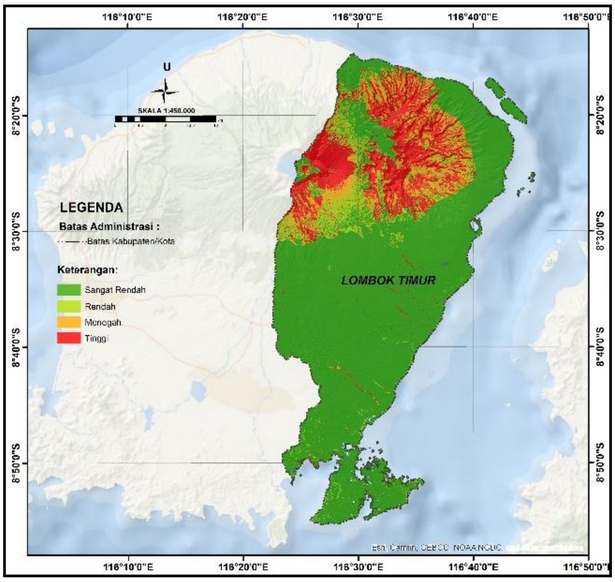

Figure 10. Landslide Vulnerability Map WoE Method

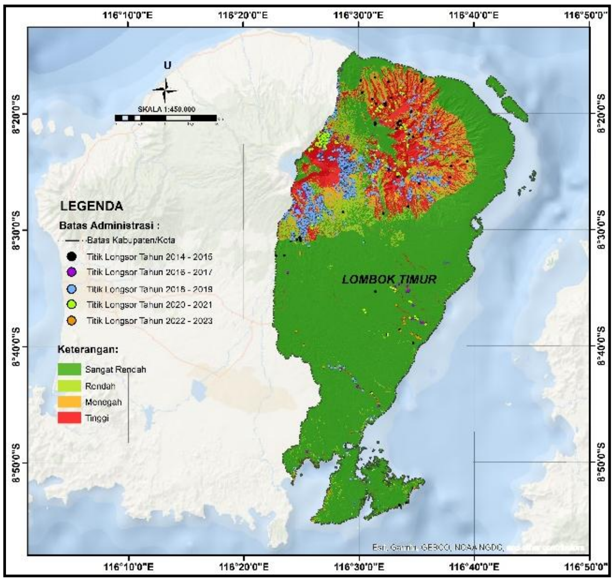

Figure 11. Landslide Points on the Map Landslide Vulnerability WoE Method

The landslide vulnerability map of East Lombok Regency using the WoE method has a distribution of vulnerability levels as shown in **Table 3.**

Table 3. Analysis of the extent of landslide vulnerability distribution using the weight of evidence method

No	Vulnerability Level	WoE Method			
		Spread Area (Km²)	Spread Area (%)	Number of Landslide Points	Number of Landslide Points (%)
1	Very Low	1.119,617	69,55	105	5,68
2	Low	126,375	7,85	172	9,30
3	Medium	108,767	6,76	279	15,08
4	High	255,008	15,84	1.294	69,95

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No	Vulnerability Level	WoE Method			
		Spread Area (Km²)	Spread Area (%)	Number of Landslide Points	Number of Landslide Points (%)
Amount		**1.609,767**	**100,00**	**1.850**	**100,00**

Looking at the results of the WoE method in mapping landslide vulnerability levels, we can see that areas with high slopes fall into the high landslide vulnerability category. Slope steepness is one of the main geomorphological factors that affect slope stability and plays a significant role in determining the potential for landslide occurrences. This is because steep slopes will generate greater gravitational forces on the mass of soil and rock, thereby increasing the likelihood of landslides. In this case, the steeper the slope, the greater the downward force acting on the material above the slope, and the higher its vulnerability to landslides. This indicates that an increase in the slope angle is directly proportional to the level of the slope's susceptibility to landslides.
Similar findings were also reported by (Yalcin, 2008) In his research in the Trabzon region of Turkey, which shows that slopes with inclinations between 30° and 45° are the most vulnerable to landslides. He stated that although other factors such as lithology, land use, and rainfall also influence, slope remains the dominant parameter in determining slope stability.

CONCLUSION

1. The main parameter influencing landslides in East Lombok Regency based on the Weight of Evidence (WoE) method is slope steepness with an AUC value of 0.842;
2. The landslide vulnerability map of East Lombok Regency using the weight of evidence method has a distribution of vulnerability levels, namely very low with an area of 1,119.617 km² or about 69.55% of the research location area, low with an area of 126.375 km² or about 7.85% of the research location area, medium with an area of 108.767 km² or about 6.76% of the research location area, and high with an area of 255.008 km² or about 15.84% of the research location area.

SUGGESTION

Based on the research conducted, there are several recommendations from the author, namely by comparing the results of data processing using the bivariate statistical method between weight of evidence (WoE) and frequency ratio (FR), as well as between the bivariate statistical method (WoE and FR) and the multivariate statistical method (logistic regression/LR) to achieve better landslide analysis results in further research.

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