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Effectiveness of Landslide Susceptibility Mapping Using the Maximum Entropy Model and Weights of Evidence Modelling in the Kuningan Regency, West Java, Indonesia

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Abstract

Kuningan is one of the regencies in the West Java region, which has had a problem with landslides every year for the last decade. In this area, there were 124 landslides recorded from 2011 to 2022. It is necessary to have extensive knowledge of the variables impacting the indicators used to geographically classify landslide susceptibility. This research attempts to create maps of landslide susceptibility based on the relationship between the parameters and inventory data of landslides. In this case, we present landslide susceptibility mapping in the Kuningan area using two methods, namely maximum entropy (MaxEnt) and weights of evidence (WoE). The results showed that for a variety of landslide susceptibility models, the two approaches generated comprehensive susceptibility distributions. Even though the two models' AUC parameters are nearly identical, the MaxEnt approach produces maps with larger low-susceptibility zones than the WoE method, according to a comparison of the maps created using the two approaches. This research offers preliminary recommendations for zonation prone to landslides, which is helpful for spatial design. In order to create landslide susceptibility maps that are more exact, accurate, and dependable in forecasting landslide events, additional studies need to be done.

Keywords:
susceptibility; landslides; WOE method; MaxEnt; AUC

1. Introduction

West Java Province is one of the areas most prone to landslides in Indonesia (**Sugianti et al., 2016**). Kuningan, which is one of the districts in the West Java region, experienced 124 landslides in one decade (2011-2022) based on the official disaster information data and information called DIBI (Data dan Informasi Bencana Indonesia) from the National Disaster Management Agency (see **Figure 1**). In this region, landslides often occur during the rainy season with significant casualties and losses (**https://dibi.bnpb.go.id/kbencana2**). In order to mitigate and manage landslide-related disasters, it is important to assess the areas prone to landslides. One of the most important and first steps in landslide mitigation is landslide susceptibility modelling (LSM). LSM generates a landslide probability map, which is often divided into three to five classes of landslide susceptibility. Therefore, one of the main topics of this research is understanding the landslide causatives of landslide susceptibility modelling. It results from efforts and effective strategies for reducing the probability of landslide disasters in the future. Landslide susceptibility modelling is required to generate susceptibility maps of landslide-prone areas in the study area. The model will increase practice and efficiency in examining landslide occurrences in remote and regional areas.

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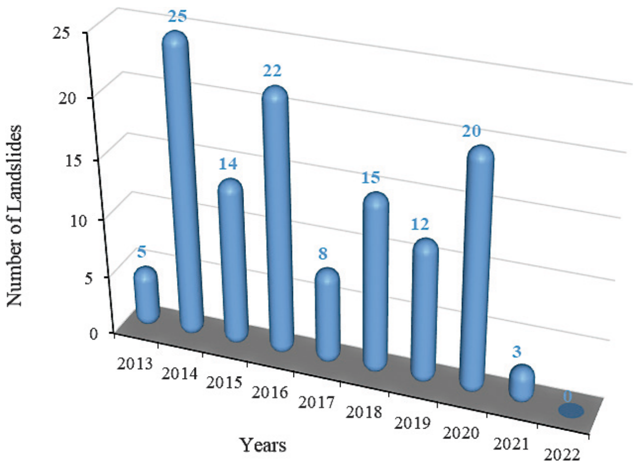

Figure 1: A number of landslide occurred in one decade from 2013 to 2022 in Kuningan Regency

Various research studies have investigated a variety of methods for landslide susceptibility modelling that have been developed using geographic information systems (GIS). Various general methods through quantitative approaches have been used to determine the distribution of landslide suseptibility mapping which are generally grouped into 3 categories, namely statistical, machine learning, and deterministic. Statistical approaches commonly applied to landslide hazard assessments include Frequency Ratio (FR), Fuzzy Logic (FL), Weight of Evidence (WoE), Statistical Index (Si), Weighted Overlay Model (WOM), and Weighting Factor (WF) methods (**Vakhshoori & Zare, 2016**). The machine learning approach is artificial intelligence-based methods including Logistic Regression (LR) (**Budimir et al., 2015**), Artificial Neural Networks (ANF) (**Lee et al., 2003**), Random Forests (RF) (**Taalab et al., 2018**), supporting vector machines (SVM) (**Huang & Zhao, 2018; Gong et al., 2022**) and adaptive neuro-fuzzy inference systems (ANFIS) (**Paryani et al., 2020**). Meanwhile, the deterministic method is a geotechnical engineering approach applied to landslide hazard assessments. Deterministic approaches include SHALSTAB, TRIGRS, SINMAP, TiVaSS, and GEOtop-FS methods (**Sugianti & Tohari, 2023**). The application of each approach is related to the purpose of study, available data, and researcher knowledge regarding specific methods.

This research applied the Weight of Evidence (WoE) method by considering the capability of the WoE technique to produce Landslide Hazard Zoning (LHZ) maps and Landslide Susceptibility Maps (LSM) to determine the relationship between landslide-causing factors and landslide locations in the past (**Cao et al., 2021; Bopche & Rege, 2022**). LSM is a map that shows landslide and non-prone areas, and LHZ is a map presenting the extent of the damaged or endangered areas under concern. The Weight of Evidence (WoE) method is a data-driven quantitative technique that uses a number of data combinations to produce maps of data weighting, both continuous and categorical, based on prior (initial) and posterior (after) probabilities (**Bonham-Carter, 1994**). The WoE is applied in landslide susceptibility mapping, a data-based method that avoids weight subjectivity in determining causal factors. This research will compare with machine learning methods, namely the principle of maximum entropy (MaxEnt). *MaxEnt* is a software package used to correlate known species distribution and environmental niche modelling (**Merow et al., 2013; Jarnevich & Young, 2015**). The MaxEnt approach is used to estimate the probability of the presence of a phenomenon. This method is an inference technique for constructing estimates of the probability distribution of landslide susceptibility using the available parameter data. In this study, determining zoning mapping of landslide susceptibility levels in the Kuningan area is an effort for disaster mitigation and spatial planning. So, an accurate and effective landslide prediction model is needed to predict the possibility of landslides occurring in the future to reduce the risk of susceptibility in a particular area (**Sugianti & Tohari, 2023**). This research attempts to map landslide susceptibility zones based on the relationship between the parameters that cause landslides as calculations and data on previous landslide events to reduce the impact of landslide events, and detailed knowledge is needed regarding the susceptibility level of the Kuningan area. This paper aims to present landslide susceptibility mapping in the Kuningan area using two methods, namely maximum entropy (MaxEnt) and weights of evidence (WoE). In addition, it evaluates the effectiveness of MaxEnt and WoE modelling in determining landslide susceptibility zoning in the Kuningan area so that it can become a consideration for government policy in regional spatial planning to handle future disaster mitigation. This paper also evaluates causative factors that influence landslide susceptibility in the Kuningan area.

2. Case study area

The research area is Kuningan Regency on the coordinates 108°23'3" – 108°47'55" S and 7°11'39" – 7°46'56" E in UTM 48 S Zone, the easternmost area of the West Java Province (see **Figure 2**). Kuningan Regency has an area of around 1,226 km^2. Cirebon Regency borders Kuningan Regency to the north, Brebes Regency to the east, Ciamis Regency and Cilacap Regency to the south, and Majalengka Regency to the west. Geographically, this area has a strategic aspect, namely that it directly borders Ciamis Regency and Central Java Province. Kuningan is one of the gateways to West Java from the east and has the nickname City of Horses. Based on the physiographic zones of West Java, the study area included the Bogor Zone, which is an anticlinorium track of strongly folded and intensively intruded Neogene layers (**Van Bemmelen, 1949**). As a result of the geological processes that form the Kuningan area, in particular, are

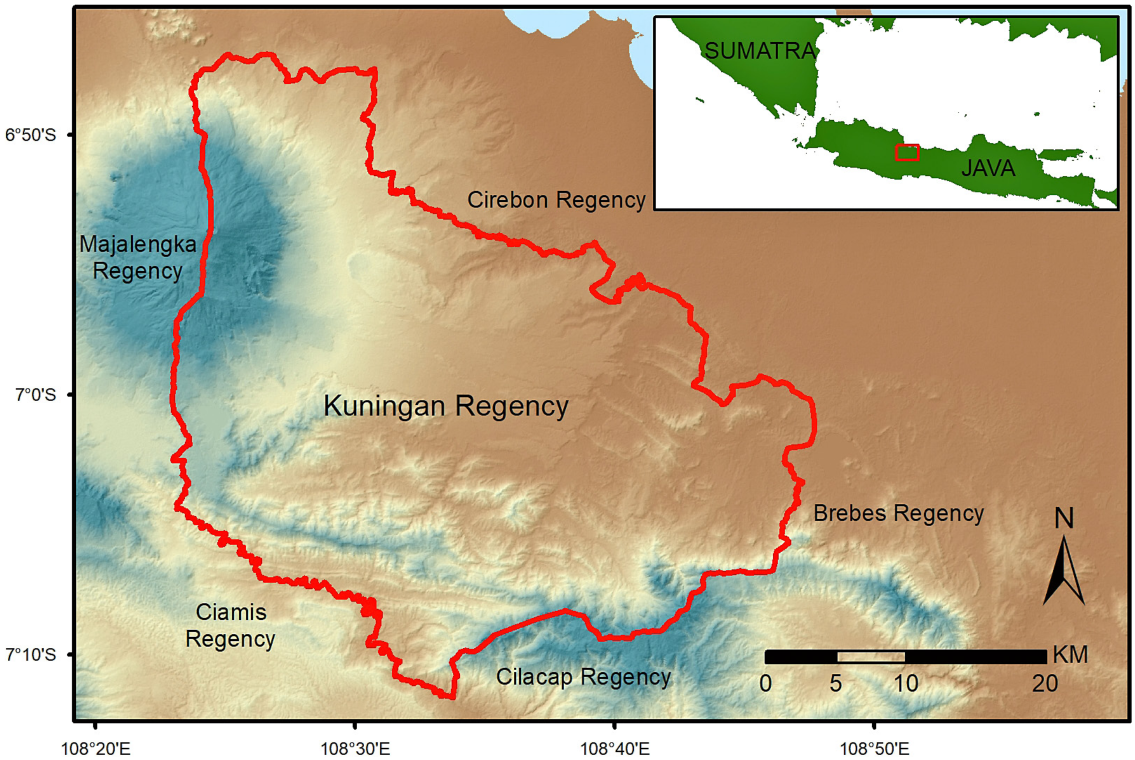

Figure 2: The red lines indicate the research location of the map

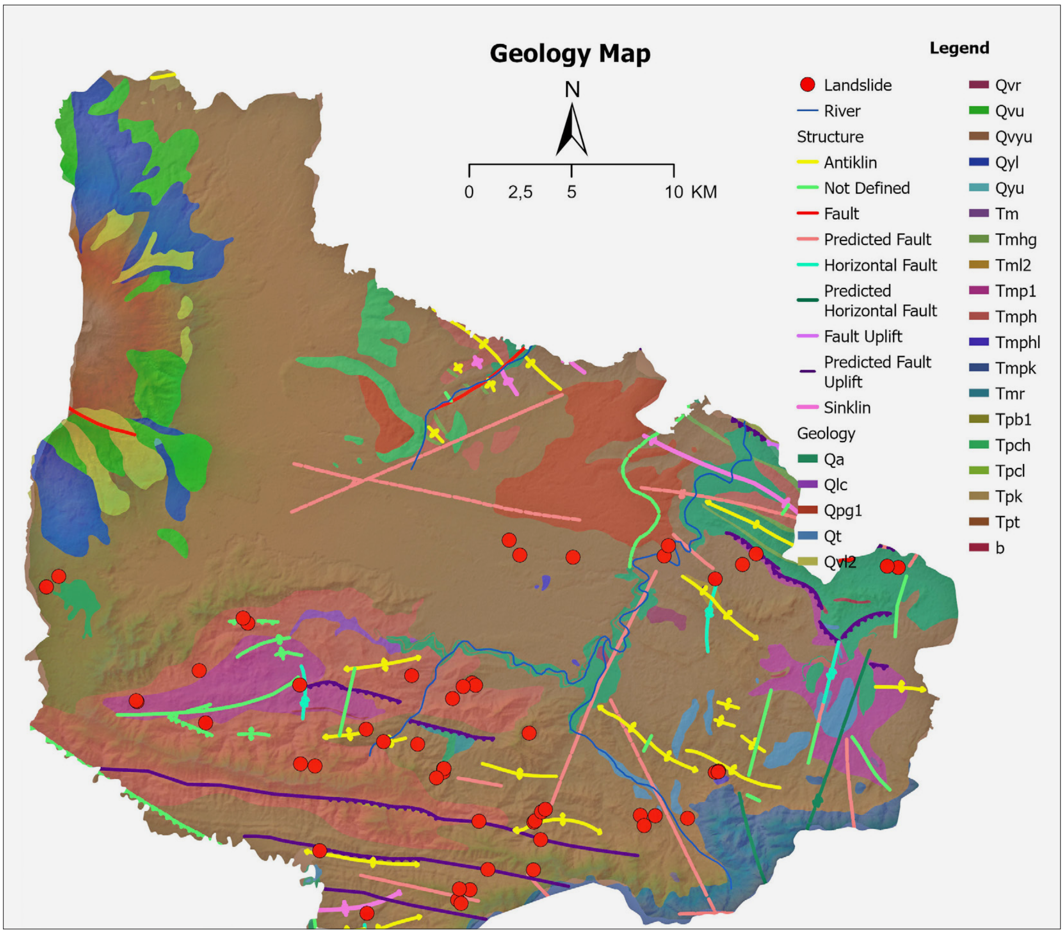

Figure 3: Map of geological condition

geological phenomena in the form of natural disasters, earthquakes, and landslides. Regarding the landslide susceptibility map for West Java of the Geological Agency Indonesia, the Kuningan region is also an area that has a moderate to high level of landslide susceptibility.

Based on the geological condition map by the Geological Survey of Indonesia, the Kuningan Regency stratigraphy is composed of tertiary sedimentary rock and quaternary volcanic rocks (see **Figure 3**). As shown in **Figure 3**, the lithological units in the study area were grouped into 24 categories based on the geological ages and formation units. The quaternary volcanic rocks found in this area are products of the volcanic activity of Mount Ciremai, which covers the western, northern, and central parts of the study area. The volcanic rocks are represented by lava, lahars, and pyroclastic rocks (breccia and tuff). Meanwhile, tertiary sedimentary rocks in the Kuningan area are strongly folded volcanic product rocks, which deposit distribution in the southern and eastern parts of the research area. Sedimentary rock deposits are represented by fine sedimentary rock characterized by claystone, siltstone, and sandstone, which are strongly folded with a high to almost vertical layer slope.

The regional geological structure developed in this study location is characterized by the Ciremai Fault and Cirebon Fault and is close to several segments of the Baribis Kendeng Fault. The Ciremai Fault is one of the active faults in West Java that has the potential to cause earthquakes. This fault has a targeted magnitude of 6.5 with a fault sliding rate of 0.1 millimetres per year (**Daryono, 2020**). A tectonic earthquake with a magnitude of 3.8 in 2022 in Kuningan Regency was a marker of the activity of the Baribis Fault in the Ciremai Segment, Kuningan, which is still active (**Ashri, 2022**). The geomorphology of the study area mainly consists of hilly landscapes and hills with slopes varying from gentle to steep. This condition contributes to most of the Kuningan area prone to landslides. The landslide hazard risk has increased along with the rapid rate of population growth, development of settlements and infrastructure in hilly areas, and global climate change that causes weather anomalies that are difficult to predict. So, an accurate and effective landslide susceptibility model is needed to predict landslides occurring in the future as mitigation efforts.

3. Methods and material

In this section, we describe the background theory of the methods used and the input data collected for landslide susceptibility mapping. This study uses two methods, namely maximum entropy (MaxEnt) and weight of evidence (WoE). Landslide inventory data and conditioning factors were prepared and processed to generate the datasets for establishing and validating the models. Furthermore, this study compares the use performance of both methods in landslide prediction. To quantitatively compare the model performance between the two models, this study uses the receiver operating characteristics (ROC) curve and the AUC (area under the curve) (**Fawcett, 2006**), where the model with the higher AUC was considered to be the better model. For this purpose, a landslide event that occurred in Kuningan Regency is considered for validation.

3.1. Weight of Evidence (WoE)

Determining the classification of landslide susceptibility levels in this study uses the Weight of Evidence (WoE) method. The Weight of Evidence (WoE) method was chosen because WoE has the technical capability to produce a mapping of landslide hazard and susceptibility zones by determining the relationship between landslide-causing factors and past landslide events (**Cao et al., 2021; Bopche & Rege, 2022**). The WoE method is a statistical method that calculates the weight of class parameters causing landslides against inventory data on past landslide events. The WoE method compares the distribution of existing landslide occurrence points with various factors that cause landslides separately. This study assumes that previous landslide events have contributed to future landslide events. In addition, each factor that causes landslides is conditionally independent. Therefore, weighing data on previous landslide events is the main causal factor and contributes to causing future landslides in the study area. The WoE method determines the weight of each class of landslide-causing factors based on the presence (Wi^+) or absence (Wi^-) of landslides in the study area. This method is the correlation between positively weighted (Wi^+) when events occur and negatively weighted (Wi^-) when events do not occur, which is defined as (**Bonham-Carter, 1994**) with geographic information systems for geoscientists modelling given in **Equations 1 and 2** as follows:

$$W_i^+ = Ln\left(\frac{P\{B_i|A\}}{P\{B_i|\overline{A}\}}\right) = \frac{\left(\dfrac{P\{B_i \cap A\}}{P\{L\}}\right)}{\left(\dfrac{P\{B_i \cap \overline{A}\}}{P\{\overline{L}\}}\right)} \quad (1)$$

$$W_i^- = Ln\left(\frac{P\{\overline{B}_i|A\}}{P\{\overline{B}_i|\overline{A}\}}\right) = \frac{\left(\dfrac{P\{\overline{B}_i \cap A\}}{P\{A\}}\right)}{\left(\dfrac{P\{\overline{B}_i \cap \overline{A}\}}{P\{A\}}\right)} \quad (2)$$

Where:

P – probability,
B_i – the presence of factor j class i,
$\overline{B}_i$ – no factor j class i,
$\overline{A}$ – no landslide,
A – the presence of landslide,

W_i^+ – probability ratio stating that the ratio in the case of presence, factor B_i then an avalanche A occurs or does not occur,

W_i^- – probability ratio which states that the ratio in the case of the absence of factor B_i then an avalanche A occurs or does not occur.

Correlation measurements can also be measured by weight contrast **Equation 3** as follows:

$$C_{wi} = W_i^+ - W_i^- \tag{3}$$

Where:

C_{wi} weight contrast.

3.2. Model Entropy Maximum

The Maximum Entropy Model (MaxEnt) is a model developed to predict species distribution in an ecosystem based on species occurrence regardless of the species considered (**Phillips et al., 2006**). The main concept of MaxEnt is to estimate the target probability distribution by looking for a geographically uniform distribution with the maximum entropy based on environmental factors at a location (**Phillips et al., 2006, 2017**). This modelling aims to find a uniform distribution of a set of probabilities. This model has been used to detect driving variables to create the most susceptibility process conditions. The MaxEnt approach is used to estimate the probability of the presence of a phenomenon. This study uses MaxEnt modelling to predict landslide distribution and determine landslide susceptibility zoning in the Kuningan area. This method is an inference technique for constructing estimates of the probability distribution of landslide susceptibility using available parameter data. The study is hoped to help the government mitigate landslides in the future. The MaxEnt model uses a statistical method for a correlative approach to landslide inventory data on the parameters that cause landslides. The entropy value *(H)* of the probability distribution *P* in region *X* is defined **Equation 4** as follows:

$$H(x) = -\sum P(X) \ln P(X) \tag{4}$$

Where:

H – the entropy value,

P – the probability distribution,

X – the region.

3.3. Input data

In landslide susceptibility modelling, this study used a total of ten input data for the conditioning factors, including slope, slope direction, curvature, flow direction, river, geological structure, land use, soil type, lithology, and rainfall. Landslide inventory and conditioning factors were prepared and processed to generate the datasets for establishing (75% datasets) and validating the models (25% datasets). Data processing for each parameter uses geographic information system software to determine its classification and weighting. Regarding the test results for each parameter, this research prioritizes five selected parameters that greatly influence the potential for landslides, as shown by the AUC values (AUC > 0.6) as follows: slope (0.8), land use (0.77), soil type (0.768), lithology (0.740), and rainfall (0.78). All data were converted to a raster format with the same pixels, and each raster map was divided into several classes according to their properties. Parameters that caused the landslide were analyzed using GIS and a raster with a 25 x 25 m cell size. This study uses a spatial and statistical approach with a raster grid as the unit of analysis.

3.3.1. Landslide data

Landslide occurrence is the main parameter for analyzing landslide susceptibility classification in this modelling. Landslide inventory data was obtained from Geological Agency data, field survey data, and landslide identification via Google Earth (see **Figure 4**). The inventory of landslide events is information on the location of landslide events that occurred in the research area in the previous period. The data retrieved from landslides was divided into two sets: the first data set was to create landslide susceptibility modelling (train set data), and the second set was to test the validity of the factor relationship to landslide events (test set data) (**Ozdemir, 2011**). Data set division is done automatically or randomly by the subset feature tool in ArcGIS. Determination of the distribution of data sets is random, and there are no special restrictions. So, the larger the presentation of the data set for analysis, the greater the validation value (AUC) obtained. The data sets are divided into two data sets. The landslide susceptibility modelling for the study area of 1226 km^2 was based on 55 landslides. In addition, the validation analysis was done with 14 landslides. The statistical approach is very dependent on the availability of existing historical landslide data.

3.3.2. Topography

For model data input, topographic parameters were obtained from DEM data. Digital Elevation Model (DEM) was data digital elevation maps produced by DEMNAS, Geospatial Information Agency, Indonesia (https://tanahair.indonesia.go.id/demnas/#/demnas). DEM is presented in a raster with a cell size of 25 x 25 m created using GIS tools. DEM is generated to obtain elevation, slope, slope direction, curvature, and flow direction data. Topographic factors describe the morphological characteristics of the study area. Landslides generally occur in hilly topography with steep slopes (**Chen & Huang, 2013**). Slope angle, slope direction, and curvature can influence the onset of landslides (**Dai & Lee, 2002**). The slope angle influences landslides through the runoff process (**Duley & Hays, 1933**). The steeper the slope of the slope, the greater the rate and amount of surface runoff, so there is the potential for landslides to oc-

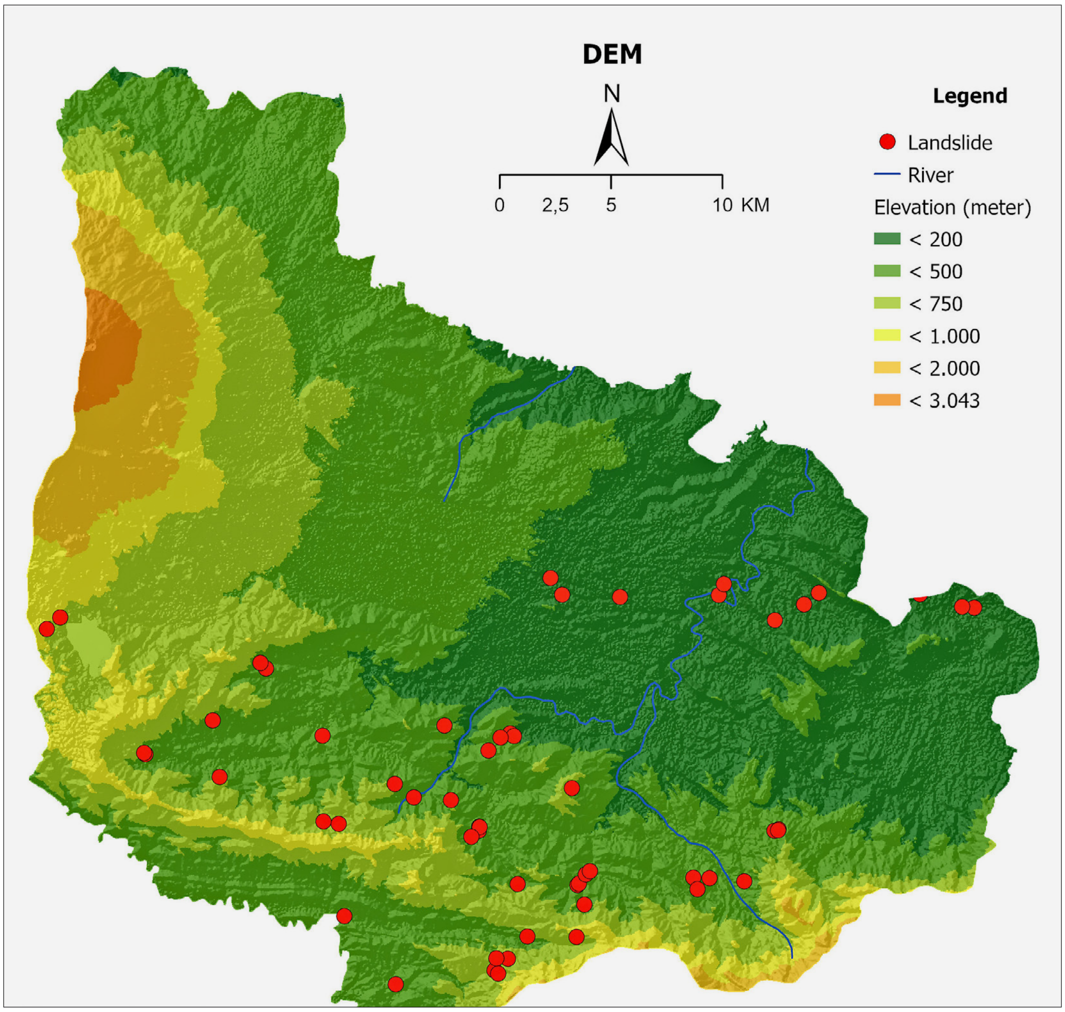

Figure 4: Distribution of landslide inventory data

cur. Raster slopes are created using the slope tool and classified in percent via internal equals. *Slope direction* is defined as the maximum slope of the terrain surface. Weak rock conditions cause this susceptibility due to weathering, the morphological condition of hills with relatively steep slopes, and high rainfall in the wet months (reaching 100 mm/day) (**Tohari et al, 2006**). In this study, the elevation values in the Kuningan area were divided into six classes as follows: <200 m, <500 m, <750 m, <1.000 m, <2.000 m, and <3.034 m (see **Figure 4**). **Figure 4** shows the dominant distribution of landslide events in hilly areas with an elevation of 350 m to 1,200 m in the southern part of Kuningan Regency. Meanwhile, in the northern part, almost no landslides were recorded. Landslide inventory data is the key factor in landslide susceptibility modelling. Without good landslide inventory data in the modelling, it is almost impossible to get good accuracy of landslide susceptibility map.

Based on topographic data processing, the parameter that has an AUC above 0.6 is the slope. The slope angle of the slope is a parameter triggering the occurrence of landslides, and then a slope raster map is made using the slope tool and classifying classes (**van Bemmelen, 1949**). **Figure 5** shows that the Kuningan area has a hilly morphology with flat to very steep slopes. 24% of the landslide locations in Kuningan Regency are in hilly areas with a slope of 15º to 30º. So, the steeper the slope in the study area, the more potential for landslides. In this respect, the runoff process will likely increase the rate and amount of surface runoff in the area. These conditions are generally connected to the stability of slopes.

3.3.3. Land use

Land use is one of the main parameters that affect slope stability. The land cover provides information on the spatial use of the research area. Surface vegetation is a variation of land cover that reduces soil erosion because it can increase soil strength by strengthening roots (**Roering et al., 2003**). So vegetation has become a factor affecting slope failure, and even reduced vegetation cover is more susceptible to landslides. The land use parameters were obtained from the Kuningan Regency area's Topographic Map of Indonesia Scale 1: 25,000.

Figure 6 shows 15 types of land covers in Kuningan Regency based on the land use map obtained from the

Kuningan topographical map, namely the RBI (Rupa Bumi Indonesia) Map. The most dominant land cover types in this study area are plantations (30.6%) and paddy fields (23.6%). The area is dominated by about 67% of landslides in land cover in the form of settlements in hilly areas and rice fields. In this study, the most susceptible land cover is non-forest (paddy field, moor, shrubs, and settlement) in hilly areas which have the potential for landslides; due to the little vegetation cover that functions as slope reinforcement, the slope area will be more susceptible to landslides. In contrast, settlement will make a load on the slope so that the driving force will be greater than the resisting force on the slope.

3.3.4. Soil types

Soil type is a parameter used in modelling landslide susceptibility. These parameters were grouping soil based on similarity, similarities in morphological, physical, chemical, and mineralogical properties, and characteristics obtained from the department of the Center for Soil and Agro-climate Research (Puslittanak) for the Kuningan Regency. Soil type maps describe an area's variation and distribution of various soil types or soil properties (such as pH, texture, organic content, depth, etc.). Weathering processes in rocks greatly affect the formation of soil types. The presence of residual soil on the ground surface can cause engineering geological problems, especially related to soil strength and shear strength. Landslide disasters are most often associated with residual soil in hills. The soil type with a higher degree of weathering will be more susceptible to landslides. Landslides often occur in residual soil, especially during the rainy season, due to the decreasing strength of soil shear (**Wibawa et al., 2018**). The influence of andosol and latosol soil types is sensitive landslide susceptibility (**Sugianti & Tohari, 2023**).

The thematic geological raster map shows that the Kuningan area comprises several soil types (see **Figure 7**). Podzolic, Latosol, and Mediterranean Complexes dominate the Kuningan area. Podzolic is a type of soil that has an argillic B horizon and does not have an albic horizon that is directly adjacent to the argillic or fragipan horizon. Latosol is a type of soil that develops from volcanic materials, clay content ≥ 40%, is crumbly, loose, and homogeneous in color, has deep soil cross-section, has horizons that characterize A ochre, umbric, or B cambric, has no plinth and vertical properties. Mediterranean is a type of soil that has an argillic B horizon and does not have an albic horizon directly adjacent to the argillic or fragipan horizon. The most susceptible soil type in this area is Podzolic, at around 54%. Podzolic soil type comes from weathered volcanic rocks. The existence of Podzolic-type residual soil is one of the factors causing the problem of landslide susceptibility in the Kuningan area.

3.3.5. Lithology

The lithological parameters were obtained from the geological distribution map of the Bandung sheet obtained from the ESDM Geological Agency. This parameter is one of the most fundamental factors that affect slope stability through the engineering properties of the soil in the form of soil shear strength. Lithology with low shear strength mechanical characteristics will have the potential for avalanche events (**Chen et al., 2011; Sugianti et al., 2022**).

The geological thematic raster map shows that the Kuningan area is composed of several types of rock, namely alluvial, young volcanic deposits, old volcanic deposits, and the Ciherang, Cijulang, Gintung, Halang, Kalibiuk, Kaliglagah, Kaliwangu, Kumbang, and Pemali Formations. Geologically, the Kuningan region is located on the eastern slope system of Mount Ciremai, which is composed of volcanic rocks resulting from the eruption of the mountain as well as tertiary sedimentary rock systems in the eastern and southern parts. Tertiary sedimentary rocks in the southern part are traversed by the Baribis thrust fault, which is indicated by the almost vertical slope of the layers. The dominant area of landslide occurrence is the young volcano Ciremai, with 70% of landslide occurrences and an area total of 43% of the research locations (see **Figure 8**). In the case of the lithology factor, the most susceptible classes were young volcanic products. The residue from young volcanic products is predicted to have a more intense weathering rank, so the slopes are more prone to landslides in the study area.

3.3.6. Rainfall

Rainfall data is data on the amount of water that falls to the ground surface during a certain period measured in millimeters (mm). Spatial rainfall data was obtained from the online daily rainfall data of the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) on March 1st-12th, 2018, which has been interpolated with the distribution of rainfall data to become an isohyet map. Rainfall is a trigger parameter that causes landslides (**Sugianti et al., 2022**). Rainwater infiltration can disrupt slope stability because of increased pore water pressure due to soil saturation (**Iverson, 2000; Tohari et al., 2013; Sugianti et al., 2022**). Considering that the distribution of precipitation is assumed to be continuous, the equal interval approach divides the data into classes depending on the range of values. Kuningan area rainfall data was obtained from CHIRP satellite data. **Figure 9** shows the average rainfall intensity of 171.231 – 361.110 mm/month. **Figure 9** shows that the Kuningan area has dry to very wet rainfall parameters. This area is dominated by moderate/humid rainfall, with an area of 37.86% and wet precipitation of 24.18%. Nearly 64% of the dominant landslide locations had rainfall intensity of 228.195 to 266.171 mm/month in the study area. Thus, the rainfall intensity in the Kuningan area can influence landslides.

3.4. Landslide susceptibility and model effectiveness

Landslide susceptibility is the possibility of landslides occurring in an area based on controlling and triggering factors. Classification and determination of the level of landslide susceptibility are then carried out using the maximum entropy (MaxEnt) and the weight of evidence (WoE) methods. The weighting is the multiplication of the parameters that have the lowest weight to the highest. The level of soil susceptibility is determined based on this multiplication from the maximum to minimum weight values so that 5 levels of susceptibility are obtained.

Table 1: Classification of AUC

Classification	AUC Value
0.9 - 1.0	Very Good
0.8 - 0.9	Good
0.7 - 0.8	Fairly Good
0.6 - 0.7	Bad
0.5 - 0.6	Incorrect

Area Under Curve (AUC) is the area under the curve that provides an overview of the overall measurement of the suitability of the model used. AUC is also a type of accuracy statistic for probability models in predicting the assessment or analysis of natural disasters (**Nefeslioglu & Gokceoglu, 2011**). The AUC value is a graphic index number with a limit between 0.5 (50%) and 1 (100%). Based on the AUC value, the evaluation of model performance accuracy can be classified into five groups, as shown in **Table 1** (**Hosmer & Lemeshow, 2010; Gorunescu, 2011**).

Model validation also uses data on landslide events. Validation is divided into 2, namely, success rate and prediction rate. Success rate or True Positive Rate (TPR) is a calculation of assessing the success of a model that shows good conformity with past events (prior). Prediction rate or False Positive Rate (FPR) validates prediction assessment calculations that show good agreement with predictions of unknown events or events that will come (posterior). The percentage of avalanche events in both validations was calculated. The calculation results are plotted in an AUC graph, the X-axis is the percentage outside the mapping area, and the Y-axis is the percentage of avalanches (**Chung et al., 1995**). In this study, the AUC value was obtained from the index value, which was formed from a comparison chart between the

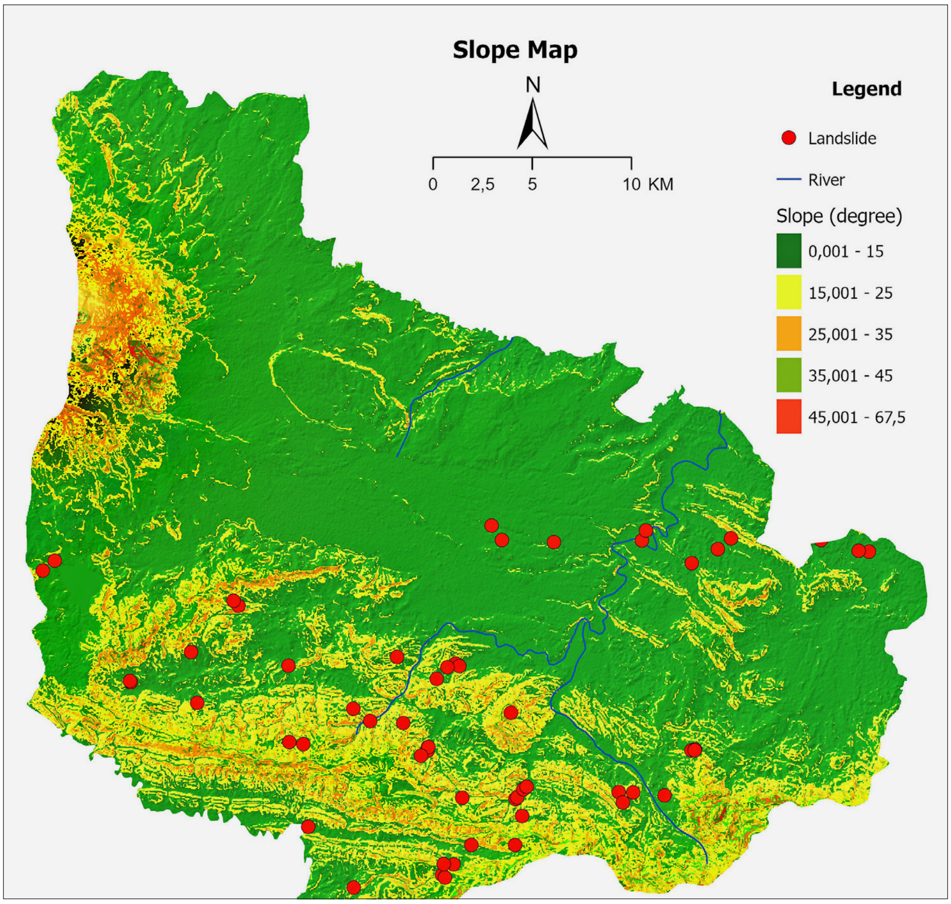

Figure 5: Slope thematic raster

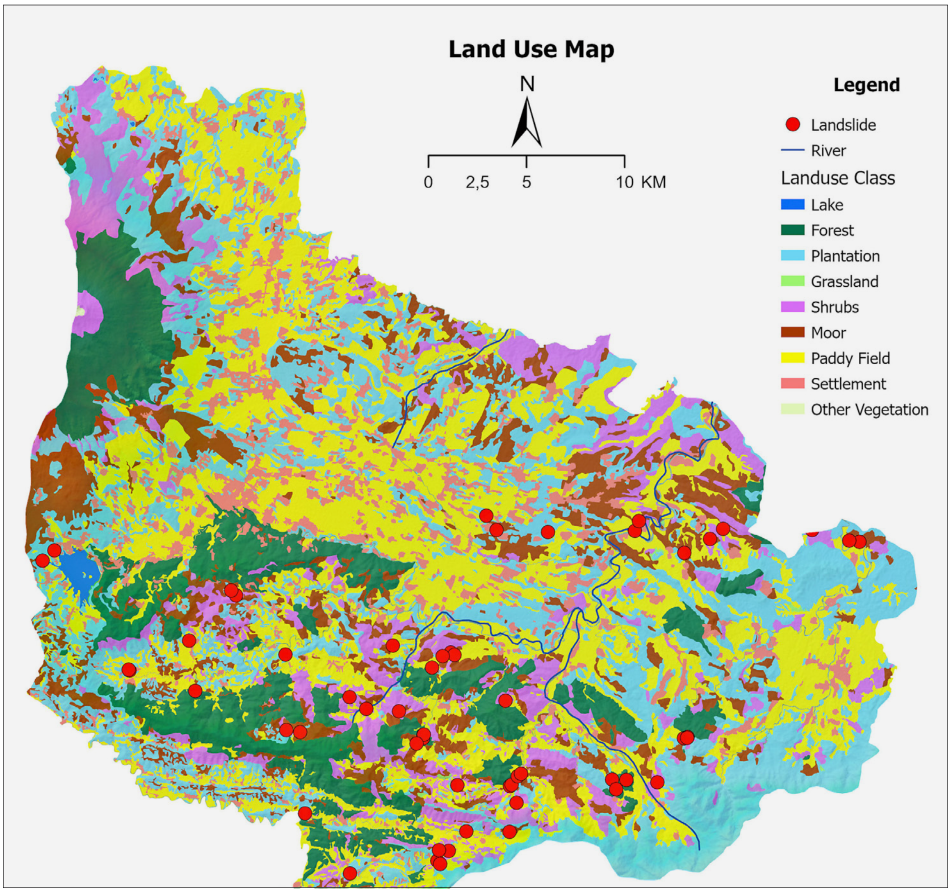

Figure 6: Land use thematic raster

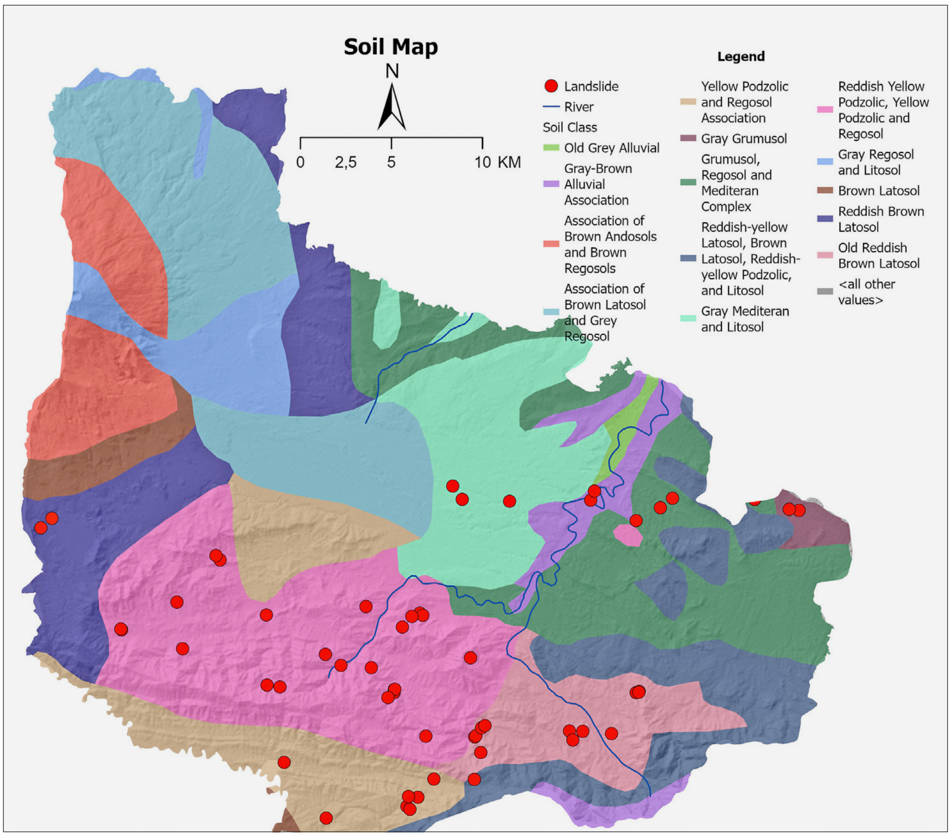

Figure 7: Types of soil map

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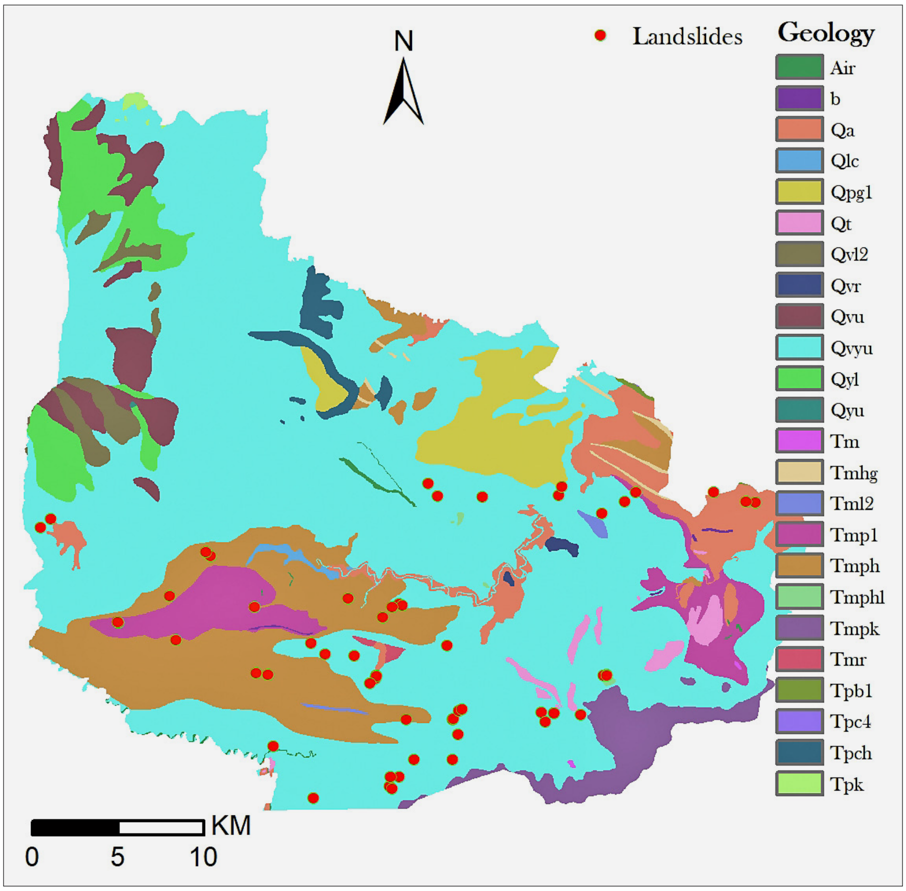

Figure 8: Geological map

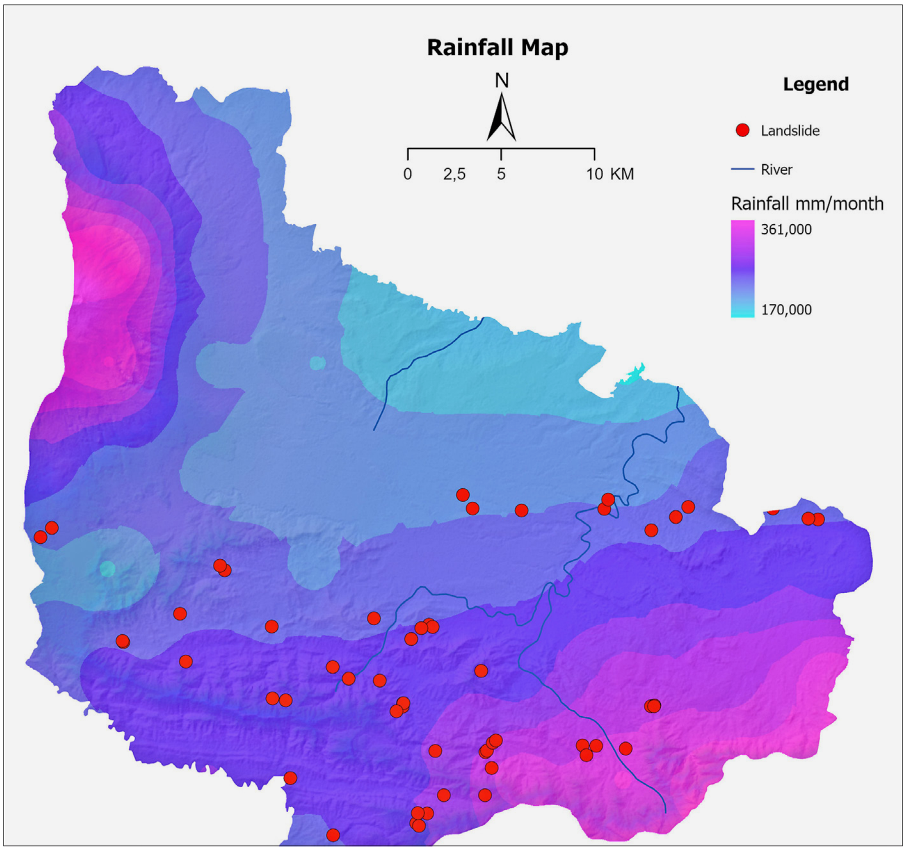

Figure 9: Rainfall map

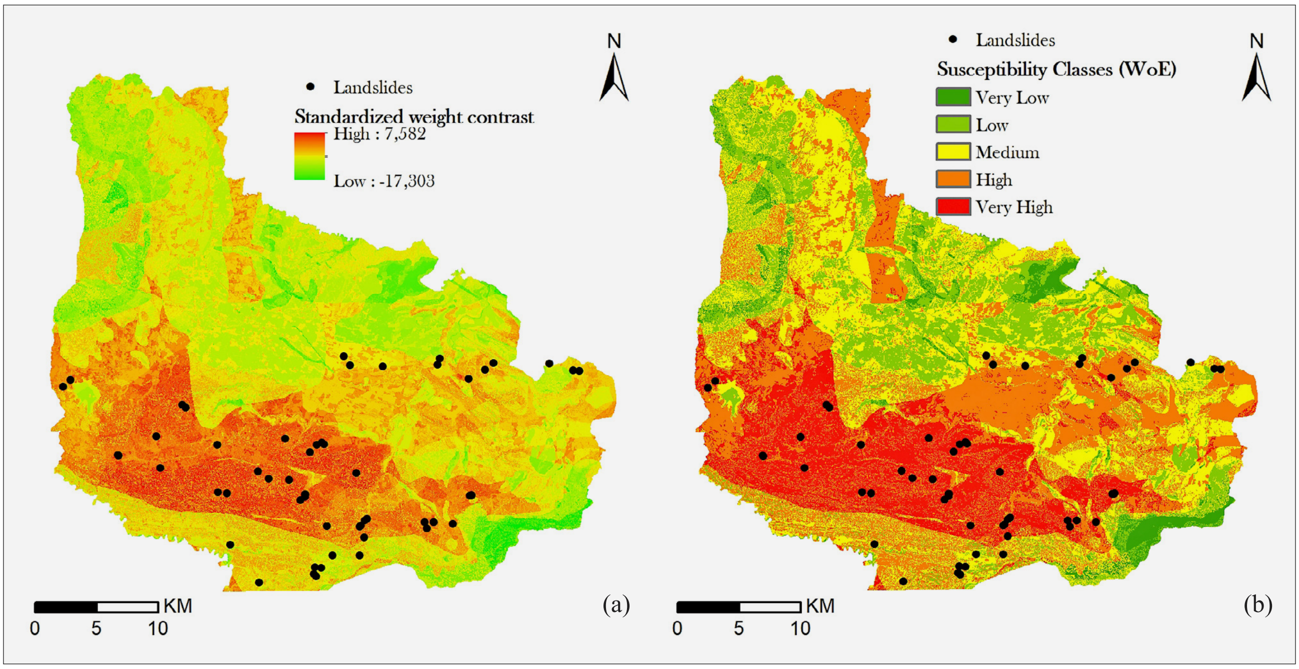

Figure 10: Weight contrast index (a) and landslide susceptibility map using WoE (b)

percentage of the total area of the class area for each parameter to the total number of landslide events.

4. Results and discussion

The landslide susceptibility maps were established after the successful model training process. The landslide susceptibility index was generated for all pixels in the study area, where each pixel was assigned a unique susceptibility index. Then, the susceptibility index was reclassified based on the natural breaks method. Based on the reclassification of the landslide susceptibility index, the landslide susceptibility maps were reclassified into five susceptibility classes: very low, low, moderate, high, and very high. This research resulted in two landslide susceptibility maps prepared utilizing WoE and MaxEnt models. The area distribution of both models is represented in Figure 10 and Figure 11.

4.1. Model of landslide susceptibility

The following are the results of landslide susceptibility map modelling obtained using the WoE and MaxEnt methods involving many important conditioning factors.

4.1.1. Model of Susceptibility Level Zoning by WoE

In the present study, the simulation of the WoE modelling presents a weighted contrast or susceptibility index that is reclassified into the landslide susceptibility class based on the natural breaks method, as shown in **Figure 10a**. This area covers the landslide susceptibility classes very low (3.915 ha), low (19.390 ha), medium (35.404 ha), high (39.244 ha), and very high (20.179 ha), as shown in **Figure 10b**. The study area's northern region has a very low to moderate rank susceptibility. Meanwhile, the south of the research area is a high to very high. **Figure 10** shows that known landslides are located in high and very high landslide susceptibility zones.

4.1.2. Model of Susceptibility Level Zoning by MaxEnt

In this research, the modelling using the MaxEnt presents a weighted contrast or susceptibility index that is reclassified into several susceptibility categories in the landslide susceptibility class, as shown in **Figure 11a**. Landslide susceptibility classification on the map uses natural break classifiers applied to the data based on their distribution histograms. This area covers the landslide susceptibility classes very low (67.982 ha), low (22.638 ha), medium (12.886 ha), high (8.183 ha), and very high (6.444 ha), as shown in **Figure 11b**. The northern area of the study area is very low to moderate susceptibility. Meanwhile, in the south of the research area, there is high to very high susceptibility.

The MaxEnt model susceptibility map shows that the dominant landslide events are in the high and very high landslide susceptibility zones. Apart from that, some of the landslide locations occurred in green areas. In the MaxEnt modelling results, several landslide points in the northern region are in the low susceptibility class. Generally, the distribution of susceptibility follows the topographic pattern of the Kuningan area. This is in line with previous research, which found that slopes had the greatest influence on landslide susceptibility maps

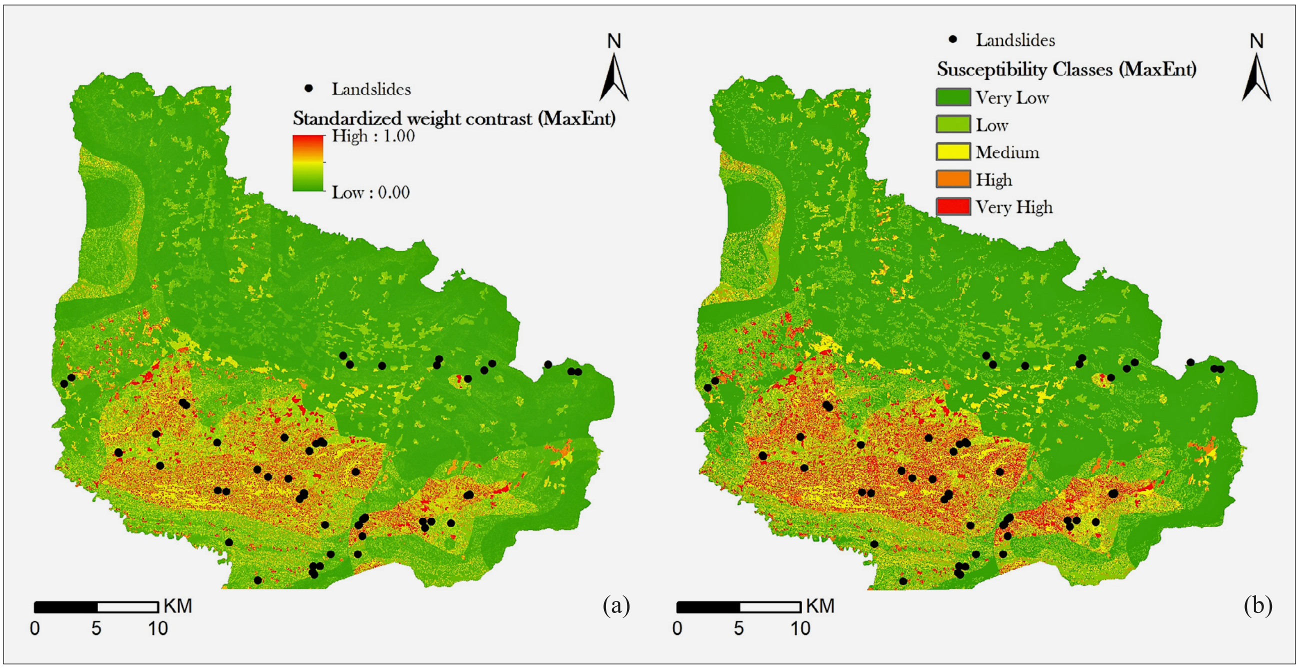

Figure 11: Weight contrast index (a) and landslide susceptibility map using MaxEnt (b)

(**Kamran et al., 2021**). However, some of landslide locations are situated on slopes that are not very steep with loose volcanic residual lithology, so they have a high potential for landslides. In addition, human activities, including plantings, rice fields, and residential areas are also responsible for landslides.

4.2. Evaluation of model parameter

Landslides occur less frequently on gentler slopes and with less rainfall. In contrast, as illustrated in **Figure 12** (**from a to e**), the level of susceptibility increases sharply at slopes above six and rainfall above 109. The four highly susceptible formations are pyroclastic and lava deposits from Mt. Ciremai (Qv), Breccia unit from the Halang Formation, volcanic breccia from the Kumbang Formation, and Marl and limestone from the Pemali Formation (Tmp). The most susceptible land use/cover classes are Wilderness Forests and Moorland/fields. **Figure 12** reflects the dependence of predicted suitability on the selected variables and dependencies induced by correlations between the selected variable and other variables. The following is the response curve model for the probability of landslide presence on the horizontal (y) axis to the conditioning factor variables on the vertical (x) axis, namely slope class (a), land use class (b), soil types class (c) geology class (d), and rainfall class (e), shown in **Figure 12**.

4.3. Evaluation of model prediction performance

One of the most important processes in modelling is the model validation process. In this study, the ROC curve is used to evaluate the accuracy of the prediction results of the landslide susceptibility model that has been carried out. The ROC model evaluation method is a method based on specificity and sensitivity (**Baldwin, 2009**). Specificity is how well the model predicts non-occurrence, while sensitivity is how well the model predicts emergence. Specificity and sensitivity are displayed in the form of an Area under the Curve (AUC) graph. Success rate curves are generated by comparing susceptibility maps and training data (75% of the training data set of 41 landslides). In addition, prediction rate curves are generated with the help of susceptibility maps and testing data (25% of the test data set of 14 landslides). In this study, the ROC (AUC) curve of model performance is shown in **Figure 13**. The graph shows that the WoE and the MaxEnt model gave a prediction rate (AUC=0.768 and AUC= 0.774) and a high success rate (AUC= 0.856 and AUC= 0.889). The AUC rounding value of both models is used to qualitatively evaluate the prediction accuracy of the models (AUC= 0.8) and the high success rate of models (AUC= 0.9). Based on the classification of AUC (see **Table 1**), both models have good performance in modelling future landslide susceptibility. The resulting map of areas susceptible to landslides has a predicted accuracy of 80% and a success rate of 90%. Based on the ROC curve, the MaxEnt and WoE methods that have been used have described the deterministic and probabilistic proficiency and landslide susceptibility prediction system. Among both models (WoE and MaxEnt) are the best-performing models in both success and prediction rate curves.

As a final point, the AUC values are almost the same for both approaches. Nevertheless, the spatial distribution of the susceptibility zone and landslide susceptibil-

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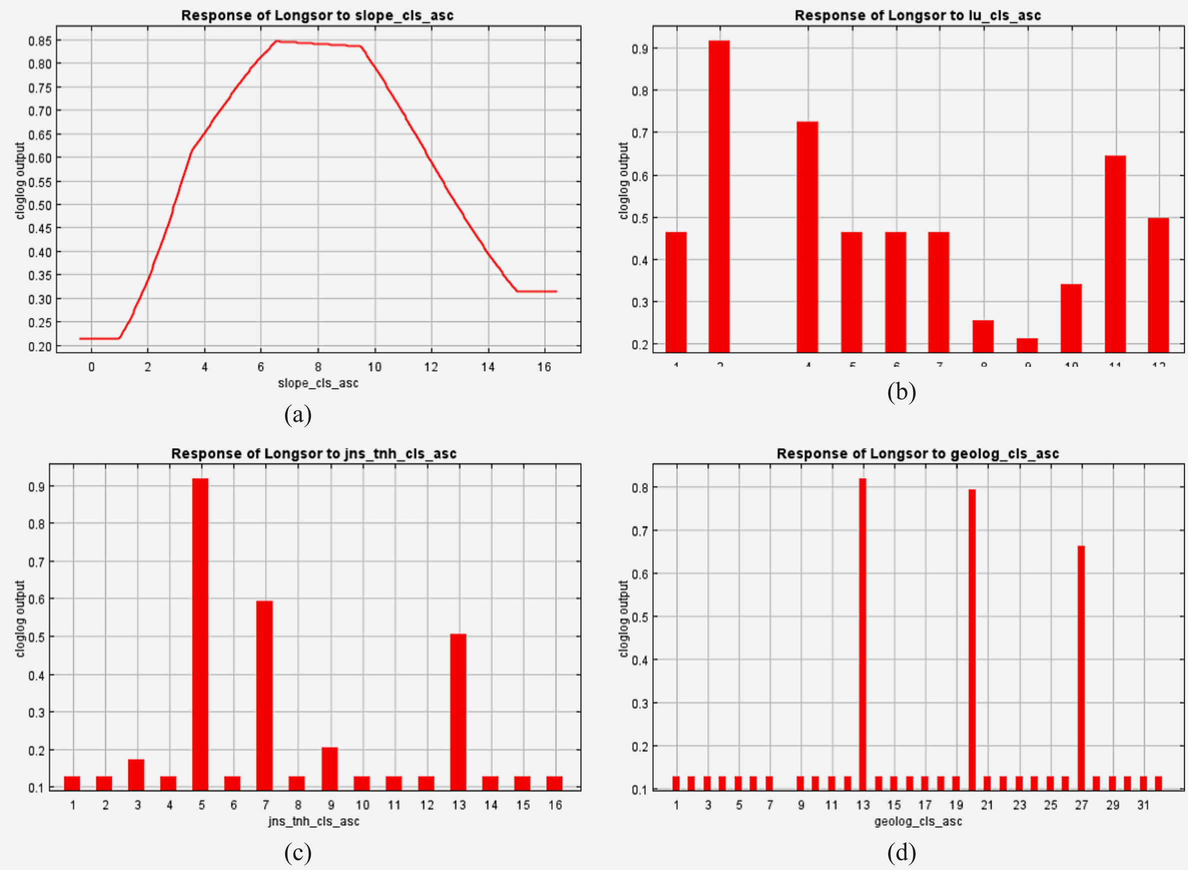

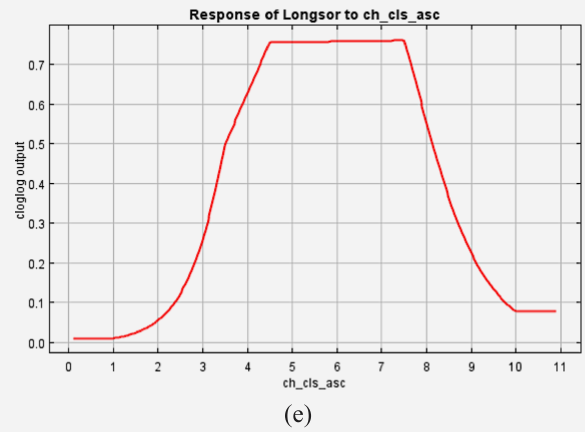

Figure 12: Marginal response curves of factors (a) slope class, (b) landuse class, (c) soil type class, (d) geology class, and (e) rainfall class

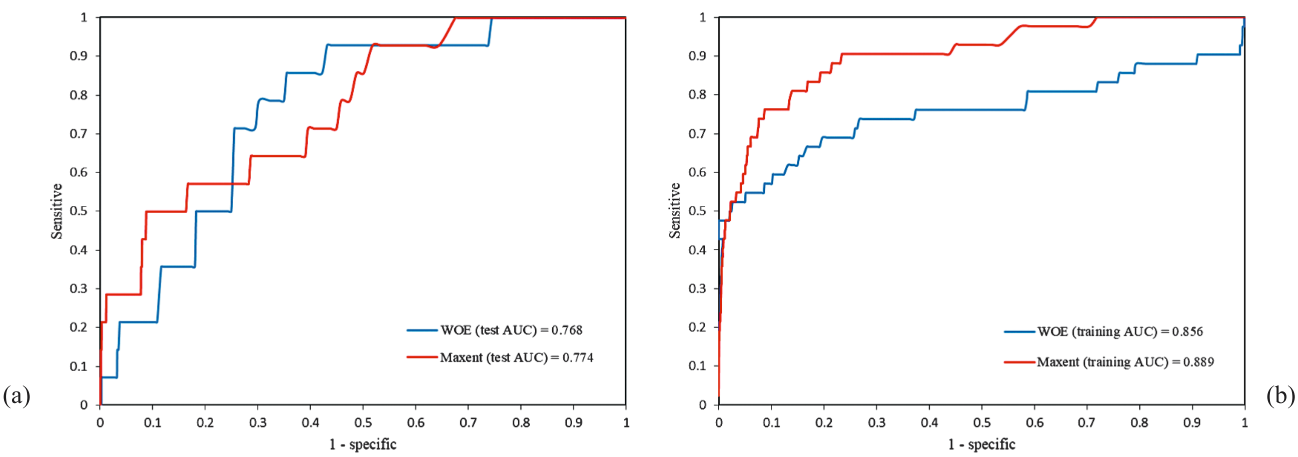

Figure 13: ROC (AUC) curve of the landslide susceptibility models using testing data set (a) and training data set (b)

ity varies significantly between the two approaches. The results show a few differences in the spatial distribution of the landslide susceptibility map modelling between the two approaches. The distribution has been few and insufficiently representative of landslide incidents, so the study and analysis presented here are merely preliminary. The use of a combination of continuous and nominal data in MaxEnt's input data results in a more precise spatial distribution of maximum susceptibility levels than in WoE. Meanwhile, every parameter in WOE is classified, and all input data is categorized.

5. Conclusions

Landslide susceptibility mapping plays a strategic role in providing a platform to policymakers. The current study addresses this problem using Maximum Entropy and Weights of Evidence Modelling in Kuningan Regency, Indonesia. Therefore, five landslide control factors were considered, namely land use, slope angle, soil type, geology, and rainfall. The research results show that the Kuningan area has four levels of susceptibility to landslides: very low, low, medium, and high. The AUC rounding value of both models is used to qualitatively evaluate the prediction accuracy of the models (AUC= 0.8) and the high success rate of models (AUC= 0.9). It shows that both models have good performance in modelling future landslide susceptibility. The resulting map of areas susceptible to landslides has a predicted accuracy of 80% and a success rate of 90%. Based on the ROC curve, the MaxEnt and WoE methods that have been used have described the deterministic and probabilistic proficiency and landslide susceptibility prediction system. Among both models (WoE and MaxEnt) are the best-performing models in both success and prediction rate curves. In addition, the AUC parameter value also shows the parameters with the highest influence level, namely slope angle and geology. A comparison of the resulting landslide maps reveals that the two models applied have high accuracy for studying sensitivity in the Kuningan area.

The study concluded that landslide inventories are an essential component of landslide susceptibility modelling. Without appropriate landslide inventory data, obtaining a reliable and accurate landslide susceptibility map is nearly impossible. The two approaches provided comprehensive distributions of susceptibility across different landslide susceptibility models. In the comparison of the results of maps produced using both methods, it was found that the MaxEnt method generates a map with larger low-susceptibility zones than the WoE method, even though the AUC parameters of the two models are essentially similar. This research also provides initial guidance regarding landslide-susceptible zonation, which is useful for spatial planning. Therefore, further research should be carried out to obtain landslide susceptibility maps that are more precise, accurate, and reliable in predicting landslide events.

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SAŽETAK

Učinkovitost mapiranja osjetljivosti na klizišta korištenjem modela maksimalne entropije i težine dokaza u pokrajini Kuningan, Zapadna Java, Indonezija

Kuningan je namjesništvo u regiji Zapadne Jave koje ima problema s klizištima svake godine u posljednjih deset godina. Klizišta su u desetljeću od 2011. do 2022. godine na ovome području zabilježena 124 puta. Potrebno je opsežno znanje o varijablama koje utječu na pokazatelje koji se koriste za geografsku klasifikaciju podložnosti klizištima. Ovim istraživanjem pokušavaju se izraditi karte osjetljivosti na klizišta na temelju odnosa između parametara i podataka inventara klizišta. U ovome slučaju predstavljamo kartiranje osjetljivosti na klizišta u području Kuningan koristeći se dvjema metodama, naime maksimalnom entropijom (MaxEnt) i težinom dokaza (WoE). Rezultati su pokazali da su za različite modele osjetljivosti na klizišta dva pristupa generirala sveobuhvatne distribucije osjetljivosti. Iako su parametri AUC dvaju modela gotovo identični, pristup MaxEnt proizvodi karte s većim zonama niske osjetljivosti od metode WoE prema usporedbi karata stvorenih pomoću tih dvaju pristupa. Ovo istraživanje nudi preliminarne preporuke za zoniranje podložno klizištima, što je od pomoći za prostorno oblikovanje. Kako bi se izradile karte osjetljivosti na klizišta koje su preciznije, točnije i pouzdanije u predviđanju događaja klizišta, potrebno je provesti dodatne studije.

Ključne riječi:
osjetljivost, klizišta, WOE metoda, MaxEnt, AUC

Author's contribution

Mamat Suhermat (1) (M.Si., junior researcher, geographic information engineering) performed MaxEnt modelling and model analysis. **Khori Sugianti** (2) (M.T., junior researcher, geological engineering) analyzed parameter data and evaluated the modelling results and presentation of the paper. **Yunarto** (3) (M.T., senior researcher, engineering) carried out WOE modelling and analyses of the model results. **Yugo Kumoro** (4) (S.T., senior researcher, geological engineering) analyzed the geological conditions of the research area. **Wawan Hendriawan Nur** (5) (M.T., junior researcher, geographic information engineering) presented all images and assisted with modelling analyses. **Sukristiyanti** (6) (junior researcher, geographic information science) evaluated and edited the manuscript, and **Hilda Lestiana** (6) (M.Si., junior researcher, remote sensing analysis) analyzed morphology and model results.