

Research article

Landslide Susceptibility Assessment in Mojokerto Regency Using Logistic Regression

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Abstract.

The impact of landslides varies from place to place, including cutting off transportation routes, destroying agricultural land, and/or destroying houses. Due to the high threat of landslides, it is necessary to make efforts to improve community preparedness by disseminating information about landslide distribution. In this research, landslide assessment was conducted using logistic regression. Twelve landslide factors were assessed including topographic position index, stream power index, slope, aspect, elevation, profile curvature, distance to drainage, soil, rainfall, land use, and distance to road. The assessment of the landslide susceptibility level in this study was highly accurate, based on the AUC value obtained, which was 0.92. The results of the assessment of the landslide susceptibility level were divided into five classes with the following areas: very low 36%, low 4.4%, moderate 2.91%, high 4.1% and very high 52.5%.

Keywords: scientific, approach, methodological, techniques, geography

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1. Introduction

Indonesia is a country with the largest number of active volcanoes in the world. It is recorded that 15% (129) of the number of active volcanoes in the world are in Indonesia [1]. Most of the volcanoes which are volcanic landscapes are located on the island of Java so that volcanic processes dominate this island [2]. The distribution of volcanoes on the island of Java is located in the middle part that extends from the east-west. Volcanic landscapes have a high level of soil thickness so that they are prone to landslides during the rainy season with the main material in the form of soil.

Pacet Subdistrict, Mojokerto Regency is included in the volcanic range of the central part of Java Island. The process of volcanism that works in the Mojokerto Regency area is triggered by the activity of the Anjasmoro Volcano and Arjuno Volcano during the Middle Pleistocene-late Pleistocene and the activity of the Welirang Volcano during the late Pleistocene to the present. The results of the geological process work provide various geomorphological, lithological, and hydrological characteristics. Landslides that occur have varied dimensions and materials. Generally impact of the landslide varies

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from place to place, such as: cutting off transportation routes, destroying agricultural land, and destroying houses.

Seeing the high level of threat of landslides, it is necessary to make efforts to improve community preparedness. One of the concrete efforts to improve preparedness is to provide information on the level of susceptibility to landslides [3]; [4]; [5]. It is necessary to pay attention to the selection of analytical methods in assessing the level of landslide susceptibility because it is related to the level of accuracy. Of course, if an analytical method has a high level of accuracy, it will be able to describe the actual conditions in the field.

This study uses a statistical model in assessing landslide susceptibility. The statistical model is considered suitable to be applied to areas with diverse physical characteristics as in this research area [6]. This study used a multivariate logistic regression statistical model. Logistic Regression is one of the three classification methods that are widely used most often [7]. The three classification methods that are widely used are: logistic regression, linear discriminant analysis, and K-nearest neighbors [7]. This study applies a validation test using an accuracy curve in order to produce an optimal level of accuracy.

2. Method

Landslide susceptibility classes can be generated using logistic regression analysis techniques by going through 4 stages of data, namely: 1) preparing data on factors that cause landslides, 2) inventorying landslide and non-landslide data, 3) logistic regression analysis, and 4) validation (Figure 1) .

2.1. Spatial Dataset Preparation

2.1.1. Landslide Triggering Factor

There are 12 factors that cause landslides that are used to assess the level of landslide susceptibility in this study. These factors are as shown in Figure 2 and Figure 3. The elevation factor, topographic wetness index, topographic position index, stream power index, slope, and curvature profile are generated from Alos Palsar DEM data after being processed in the QGIS 3.18 application. The soil factor was obtained from the 1:25,000 Soil Map of Mojokerto Regency made by the Ministry of Agriculture of the Republic of Indonesia. The distance factor from the road is obtained through the Mojokerto Regency Map from the Geospatial Information Agency of the Republic of Indonesia. The rainfall

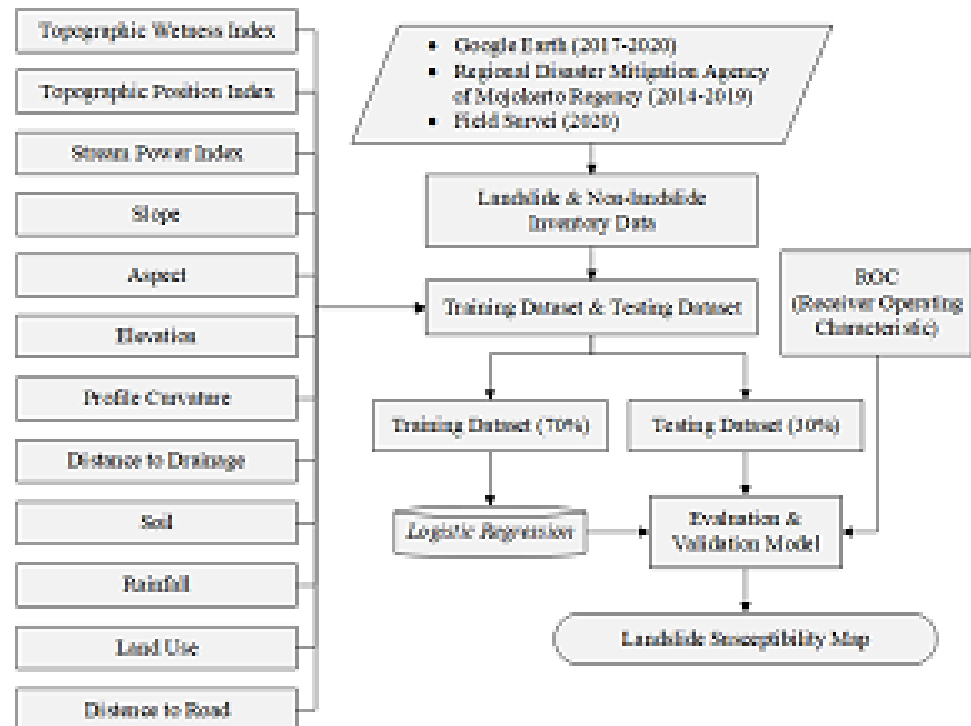


Figure 1: Research Flowchart.

factor was obtained from the distribution of monthly rainfall data for 10 years from the Public Works Department of Mojokerto Regency. Meanwhile,

Aspect or the direction towards the slope in landslide susceptibility assessment can identify geomorphic characteristics such as erosion, run-off, and sediment deposition on a slope. The aspect value also has implications for the intensity of sunlight and high rainfall. This phenomenon has an impact on the decomposition of the material composer slopes resulting in erosion and weathering. Besides that, intensitySunlight and rainfall affect soil moisture which can trigger slope instability. The aspect class in this study is divided into eight classes as shown in Figure 2a. The eight classes include flat, north, northeast, east, southeast, south, northwest, west, and southwest.

Distance from drainage (Figure 2b) is a hydrological factor that affects the level of infiltration, runoff, and the level of moisture in the soil. The stability of the slope is influenced by the distance between the drainage structures, the closer it is to the drainage, it generally has a landslide [8]. Therefore, slopes that are closer to the main drainage system will have a higher level of landslide susceptibility. Variations in the value of the distance from the drainage in this study were from 0-820 m. In this study, it was divided into five in order to determine the characteristics of drainage that have a high level of susceptibility based on the distance.

The distance of an area from a road is also very influential on the level of susceptibility to landslides. This is triggered by human activities that change the landscape, such as cutting slopes due to road openings, residential development, and agricultural or other activities, thus allowing the formation of slip fields. As for the activity of passing vehicles that cause vibrations along the road, it can trigger slope failure on unstable roadside slopes. The distance factor from the road in the study area is 0-4,300 m (Figure 2c).

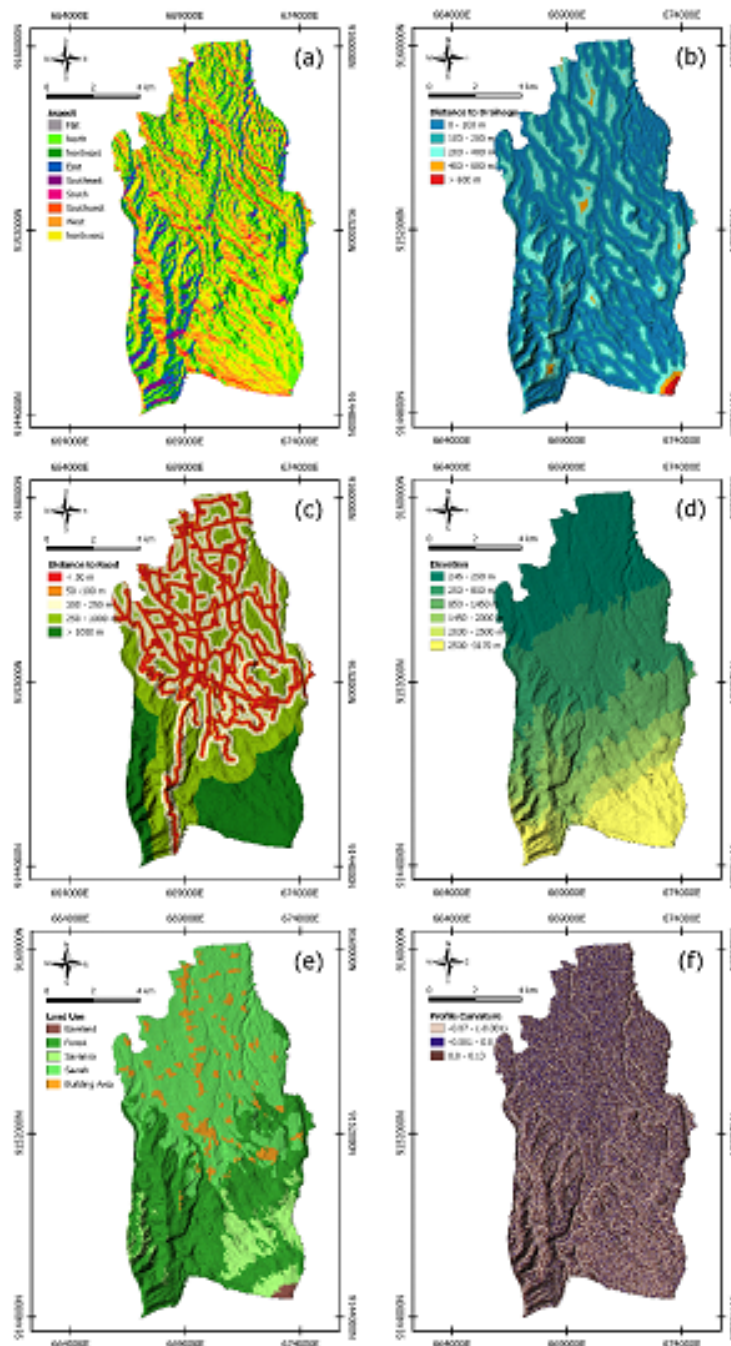


Figure 2: Factors causing landslides: a) Aspect, b) Distance to Drainage, c) Distance to Road, d) Elevation, e) Land Use, f) Profile Curvature.

The variation of altitude in the research area from the lowest is 250 masl to the highest is 3160 masl. The highest altitude point is the peak of Welirang Volcano which is in the southern part of Pacet District. The lowest elevation tends to be in the northern part of Pacet District while the highest elevation is in the southern part of Pacet District (Figure 2d). In general, landslides tend to occur in areas with higher elevations [9,10]. This is because the level of soil moisture and rainfall distribution tends to be higher, and the relief conditions are generally rougher.

Land use in the study area is grouped into five categories, namely: 1) barren land, 2) forest, 3) grassland, 4) agriculture, and 5) built-up area (Figure 2e). Land use in Pacet District is dominated by agricultural land with an area of 43,322,047 ha. The main agricultural land is in the central and northern areas of Pacet District. Commodities in it include rice, corn, sweet potatoes, shallots, leeks, cayenne pepper, cloves, and sugar cane.

curvature profile (Figure 2f) is a parameter that shows the slope gradient values such as convex, flat, and concave [11]. A negative value represents a concave, a zero value (0) represents a flat, and a positive value represents a convex formation. Concave is a basin, flat is a plain, and convex is a convexity. The implication for slope susceptibility is that if there are positive or negative values that are too high from the curvature profile, it will trigger the instability of a slope [12].

The variation of rainfall in Pacet District is 2113-3000 mm/year (Figure 3a). The northern part of Pacet District has a lower annual rainfall rate. The value of annual rainfall will gradually increase towards the southern part of Pacet District. Pacet sub-district belongs to climate type C based on the climate classification of Schmidt and Fergusson. Climate type C has a slightly wet climate characteristic with jungle vegetation characteristics. The highest rainfall in Pacet District is in January with a value of 500-590 mm.

The level of slope in Pacet District varies from 0°-70° (Figure 3b). Slope classification is made into seven classes based on Van Zuidam (1973) [13]. The seven grades include grades 0-2° (flat or almost flat), 2-4° (wavy/tends to slope), 4-8° (wavy—rolling/sloping), 8-16° (rolling—hilly/slightly steep), 16- 35° (hilly—steep), 35-55° (steep-mountain/steep), and >55° (mountainous/very steep). Slope slope is the most important parameter in slope stability analysis [13,14]. Slopes with steep grades have a high amount of flow and energy of water transport rates, so they tend to be unstable and prone to landslides [15]. This process is caused by an increase in gravity that is directly proportional to the slope [8,16,17].

Stream Power index (Figure 3c) indicates the potential for erosion as a description of the geomorphological process [14]. Stream Power index is a visualization of the power of water flow at a certain point that affects the potential for erosion strength [6]. The higher the SPI value, the higher the risk of slope erosion. Variations in the value of the stream power index are divided into four classes, namely: 1) <100, 2) 100-500, 3) 500-1200, 4) >1200.

Soil has unique properties and characteristics in terms of physical, chemical, biological and morphological [18]. In relation to slope stability, soil physical conditions are the most influential, such as: texture, structure, porosity, bulk density, and depth. As for the chemical properties is the content of soil organic matter. Biological properties are influenced by plant roots. While the morphological characteristics of the soil are related to how the appearance, characteristics, and properties of the soil are shown by the soil profile. Pacet sub-district based on the USDA soil taxonomic system has five soil subgroups, namely: lithic udorthents, typic epiaquepts, typic eutrudepts, typic hapludalfs, and typic paleudults. (Figure 3d).

Topographic Position Index (Figure 3e) reflects the difference in elevation of a place with the surrounding area. Through the TPI value, it can be seen which part of the valley, slope and ridge of a terrain. Gradually the shape of the terrain in the form of valleys to ridges is represented by the lowest to highest values in a row. The TPI value will always be unique in each different place. Therefore, each region will have a different value. The Topographic Position Index class in this study is divided into six classes to determine which ones are part of plains, valleys, downslopes, middle slopes, upper slopes, and ridges. The topographic conditions in the form of plains worth <-3,399, valleys -3.399 – (-1.504), lower slopes -1.504 – 0.390, middle slopes 0.390 – 2.285, upper slopes 2.285 – 4.181 and ridges > 4.181.

Topographic wetness index displays hydrological processes associated with the accumulation of water flow based on slope control [19,20]. The topographic wetness index in the research area is divided into three classes, namely: 1) <= 6,842, 2) 6,842–14,303, 3) >14,303 (Figure 3f). The higher the value of the Topographic wetness index, the higher the level of water accumulation due to the influence of the slope. Slopes with a high Topographic wetness index value have the possibility of landslides due to loadsmass soil increased by water. Mark Topographic wetness index always related to the drainage system in an area. MarkTopographic wetness indexThe high altitude allows landslides to occur due to the higher mass load of the soil, making it prone to displacement of slope-forming materials by the gravitational pull. However, still pay

attention to the value of the slope because it is closely related to the strength of the gravitational force.

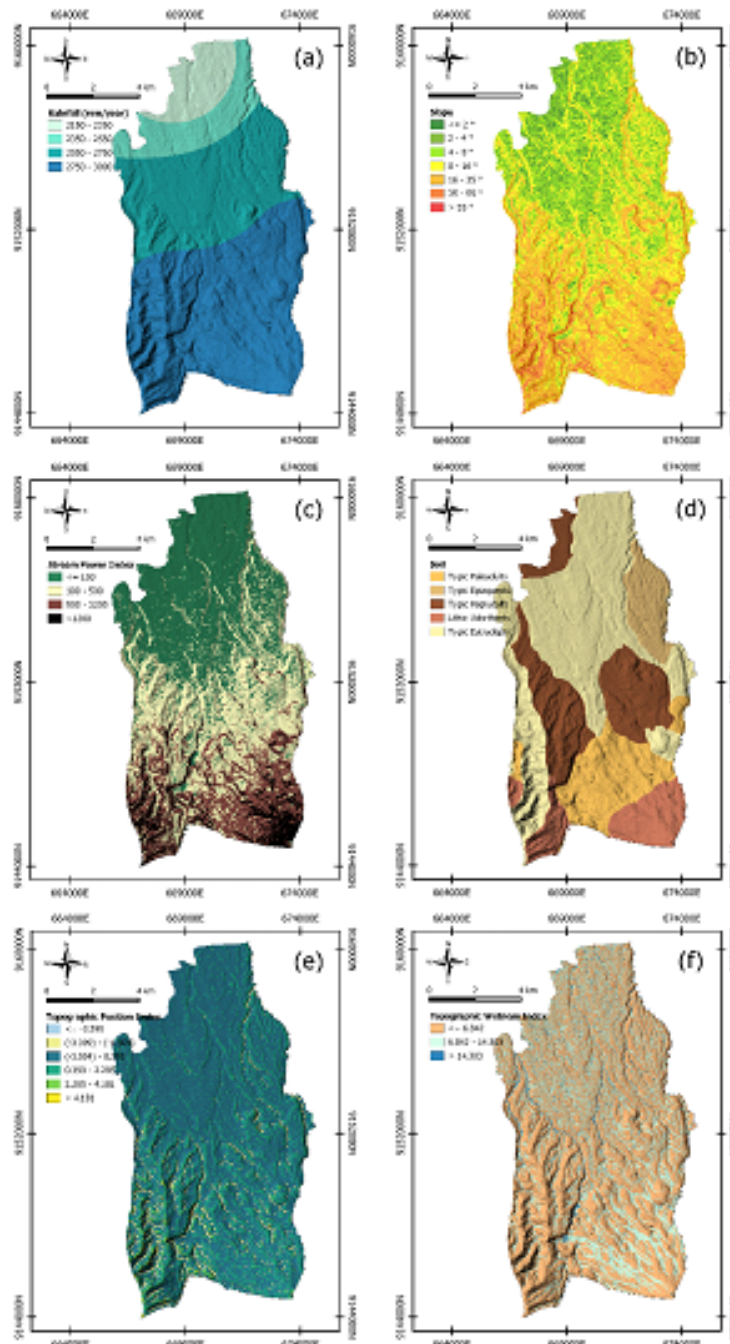


Figure 3: Factors causing landslides: a) Rainfall, b) Slope, c) StreamPoert Index, d) Soil, e) Topographic Position Index, f) Topographic Wetness Index.

1. Training Dataset & Testing Dataset

There are a sample of 383 landslide accident inventory points and 383 non-landslide inventory points which are useful as training datasets and testing datasets in this study

(Figure 4). Correct inventory of landslide data is one of the prerequisite factors in various studies on landslides [21,22]. Source of landslide inventory data in this study obtained from three sources, namely: 1) BPBD Mojokerto Regency, 2) Google Earth interpretation in 2017-2020, and 3) field survey in 2020. Meanwhile, non-landslide data inventory points were obtained through two sources, namely the 2017 Google Earth interpretation. —2020 and field survey. Non-landslide sample points are identified through the characteristics of their physical conditions, which are unlikely or even impossible for landslides to occur. The land is mainly viewed from the level of the slope which has a slope of 0-4° with flat-wavy topography [5,24].

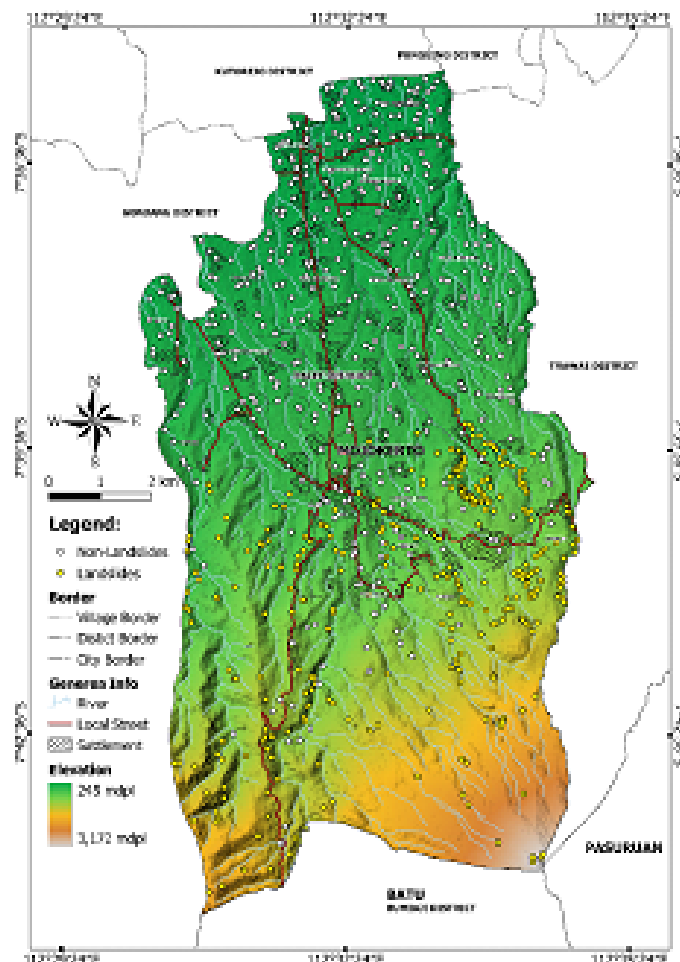


Figure 4: Avalanche and Non-landslide Data Inventory Distribution Map.

The distribution of the portion of training data and data testing in this study uses a portion of 70% and 30%. There are independent variables which are factors that cause landslides and dependent variables which are descriptions of landslides or non-landslides. The proportion of dependent variables (landslides and non-landslides) has the same number of proportions because a balanced proportion is highly recommended in order to obtain good quality logistic regression modeling results [24].

2.2. Logistic Regression

Logistic regression is a multivariate statistic that has been widely used in mapping the level of landslide susceptibility [23]. Mark Probability Landslides with a range between 0-1. A value of 0 indicates a 0% possibility of landslides and 1 indicates a 100% landslide occurrence [25]). Landslide probability values through logistic regression analysis can be obtained using Equation 6. Basically, logistic regression connects the probability of landslide events to the link function (in this case “logit”) which assumes the level of dependence of landslide-causing factors on the probability of landslide events [26].

$$P = \frac{1}{1 + e^{-z}} = \frac{e}{1 + e^z} \quad (1)$$

Where P is landslide probability; e is exponential; z is a combination score from an independent variable which is calculated using Equation 7.

$$Z = b_0 + b_1X_1 + b_2X_2 + \dots + b_nX_n \quad (2)$$

Where b_0 is a constant from the model; b_n is score from landslide triggering factor of X_n .

2.3. Model Validation

The accuracy of the test results in the ROC analysis is measured through the area under the ROC curve (AUC). The ROC curve is formed by plotting the true positive rate (sensitivity) value of the test results versus the false positive rate (1-specificity) for various parameter point limits. The true positive rate in the ROC graph is on the x-axis while the false positive rate is on the y-axis (Figure 2.7). There are other terms for true positive rate and false positive rate, namely recall and false alarm rate. If the results of plotting the value on the curve are getting closer to the upper left corner, the results are getting better. Table 1 below is a description of each AUC value that shows the quality of the model being tested.

TABLE 1: AUC . Value Index.

AUC value	Information
0.9	Very Good Model
0.8 – 0.9	Good Model
0.7 – 0.8	Moderate / Fairly Good Model
< 0.6	Ugly Model

Source: Purgasemi et al (2020) [27]

3. Result and Discussion

3.0.1. Logistic Regression Result

The statistical analysis of logistic regression in this study was carried out in the Jupyter Notebook 6.0.1 application which is a computing environment using the Python programming language. The landslide probability value generated by the logistic regression has a value range of 0-1. This means that the closer to 1, the higher the probability of landslides. Conversely, if the value is close to 0 then the possibility of landslides will be smaller.

Based on the logistic regression analysis, the significant value of each factor causing landslides can be determined. The Z value is formed by adding the value of the model constant and the weight of each factor causing the landslide. The result of the model constant is -12.4515. The weight value of each factor obtained indicates how much the significant value of the factor is. If it is higher, these factors increasingly affect the level of landslide susceptibility. Stream power index has the highest value (2,4179) meaning that it is the most influential factor on the level of landslide susceptibility in Pacet District. Meanwhile, land use as a factor that has the lowest value (-1.7102) is a factor causing landslides with the lowest impact.

$$Z = -0.6645 - 0.6645 [TWI] + 0.581 [TPI] + 2.4179 [SPI] - 0.0316 [Soil] + 1.6111 [Slope] \\ 1.7102 [Landuse] + 0,5661 [Rainfall] - 0,5135 [ProfileCurvature] + 0.5230 [Elevation] - \\ 0.1229 [Aspect] - -0.7510 [distance to road] - 1.5240 [distance to Drainage]... (3)$$

The most significant landslide-causing factors in each place can have different results. Other studies have shown that the slope has the most significant effect [27] There are also other studies that produce other more significant factors such as land use [28], elevation [29] and others. Based on these results, it can be concluded that the most dominant or significant factor as the cause of landslides varies depending on the research area studied.

3.1. ROC Validation

The level of accuracy through the accuracy test using the ROC curve is known based on the AUC value obtained [30]. The AUC value ranges from 0.5 to 1. If the AUC value is closer to 1, the accuracy of the prediction model for the probability of landslide events

will be better. Meanwhile, if the AUC value obtained is close to 0.5, the accuracy of the probability prediction model will get worse. The validation of the results in the ROC is done by using a testing dataset. The number of testing datasets is 230 points (30% of the total landslide and non-landslide data inventory) with 115 as landslide points and 115 as non-landslide points.

The accuracy value obtained in modeling landslide susceptibility using logistic regression model in this study is 0.92 (Figure 5). The AUC value is obtained based on the intersection value between the true positive rate (x-axis) and the false positive rate (y-axis) where the true positive rate = 0.93 and the false positive rate = 0.10. The AUC value shows the accuracy of the landslide probability prediction model is very good.

In general, the logistic regression model in mapping the level of landslide susceptibility produces good model quality. This is based on the AUC value obtained from previous studies which resulted in the AUC value = 0.83-0.89 [22,24,29,30]. Even in the research of Ozdemir & Alural (2013) the logistic regression model produces a very good quality value, namely the AUC value = 0.93.

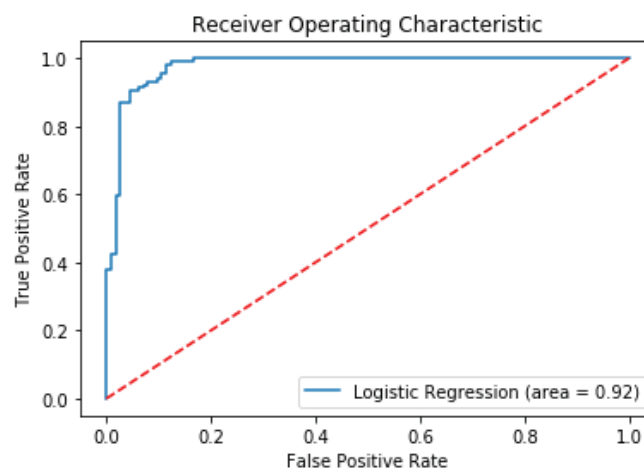


Figure 5: ROC Curve.

The high quality produced in Ozdemir & Alural (2013) with an AUC value of 0.93 is made possible by the large number of landslide and non-landslide data inventories as training datasets and testing datasets. The number of landslide and non-landslide point inventories in the study in Ozdemir & Alural (2013) [31] were 3068 and 3016, respectively, so that there was a total data inventory of 6084 points. Meanwhile, in this study, the total number of data inventory was 766 points (383 landslide points and 383 non-landslide points). When compared in the form of a ratio between data inventory points and the total area, the research by Ozdemir & Alural (2013) [31] is 6084:932780 or 1:153. While in this study it is 766:634629 or 1:828. Therefore,

3.2. Landslide Susceptibility Map

Areas with a very high level of susceptibility have the largest percentage of 52.5% (Figure). Other susceptibility classes, namely: high has an area of 4.1%, moderate 2.9%, low 4.4%, and very low 36%. The division of this susceptibility class uses the natural break technique so that the division of landslide susceptibility classes is divided proportionally based on the data interval.

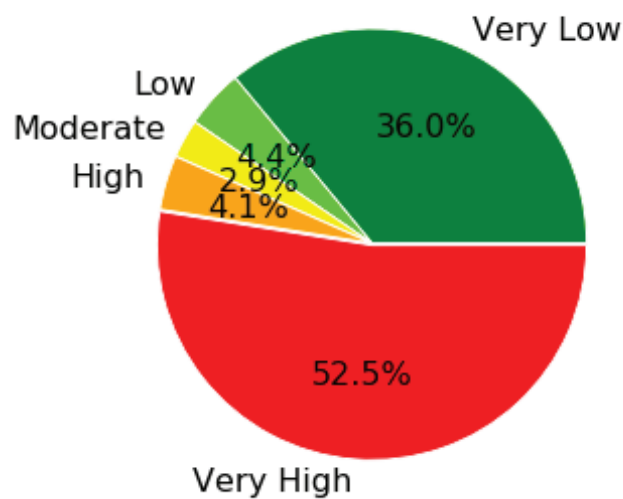


Figure 6: Percentage of Landslide Susceptibility Level in Pacet District, Mojokerto Regency.

The southern area part of Pacet District has a very high dominant landslide susceptibility class. The southern area with a high level of landslide susceptibility is included in the denudational mountainous landforms of Mount Anjasmoro and on the volcanic peaks – the middle slopes of the Welirang Volcano. Overall, the landslide points found in Pacet District were spread out as many as 104 landslide points in the Mount Anjasmoro area and 279 landslide points in the Welirang Volcano area.

4. Conclusion

The assessment of the landslide susceptibility level in this study has a very high level of accuracy based on the AUC value obtained, which is 0.92. The results of the assessment of the landslide susceptibility level are divided into five classes with the following areas, namely: very low 36%, low 4.4%, moderate 2.91%, high 4.1% and very high 52.5%. The southern part of Pacet District is dominated by a very high level of landslide susceptibility and the northern part is dominated by a very low susceptibility class.

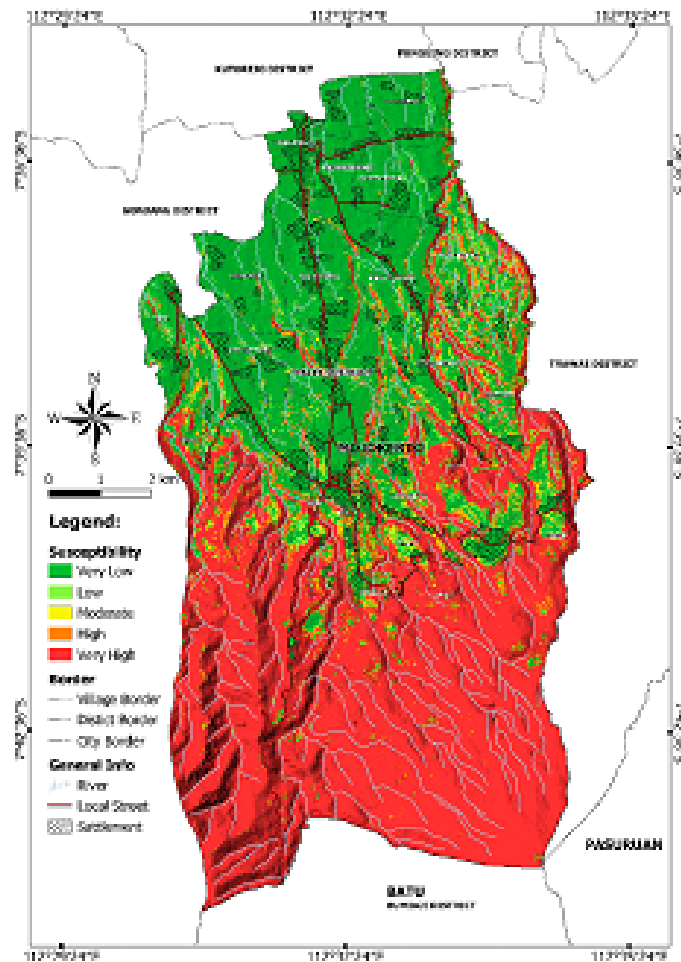


Figure 7: Landslide susceptibility Map, Pacet District, Mojokerto Regency.

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