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Optimizing Tourism Development Through Landslide Hazard Mapping in Raung Volcano

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ABSTRACT

The series of volcanic activities of Mount Raung triggered primary and secondary hazards in the area around the volcano. Kalibaru watershed is one of the areas prone to landslides due to secondary hazards of eruption activity in the direction of west and northwest part of this region. This study aims to optimize tourism by mapping landslide hazard using Spatial Multi-Criteria Evaluation (SMCE) around Mount Raung. This research used 46 points of landslide data through remote sensing, field observation. Ten landslide triggering factors, namely TPI (Topographic Position Index), TWI (Topographic Wetness Index), SPI (Stream Power Index), slope, distance to river, rainfall, geology, land use, distance to road, and soil type was used to map the landslide hazard. This study used ROC (Receiver Operating Characteristic) analysis to validate the landslide susceptibility mapping with an AUC (Area Under Curve) value of 0.93, which indicates that the mapping has a high accuracy value. The results showed that the landslide susceptibility is divided into three classes: high susceptible, moderate susceptible, and low susceptible. The high susceptible area covers 151.62 km^2 (21%), the moderate susceptible area covers 407.99 km^2 (56%), and the low susceptible area covers 166.79 km^2 (23%). Based on the results of the mapping, tourism development in the area of Mount Raung is recommended in areas that are classified as medium and low landslide susceptibility.

INTRODUCTION

Mount Raung is an active volcano in Indonesia located in East Java (3,344 m above sea level) with a relatively short eruption frequency cycle. It has a strombolian eruption type and the existence of the largest caldera on the island of Java in the summit area, which implies traces of past eruptions (Febriyanti & Anjasmara, 2017). The horseshoe-shaped caldera and hummocky hills west of the eruption center are forms of large-scale sector collapse activity (AM, 2022). Sector collapse is the most dangerous volcanic event, resulting in lateral explosions, landslides and eruptive changes (Sabila & Abdurrachman, 2020). Mount Raung's eruptive activity has been recorded since 1586, with diverse eruptive types in the west and northwest directions with high hazard levels (Rini, 2020).

Eruption hazards include primary and secondary hazards that can cause physical, environmental and social losses. Secondary hazards from volcanoes include lava dome collapse, lahars, landslides, rain lava and flash floods (Azizah et al., 2023). Mount

Raung is included in the landslide-prone area due to volcanic activity. Geological activity triggers landslides due to vibration or slope shaking, while volcanic activity triggers secondary hazards (Irawan, 2020; Irawan et al., 2020). Landslides are caused by high-intensity rain that erodes the soil surface on the slopes of Mount Raung, resulting in groundmass movement (Larasati et al., 2021).

Landslides are a high-threat disaster with steep slope morphological characteristics. Morphological characteristics of areas with steep slopes have a higher chance of landslide frequency (Bachri & Shresta, 2010; Irawan, 2020). Banyuwangi Regency is one of the landslide-prone areas in a series of activities that occur fluctuatively due to complex activities between geological, geomorphological, hydrological, rainfall and land use aspects. Archival data shows the highest incidence occurred in 2018 with 24 landslides, including 5 landslide incidents occurred in kalibaru district and 1 incident occurred in glenmore district (Table 1).

Table 1. Landslides in Kalibaru Watershed

Location	Total	Impact
Kalibaru District	5	Plengsengan non-technical collapse and road access to tourism is hampered
Glenmore District	1	Increase sedimentation in river bodies

Kalibaru Watershed is one of the streams in Mount Raung that is prone to landslides due to the direction of eruption activity that leads to this area. Based on morphogenesis conditions, the Kalibaru watershed area is dominated by the volcanic processes of Mount Raung. The area is composed of loose volcanic sedimentary material and is prone to landslides (Irawan, 2020). Kalibaru watershed is prone to landslides, especially in the upstream area. Based on the physical condition of the geology and geomorphology of the area, part of the Kalibaru watershed is a potential area for landslide threat because the morphology of the area in the upstream area has tight contours and steep slopes, while the downstream area is in a lowland morphology associated with the coast. Translational landslide is the most common type in the Kalibaru watershed area, especially in Kalibaru and Glenmore sub-districts (Prasindya et al., 2020).

The characteristics of Mount Raung, although referred to as an active volcano, are classified as having a relatively short eruption frequency cycle. Still, Mount Raung has a beautiful natural charm, supporting the development of nature tourism. Tourism optimization can be carried out by mapping the areas potentially prone to disasters in detail. The configuration is dominated by slopes with intensive material support from eruptions, making the area around Mount Raung have a high potential for landslides. Therefore, disaster management efforts are needed to reduce the impact on tourism areas that may occur in the future. One of the concrete efforts that can be made is to conduct mapping as a means of information on the level of landslide susceptibility.

Mapping aspects of susceptibility can be conducted in various methods, one of them by utilizing the Spatial Multi-Criteria Evaluation (SMCE). SMCE method was used because it has high accuracy and more efficient (Oktaviani et al., 2020), then validated using ROC to test credibility. Practically, ROC validation was used because it is a strong validation method to predict the accuracy of landslide susceptibility maps (Oktaviani et al., 2020). This research is different from previous studies because it adopts the SMCE method which was first applied for tourism development in the Kalibaru watershed. The use of SMCE not only improves the accuracy of landslide susceptibility prediction, but also provides deep insight into the environmental complexity of the Kalibaru watershed. The novelty of the SMCE method in this context becomes the main driver to develop tourism potential in landslide-prone areas. This research aims to optimize tourism around Mount Raung by mapping landslide hazard using the SMCE model.

RESEARCH METHODS

Research Location

This study was conducted at the ecological boundary of Kalibaru Watershed, which is administratively located in Banyuwangi Regency. The area of Kalibaru Watershed is 728.12 km². The location selection was based on the series of eruption activities of Mount Raung in 2015 and 2022 to the west and northwest that could result in secondary hazards in the form of landslides. Map of the research location in Figure 1.

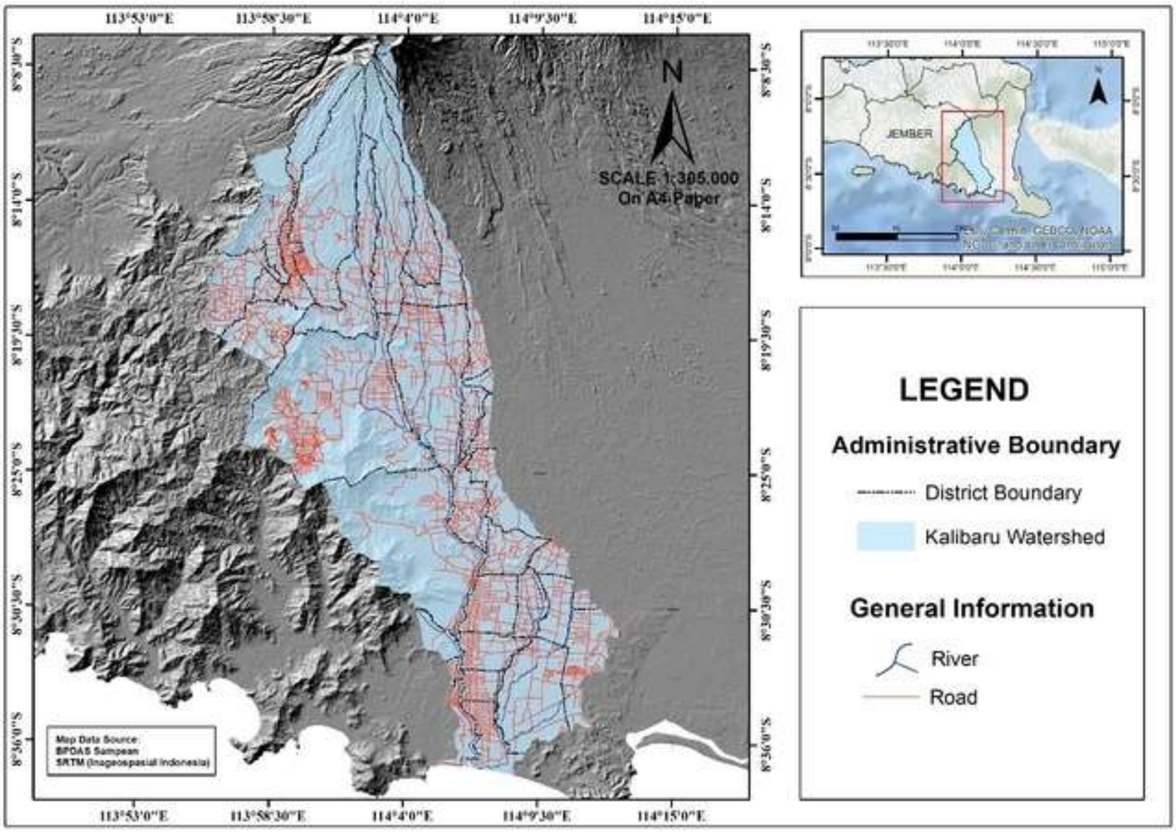

Figure 1. Research Location

Data Collection Procedure

This study used primary data obtained from field surveys such as validation of landslide points, validation of land use data, and soil dampling for texture and cole index tests in the laboratory. The secondary data was obtained from data processing using GIS which includes vector and raster data (dem data, geological maps, rainfall data) and remote sensing (Sentinel 2A imagery) to create landform maps and landslide susceptibility maps. Landform maps are derived from morphology, morpho-processing, morpho-chronology and morpho-arrangement data. Its preparation determines landslide condition factors, which are then modeled using SMCE (Spatial Multi-Criteria Evaluation).

SMCE has a high level of accuracy and does not require expert judgment in determining the most rational weight (Permanajati et al., 2023; Zulkarnain, 2012). Landslide mapping using the SMCE method involves four stages, which are: 1) preparing the spatial dataset, 2) normalizing the data, 3) landslides modeling, and 4) validating the model using ROC. The stages of this research almost the same as previous research (Irawan, et al., 2021), but the difference is in the data processing method using the SMCE. The research flow chart can be seen in Figure 2.

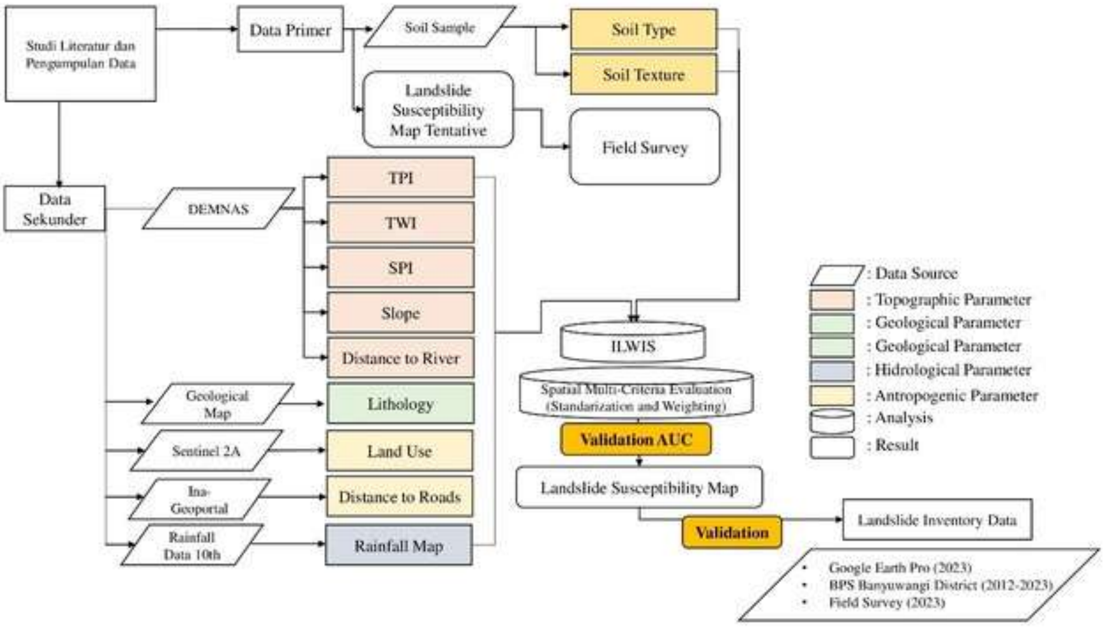

Figure 2. Research Flow Chart

A more detailed explanation of the research stages, including the data source and processing techniques, is explained in Table 2.

Table 2. Research Stages

Stages		Source	Processing Technique
a. Reparation of Tentative Land Unit Map			
Landform Identification	Morphology	• DEMNAS 8.1m Resolution	Interpretation and analysis of hillshade slope, contours
	Morphogenesis	• DEMNAS Resolution 8.1m • Geological Map of BanyuwangiSheet Scale 1:50,000	Interpretation of landforms based on the origin of processes associated with geological materials
	Morphoarrangement	• DEMNAS Resolution 8.1 m • Geological Map of BanyuwangiSheet Scale 1:50,000	Interpretation using hillshade, slope analysis
	Morphochronology	• DEMNAS Resolution 8.1 m • Geological Map of BanyuwangiSheet Scale 1:50,000 • Digital Map of Soil Types DPUPRBanyuwangi Regency	Analysis of geological material aspects andsoil types
Rainfall		• Rainfall Data Banyuwangi Regency, East Java Natural Resources Agency	Interpretation of average rainfall data for 2012-2023 using Inverse Distance Weighted (IDW) method
Land Use		Sentinel 2A	Interpretation of land use data using the CART method
Landslide Parameters		• DEMNAS Resolution 8.1 m	Analysis of Slope, TWI, TPI, SPI, Distance to River using ArcGIS tools
		• Geological Map of Banyuwangi Sheet	Lithology analysis
		• Ina-Geoportal	Road to Distance Analysis
Soil Samples		• Laboratory Test	Analysis of texture, structure, cole index and soil color

Landslide Parameters

Ten factors cause landslides, including topography, geology, hydrology and anthropogenic aspects. Topography includes TPI (Topographic Position Index) and slope. Geological parameters include the lithology of the area. The hydrological aspect uses the distance from the river, rainfall data, TWI (Topographic Wetness Index), and SPI (Stream Power Index). The anthropogenic aspect includes soil type data, land use data, and distance from road.

TPI parameter shows the difference in elevation to analyze the valley, slope, mountain ridge, and ridge sections (Bachri et al., 2019; Irawan, Sumarmi, Bachri, Panoto, Nabila, et al., 2021). The TPI calculation results (Figure 2) at the lowest number indicate valley topography, and the highest value indicates a ridge. TWI indicates the water content of the slope materials due to the flow or accumulation of water in the hydrological system that affects slope stability. TWI is considered an essential factor in identifying an area's water saturation zone by considering the slope (Singh et al., 2021). Kalibaru watershed in the TWI parameter shows a high value of slope dominance in the downstream area associated with the coast, so it has the possibility of landslides due to soil mass load increased by the accumulation of water flow.

The lowest value is in areas with tight contours, which are part of the ridge because the characteristics of the ridge are not water accumulation. The higher the TWI value, the more likely there is inundation or surface flow with high (Irawan et al., 2020). SPI presents the erosion potential of streams that affect landslides (Bachri et al., 2019; Singh et al., 2021). SPI as an erosion potential is associated with geomorphological processes; high SPI values indicate high soil surface layer erosion levels. Low SPI values are located in plain areas, which are morphologically process areas of material deposition. Stream erosion capacity positively correlates with increasing slope and catchment area (Singh et al., 2021). An increase in water catchment in the upper slope area increases the speed of water flow, so the potential for landslides is also higher (Pradhan et al., 2019).

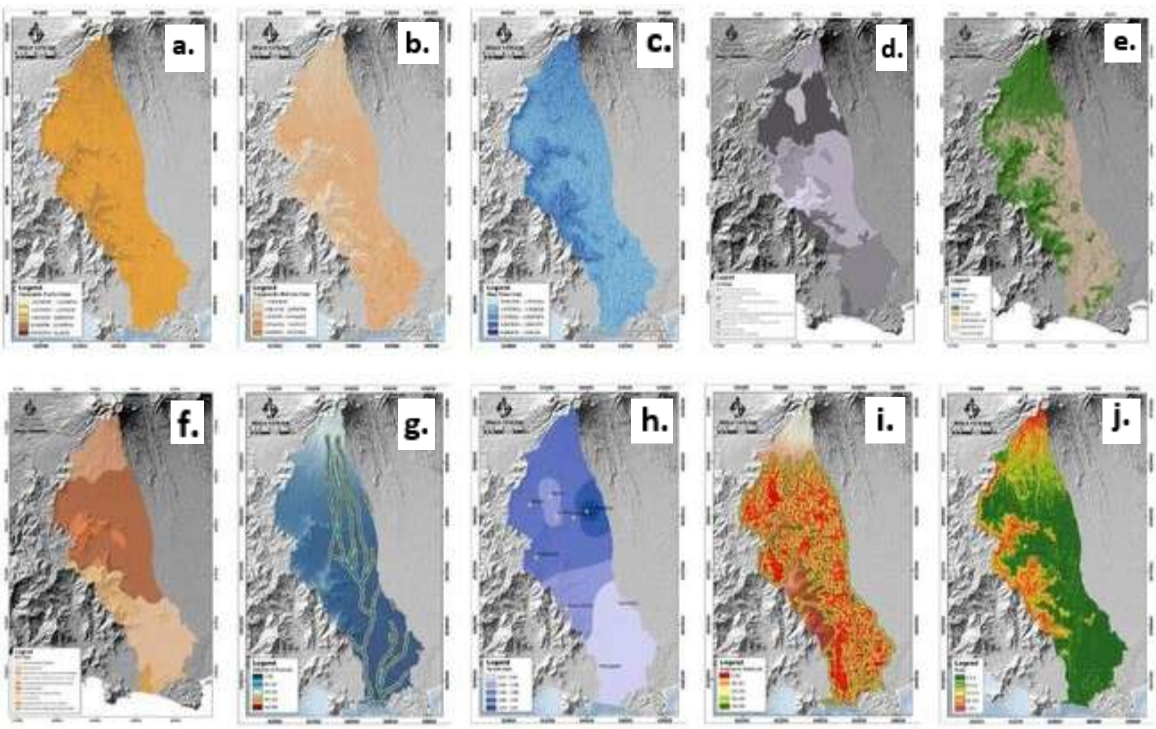

Figure 2. Landslides Causal Parameters (a. TPI, b. TWI, c. SPI, d. Lithology, e. Landuse, f. Soil Type, g. Distance to River, h. Rainfall, i. Distance to Road, j. Slope)

Data Analysis

Landslide parameters were then analyzed by the SMCE method using ILWIS (Integrated Land and Water Information System) software. The process performed in ILWIS is to assign a value to each parameter in the range of 0-1. Value 0 is for parameter factors that do not affect landslides, and value 1 is for factors that affect the occurrence of landslides. To test the most influential factors in this study using Relative Importance (RI). Relative Importance presents low-impact and high-impact variables. Then, SMCE uses all parameters to generate a composite map showing several susceptibility areas. To measure the accuracy of the landslide susceptibility map using Receiver Operating Characteristic (ROC) and Relative Landslide Density (R-Index) by comparing the landslide susceptibility pixels on the map with the landslide occurrence point described in the following formula (Gudiyangada et al., 2020):

$$R = \frac{ni}{Ni} \Sigma \left(\frac{ni}{Ni}\right) x \; 100\%$$

Where ni is the number of landslide events in category x and Ni is the number ofpixels in category x. ROC application for AUC with value 0.5-1 to validate the susceptibility map that has been created by using ArcSDM toolbox in ArcGIS software.

RESULTS AND DISCUSSION

Landslide Data Inventory

An inventory of landslide occurrence data through field observation and remote sensing data is conducted for landslide susceptibility assessment. The sampling amount of landslide inventory data affects the mapping results' quality.

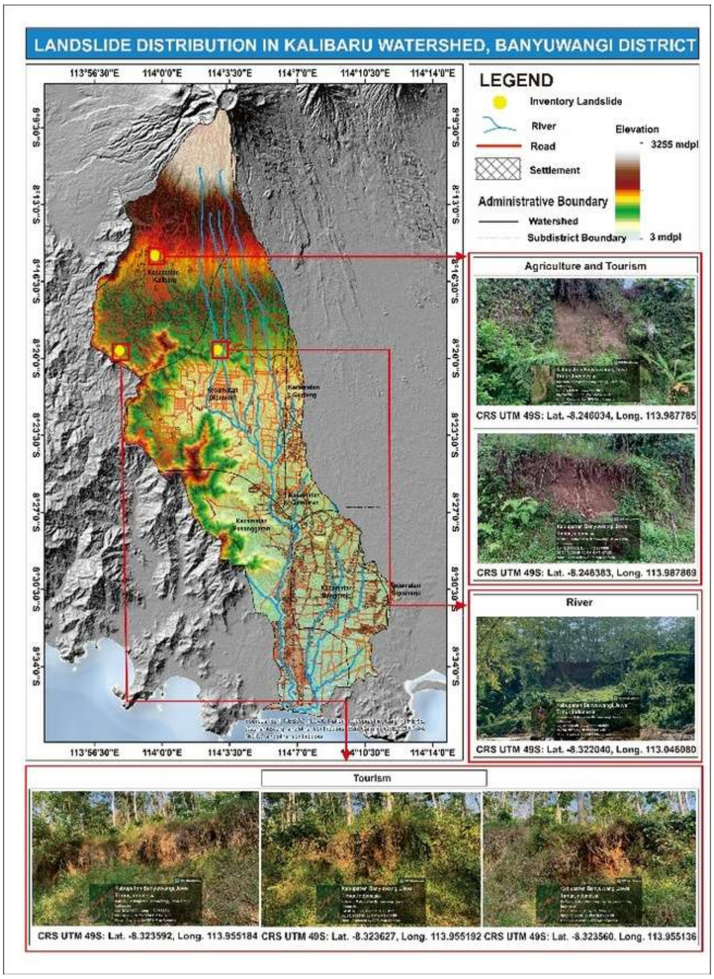

Figure 3. Landslide Data Inventory

Based on the landslide occurrence points, 46 sample points were obtained in the Raung Volcano area. There are at least 3 points of landslide locations that were found directly when in the field that occurred at the tourism site (Figure 4), predominantly in steep morphology with volcanic and structural landforms. The type of landslide is the most common in the field, especially in tourist attraction areas with steep slopes. Due to geological conditions, morphology and material from volcanic eruptions have loose properties, making them prone to land movements, especially with high rain intensity (Irawan et al., 2020). Landslides can disrupt transportation access, causing economic and social losses and environmental damage.

Geomorphology of Kalibaru Watershed

Landform analysis is obtained by identifying four aspects: morphology, morphogenesis, morpho-arrangement, and morphochronology. Morphology is obtained from the slope, morphogenesis by the origin of morphological processes, morpho-arrangement by the arrangement of landforms, and morphochronology by the type of rock or geology. Kalibaru watershed has 15 landform units dominated by volcanic activity of Mount Raung in the north, east, and partly west and structural movement in the west of the upstream area (Table 3). Kalibaru watershed has a variety of morphological conditions: flat, sloping, undulating in the east and south, and gradually increasing slope to the west and north, ranging from steep to very steep. Morphological condition is a factor that significantly influences landslide occurrence (Wang et al., 2016; Irawan et al., 2020).

Karst landforms are formed from the dissolution process of carbonate rocks. In contrast, fluvial and marine landforms are formed from river evolution processes and are influenced by exogenous forces (Araujo, 2019; Kassouk et al., 2014). Fluvial landforms are located in plain areas as material deposition by sedimentation and erosion processes in the valley area of river bodies. The landform map is shown in Figure 4.

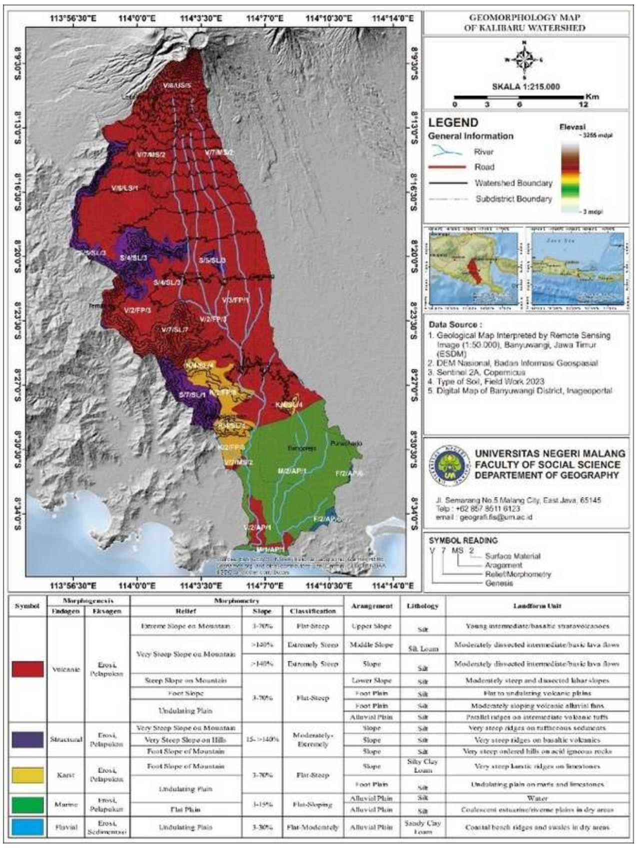

Figure 4. Geomorphology Map of Kalibaru Watershed

The landform of Kalibaru watershed is dominated by volcanic processes or activities, which are based on the constituent rock type material in the form of volcanic rocks (Dibyosaputro, 1997). Volcanic activity is due to endogenous forces in the form of magma movement and exogenous in the form of lava and lava flows that affect the morphological shape of the slopes and landforms of Mount Raung.

Table 3. Geomorphological Landform Unit

No	Genesis	Simbol	Landform Unit
1	Volcanic	V/8/US/5	Young intermediate/basaltic stratovolcanoes
2		V/7/MS/2	Moderately dissected intermediate/basic lava flows
3		V/7/SL/7	Moderately dissected intermediate/basic lava flows
4		V/6/LS/1	Moderately steep and dissected lahar slopes
5		V/3/FP/1	Flat to undulating volcanic plains
6		V/2/FP/3	Moderately sloping volcanic alluvial fans
7		V/2/AP/1	Parallel ridges on intermediate volcanic tuffs
8	Structural	S/7/SL/1	Very steep ridges on tuffaceous sediments
9		S/5/SL/3	Very steep ridges on basaltic volcanics
10		S/4/SL/3	Very steep ordered hills on acid igneous rocks
11	Karst	K/4/SL/4	Very steep karstic ridges on limestones
12		K/2/FP/8	Undulating plain on marls and limestones
13	Fluvial	F/2/AP/6	Water
14	Marine	M/2/AP/1	Coalescent estuarine/riverne plains in dry areas
15		M/1/AP/1	Coastal beach ridges and swales in dry areas

Soil Texture and Type

Soil physical properties such as texture, structure, permeability, porosity, and consistency can influence the occurrence of landslides (Wida et al., 2019). Based on the laboratory test results (Table 4), there are four soil textures in the study area: dust texture, dusty loam, dusty clay loam, and sandy clay loam. Based on the sampling points in the Kalibaru watershed area (Table 5), it is dominated by silt texture.

Silt texture has a significant influence on landslide occurrence. The characteristics of silt texture have coarse particles that result in more soil pores and faster infiltration. The coarser the soil texture, the faster the infiltration process and the easier it is to saturate the soil with water, thus triggering more significant landslides (Arsyad et al., 2018). Soils with sand and dust textures are prone to landslides because they do not have good water-holding capacity (Kocher & John, 2006; Priyono, 2015). Thus, the study site has a high potential for landslides or other land mass movements.

Table 4. Soil Physical Properties

No	Coordinat		Sample	Horizon	Color	Documentation
	Long	Lat				
1	114.152447	-8.467037	Karst	B	10 YR 4/4 (Dark Yellowish Brown)	

2	114.152447	-8.467037	Marine	A	10 YR 5/3 (Brown)	
3	114.093895	-8.520649	Karst	B	10 YR 5/3 (Brown)	
4	114.152447	-8.467037	Karst	B	10 YR 5/4 (Yellowish Brown)	
5	114.120027	-8.611909	Volcanic	O	10 YR 5/3 (Brown)	
6	114.112678	-8.614423	Marine	E	10 YR 5/3 (Brown)	
7	114.130897	-8.389786	Volcanic	A	10 YR 4/3 (Brown)	
8	114.064141	-8.325311	Structural	O	10 YR 4/4 (Dark Yellowish Brown)	
9	113.976892	-8.381034	Volcanic	A	10 YR 5/4 (Yellowish Brown)	
10	113.956088	-8.322990	Structural	O	10 YR 5/4 (Yellowish Brown)	
11	113.987785	-8.246034	Volcanic	O	10 YR 6/3 (Pole Brown)	
12	114.091085	-8.270283	Volcanic	O	10 YR 4/3 (Brown)	

13	114.202572	-8.548990	Fluvial	O	10 YR 4/1 (Dark Grey)	

Table 5. Soil Texture

Sampling Point	Location	%Sand	%Silt	%Clay	Texture
1	K/4/SL/4	6.88	86.04	7.08	Silt
2	M/2/AP/1	5.20	92.93	1.87	Silt
3	K/2/FP/8	0.32	99.44	0.24	Silt
4	K/4/SL/4	2.68	66.92	30.41	Silty Clay Loam
5	V/2/AP/1	1.33	97.63	1.04	Silt
6	M/1/AP/1	4.39	94.04	1.58	Silt
7	V/3/FP/1	2.71	94.84	2.45	Silt
8	S/5/SL/3	0.62	99.03	0.34	Silt
9	V/2/FP/3	2.66	96.07	1.28	Silt
10	S/5/SL/3	0.54	98.79	0.67	Silt
11	V/6/SL/1	3.59	95.39	1.02	Silt
12	V/7/MS/2	5.56	80.50	13.94	Silt Loam
13	F/2/AP/6	66.54	0.00	33.46	Sandy Clay Loam

Landslide Susceptibility and Factors

Based on the results of data processing using SMCE with Relative Importance Index (RII) to identify the factors that most influence the occurrence of landslide (Figure 5), it is known that the most influential parameters are the TPI (Topographic Position Index) parameter with RII value of 0.397 and a slope with RII value of 0.219. The factor with the most minor influence is the distance to river parameter, with RII value of 0.025.

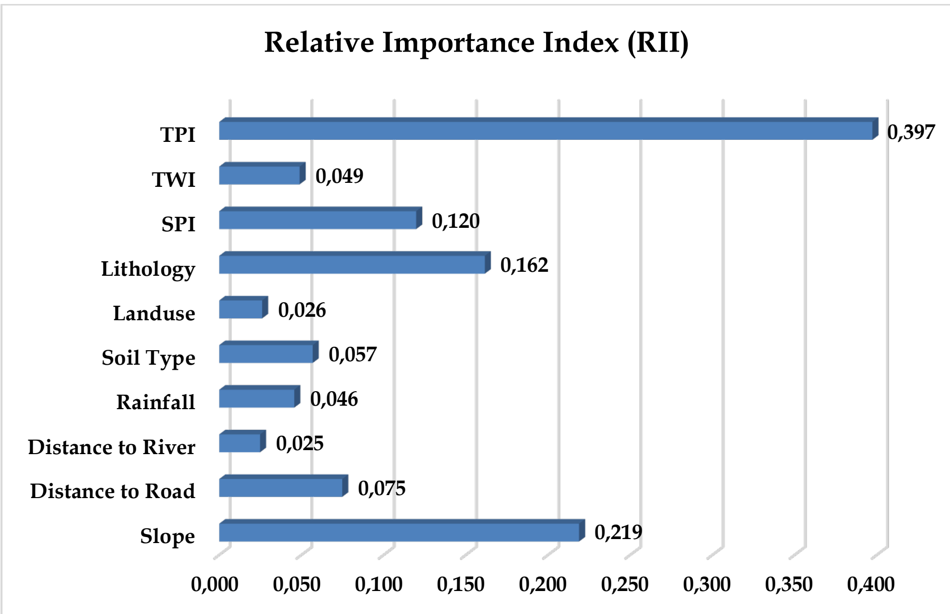

Figure 5. RII Bar Chart for each Landslide Parameters

Several studies have shown different results on the factors that cause landslides. These studies showed slope as a significant factor (Okoli et al., 2023; Pamela et al., 2018), but other studies that also used slope did not show the most significant results among the factors used such as elevation (Ling et al., 2022; Pourghasemi et al., 2020); distance to road (Wang et al., 2019; Zhao et al., 2024); fault (Guo et al., 2021), landuse (Hemasinghe et al., 2018) and manymore.

In this study's result shows that slope parameter is the second most crucial factor in landslide occurrence. The study results are supported by several studies that produce slope as the second most crucial factor (Baboli Moakher et al., 2018; Huang F, 2023). In this case, it is concluded that the factors that influence the occurrence of landslides are based on the condition of the study area.

Based on the landslide classification reffering to (Dewi et al., 2022), itis known that the level of landslide susceptibility in Kalibaru watershed is divided into three classes, namely low susceptible, moderate susceptible, and high susceptible. In table 6 and figure 6, the Kalibaru watershed area is dominated by moderate susceptible of 56% with an area of 407.99 km², high susceptible of 21% with an area of 151.62 km² and low susceptible of 23% with an area of 166.79 km².

Table 6. Landslide Classification

Landslide Classification in Kalibaru Watershed	Area (km²)
Low Susceptible	166.79
Moderate Susceptible	407.99
High Susceptible	151.62

Figure 6. Precentage of landslide susceptibility area

The results of landslide susceptibility in the Kalibaru watershed then validated using ROC, which was realized on the Area Under Curve (AUC) curve using the ArcSDM toolbox in ArcGIS. Based on Figure 7, it is known that the graph has an AUC value of 0.939. This value is close to 1, which means that the model used in the study to assess landslide susceptibility in the Kalibaru watershed area has good accuracy.

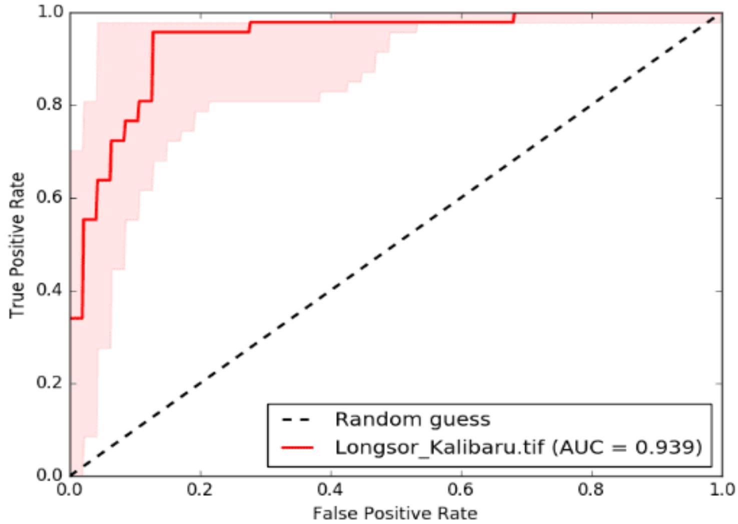

Figure 7. AUC Curve of Landslide Susceptibility in Kalibaru Watershed

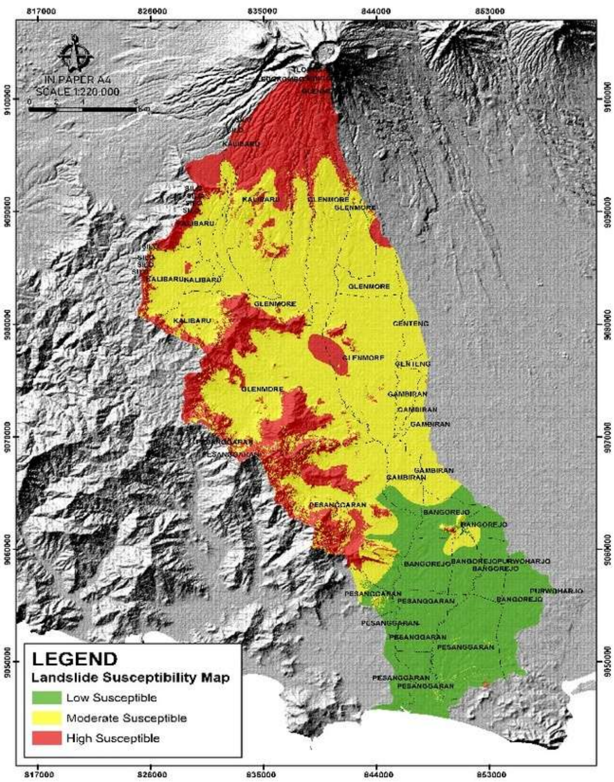

Figure 8. Landslide Susceptibility Map of Kalibaru Watershed

Based on Figure 8, the distribution of areas in classifying low susceptible landslides is in flat to gentle morphology, such as in Bangorejo, Purwoharjo, and parts of Gambiran sub-districts. The classification of areas moderate susceptible to landslides dominates in the Kalibaru watershed, which is located in undulating, hilly, and rather steep morphology covering the foothill slopes of Mount Raung such as in Glenmore, Genteng, Genteng and parts of Pesanggaran sub-districts. The classification of areas high susceptible to landslides is in steep to very steep morphology in the foothill to upper slopes of Mount Raung in the west and north such as in Silo, Kalibaru, Ledok Ombo, and parts of Pesanggaran sub-districts. High susceptible is caused by the high value of TPI and slope in this area. The TPI analysis results show that the high susceptible area has the highest value of 42.2, a ridge/mountain hill area. TPI processing with structural geological formations and hilly, undulating, and choppy morphology can be identified as one of the disasters that can occur in landslides (Apriyeni et al., 2022).

Based on the mapping results, optimizing tourism development in landslide-prone areas is necessary because tourism is one of the most susceptible aspects (Mahendradevi et al., 2022). Landslide susceptibility mapping can be used to consider regional and spatial management in tourist areas (Ady et al., 2019). The mapping results are used as information about the level of landslide-prone sites. Thus, tourism development in the Mount Raung region can be carried out in areas with low to moderate levels of susceptibility. In contrast, tourism in high-susceptibility areas prioritizes tourism with conservation and environmental preservation.

CONLUSION

Landslides are a severe threat due to the secondary hazard of Mount Raung volcanic activity in 2015 and 2022. Landslide susceptibility mapping was conducted using SMCE (Spatial Multi-Criteria Evaluation), which has high accuracy, indicated by the AUC value of 0.93 from the ROC curve. This research distinguishes itself from previous studies with a more holistic approach to landslide probability through the integration of SMCE. The advantage lies in the ability to handle spatial data more effectively, but future challenges include extending model validation to improve prediction accuracy. There are three levels of landslide susceptibility, namely, low susceptible, moderate susceptible, and high susceptible. The classification of low susceptible areas has an area of 166.76 km^2, the classification of moderate susceptible areas with an area of 407.99 km^2, and the classification of high susceptible areas with an area of 151.62 km^2. In contrast to other studies, the results of this research show that Topographic Position Index (TPI) and Slope have the highest influence on the frequency of landslides in the Kalibaru watershed area. Landslide susceptibility mapping can be used as information on the level of landslide susceptibility to consider sustainable management of the tourism area. Tourism development in the area of Mount Raung is recommended in areas that are classified as moderate and low landslide susceptible.

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