Spatial Analysis of Landslide Potential in Agricultural Areas of Wadaslintang Catchment Area, Central Java Province Indonesia

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Abstract: Landslides have occurred in several tropical regions of Indonesia and caused many losses in both upstream and downstream areas. This study aims to identify landslide prone areas in the Wadaslintang catchment area, Central Java Province Indonesia. Nine parameters were used to analyze landslide potential such as land use, land slope, rainfall, constituent rocks, soil type, soil permeability, population density, drainage density and runoff coefficient. Each parameter has five possibility scores (1 to 5) determined based on certain criteria. The value of each parameter was presented in a raster map with 15 meters of resolution and analyzed in ArcGIS 10.8. The level of landslide susceptibility was classified into five categories. The relationship between landslides and the triggered factor was analyzed using Frequency Ratio (FR). The result showed that the parameters with the highest FR values were land use, land slope, rainfall, and soil permeability, indicating a strong influence on landslides. Very high vulnerability areas were found in mixed farmland and settlements especially on steep slopes. Area with moderate and low categories of landslide vulnerability covers the largest area of the study site with an occupied area of 98.54 km^2 (51.04% of the total area) and 57.91 km^2 (29.99% of the total area), respectively. While the others i.e., areas with the very low, high and very high categories, occupy around of 3.74 km^2 (1.94% of the total area), 30.94 km^2 (16.02% of the total area), and 1.93 km^2 (1% of the total area) respectively. Validation results indicated that landslides mostly occurred in areas with medium and high categories of landslide vulnerability.

Keywords: Catchment Area; GIS; Landslides; Spatial Analysis

INTRODUCTION

National Board for Disaster Management of Indonesia or BNPB (2016) reported that hydrometeorological disasters have occurred in large numbers in Indonesia especially in the form of floods at 32.5%, followed by tornadoes at 30.2%, and landslides at 22.3%, while the remaining 15% are other types of disasters. Wonosobo Regency of Central Java Province is included in the high risk class of landslides with a score of 15.18 in 2021 and 525 landslide events in 11 sub-districts throughout 2022. The trend of disaster occurrence has increased over the last 10 years and has an impact on the number of human casualties and facility losses reaching billions of Indonesian Rupiah (IDR). Extreme weather factors of heavy rain intensity with 10 hours duration occurred in Wonosobo triggering a number of landslides in some sub-districts (BNPB, 2022)

Donie et al. (2018) explained that two factors are considered in landslides, namely biophysical factors and human factors. Biophysical factors that influence the occurrence of landslides include precipitation Kuradusenge et al. (2020), land use and land cover crops (Sharma et al., 2020; Wahidah et al., 2022); slope stability and soil type (Ahmad et al., 2022), and human factor (Sulastriningsih et al., 2021). Human activities that play a significant role in slope stability are land excavation , deforestation, and urban expansion, all of which affect land use (Muñoz-Torrero Manchado et al., 2022; Xiong et al., 2023). In addition, BNPB (2016) states that the triggering parameters of landslides include aspects of slope, geology, soil, and hydrology. Landslides in the Wadaslintang catchment occur in agricultural and residential lands due to land use and slopes of more than 15°. Intensive farming in plantations and production forests indirectly increases the potential for landslides (Nseka et al., 2019).

Presently, the largest land use in Wonosobo is mixed farmland and moorland covering about 42,952 ha area, while the other part is covered by forest occupying about 35 ha area and spread across 15 sub-districts. Until 2019, there was an increase in the number of gardens and moorland, which was 59,824 ha. Meanwhile, Arrofiqoh & Harintaka (2016) reported that bush and forest land have changed into rice fields and gardens. The area of forest and bushes decreased by 308.52 ha and was converted into rice fields and gardens. This condition increases the potency of land degradation and reduces root reinforcement, making the soil more prone to erosion and slope instability. Intensive farming practices, such as monoculture and excessive tillage, can further weaken soil structure and increase surface runoff, leading to higher landslide susceptibility. However, proper land conversion with soil conservation techniques like terracing, agroforestry, and cover crops can help mitigate these risks and maintain slope stability (Firdaus et al, 2021).

The important role of gardens and moor for the community as a livelihood and their dominant use in the Wadaslintang catchment prompted research related to spatial analysis of landslide occurrence in agricultural land to be conducted. In this study, nine parameters were used, including socioeconomic aspects, which have never been used in previous related studies.

RESEARCH METHODS

Tools and Materials

This study used ArcGIS 10.8 software, GPS, and a set of undisturbed soil sampling tools. While the materials used for landslide susceptibility map making include a Land Use Map, river network map, and administration map downloaded from Indonesia Topographic Map (RBI) of Central Java Province (Ina-Geoportal; https://tanahair.indonesia.go.id) *issued by Indonesian Geospatial Information Agency* (BIG); Slope Map of 8.23 × 8.23 m resolution accessed through National Digital Eelevation Model or DEM (Ina-Geoportal; https://tanahair.indonesia.go.id); Geological Map with scale 1:300.000 scale sourced from regional spatial planning plan of regional development planning agency (RTRW BAPPEDA) Wonosobo Regency in 2007; Soil Type Map accessed from the Center for Research and Development of Agricultural Land Resources (BBSDLP, 2016); Rainfall map from analysis of annual rainfall data of main office of Serayu Opak river the ministry of public works of Indonesia; Population Density Map of Wonosobo Regency analyzed based on population data of each village obtained from Central Bureau of Statistics (BPS) Wonosobo Regency. Meanwhile, the data on landslide occurrence in the Wadaslintang catchment was obtained from BNPB inventory (https://dibi.bnpb.go.id/) , Regional Disaster Management Agency (BPBD) Wonosobo regency, and NDVI analysis of Sentinel 2 satellite image (https://dataspace.copernicus.eu/), Landsat 8 (https://earthexplorer.usgs.gov/), and Google Earth (https://earth.google.com/web/). The research stage used in this study can be seen in Figure 1.

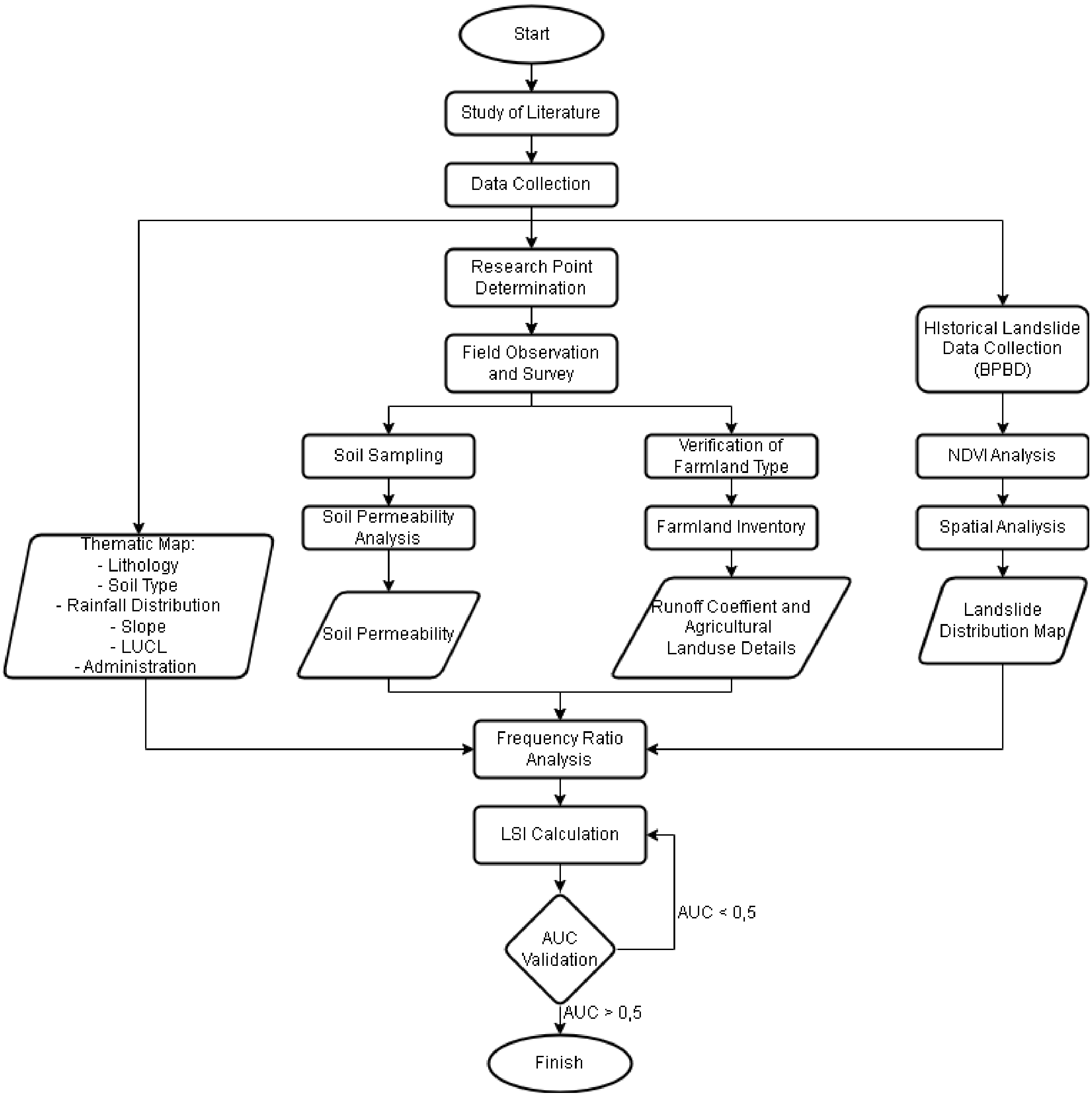


Figure 1. Research Flow Chart

Method

The Wadaslintang catchment is geographically located at -7.44 to -7.61 and 109.74 to 109.93. The total area of the Wadaslintang catchment, which includes Wadaslintang, Kaliwiro and Kalibawang sub-district is 192.93 km^2. The research site map is shown in Figure 2.

This study used nine parameters to determine landslide vulnerability and applied five scores (1 to 5) for each parameter, as shown in Table 1. The parameters used are biophysical factors and human activities that affect slope stability in Wonosobo (Astuti et al, 2015; Radjah, 2020). The parameters influencing landslide susceptibility are often classified into five categories. This classification enables an understanding the contribution of each parameter to landslide occurrences.

Field verification of existing land use and soil samples for soil permeability analysis were taken from undisturbed soil samples at 3 points in the study site (see Figure 2). Landslide occurrence data in the study area for result validation was obtained from BNPB, BPBD, and media news coverage. Image interpretation is used to determine the specific location and extent of related landslides (Arekhi et al., 2019). Inventory and verification of landslides were also conducted by direct observation and interviews with local residents.

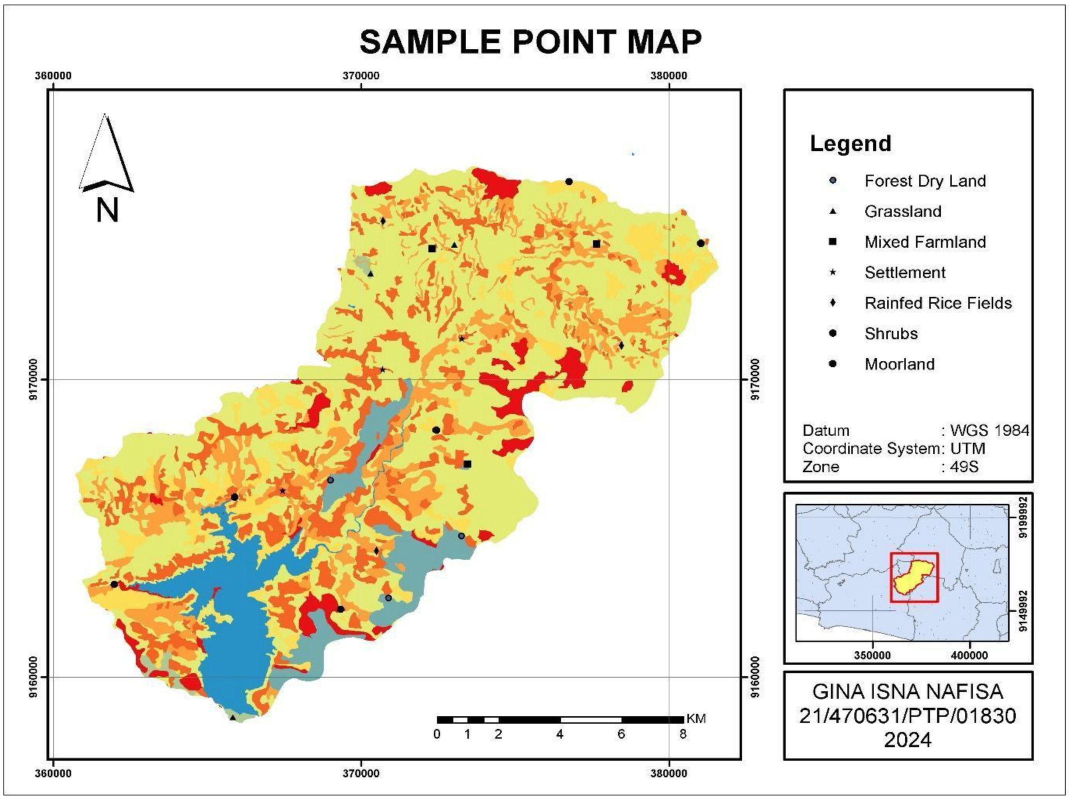


Figure 2. Distribution of Research Sample Sites

All parameter values were presented in raster maps form and were analyzed by using spatial analysis tools in ArcGIS 10.8. Each parameter has a similar weighting factor.

Table 1. Landslide Factor Weighting Class

Parameter	Class and Score					Source
	1	2	3	4	5	
Land Use	Water body, Forest Dry Land	Grassland, Shrubs	Mixed farmland	Rainfed Rice Fields, moorland	Settlement	Karlina et al. (2019)
Slope	0 - 8%	8 - 15%	15 - 25%	25 - 45 %	>45%	Muzani (2018)
Rainfall (mm/year)	<2,000	2,000 – 2,500	2,500 – 3,000	3,000 – 4,000	>4,000	Silalahi et al. (2019)
Lithology	Alluvium	Damar, Ligung Formation	Peniron Formation	Halang Formatio n	Waturanda, Penasongan Formation	Yogiswara et al. (2020)
Soil type	Aluvial, Andosol	Yellow-Red Latosol and Litosol	Podsolik RedYellow, Regosol	Meditera n and litosol	Yellow Red Latosol	Arsyad, (2006)
Soil Permeability (cm/hour)	>12.7	6.3 – 12.7	2 – 6.3	0.5 – 2	<0.5	Rusdi et al. (2015)

Population (person/ km2)	<500		500 – 1,000		> 1,000	BNPB (2016)
Drainage Density	<2	2 – 4	4 – 6	6 – 8	>8	Sukristiyanti et al. (2018)
Runoff Coefficient	0 – 0.2	0.21 – 0.4	0.41 – 0.6	0.61 – 0.8	0.81 – 1.0	Mahmoud & Alazba (2015)

The score category in each parameter with the most influence on landslides was determined using the FR method, as written in Equation 1.

$$FR = \frac{\frac{D_i}{A_i}}{\frac{\sum_{i=1}^{N} D_i}{\sum_{i=1}^{N} A_i}} \tag{1}$$

Where:
FR : frequency ratio of a class in a factor
Di : number of landslide events of a class in a factor
Ai : area of a class in a factor (pixel)
$\sum_{i=1}^{N} D_i$: number of landslide events in a factor of a class
$\sum_{i=1}^{N} A_i$: area of a factor of a class (pixel)

Equation 1 shows the ratio of the number of landslide events in a class to the class area of a certain factor called FR value. The bigger FR value means that the landslide triggering factor significantly influences landslide occurrence in a class. While the level of influence of each parameter on landslide was determined from the value of the Landslide Susceptibility Index (LSI) obtained from the sum of the FR value (Youssef et al., 2023). The formula is expressed as Equation 2.

$$LSI = FR1 + FR2 + FR3 + FR4 + \dots + + FRn \tag{2}$$

The most commonly used approach to measure statistical accuracy in disaster assessment is the Area Under Curve (AUC) method. AUC measures the model's performance in predicting landslide occurrences based on the generated susceptibility map. AUC is calculated as the area under the curve, representing the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR). The curve is created by comparing the proportion of areas classified as landslide-prone with the number of actual landslide points in each category. The total AUC area is mathematically determined by summing the partial areas calculated under the curve. This is done using the trapezoidal rule, which approximates the area under the curve by dividing it into smaller trapezoidal sections. The formula is expressed as Equation 3.

$$\text{Area} = \left(\frac{y_0 + y_1}{2}\right)\Delta x \tag{3}$$

The total AUC value represents the quality of the model formed to predict landslides reliably. A model is well validated if the AUC value is closer to 1. If the AUC value is less than 0.6, the model is considered invalid or failed.

RESULT AND DISCUSSION

The data from BPBD of Wonosobo Regency revealed the total number of landslide events in Wadaslintang catchment was 210 events from 2015 to 2023. All landslide event points were overlaid with nine of parameter maps such as land use, land slope, rainfall, constituent rocks, soil type, soil permeability, population density, drainage density and runoff coefficient to understand the relation between parameters and landslide events.

Land use indicates a factor that highly influences landslide vulnerability, especially agricultural land. The type of land used in the Wadaslintang catchment is divided into eight class categories, as shown in Figure 3a and Table 2. Mixed farmland dominates 55.4% of the total area while grassland is the least distributed at 6.5%. There were three landslide events in the dryland forest based on an overlaid map with landslide event points data from BPBD of Wonosobo. The application of conservation practices using vegetation method on agricultural land in the Wadaslintang catchment includes annual perennials in the form of dryland forest with an agroforestry system planted with high-density pine and has thick soil cover in the form of pine leaves have good results in reducing runoff water (Hairiah et al., 2020).

The land use type that has the biggest effect on landslides, based on FR value (3.167), is the settlement area. Based on field data from BPBD, there are 92 landslides in this type of land use (settlement). A dense residential area is located on flat slopes close to the highway. Some residential housing is directly adjacent to plantation areas and moorland on rather steep slopes. Vegetation coverage in residential areas is low, and mostly in the form of ground cover grasses.

Table 2. Land Use in Study Site

Land Use	Area (km^2)
Water body	14,3359
Dry land Forest	9,6767
Grassland	1,1100
Mix Farmland	93,8892
Settlement	24,4643
Rainfed Rice Fields	23,9026
Shrub	8,6130
Moorland	16,9417

Meanwhile, grassland land use is used as a public field and grass covers the banks of the Wadaslintang Reservoir. The public field is located on flat land surrounded by community plantations with moderate vegetation density dominated by coconut and banana trees. Meanwhile, bushland has been converted into rain-fed rice paddies due to the expansion of surrounding rice fields. Vegetation categorized as a bush is found in the form of low-level plants such as shrubs. The role of shrubs is important to suppress surface water runoff and maintain the balance of the ecosystem. The shrub is also a source of food for animals and maintains soil quality with microorganisms underneath. Therefore, there are no landslides in the bush and grassland land use classes.

Mixed gardens are relatively used as fruit production gardens such as durian, coconut, banana, and seasonal crops such as cardamom, ginger, turmeric, and cassava. Technical conservation efforts in plantations include the application of terraces and mounds. Seventy-four landslides were recorded on mixed plantation land. This is attributed to the soil cover of the observed plantation which is formed of thin leaf litter and grass so that the potential amount of surface runoff is high. Landslides on mixed farmland are found on very steep slopes (Senanayake et al., 2020).

The paddy fields are all rain-fed paddy fields with a rice-paddy-cropping period. The beds and surrounding land are planted with banana and coconut trees. Rice fields are located on flat and gentle slopes with the application of terraces. 32 and 9 landslides were recorded in paddy fields and moorlands, respectively. The variety of commodities planted on moorland are cassava and coconut. Although the cropping system applies guludan and terrace techniques to provide opportunities for water infiltration, there is no grass cover on the surface of each moorland. In addition, intensive tillage activities greatly increased the rate of sheet erosion in the fields.

Topography or slope plays a role in controlling erosion and increasing infiltration capacity. The higher the slope indicates a steeper slope, the greater the angle of the slope, the greater the shear stress (Nelson, 2013) and increases the potential for erosion (Çellek, 2020). Most landslides in this study occurred on slopes of 25 - 45%, namely steep class, with a FR value of 2.342 shown in Figure 3b. Landslides in this class mostly occur due to shallow landslides and at landslide points that have occurred before (Nakileza and Nedala, 2020).

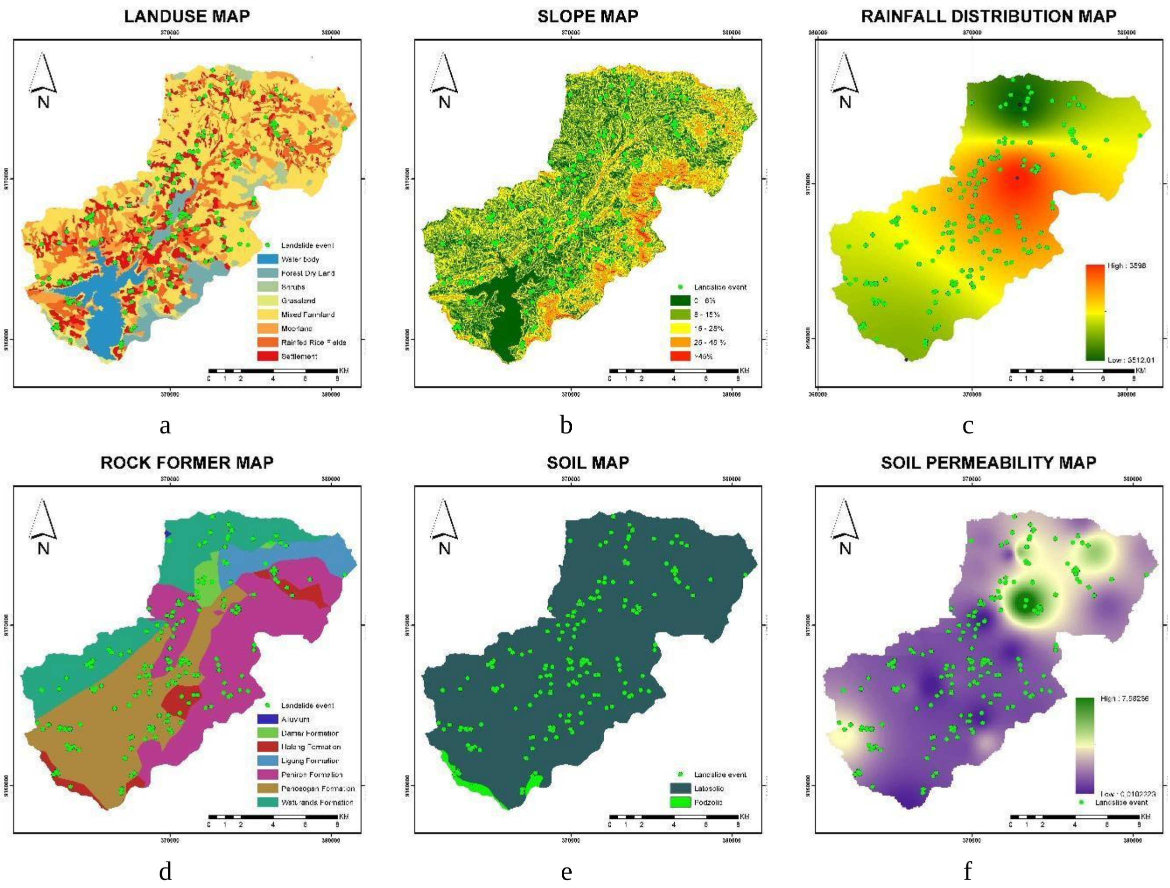
The study site is characterized by rainfall of more than 3,000 mm/year from the analysis of 3 rainfall stations in the study area, as shown in Figure 3c. The FR value of the rainfall factor is 2.45. The calculation of FR model for each class with exposure to the number of class pixels and landslide event pixels, and frequency ratio (FR) values are shown in Table 3. The high rainfall and duration indicate the large amount of cumulative water received by the soil, as a result of which the infiltrated water further increases the soil moisture and soil load on the slope, thus encouraging landslide collapse even on a small scale (Jeong et al., 2017; Qin et al., 2022).

Table 3. Frequency Ratio Values of Parameters

Parameter	Class	Class Pixel	% Class Pixel	Landslide Pixel	%Landslide Pixel	FR
Landuse	Water body, Forest Dry Land	87437	12,477	2	1.099	0.088
	Grassland, Shrubs	35416	5,041	0	0.000	0.000
	Mixed farmland	403619	57,455	63	34.615	0.602
	Rainfed Rice Fields, moorland	87052	12,392	44	24.176	1.951
	Settlement	88976	12,666	73	40.110	3.167
Slope	0 - 8%	180516	25.964	50	27.473	1.058
	8 - 15%	231902	33.355	16	8.791	0.264
	15 - 25%	198193	28.506	67	36.813	1.291
	25 - 45 %	78306	11.263	48	26.374	2.342
	>45%	6345	0.913	1	0.549	0.602
Rainfall	3.497 - 3.500 mm/year	17742	2.526	4	2.721	1.077
	3.500 - 3.525 mm/year	168207	23.944	45	30.612	1.278
	3.525 - 3.550 mm/year	215675	30.701	37	25.170	0.820
	3.550 - 3.575 mm/year	194603	27.701	9	6.122	0.221
	3.575 - 3.600 mm/year	101430	14.438	52	35.374	2.450
Lithology	Alluvium	433	0.062	0	0.000	0.000
	Damar and Ligung Formation	65170	9.293	9	4.945	0.532
	Peniron Formation	224505	32.012	45	24.725	0.772
	Halang Formation	34791	4.961	13	7.143	1.440
	Waturanda and Penasongan Formation	376413	53.673	115	63.187	1.177

Soil Type	Latosolic	692282	98.708	181	99.451	1.008
	Podzolic	9061	1.292	1	0.549	0.425
Soil Permeability	6.3 - 12.7 cm/hour	4206	0.601	3	1.648	2.745
	2 - 6.3 cm/hour	210781	30.095	51	28.022	0.931
	0.5 - 2 cm/hour	456366	65.159	119	65.385	1.003
	<0.5 cm/hour	29034	4.145	9	4.945	1.193
Population	<500 people/ km²	490903	70.282	96	52.747	0.751
	500 - 1000 people/ km²	162500	23.265	64	35.165	1.511
	> 1000 people/ km²	45071	6.453	22	12.088	1.873
Drainage Density	<2 km/ km²	280168	40.172	65	35.714	0.889
	2 - 4 km/ km²	352380	50.526	103	56.593	1.120
	4 - 6 km/km²	64869	9.301	14	7.692	0.827
Runoff Coefficient	0.41 - 0.6	3	0.000	0	0.000	0.000
	0.61 - 0.8	54557	7.784	15	8.242	1.059
	0.81 - 1	646370	92.216	167	91.758	0.995

The rock constituent factor of the study site obtained the highest FR value of 1.44. A total of 126 landslides are scattered in the Waturanda and Penasongan formations formed from sedimentary rocks and carbonate sandstone and breccia rocks with a high degree of weathering (Setiadi et al., 2014). The distribution is shown in Figure 3d.



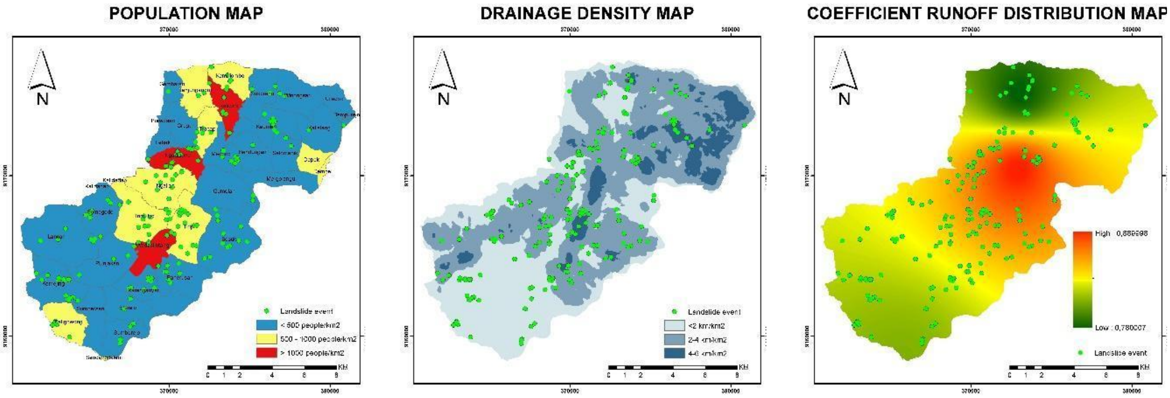


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Figure 3. Distribution of Landslide Points on each Parameter Land Use (a); Slope (b); Rainfall (c); Rocks (d); Soil Type (e); Soil Permeability (6); Human Population (g); Drainage Density (h); and Runoff Water Coefficient (i).

According to Deristani et al. (2023), landslides occur on latosol soils due to the loamy to sandy loam texture of this type of soil, which has moderate organic matter content. In comparison, podzolic is rich in organic matter and clay-textured soil aggregates due to accumulation with iron and aluminum. Based on these soil erodibility values, the potential for landslides is high for the podzolic type, but the distribution of landslide points is dominant in latosol soil due to differences in area, shown in Figure 3e. The soil type FR value for latosol soil is 1.008.

Soil permeability classes in the study site are categorized into slow (0.5 - 2 cm/h), moderate (2 - 6.3 cm/h), and fast (6.3 - 12.7 cm/h). Landslides were dominant in the slow permeability class with 130 occurrences, shown in Figure 3f. The permeability factor has the largest FR in very fast permeability which is 2.745. Slow permeability triggers soil pore water dynamics and causes percolation to be blocked. Thus lateral drainage occurs and promotes shallow landslides (Octaviarini et al., 2023; Schneider et al., 2015). Soil permeability in the dry period has a greater value, so hydraulic conductivity reaches a high value and affects the shear stress of the soil (Wei et al., 2019).

In addition to natural factors, socioeconomic conditions and interactions between humans and land also contribute to landslide occurrence and risk. The highest FR value in population >1,000 people/km^2 which is 1.873 indicates damaging activities of residents such as hill dredging, the establishment of infrastructure on fragile slopes, and road construction without sufficient drainage system support (Froude & Petley, 2018). Meanwhile, most landslide incidents were distributed in villages with a population <500 people/km^2, which amounted to 27 out of 40 villages, shown in Figure 3g. Lin et al. (2023) stated that population density does not significantly trigger landslides because it can help maintain slope stability with the application of gully control techniques.

The presence of a high river network is equivalent to the density of drainage, which increases the potential for landslides due to the increase in pore water pressure on the land around the river (Çellek, 2019). The opposite result in this study indicates that landslide occurrence is mostly found in low density with FR value of 1.12 as shown in Figure 3h. Low drainage density indicates poor hydrological response to high rainfall. Increased infiltration and pore water pressure trigger the soil layers to slide (Tang et al., 2019).

The runoff coefficient is classified at a high influence weight with an FR value of 1.059 and corresponds to the number of landslides in that class. The surface runoff's drag effect positively contributes to slope failure (Zheng et al., 2020). This is consistent with high landslides occurring in settlements and farms that have high runoff coefficient factors.

Landslide vulnerability map is formed from the nine factors. Landslide vulnerability zones were classified into 10 classes. Model validation was conducted with training (field verification) points to determine the AUC success rate and model validation points to determine the AUC prediction rate. Model training points were calculated on 10 landslide vulnerability classes from the model. The calculation results are shown in Figure 4. with an AUC success rate value of 0.763 and an AUC prediction rate value of 0.754. Both values are the basis for the model's success rate to be good enough.

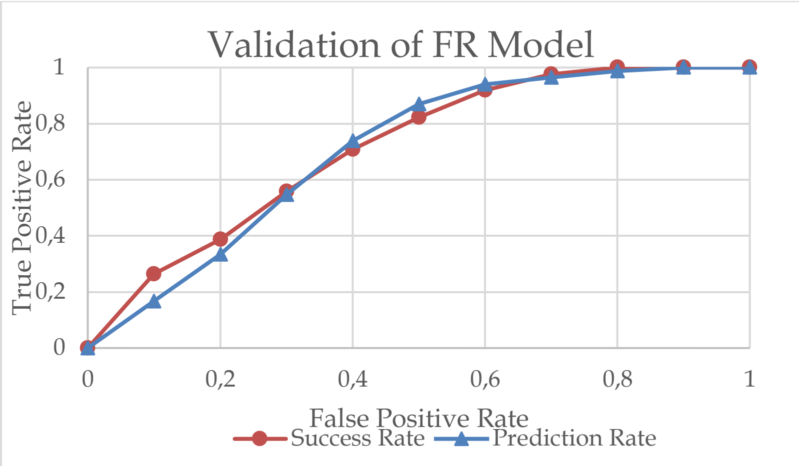

Figure 4. Validation of FR Model

The landslide vulnerability map of the study site is shown in Figure 5. The classification of landslide susceptibility is divided into five categories to provide a clearer and more balanced representation of risk, ensuring both detail and ease of interpretation. This division is based on statistical methods and disaster mapping standards used by institutions such as BNPB and BIG, facilitating analysis and data comparison. The five categories enable more accurate mapping in identifying variations in risk levels in the field and support decision-making in disaster mitigation (BNPB, 2016; Ayudya and Muryamto, 2024).

The area of each class is very low covering 3.74 km² (1.94%), low covering 57.91 km² (29.99%), medium covering 98.54 km2 (51.04%), high covering 30.94 km² (16.02%), and very high covering 1.93 km² (1%). A total of 210 landslide occurrence points were distributed in the low vulnerability class of 2 occurrences (0.95%), 25 occurrences (11.9%) in low class, 99 occurrences (47.14%) in medium class, 76 occurrences (36.19%) in high class, and eight occurrences (3.8%) in very high class.

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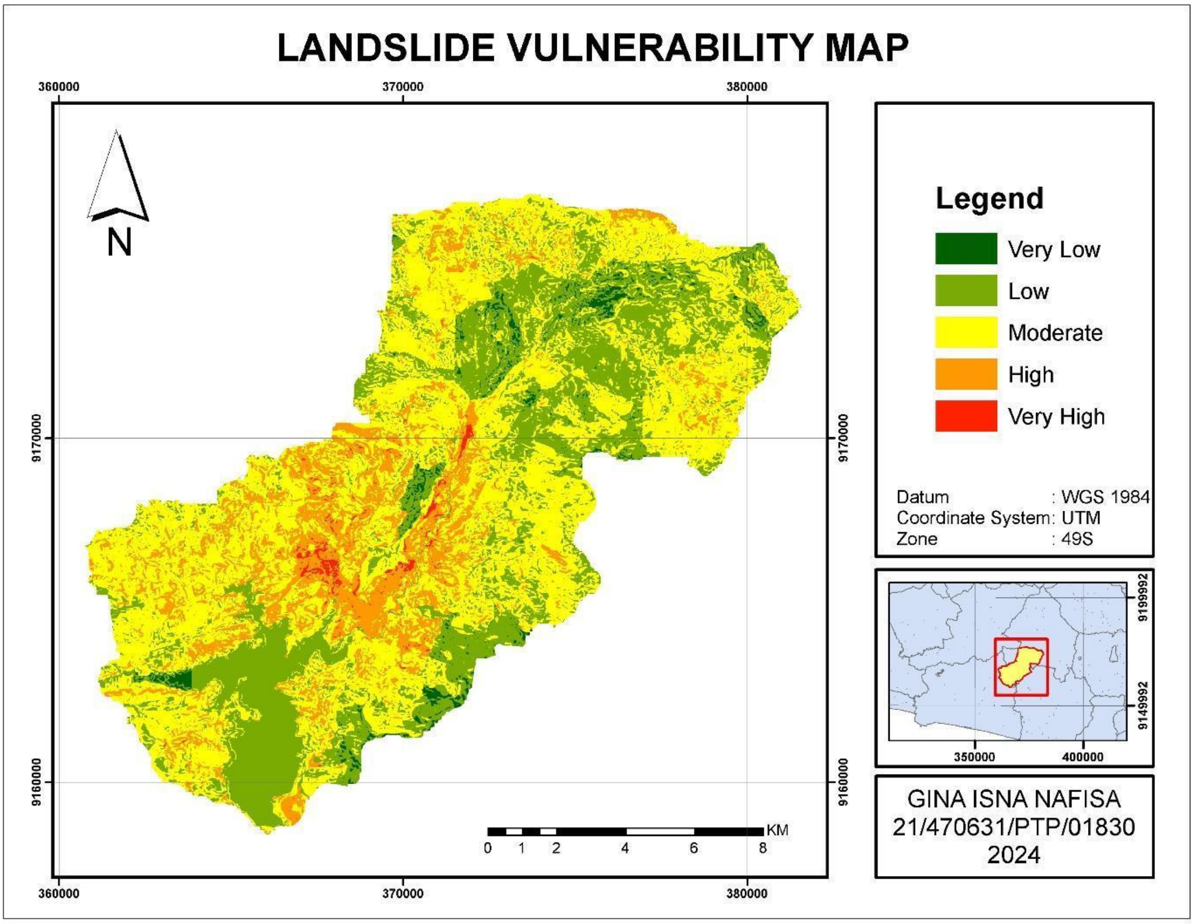

Figure 5. Landslide Vulnerability Map of the Study Site

The high landslide vulnerability level was found in settlements, especially mixed farmland and rice fields, by analogizing it with land use. The distribution was also dominant on moderately steep to steep slopes. Settlements often experience landslides due to poor drainage systems, slope excavation, and reduced vegetation (Froude & Petley, 2018). Landslides in mixed farmland frequently occur due to agricultural practices that neglect soil conservation, such as monoculture or land use on steep slopes without terracing (Senanayake et al., 2020). The use of land for rainfed rice fields can increase the risk of landslides if the irrigation system is not properly managed, as excessive water saturation can weaken soil stability (Hairiah et al., 2020).

Regarding the associated river network, high vulnerability was found along Kali Gede, one of the rivers that flows into Wadaslintang Reservoir. The presence of dryland forests on very steep slopes in the eastern part of the Wadaslintang catchment greatly helps the resilience of the slopes so that landslide vulnerability is low.

CONCLUSION

The landslide vulnerability of the Wadaslintang catchment with high levels is found in mixed gardens and rice fields with slightly steep to steep slopes. The most contributing factors to landslides indicated by the highest FR are land use, slope, rainfall, and soil permeability. The success rate calculation of the FR model is 0.763 and the prediction rate is 0.754 which shows the accuracy of the model is quite good. Areas with moderate and low categories of landslide vulnerability cover 98.54 km^2 (51.04%) and 57.91 km^2 (29.99%) of the study site respectively. While the others i.e. areas with the very low, high and very high categories, occupy around 3.74 km^2 (1.94%), 30.94 km^2 (16.02%), and 1.93 km^2 (1%) of the study site.

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CONFLICT OF INTEREST

There is no conflicts on interest with the result of this study.

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