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Research Article

Landslide Hazard Mapping using Weight Overlay Based-GIS with Multi-criteria Evaluation Techniques in Tawangmangu District, Indonesia

Pipit Wijayanti[1]*, Sofyan Sholeh[2], Fathi Muzaqi[1]
[1]Department of Geography Education, Universitas Sebelas Maret, Surakarta, 57126, Indonesia
[2]Department of Environmental Science, Universitas Sebelas Maret, Surakarta, 57126, Indonesia
*Corresponding author: pipitwijayanti@staff.uns.ac.id

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ABSTRACT

Landslides are natural events that can be worsened by human activities, leading to significant destruction of life and property. In Tawangmangu District, situated on the slopes of Mount Lawu, the landslide risk is amplified due to factors such as volcanic soil, steep terrain, and high rainfall. This research seeks to map landslide hazards in the area by utilizing a Geographic Information System (GIS) and the Analytical Hierarchy Process (AHP), combining both static and dynamic factors contributing to landslide occurrences. The study considers seven critical factors: slope, distance from roads, geology, land use, soil type, rainfall, and proximity to geological faults. Expert opinions are used to assign weights to these factors, which are then integrated into a GIS model to assess susceptibility to landslides. The area is classified into five risk zones. The results show that 21.97% of the region faces high and very high risks, while 39.57% is moderately vulnerable. The highest-risk areas are those with steep slopes and significant human activity, such as road construction and land-use changes for tourism. Model validation, comparing the predicted landslide zones with actual landslide locations, shows that over 75% of landslides occurred in high and very high-risk areas, confirming the model's accuracy. This study underscores the importance of sustainable land use planning, effective infrastructure management, and vegetation preservation in reducing landslide risks. Future mitigation efforts should focus on monitoring land use changes, strengthening vulnerable infrastructure, and enhancing early warning systems to minimize further landslide damage in the region.

Keywords: AHP; GIS; Landslide; Tawangmangu

INTRODUCTION

These Landslides are natural phenomena (e.g., heavy rain, fault lines, etc.) or the influence of human activities that accelerate the process. As one of the geological disasters, landslides cause thousands of victims and deaths, billions in damage, and yearly losses [1]. The movement of land masses is due to gravity, and unstable rocks are due to natural phenomena, geomorphological climate, geology, or human activities. Soil susceptible to landslides is clay, marl, gypsum, or shallow laterite formations. Landslide motions are determined and caused by a combination of natural elements and human activity (topography, geology, hydrogeology, urbanization, land management, slope cutting, etc.)[2],[3],[4]. However, anthropogenic activities have the potential to increase the landslide phenomena.

Tawangmangu District is a part of Karanganyar that often experiences landslides [5]. Its location is on the slopes of Mount Lawu, which is dominated by volcanic materials, especially in the sand texture. This condition causes thick soils to develop directly on top of volcanic bedrock. As a result, when high rainfall occurs, this location is vulnerable to landslide hazards [6]. The massive human activity, especially for tourism needs, is increasing, which can trigger landslide activity.

Research on landslide mapping using Geographic Information System (GIS) technology has significantly developed in recent decades. Recent studies related to landslides describe the methodology for determining the impact of landslides [2],[4],[7],[8],[9]. However, the study only involved static factors in its research. In addition, some recent studies have focused on the analysis of landslide data using various GIS-based methodologies. For example, some studies use a comparative approach to engine kernel functions [10] and assessment and validation of landslide vulnerability using GIS [11]. Landslide vulnerability maps were also created using the probability ratio approach [12]. Moreover, the Generalized Method of Data Handling was used to zone landslide vulnerability [13].

However, in the context of a multi-criteria assessment that combines static and dynamic factors according to the study area and is then applied through the weight overlay method on GIS, its use still needs to be improved in research, especially in landslide research. This landslide hazard mapping study uses a deterministic model and a probabilistic approach, which considers the landslide requirements. This strategy was previously used in studies on whether land was suitable for wheat farming [14] and evaluation of agricultural land use [15]. Both studies show that the fuzzy-AHP and GIS methods are effective in assessing land suitability, however have the weakness of subjectivity in determining parameter weights by experts. In addition, this method has not been widely used in mapping landslide hazards in case studies in the Tawangmangu area.

This landslide hazard mapping study uses a deterministic model and a probabilistic approach, which considers the landslide requirements. The qualitative method is based on expert opinions regarding landslide occurrence [16]. Knowledge and History have helped experts determine and evaluate landslides, determine causative factors, and identify locations with geology and geomorphology similar to landslide occurrence areas. The qualitative method will be quantitative, giving weight to each factor [17]. This method measures opinions and changes the decision model. Researchers around the world widely use this method [1],[2],[4],[9],[18]. The study used geospatial analysis to create a map of landslide hazards and estimate rainfall thresholds to determine expected losses. However, data limitations, incomplete damage records, and simplification of vulnerability scores reduce the accuracy of risk assessments and do not fully reflect the potential impacts of landslides.

For this reason, the study aims to explore the threats of landslides within the Tawangmangu district. This study focuses on making landslide hazard maps by combining Geographic Information System (GIS) techniques and Analytical Hierarchy Process (AHP) methods. Furthermore, the results of this technique are compared to the incidence of landslides statistics to assess the map's accuracy.

METHODS

This study was conducted in Tawangmangu, Karanganyar, Central Java, Indonesia (Figure 1). Hazard to landslides begins with providing an inventory of landslide event data [9]. This study begins with developing a landslide event map using field observations and satellite image interpretations through Google Earth. Seven factors that influence landslides, namely slope, distance to road, geology, land use, soil, rainfall, and distance fault, are used for landslide analysis in the research area [19],[20],[21],[22]. These different data layers are aggregated in the AHP process to provide factor and sub-factor weights for landslide hazards ultimately. Once the potential landslide areas were identified based on existing literature, the soil hazard was validated by comparing inventory data about recorded events and available susceptibility maps.

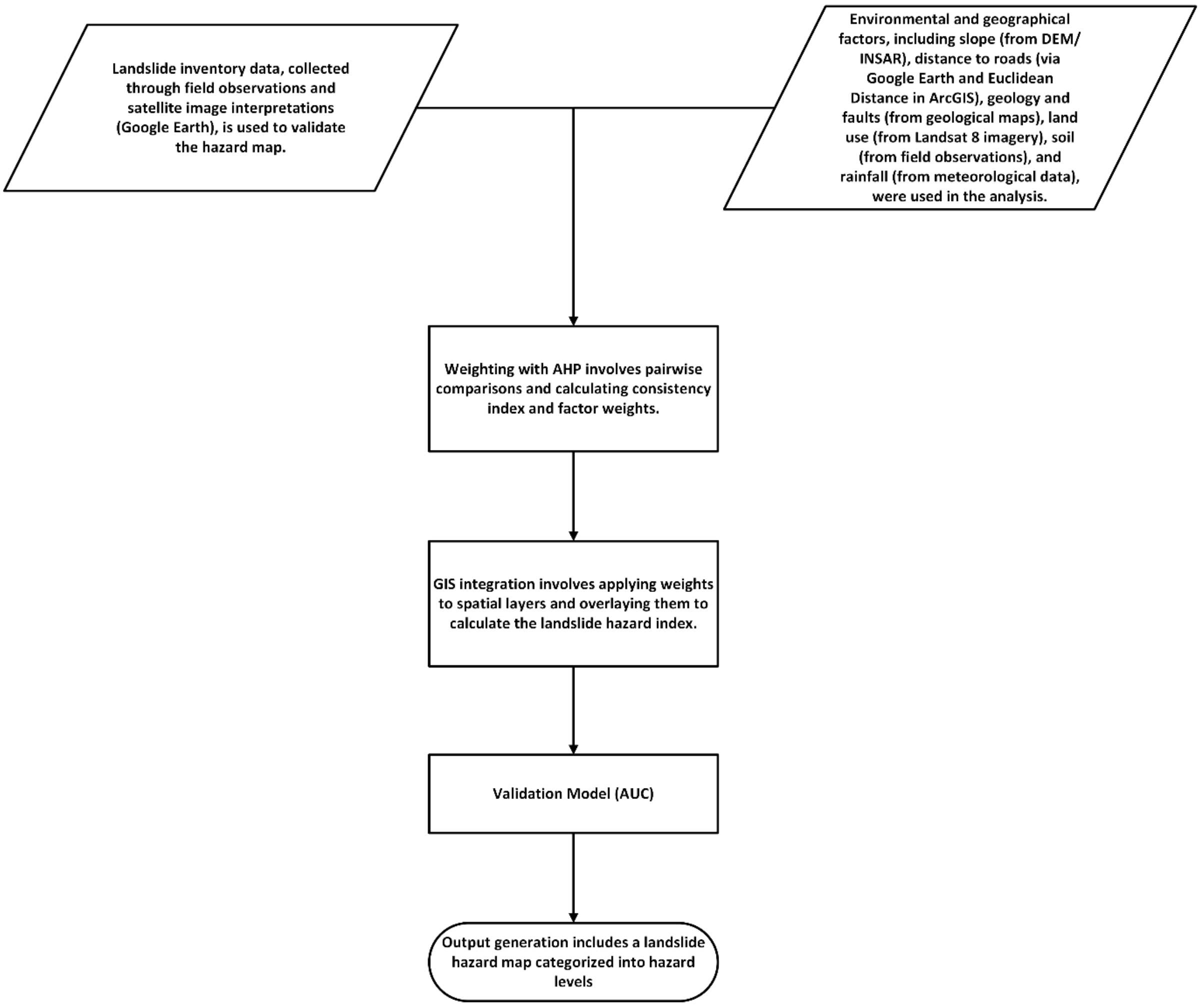

Figure 1. Research framework

The study collected primary data from multiple locations (Table 1) and analyzed it using a geographic database. Landslide factor maps were classified, and AHP-derived weights for factors and sub-factors were applied to combine the layers. Leveraging AHP, the layers were embedded into the GIS platform, and distances to roads and faults were determined using the Euclidean Distance Tools available in ArcGIS 10.8. Land use data was acquired by analyzing Landsat 8 OLI imagery collected on November 10, 2023, with radiometric and atmospheric corrections applied during the process. Topographic factors, such as slope, were extracted from the analysis of the National Digital Elevation Model (DEMNas). For validation use area of curve (AUC) model validation to measure the extent of the model's accuracy [8]. The ideal model for assessing AUC yielded a value close to 0.1, indicating high accuracy, and 0.5, indicating inaccuracy.

Table 1. Research Data Sources

Information	Explanation	Reference
Landsat 8 OLI	Retrieved	https://earthexplorer.usgs.gov/
Digital Elevation Model National Indonesia (DEMNAS)	Retrieved	https://tanahair.indonesia.go.id/
Slope	DEM National Indonesia	DEM National Indonesia
Landuse	Landsat 8 OLI and Field Observations	https://earthexplorer.usgs.gov/ and Field observation
Fault	Geological Map 1: 100.000	Geological Map of Ponorogo 1: 100.000
Road	Extracted	Google Earth
Landslide Point	Field observation and Google Earth	Field observation and Google Earth

Hazard Mapping

AHP is a decision-making method designed for handling multiple objectives and criteria Click or tap here to enter text. [23],[24]. The making of choices is assisted by this in determining the options that best align with the objectives, understand the problem, and analyze the landslide hazard.

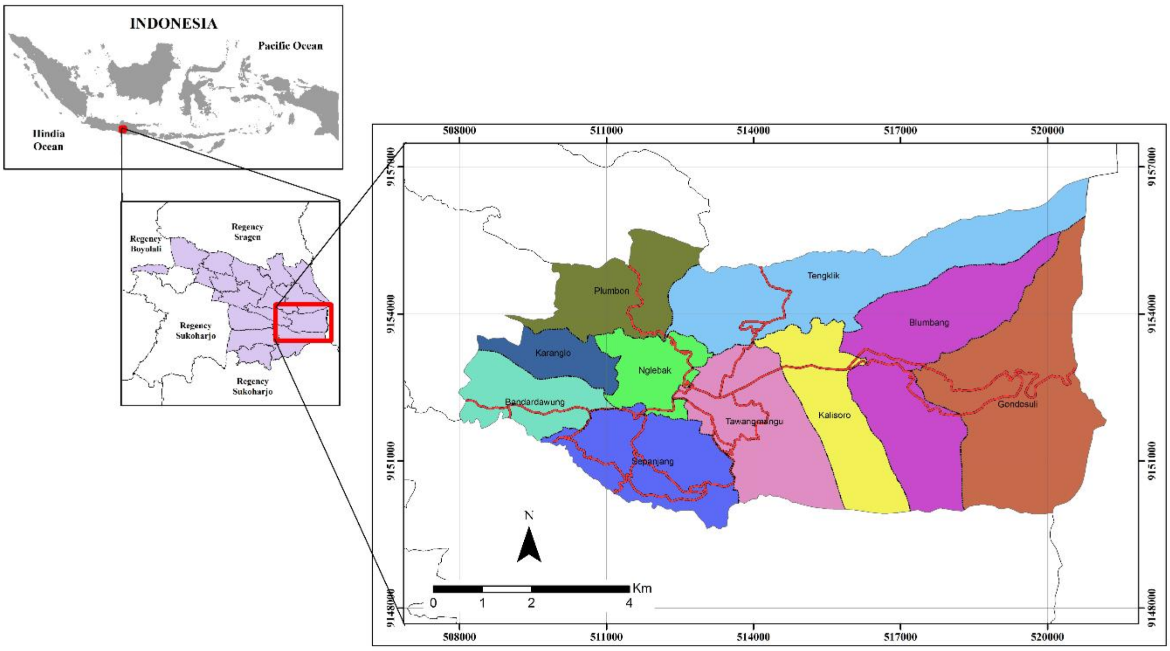

Figure 2. Study Area

This process involves building a hierarchical structure for criteria, comparing them to objectives, creating a comparative matrix, calculating priorities, and determining RI, λmax, CI, and CR. Create a factor table, determine sub-factors based on The quantity of criteria examined, create a sub-criteria comparison table, calculate the aggregate to compare options, report the aggregation to figure out the efficacy of each alternative's relative value, calculate the final aggregation and determine the ultimate decision (Table 2).

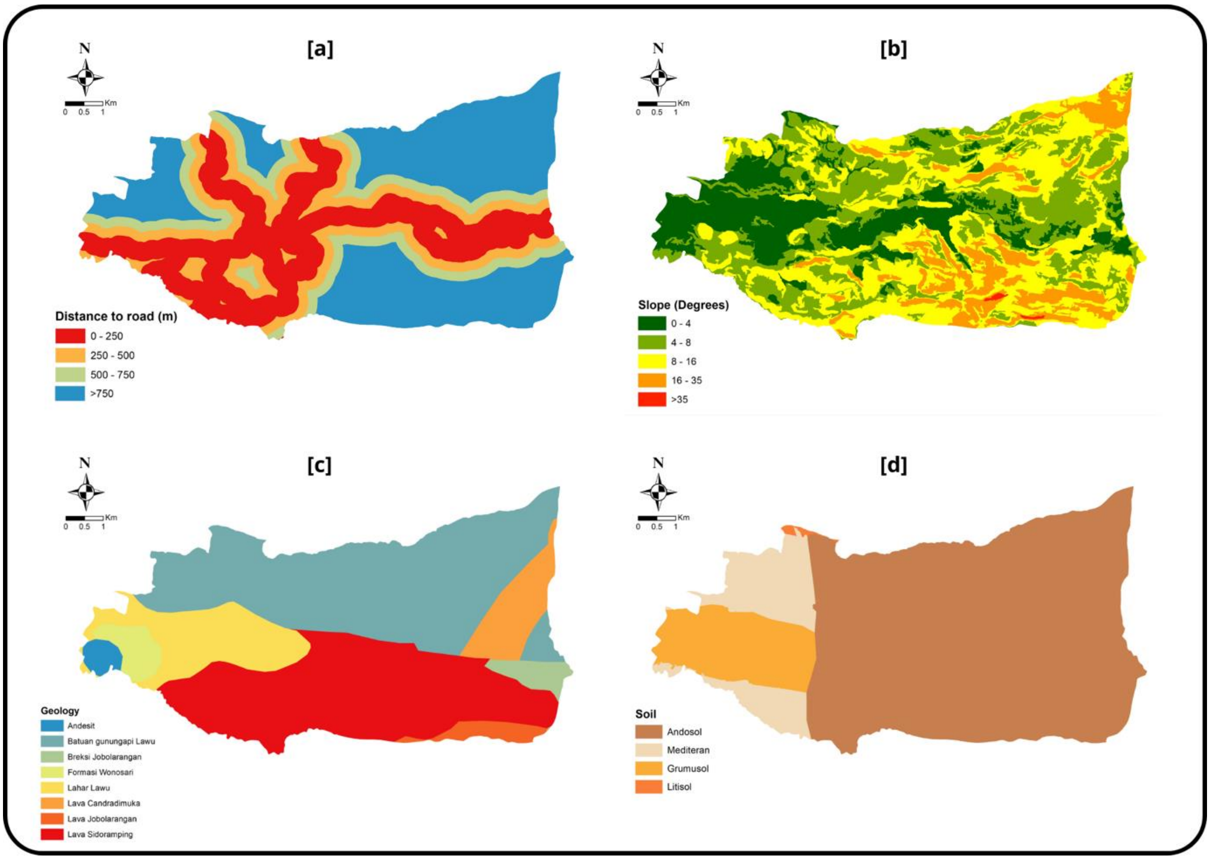

Figure 3. Landslide factors in the research area: (a) Distance to the road (b) Slope (c) Geology (d) Soil

A hierarchical classification approach is carried out to determine inconsistencies when comparing each analysis criterion. This approach also allows you to check the strategy's coherence by computing the consistency ratio (CR), Shown through the equation (1)[58].

$$CR = \frac{CI}{RI} \tag{1}$$

The formula demonstrates that the consistency index, represented by equation (2)[59], is called CI, while the random consistency index is called RI.

$$CI = \frac{\lambda maks}{n-1} \tag{2}$$

The matrix determines the eigenvalue, represented by λmax, and n denotes the matrix's numerical order [23],[24].The consistency ratio should not exceed 10%, ensuring consistency in decision-making compared to random element weightings. Lastly, the assigned weights are systematically incorporated into different categories of causative factors within the landslide hazard index, calculated using a specific equation (3) [58].

$$KTL = \sum_{i-1}^{n} R_1 * W_1 \tag{3}$$

The landslide hazard is denoted by KTL, the class rating of each factor is represented by Ri, and the weight of each landslide conditioning factor by Wi.

The resultant landslide hazards map is categorized into five categories: deficient, low, medium, high, and extremely high, using equation (4)[60].

$$IK = \frac{t-r}{n} \tag{4}$$

Where IK represents the class interval, t is the most significant value, r is the lowest value, and n is the total amount of classes.

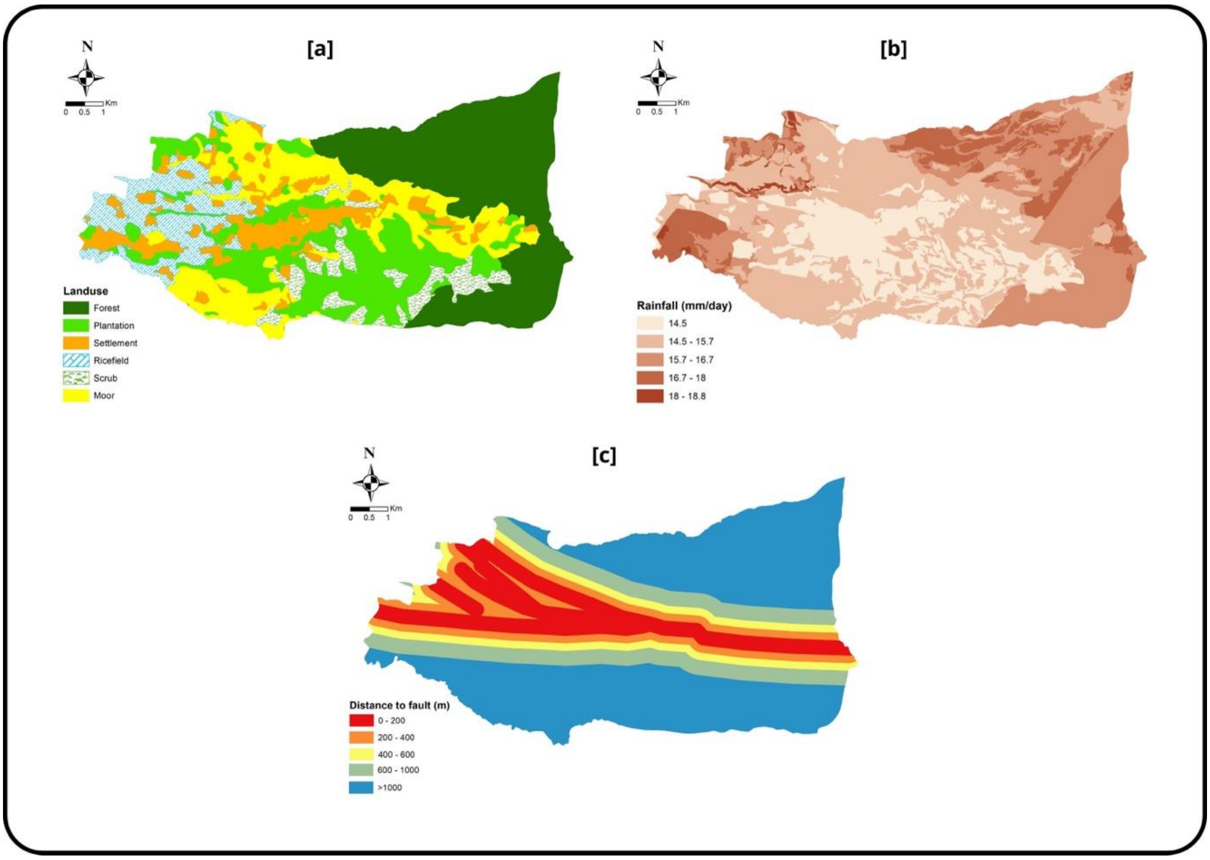

Figure 4. Factors causing landslides resulting from the research area: (a) Land Use, (b) Rainfall, (c) Fault Distance.

Table 2. Scale of AHP [24]

Value	Description	Justification
1	Equally important	Two choice components have the same impact on the parent determination element.
3	Moderately more important	One choice factor is somewhat more significant than the other.
5	Much more important	One option aspect has a greater impact than the other.
7	Very much more important	One decision factor has a far greater effect than the other.
9	Extremely more important	The influence of the two choice components differs significantly.
2,4,6,8	Intermediate judgment values	Values range from equally, somewhat, substantially, very much, and tremendously.

The runoff in each cell is the volume of the excess rainfall in each time fraction[60], Δt, calculated as follows:

Q(t)i=(Pe(t))iΔtA (3)

where $Q(t)$ is the runoff in a cell at time step i (m^3/s), $P_e(t)_I$ is the excess rainfall depth at time step i (m), Δt is the time fraction (s), and A the cell size (m^2). Based on eq. (3), the runoff volume, $V(t)$, in each cell can be written as follows:

V(t)i=(Pe(t))iA (4)

The excess rainfall, $P_e(t)$ in eq. (3) was calculated using the NRCS-CN method as follows: (USDA, 2004a)

Pe=P-0.2S-S(P-0.2S)P+0.8S (5)

where P is the rainfall depth (mm) and S is the maximum soil water retention parameter (mm).

RESULTS AND DISCUSSION

A multi-criteria method is implemented in this research through the GIS-based AHP approach to measure the possibility of landslide disaster events in Tawangmangu Regency. The factors considered in identifying landslide potential are seven developed in this study. These factors are divided into two types: dynamic factors, namely rainfall, land use, and distance from roadways, and static factors, namely slope, geology, soil type, and distance from geological faults.

This AHP model relies on assessments and ratings from experts in the field. Expert opinions are invaluable in dealing with complex issues such as vulnerability evaluation to landslides. However, analysis based on expert views has limitations related to the possibility of cognitive changes, uncertainty, and subjectivity of individual experts. Therefore, it is essential to carefully and critically consider any input from experts and utilize data and other information to strengthen the validity and accuracy of the analysis results.

Table 3. Principal comparison and eigen matrices

	Comparison matrix							
	Distance to road	**Slope**	**Geology**	**Soil**	**Land use**	**Rainfall**	**Distance to fault**	**Weight**
Distance to road	1							0.46
Slope	7	1						13.38
Geology	3	1/5	1					1.30
Soil	3	1/5	1/2	1				1.01
Land use	1/5	1/9	1/3	1/4	1			0.10
Rainfall	1/3	1/9	1/4	1/4	1	1		0.10
Distance to fault	7	1	3	4	6	9	1	10.46

The Saaty method [24] was utilized to process the pairwise comparison arrays for both relative and sub-factors (Tables 3 and 4). For all factors, CR is determined, and the measurements must be less than 0.10, signifying that the weights are correctly and consistently distributed. Hence, GIS allows for the production of a landslide hazard map. The analysis data presented in Table 5 demonstrate that extremely low, low, and medium hazards have a percentage of 11.36%, 27.10%, and 39.57%, in the same order. While high and very high hazard were 20.43% and 1.54%, respectively.

Table 4. Factor Weights Derived from the AHP Pairwise Matrix

Factor	Sub-Factor	Score	Weight
Distance to road	0 - 250	0.03	0.07
	250 - 500	0.07	
	500 - 750	0.13	
	750 - 1000	0.26	
	>1000	0.50	
Slope	0 - 7	0.03	0.36
	7 - 14	0.07	
	14 - 23	0.13	
	23 - 41	0.26	
	>41	0.50	
Geology	Not clay or landslide debris	0.50	0.12
	Lava, lava, and volcanic breccia	0.13	
	Sedimentary rocks: claystone, marl, sandstone; lava, tuff and breccia	0.03	
Soil	Regosol	0.50	0.10
	Andosol, Podsolic	0.26	
	Latosol	0.13	
	Mediterranean	0.07	
	Alluvial	0.03	
Landuse	Space Area	0.50	0.03
	Settlement	0.26	
	Plantations, Rice Fields, Moors	0.13	
	Scrub	0.07	
	Forest, Waterbody	0.03	
Rainfall (cm/hari)	0-13.6	0.03	0.03
	13.6-20.7	0.07	
	20.7 – 27.7	0.13	
	27.7 – 34	0.26	
	>34	0.50	
Distance to fault	0 - 200	0.50	0.03
	200 - 400	0.26	
	400 - 600	0.13	
	600 - 1000	0.07	
	>1000	0.03	

The landslide hazard map (Figure 5) shows that the southern region of Tawangmangu District is the most vulnerable to landslides. The region is known for its very steep slopes, which are the dominant factor in increasing the hazard of landslides [25],[26],[27]. The steeper slope worsens soil stability, increasing the likelihood of soil material slipping down the slope. Hence mostly, slope steepness leads to awesomeness, but it carries a danger: as the gradient of the slope increases[28]. Furthermore, the high rainfall rate at the streaming stage was also a significant factor in soil detachment. Unusually high rainfall can cause the soil to become saturated, or more moisture builds up in it as less water can be absorbed by runoff processes, making soils prone to landslides [29]. This helps to enhance the relationship between natural conditions and weather activities as factors in predicting a region's vulnerability to landslide disasters.

In addition to natural causes such as landslide-prone slopes and landforms, infrastructure development, such as roads that run through hills in Tawangmangu District, increases the risk of landslides. Much research has proved that road construction can change or influence stability on a slope [30],[31]. In the study location, road construction may also increase land slope and, in turn, affect landslides. Furthermore, the presence of vehicle traffic stimulus through vehicular vibrations is a factor that exacerbates indication due to credibility for this moving-induced vibration might decrease slope steadiness, additionally put at risk because of street construction works [32]. The high-intensity activity can also speed up soil erosion and increase the risk of landslides along both sides. Landslides generally occur near major transportation routes, implying the relationship between human activities and susceptibility to natural disasters such as landslides in the field research area.

Another static factor, namely the existence of geological faults that cross the research area, is the main factor that has the potential to trigger landslides. Large earthquakes may result in a sizeable seismogenic slip and substantial soil movements, potentially damaging the adjacent earth materials [33],[34]. The possible movement of the soil due to this fault may lead the top strata to become weak. The bed layer becomes worried about landslides and then threatened by landslides [35]. Understanding the geomorphological context in which landslides are likely to occur is vital to a successful assessment, as well as detailed information about the soil types present at that location. The Andosol and Regosol soils that dominate the study site are brownish-grey colored and contain significant proportions of volcanic debris originating from previous volcanic eruptions [36]. These two types of soils have little cohesiveness, making them readily moved by water or seismic activity, increasing the risk of landslides in the impacted regions.

The variation in land use significantly affects landside risk. Plant cover more excellent than 1 m can reduce the occurrence of landslides since vegetation significantly contributes to holding the soil together (by reducing erosion and root entanglement), holding soil in place and making it less susceptible to slides [37]. Vegetation, namely foundation plants, provides resistance that prevents damage such as ground crumbling from causing slope landslides [38]. Even though most of the land surrounding the study location is utilized for agriculture, more people have converted a more significant portion to settlements for people on vacations [39]. These changes result in a likely scenario of landslide deformation due to a decrease in green cover or a change in the soil bed profile by disturbing its stability [40],[41],[42],[43].

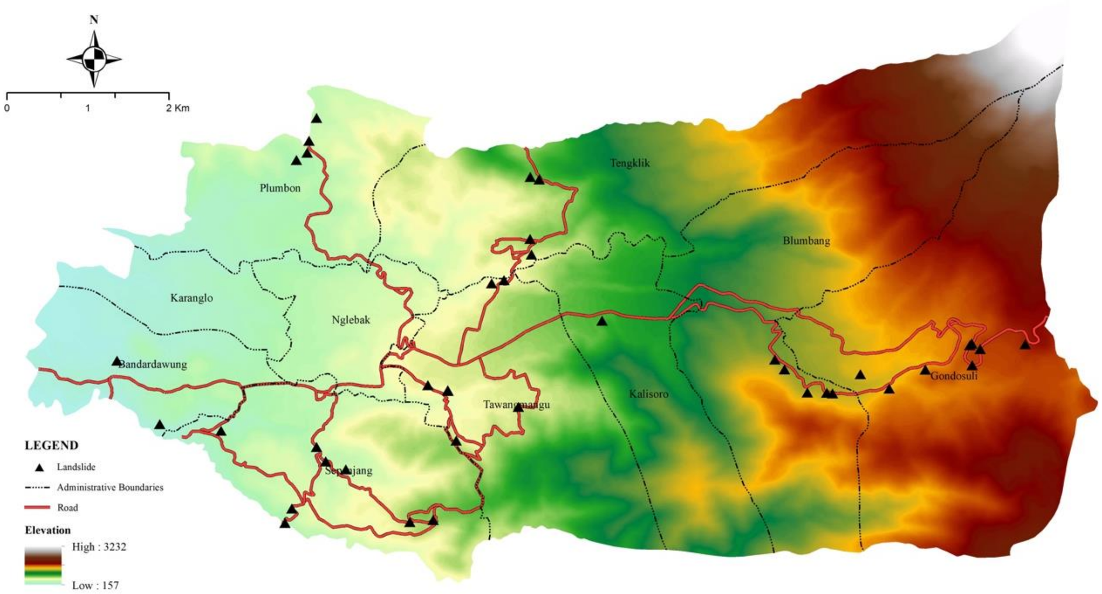

Figure 5. Landslide inventory map overlays elevations

All these elements increase the likelihood of landslides. Landslides have caused significant damage to infrastructure and facilities such as homes, highways, and agricultural land [44],[45]. Therefore, slimming down the risk of landslides through conservation activities is required [46],[47]. Another point is that further improving our early warning system and disseminating disaster risk information to the public is essential. Individual disasters may occur and are unpredictable suddenness at any time that people are not conscious of happening, e.g., floods and landslides, among others [48],[49]. Thus, it is hoped that these efforts can reduce the potential risks and negative impacts of future landslides and increase awareness of the importance of sustainable environmental management.

The study area values were reclassified into five classes of vulnerability to landslides: very low, low, moderate, high, and very high—using a natural break classifier (Figure 4). As demonstrated by the analysis results in Table 5, the incidence of very low, low, and medium vulnerabilities covers 11.36%, 27.10%, and 39.57% across the complete study zone, in the corresponding order. The areas with high and very high vulnerability cover 20.43% and 1.54% across the entire study region, respectively (Table 5).

Based on the map (Figure 5), the area with a very high landslide risk is located in the time and study areas along the slope close to the road network and steep slopes that encourage erosion and landslides. There is a very low level of vulnerability in the western area, with relatively flat topographic conditions and land cover dominated by human cultivation. As also seen on the landslide vulnerability map, landslides are mainly located in the characteristics of the Andosol soil type, which has moderate absorption and high humidity, which causes its characteristics to be sensitive to erosion located on steep road slopes [50].

Other factors contribute to landslides in this area, with the most critical being the distance to the fault and the road network. Other factors, such as slope and elevation, also play a role. On the other hand, pre-conditioned factors such as distance to roads and land use have a lesser influence, although they can sometimes be triggering factors in certain conditions. For example, digging new roads or construction activities in landslide-prone areas can trigger landslides and temporary water accumulation [51].

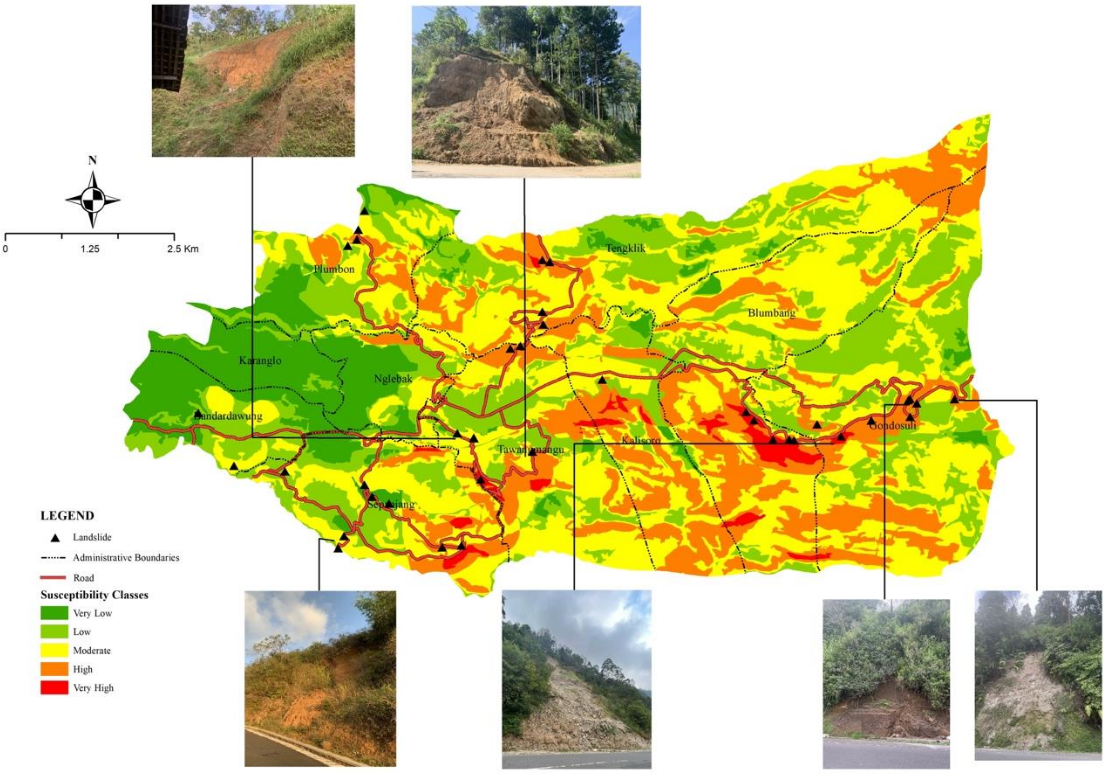

Figure 6. Landslide Hazard Map utilizing the AHP Method

Table 5. Regional Hazard Map Classes

Hazard classes	Area (km^2)	Area (%)
Very low	6.95	11.36
Low	16.58	27.10
Moderate	24.20	39.57
High	12.49	20.43
Very high	0.94	1.54
Total	**61.16**	**100**

Blumbang Village, Gondosuli Village, and Tawangmangu Village are the places that have high slope levels where landslides usually occur, as per Blumbang, Gondosuli, and Tawangmangu village administration. Unplanned land use conversion from agriculture to dwelling houses serving as restaurants or villas is among the key factors contributing to this situation. The primary cause of landslides in such areas is increased human activities like constructing tourism facilities [52].

Tengklik Village, as part of the research area, is located in an area crossed by geological faults. Every year, the region experiences soil movement of 0.3 millimeters, indicating seismic activity that can affect slope stability [53],[54]. Data shows that the total area of Tawangmangu District, which has a high and very high landslide danger level, reaches 21.97%, while 39.5% of this sub-district has a moderate landslide danger level. The sub-district also has an enormous potential for moderate hazards, which can escalate to a higher hazard level if not handled properly.

Most of the landslides in our study area were recorded mainly near roads (Figure 5). The risk of landslides is significantly high in the Gondosuli and Blumbang areas, attributable to their steep slopes and lack of proper land use planning and development. This study observed 36 landslide locations to evaluate the vulnerability model's accuracy. The AUC method was used to validate the landslide susceptibility map.

Landslide risk mitigation efforts are significant in this region. Maintenance of landslide-triggering factors such as steep slopes, vulnerable soil conditions, and human activities that change land use patterns to more vulnerable areas need to be prioritized. These measures include closely monitoring land-use changes, restructuring infrastructure that affects slope stability, and vegetation management to strengthen soil bonds and reduce erosion.

Validation Model

The landslide inventory process recorded 36 landslide locations. The landslide inventory map (Figure 4) was created based on field researchers' findings. Subsequently, the map was juxtaposed with the landslide susceptibility map (Figure 6) to confirm the precision of the vulnerability zoning. Most, namely more than 75%, of the landslides inventoried were in the high and very high vulnerability zones. Meanwhile, a small portion of the recorded landslides were in the low, very low, and medium vulnerability zones, with percentages of 0%, 8.33%, and 16.67%, respectively. In contrast, the high and very high vulnerability zones showed much higher figures, namely 38.89% and 36.11% of the total recorded landslide area.

These findings align with previous studies, such as Vakhshoori et al. [55] and (Shahabi & Hashim [4], which highlighted the importance of integrating spatial analysis and expert judgment in hazard assessments. Similarly, (Melati et al. [56] and (Sciarra et al. [11] demonstrated the efficacy of GIS in landslide mapping and validation, emphasizing the role of multi-criteria approaches in addressing both natural and anthropogenic influences on hazard susceptibility.

The lower percentage of landslides occurring in low and medium-risk zones (8.33% and 16.67%, respectively) highlights the model's reliability while suggesting areas for improvement. This aligns with (Bruzón et al. [57], who noted that incorporating dynamic, real-time data could enhance model accuracy by capturing temporal variations and localized anomalies. It refers to the fact that the growth of plants in a given environment reduces the possibility of soil displacement in sloped areas [58]. By validating the GIS-based AHP approach, this study strengthens its application as a reliable tool for disaster risk management. It provides actionable insights for prioritizing mitigation in high-risk zones and contributes to the broader understanding of integrating multi-criteria decision-making processes in hazard assessment and sustainable land management

CONCLUSION

This study utilized GIS and AHP methods to create a comprehensive landslide hazard map for Tawangmangu District, integrating static factors (e.g., slope, soil, geology) and dynamic factors (e.g., rainfall, land use, and proximity to roads). The results indicate that steep slopes, Andosol and Regosol soils, and high rainfall are the primary drivers of landslides, exacerbated by human activities such as unplanned land use changes and infrastructure development. Geological faults also contribute significantly to landslide risks, particularly in areas like Tengklik Village, where seismic activity destabilizes slopes.Validation using AUC confirmed the model's reliability, with over 75% of recorded landslides occurring in high and very high-risk zones. The study highlights the effectiveness of GIS-based AHP in assessing landslide vulnerability, providing a valuable tool for identifying high-risk areas. The findings emphasize the need for targeted mitigation measures, including improved land use planning, slope stabilization, and vegetation management, to reduce landslide risks. Early warning systems and public awareness campaigns are also essential for minimizing impacts and promoting sustainable environmental management in Tawangmangu District. This approach offers actionable insights for reducing disaster risks and enhancing resilience in landslide-prone areas.

DECLARATIONS

Conflict of Interest

We declare no conflict of interest, financial or otherwise.

Ethical Approval

On behalf of all authors, the corresponding author states that the paper satisfies Ethical Standards conditions, no human participants, or animals are involved in the research.

Informed Consent

On behalf of all authors, the corresponding author states that no human participants are involved in the research and, therefore, informed consent is not required by them.

DATA AVAILABILITY

Data used to support the findings of this study are available from the corresponding author upon request.

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