



Landslide Susceptibility Mapping Using GIS-Based Analytical Hierarchy Process in Pejawaran District, Banjarnegara

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Abstract

Landslide susceptibility mapping is an important tool for identifying relatively unstable zones and facilitating disaster mitigation and land-use planning. This study assesses landslide susceptibility in Pejawaran District, Banjarnegara, Central Java, Indonesia, using a GIS-based Analytical Hierarchy Process (AHP). Six conditioning factors were integrated: distance to road, normalized difference vegetation index (NDVI), distance to stream, lithology, elevation, and slope. Pairwise comparison was used to assess the relative importance of these factors. The resulting weights were: distance to road (28%), NDVI (22%), distance to stream (17%), lithology (14%), elevation (10%), and slope (9%). The final landslide susceptibility map was created by combining the weighted thematic layers in a GIS environment. The 54.02 km² study area was classified into five susceptibility levels: very low (8%), low (19%), moderate (28%), high (28%), and very high (16%). High- to very-high-susceptibility areas are mainly concentrated in the central, northern, and eastern parts of the study area, while the western and southwestern sectors generally show lower susceptibility. The spatial distribution of the landslide inventory closely matches the moderate-to-high susceptibility zones. These results indicate that the GIS-AHP approach provides a practical preliminary framework for identifying landslide-prone areas in Pejawaran District.

Keywords: *Analytical Hierarchy Process; GIS, Landslide Susceptibility, Pejawaran, Banjarnegara, Spatial Analysis*

INTRODUCTION

Landslides are among the most common geological hazards in hilly and mountainous areas and often damage human life, agricultural land, settlements, and infrastructure (Javier & Kumar, 2019; Sur et al., 2022). Topographic, geological, hydrological, environmental, and anthropogenic factors govern their occurrence (Arabameri et al., 2020; Sur et al., 2022). Thus, slope, elevation, lithology, vegetation condition, distance to drainage networks, and distance to roads are popularly accepted as important landslide conditioning factors (Javier & Kumar, 2019; Arabameri et al., 2020; Sur et al., 2022).

These parameters affect gravitational driving forces, material strength, infiltration, erosion, slope disturbance, and overall slope stability (Miklin et al., 2022). Landslides are common in Indonesia because of its steep topography, complex geology, tropical climate, and widespread use of mountainous areas (Bachri et al., 2020; Priyono, 2020; Soma et al., 2019). Banjarnegara Regency, Central Java, is one of the areas prone to landslides (Suharini et al., 2021; Susanti et al., 2021).

Landslides in this area are associated with terrain changes, geological conditions, and

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environmental features (Muntohar et al., 2021; Permanajati et al., 2023). Landslide activity reported in Sarwodadi Village, Pejawaran District, further indicates the need for susceptibility assessment at a more detailed local scale (Saputra et al., 2024).

The Geographic Information System (GIS) is an efficient platform to integrate different spatial datasets in landslide susceptibility assessment. Standardized, weighted, and spatially overlapped susceptibility maps of different susceptibility levels can be obtained based on some conditioning factors (Bachri et al., 2020; Nhu et al., 2020; Banuzaki & Ayu, 2021). The Analytical Hierarchy Process (AHP) is a widely used multi-criteria decision analysis technique that systematically evaluates the relative importance of conditioning factors using pairwise comparisons and consistency checks (Ibrahim et al., 2022; Agrawal & Dixit, 2022).

In the scope of this study, GIS has been successfully applied to the tropical and mountainous regions of Malaysia, Vietnam, and Indonesia, where landslide susceptibility is determined by the spatial variations in terrain, lithology, rainfall, land use, drainage, and other environmental factors (Banuzaki & Ayu, 2021; Ibrahim et al., 2022; Kieu & Ngo, 2022; Manyvanh & Setiawan, 2023). However, AHP still depends somewhat on expert judgment and can introduce subjectivity.

In some cases, comparative studies have shown that AHP's predictive performance can be comparable to or higher than Frequency Ratio (FR) and fuzzy-AHP (Agrawal & Dixit, 2022). In contrast, data-driven and machine learning methods may perform better when sufficient landslide inventory data are available (Trinh et al., 2022). Thus, AHP remains a practical approach for local-scale susceptibility assessment, particularly in areas with limited inventory data (Ibrahim et al., 2022).

A more detailed landslide susceptibility assessment is therefore needed for Pejawaran District, as landslide-controlling factors can vary considerably from one location to another. Although landslide susceptibility has been assessed at the broader Banjarnegara Regency scale, local variations in slope, geology, rainfall, land use, and other environmental conditions can produce distinct susceptibility patterns (Usman et al., 2023).

Therefore, this study applies a GIS-based Analytical Hierarchy Process to integrate topographic, geological, environmental, and hydrological factors and generate a landslide susceptibility map for Pejawaran District. The resulting map is intended to support preliminary mitigation, land-use planning, and identifying areas requiring more detailed investigation.

LITERATURE REVIEW

Geology of the Study Area

Geologically, Pejawaran District, Banjarnegara Regency, comprises several Tertiary sedimentary units and younger volcanic rocks, including the Rambatan, Halang, Tapak, Kalibuk, and Ligung Formations, as well as the Jembangan and Dieng Volcanic units. The Rambatan and Halang Formations generally represent marine sedimentary environments, with the Halang Formation characterized by turbidite deposits consisting mainly of interbedded sandstone and claystone.

Such lithological contrasts may produce differences in mechanical strength, permeability, and weathering behavior, thereby influencing slope stability (Astuti et al., 2019). The Tapak and Ligung Formations also occur within the Banjarnegara region and locally contain sedimentary and volcanic breccia units; when intensely weathered, these materials may develop weaker zones and loose surficial materials that increase susceptibility to slope failure (Raharjo et al., 2019).

In addition to these sedimentary formations, the geology of Pejawaran is influenced by the Jembangan and Dieng volcanic products, which include lava, tuff, pyroclastic breccia, and other volcanoclastic deposits. Studies of the Dieng Volcanic Complex indicate a complex history of volcanic activity characterized by successive lava and pyroclastic deposits (Suhendro et al., 2022).

The combination of heterogeneous sedimentary and volcanic lithologies, intensive tropical

weathering, and relatively steep mountainous terrain produces complex geological and geomorphological conditions in the Pejawaran area. These conditions may promote slope instability, particularly where highly weathered materials, weak lithological contacts, and increased water infiltration occur, making geology an important conditioning factor for landslide susceptibility assessment (Amarasinghe et al., 2024).

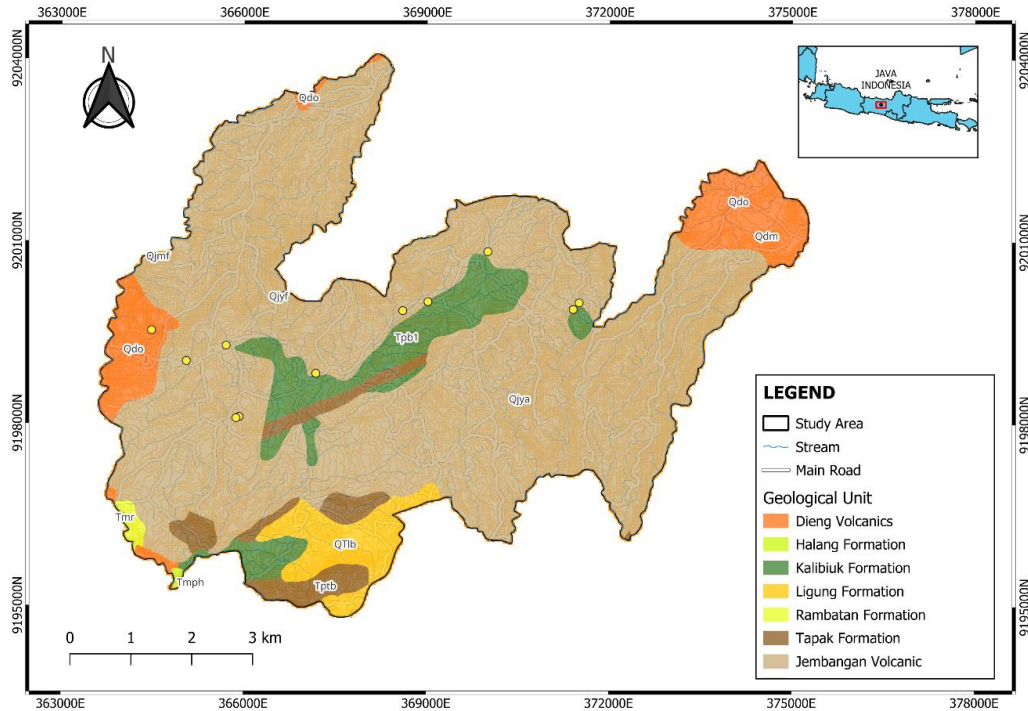


Figure 1. Geology Map of Pejawaran District

Analytical Hierarchy Process

The Analytical Hierarchy Process (AHP) is a multi-criteria decision-making method that determines the relative importance of several criteria through pairwise comparison. In landslide susceptibility assessment, AHP is commonly integrated with GIS to assign weights to landslide conditioning factors before combining them spatially.

The relative importance between criteria is evaluated using Saaty's nine-point scale, as shown in Table 1, where 1 represents equal importance, and 9 indicates extreme importance of one criterion over another (Saaty, 1980; Saaty & Vargas, 1984).

Table 1. Saaty's Pairwise Comparison Scale Used in the AHP Weighting Process

Importance level	AHP scale
Equal importance	1
Equal to slightly more important	2
Slightly more important	3
Slightly to much more important	4
Much more important	5
Much to very much more important	6
Very much more important	7
Very much to extremely important	8
Extremely important	9

The consistency of the pairwise comparison matrix is evaluated using the Consistency Ratio (CR):

$$CR = (\lambda_{max} - n) / [RI(n - 1)] \quad (1)$$

where λ_{max} is the maximum eigenvalue, n is the number of criteria, and RI is the Random Index. A comparison matrix is generally considered acceptable when $CR < 0.10$. After acceptable consistency is achieved, the resulting weights are integrated with the standardized spatial layers in GIS to calculate the Landslide Susceptibility Index:

$$LSI = \sum (w_i \times x_i) \quad (2)$$

where w_i is the weight of each conditioning factor, and x_i is the corresponding standardized factor score.

RESEARCH METHOD

Data Collection

This study developed the landslide susceptibility assessment by integrating several topographic, geological, hydrological, environmental, and anthropogenic parameters within a GIS-based framework. The selected parameters include elevation, slope, lithology, distance to streams, distance to roads, and NDVI, and the landslide inventory served as reference information for model evaluation.

These factors have been widely applied in previous landslide susceptibility studies because they represent important controls on slope instability and can be efficiently derived from remote sensing and geospatial datasets (Wicaksono et al., 2020; Shahabi & Hashim, 2015). Most spatial datasets were accessed and processed using Google Earth Engine (GEE) and GIS, as summarized in Table 2.

Table 2. Input Data Type and Source

No.	Data / Parameter	Source	Processing Platform
1	Elevation	SRTM Digital Elevation Model, NASA/USGS	Google Earth Engine (GEE) / GIS
2	Slope	Derived from SRTM Digital Elevation Model, NASA/USGS	Google Earth Engine (GEE) / GIS
3	Lithology	Regional Geological Map, Geological Agency of Indonesia	GIS
4	Distance to Stream	Ina-Geoportal	Google Earth Engine (GEE) / GIS
5	Distance to Road	Ina-Geoportal	Google Earth Engine (GEE) / GIS
6	NDVI	Sentinel-2 MSI Level-2A Surface Reflectance, ESA/Copernicus	Google Earth Engine (GEE) / GIS
7	Landslide Inventory	BPBD records and news reports	GIS

The Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP) was applied to determine the relative importance of the landslide conditioning factors used in this study. The level of importance of each factor was

established based on its potential contribution to slope instability, supported by previous landslide susceptibility studies and expert judgment.

In AHP-based landslide assessment, researchers commonly determine the relative importance of conditioning factors by considering their contribution to landslide occurrence and then expressing these judgments using Saaty's pairwise comparison scale. Based on this evaluation, the susceptibility classes were ranked as very low (ranking 1), low (ranking 2), moderate (ranking 3), high (ranking 4), and very high (ranking 5), as summarized in Table 3.

Table 3. Structuring and Weight Evaluation for Landslide Susceptibility Mapping

Parameter	Class	Susceptibility Class	Ranking
Slope (°)	<= 15	Very Low	1
	15 - 25	Low	2
	25 - 35	Moderate	3
	35 - 45	High	4
	> 45	Very High	5
Elevation (m)	<= 700	Very Low	1
	700 - 975	Low	2
	975 - 1250	Moderate	3
	1250 - 1500	High	4
	> 1500	Very High	5
Lithology	Lava-dominated volcanic rocks	Very Low	1
	Volcanic breccia-lava	Low	2
	Volcanic breccia-tuff	Moderate	3
	Tuffaceous sandstone-breccia	High	4
	Marl-claystone-shale dominated	Very High	5
Distance to Stream (m)	<= 100	Very High	5
	100 - 250	High	4
	250 - 500	Moderate	3
	500 - 750	Low	2
	> 750	Very Low	1
Distance to Road (m)	<= 100	Very High	5
	100 - 250	High	4
	250 - 500	Moderate	3
	500 - 750	Low	2
	> 750	Very Low	1
NDVI	<= 0.17	Very High	5
	0.17 - 0.35	High	4
	0.35 - 0.54	Moderate	3
	0.54 - 0.72	Low	2
	> 0.72	Very Low	1

The relative importance values were subsequently arranged into a reciprocal pairwise comparison matrix, as shown in Table 4. Each element represents the relative importance of the factor in the row compared with the factor in the corresponding column. The diagonal elements are equal to 1 because each factor has equal importance when compared with itself, whereas the values below the diagonal are the reciprocals of those above the diagonal. This matrix forms the basis for

calculating the priority weights of the conditioning factors.

Table 4. Pairwise Comparison Matrix of Landslide Conditioning Factors

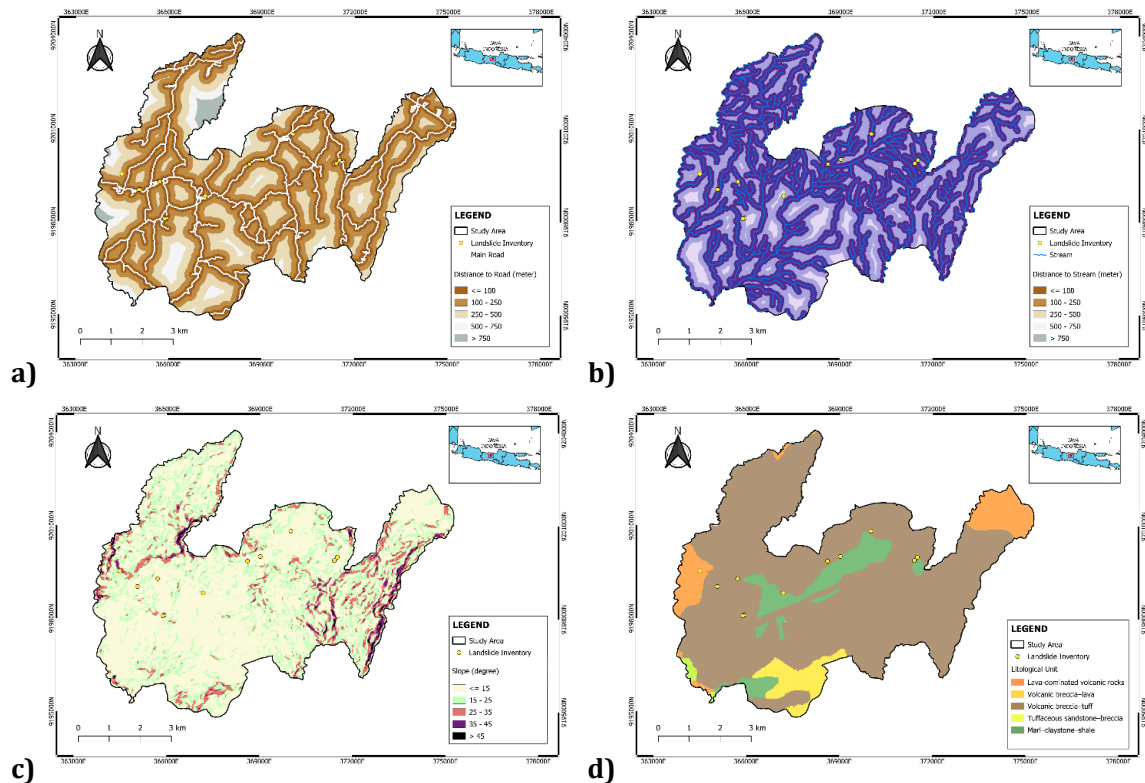
	Slope (°)	Elevation (m)	Lithology	Distance to Stream (m)	Distance to Road (m)	NDVI
Slope (°)	1	1	0.5	0.5	0.3	0.5
Elevation (m)	1	1	1	0.5	0.3	0.5
Lithology	2	1	1	1	0.5	0.5
Distance to Stream (m)	2	2	1	1	0.5	1
Distance to Road (m)	3	3	2	2	1	1
NDVI	2	2	2	1	1	1

The pairwise comparison matrix was then normalized to derive the priority weight of each conditioning factor. The resulting weights indicate each factor's relative contribution to landslide susceptibility.

FINDINGS AND DISCUSSION

Results of Landslide-Conditioning Factors

Five landslide-conditioning factors were prepared and analyzed in the GIS environment, consisting of: distance to road, distance to stream, lithology, slope, elevation, and NDVI. All thematic layers were standardized to the same coordinate system, spatial extent, and analysis grid before integration. Figure 2 (a–f) shows their spatial distributions.



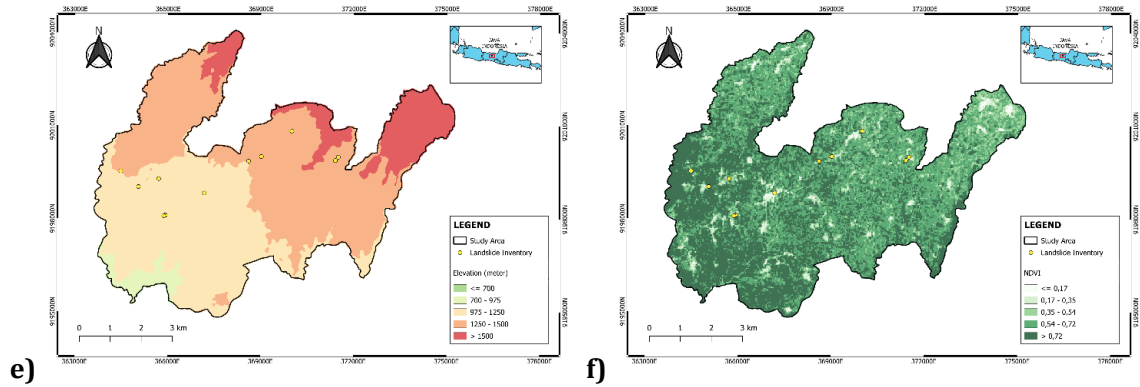


Figure 2. Landslide-conditioning factors: (a) distance to road, (b) distance to stream, (c) slope, (d) lithology, (e) elevation, and (f) NDVI.

The thematic maps were overlaid with the landslide inventory to identify the dominant classes associated with observed landslide occurrences. For road distance, most inventory points are concentrated within the ≤ 100 m and 100–250 m classes, indicating that landslides tend to occur relatively close to road networks.

This pattern may relate to slope cutting, drainage modification, and local disturbance from road construction. A similar pattern is observed for distance to stream, where most landslides occur within the ≤ 100 m and 100–250 m classes, suggesting the influence of stream erosion, increased moisture, and toe undercutting on slope instability.

The lithological unit shows several units, including lava-dominated volcanic rocks, volcanic breccia-lava, volcanic breccia-tuff, tuffaceous sandstone-breccia, and marl-claystone-shale. The spatial overlay shows that the landslide inventory is predominantly concentrated within the volcanic breccia-tuff unit, which also occupies the largest proportion of the study area.

Only a limited number of landslide points occur within the lava-dominated volcanic rocks and other lithological classes. This distribution suggests that volcanic breccia-tuff represents an important geological setting associated with the observed landslides in Pejawaran.

For slope, most landslide points occur within the $\leq 15^\circ$ and $15\text{--}25^\circ$ classes rather than on the steepest slopes. This indicates that slope gradient alone does not fully control landslide occurrence and should be interpreted together with geological and hydrological conditions. For elevation, the landslide inventory is mainly distributed within the 975–1250 m and 1250–1500 m classes, showing that intermediate-to-high elevations represent the dominant geomorphological setting of the observed landslides.

The NDVI values were classified into five classes, ranging from very low to high vegetation density. The spatial overlay indicates that the landslide inventory is predominantly concentrated within the 0.17–0.35 and 0.35–0.54 classes, which represent low-to-moderate vegetation density. This pattern suggests that landslide occurrence in the study area is more frequently associated with relatively sparse to moderately dense vegetation than with densely vegetated zones.

Overall, the spatial pattern suggests that landslide occurrence in Pejawaran results from the combined influence of road and stream proximity, lithological conditions, terrain morphology, and vegetation characteristics rather than from a single conditioning factor.

Influence and Ranking of Landslide-Conditioning Factors

Table 5 summarizes the AHP weighting results for the six landslide-conditioning factors. The AHP weighting results indicate that road distance is the most important factor (28%), followed by NDVI (22%), distance to stream (17%), lithology (14%), elevation (10%), and slope (9%). This ranking was subsequently used in the GIS-based weighted overlay to generate the landslide

susceptibility map.

The reliability of the pairwise judgments was evaluated using the Consistency Index (*CI*) and Consistency Ratio (*CR*). The analysis produced a λ_{max} of 6.009, a *CI* of 0.018, and a *CR* of 0.014. A *CR* value of 0.10 or less is generally considered acceptable in AHP, whereas a higher value indicates that the pairwise judgments should be reviewed. Because the calculated *CR* in this study was below 0.10, the comparison matrix was considered consistent, indicating that the derived factor weights were acceptable for subsequent GIS-based weighted overlay analysis.

Table 5. AHP Weights and Consistency Evaluation

Parameter	Weight	Weight (%)
Distance to Road (m)	0.28	28
NDVI	0.22	22
Distance to Stream (m)	0.17	17
Lithology	0.14	14
Elevation (m)	0.10	10
Slope (°)	0.09	9
λ_{max}		6.009
Consistency Index (CI)		0.018
Random Index (RI)		1.240
Consistency Ratio (CR)		0.014

Landslide Susceptibility Map Based on the AHP Model

The AHP-based landslide susceptibility map in Figure 3 classifies the study area into five susceptibility levels: very low, low, moderate, high, and very high. As summarized in Table 6, the moderate and high classes dominate the study area, covering 15.02 km² (28%) and 15.11 km² (28%), respectively. The low susceptibility class occupies 10.41 km² (19%), followed by the very high class with 8.91 km² (16%), while the very low class covers only 4.57 km² (8%) of the total 54.02 km² area.

Spatially, Figure 3 shows that high- to very-high-susceptibility zones are mainly concentrated in the central, northern, and eastern sectors, whereas the western and southwestern parts are generally characterized by low- to very-low susceptibility. The landslide inventory plotted on the same map also shows a reasonable spatial correspondence with the modeled susceptibility pattern, as most recorded landslides occur within moderate to high susceptibility zones, with several points located near very high susceptibility areas.

Overall, the combined moderate and high classes account for 56% of the study area (Table 6), indicating that a substantial proportion of the region has conditions favorable for slope instability. The additional 16% classified as very high susceptibility further highlights areas requiring greater attention for land-use planning and landslide mitigation.

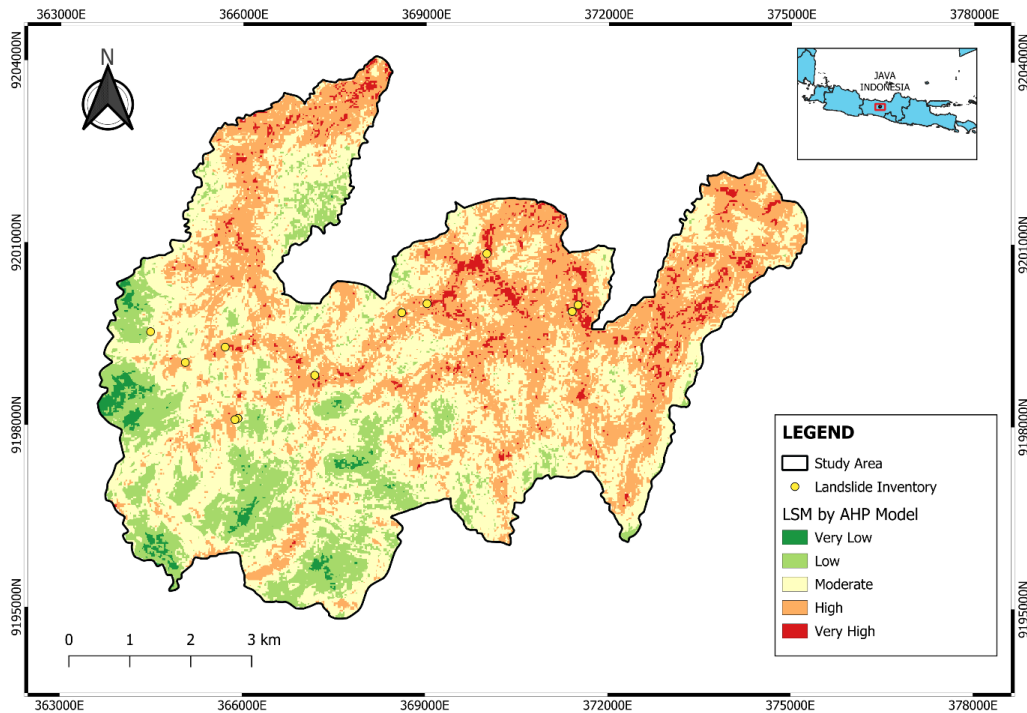


Figure 3. Landslide Susceptibility Map of Pejawaran District, Banjarnegara

Table 6. Spatial Distribution of Landslide Susceptibility Classes

Susceptibility Class	Area (km ²)	Percentage (%)
Very Low	4.57	8%
Low	10.41	19%
Moderate	15.02	28%
High	15.11	28%
Very High	8.91	16%
Total	54.02	100%

CONCLUSIONS

This study successfully applied a GIS-based Analytical Hierarchy Process (AHP) to assess landslide susceptibility in Pejawaran District using six conditioning factors: distance to road, NDVI, distance to stream, lithology, elevation, and slope. The AHP weighting results identified distance to road as the most influential factor (28%), followed by NDVI (22%), distance to stream (17%), lithology (14%), elevation (10%), and slope (9%).

The resulting susceptibility map classified the 54.02 km² study area into five classes: very low (8%), low (19%), moderate (28%), high (28%), and very high (16%). High- to very high-susceptibility zones are predominantly distributed in the central, northern, and eastern parts of the study area, while the western and southwestern sectors generally exhibit lower susceptibility.

The spatial agreement between the landslide inventory and the moderate-to-high susceptibility zones suggests that the GIS-AHP approach provides a practical preliminary framework for identifying landslide-prone areas and supporting land-use planning and mitigation strategies in Pejawaran District.

LIMITATIONS & FURTHER RESEARCH

Despite these findings, several limitations warrant acknowledgment. The model relies on a relatively limited set of conditioning factors and on expert-based AHP weighting. At the same time, uncertainties in the completeness and positional accuracy of the landslide inventory may also influence the resulting susceptibility pattern. In addition, the analysis did not explicitly incorporate temporal triggering factors or detailed subsurface conditions.

Future studies should therefore integrate additional variables such as rainfall variability, soil properties, and land-use change, along with more comprehensive and updated landslide inventories. Including geotechnical or geophysical data and independent validation methods would further improve the robustness, reliability, and physical interpretation of the landslide susceptibility assessment.

REFERENCES

- Agrawal, N., & Dixit, J. (2022). Assessment of landslide susceptibility for Meghalaya (India) using bivariate (frequency ratio and Shannon entropy) and multi-criteria decision analysis (AHP and fuzzy-AHP) models. *All Earth*, 34, 179–201. <https://doi.org/10.1080/27669645.2022.2101256>
- Amarasinghe, M. P., Kulathilaka, S. A. S., Robert, D. J., Zhou, A., & Jayathissa, H. A. G. (2024). Risk assessment and management of rainfall-induced landslides in tropical regions: A review. *Natural Hazards*, 120(3), 2179–2231. <https://doi.org/10.1007/s11069-023-06277-3>
- Arabameri, A., Pradhan, B., Rezaei, K., Lee, S., & Sohrabi, M. (2020). An ensemble model for landslide susceptibility mapping in a forested area. *Geocarto International*, 35, 1680–1705. <https://doi.org/10.1080/10106049.2019.1585484>
- Astuti, B. S., Isnaniawardhani, V., Abdurrokhim, A., & Sudradjat, A. (2019). Sedimentation process of Rambatan Formation in Larangan Brebes, North Serayu Range, Central Java. *Indonesian Journal on Geoscience*, 6(2), 141–151. <https://doi.org/10.17014/ijog.6.2.141-151>
- Bachri, S., Shrestha, R., Yulianto, F., Sumarmi, S., Utomo, K. S. B., & Aldianto, Y. E. (2020). Mapping landform and landslide susceptibility using remote sensing, GIS, and field observation in the Southern Cross Road, Malang Regency, East Java, Indonesia. *Geosciences*, 11(1), 4. <https://doi.org/10.3390/geosciences11010004>
- Banuzaki, A. S., & Ayu, A. (2021). Integrated remote sensing and GIS analysis for landslide susceptibility assessment along the Trenggalek–Ponorogo Road, East Java Province, Indonesia. *Indonesian Association of Geologists Journal*. <https://doi.org/10.51835/iagij.2021.1.1.14>
- Ibrahim, M., Mustaffa, Z., Balogun, A., Indra, S., & Nur Ain, A. N. (2022). Landslide's analysis and hazard mapping based on Analytic Hierarchy Process (AHP) using GIS, in Lawas, Sabah-Sarawak. *IOP Conference Series: Earth and Environmental Science*, 1064, 012031. <https://doi.org/10.1088/1755-1315/1064/1/012031>
- Javier, D., & Kumar, L. (2019). Frequency ratio landslide susceptibility estimation in a tropical mountain region. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. <https://doi.org/10.5194/isprs-archives-XLII-3-W8-173-2019>
- Kieu, L. Q., & Ngo, G. V. (2022). Landslide susceptibility assessment for warning of dangerous areas in Tan Uyen district, Lai Chau province, Vietnam. *Geografiska Annaler: Series A, Physical Geography*, 104, 183–200. <https://doi.org/10.1080/04353676.2022.2091915>
- Manyvanh, B., & Setiawan, H. (2023). Landslide susceptibility mapping in Jurangjero and Kampung Villages, Ngawen Sub-District, Gunung Kidul Regency, Special Region of Yogyakarta, Indonesia. *IOP Conference Series: Earth and Environmental Science*, 1233, 012024. <https://doi.org/10.1088/1755-1315/1233/1/012024>

- Miklin, L., Podolszki, L., Gulam, V., & Markotić, I. (2022). The impact of climate changes on slope stability and landslide conditioning factors: An example from Kravarsko, Croatia. *Remote Sensing*, 14, 1794. <https://doi.org/10.3390/rs14081794>
- Muntohar, A., Prasetyaningtiyas, G. A., & Hidayat, R. (2021). The spatial model using TRIGRS to determine rainfall-induced landslides in Banjarnegara, Central Java, Indonesia. *Journal of the Civil Engineering Forum*. <https://doi.org/10.22146/jcef.55282>
- Nhu, V.-H., Mohammadi, A., Shahabi, H., Ahmad, B., Al-Ansari, N., Shirzadi, A., Geertsema, M., Kress, V. R., Karimzadeh, S., Kamran, K. V., Chen, W., & Nguyen, H. (2020). Landslide detection and susceptibility modeling on Cameron Highlands (Malaysia): A comparison between Random Forest, Logistic Regression and Logistic Model Tree algorithms. *Forests*, 11(8), 830. <https://doi.org/10.3390/f11080830>
- Permanajati, I., Suranda, A. H., & Zaenurrohman, J. A. (2023). Assessment of landslide susceptibility in the Pagentan area, Banjarnegara Regency: A spatial multi-criteria evaluation approach. *Riset Geologi dan Pertambangan*. <https://doi.org/10.55981/risetgeotam.2023.1229>
- Priyono, K. (2020). Risk analysis of landslide impacts on settlements in Karanganyar, Central Java, Indonesia. *International Journal of GEOMATE*, 19. <https://doi.org/10.21660/2020.73.34128>
- Raharjo, S., Paripurno, E. T., Hartadi, J., Alfiani, O. D., Widyastuti, M., & Mardziah, M. (2019). Landslide zoning and mitigation in Clapar Area, Madukara District, Banjarnegara Regency, Central Java. *IOP Conference Series: Earth and Environmental Science*, 375(1), 012003. <https://doi.org/10.1088/1755-1315/375/1/012003>
- Saaty, T. L. (1980). *The analytic hierarchy process: Planning, priority setting, resource allocation*. McGraw-Hill.
- Saaty, T. L., & Vargas, L. G. (1984). Comparison of eigenvalue, logarithmic least squares and least squares methods in estimating ratios. *Mathematical Modelling*, 5(5), 309–324.
- Saputra, G. T., Azizi, A., & Salim, M. A. (2024). Landslide vulnerability analysis Sarwodadi Village, Pejawaran District Banjarnegara Regency with scoring methods. *Calamity: A Journal of Disaster Technology and Engineering*, 2(1), 40–52. <https://doi.org/10.61511/calamity.v2i1.2024.1833>
- Shahabi, H., & Hashim, M. (2015). Landslide susceptibility mapping using GIS-based statistical models and remote sensing data in tropical environment. *Scientific Reports*, 5, 9899. <https://doi.org/10.1038/srep09899>
- Soma, A. S., Kubota, T., & Aditian, A. (2019). Comparative study of land use change and landslide susceptibility using frequency ratio, certainty factor, and logistic regression in upper area of Ujung-Loe Watersheds, South Sulawesi, Indonesia. *International Journal of Erosion Control Engineering*. <https://doi.org/10.13101/ijece.11.103>
- Suharini, E., Arfina, F., & Kurniawan, E. (2021). The level of threats and community capacity concerning to landslide emergency in Banjarnegara Indonesia. *International Journal of Environmental Science and Development*, 12, 118–125. <https://doi.org/10.18178/ijesd.2021.12.4.1328>
- Suhendro, I., Isnain, M. N., & Wahyudi, R. (2022). Rock characteristics of post-caldera volcanoes in Dieng volcanic complex (DVC), Central Java, Indonesia. *Journal of Geoscience, Engineering, Environment, and Technology*, 7(4), 151–157. <https://doi.org/10.25299/jgeet.2022.7.4.10015>
- Sur, U., Singh, P., Meena, S., & Singh, T. (2022). Predicting landslides susceptible zones in the Lesser Himalayas by ensemble of per pixel and object-based models. *Remote Sensing*, 14(8), 1953. <https://doi.org/10.3390/rs14081953>
- Susanti, P. D., Miardini, A., & Harjadi, B. (2021). Disaster mitigation on lands affected by landslides in Banjarnegara Regency. *IOP Conference Series: Earth and Environmental Science*, 916(1),

012026. <https://doi.org/10.1088/1755-1315/916/1/012026>
- Trinh, T., Luu, B. T., Le, T., Nguyen, D., Tran, T. V., Nguyen, T. H. V., Nguyen, K. Q., & Nguyen, L. T. (2022). A comparative analysis of weight-based machine learning methods for landslide susceptibility mapping in Ha Giang area. *Big Earth Data*, 7, 1005–1034. <https://doi.org/10.1080/20964471.2022.2043520>
- Usman, M., Zen, B. P., Ananda, Z. W., Roqayah, S., Mulyadani, L. C., Muna, B. L., & Prasetya, A. (2023). Landslide hazard mapping using the score and weight method in Banjarnegara. *Jurnal Teknik Informatika (Jutif)*. <https://doi.org/10.52436/1.jutif.2023.4.1.638>
- Wicaksono, Y. S., Sihombing, F. M. H., & Indra, T. L. (2020). Landslide susceptibility map of Bogor Area using analytical hierarchy process. *IOP Conference Series: Earth and Environmental Science*, 538(1), 012050. <https://doi.org/10.1088/1755-1315/538/1/012050>