Flood Susceptibility Zonation Using Multi-Criteria Decision Analysis for Disaster Risk Reduction in the Klawing River

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Abstract

Flood-prone river corridors require spatial assessments to improve disaster risk reduction and land-use planning. Integrating environmental factors into a susceptibility framework helps identify areas where topographic, hydrological, climatic, geological, and land-surface characteristics converge. Despite their importance, spatial flood susceptibility assessments along the Klawing River using an integrated multi-criteria framework remain limited. This study develops a flood susceptibility zonation for the Klawing River, delineating areas with different susceptibility levels to support targeted flood preparedness. A GIS-based Multi-Criteria Decision Analysis (MCDA) combined with the Analytic Hierarchy Process (AHP) used eight conditioning factors: slope, elevation, land cover, distance from the river, rainfall, lithology, Topographic Wetness Index, and river density. Slope (0.291) and elevation (0.214) received the highest weights, together accounting for 50.5% of the total, with a consistency ratio of 0.058, indicating acceptable consistency. The susceptibility map classified the 25 km² area into five classes, with High susceptibility covering 14.41 km² (57.62%), followed by Moderate (6.87 km², 27.47%) and Very High (1.22 km², 4.87%). The combined High and Very High zones covered 15.62 km² (62.49%), highlighting regions requiring prioritized flood preparedness. This zonation offers a spatial screening tool to guide field assessments, disaster risk reduction, and land-use management along the Klawing River corridor.

Keywords: AHP, flood susceptibility; GIS; Klawing River; MCDA

I. INTRODUCTION

Flooding is a significant natural hazard that threatens human safety, infrastructure, economic assets, agricultural land, and environmental systems. Interacting climatic and non-climatic factors influence its occurrence and spatial extent, including rainfall, topography, drainage characteristics, land cover, and catchment conditions. Intense rainfall can rapidly increase surface runoff, river discharge, and water levels beyond channel or drainage capacity, resulting in the inundation of adjacent low-lying areas. The increasing frequency and severity of flood impacts underscore the importance of long-term disaster management supported by spatial assessments that identify areas with different levels of flood susceptibility (Giovannettone et al., 2018; Lee & Rezaie, 2022).

Geographic Information System (GIS)-based methods effectively integrate environmental and hydrological data to identify spatial patterns of flood susceptibility, particularly where detailed hydrological records are limited (Liuzzo et al., 2019; Talukdar et al., 2020). Because no single variable can fully represent the spatial complexity of flooding, susceptibility assessments commonly combine multiple conditioning factors. Slope and elevation affect runoff movement and water accumulation, rainfall represents the principal climatic input, and land cover influences interception and infiltration. Distance from rivers and river density represent spatial relationships with drainage networks, while lithology and the Topographic Wetness Index (TWI) provide information on geological controls, terrain

wetness, and the tendency for water to accumulate. Selecting appropriate factors is therefore essential to represent the physical conditions associated with flood susceptibility.

Multi-Criteria Decision Analysis (MCDA) offers a structured framework for integrating conditioning factors with different units, scales, and relative contributions. The Analytic Hierarchy Process (AHP), one of the most widely applied MCDA techniques, determines the relative importance of factors through pairwise comparisons and systematic weighting. Integrating AHP with GIS enables the combination of standardized spatial layers into a composite susceptibility index and its subsequent classification into susceptibility levels. This approach has been widely applied in flood susceptibility mapping across different geographic settings (Swain et al., 2020), while MCDA-based methods have also been combined with hydrological, statistical, and soft-computing approaches to improve spatial flood assessment (Kaya & Derin, 2023). Nevertheless, the reliability of the resulting zonation depends on the suitability of the selected factors, the consistency of the assigned weights, and the physical characteristics of the study area.

The Klawing River is an important component of the Serayu drainage system in Purbalingga Regency, Central Java. Flooding along the Klawing watershed can affect settlements, agricultural land, infrastructure, and other land uses located near the river corridor (Santoso et al., 2023). However, spatial assessments that specifically examine flood susceptibility along the Klawing River by integrating topographic, hydrological, climatic, geological, and land-surface factors within a unified MCDA framework remain limited. Therefore, this study applies a GIS-based MCDA using AHP to integrate eight conditioning factors: slope, elevation, land cover, distance from the river, rainfall, lithology, TWI, and river density. The study aims to develop a flood susceptibility zonation for the Klawing River corridor and identify areas with different relative susceptibility levels to support field assessment, flood preparedness, disaster risk reduction, land-use planning, and sustainable river management.

II. METHOD

A. Study Area

The study area covers approximately 25 km² of the Klawing River corridor in Purbalingga Regency, Central Java, Indonesia (Figure 1). It spans parts of Bojongsari, Kaligondang, and Purbalingga districts and is bounded by 7°21'11.78"–7°23'54.92" S and 109°21'31.01"–109°24'13.19" E. The Klawing River flows through the study area from the northern uplands toward the lower-lying southern sector, forming the principal drainage axis. Elevation ranges from 14 to 222 m above sea level, with hilly terrain predominantly in the north and along the western and eastern margins of the upstream area. The northwestern part of the study area is associated with the slopes of Mount Slamet, whereas relatively low-lying terrain is concentrated along the central river corridor and toward the southern part of the study area.

The landscape comprises settlements, agricultural areas, including paddy fields and plantations, and open land. These land-cover types have different hydrological characteristics related to rainfall interception, infiltration, surface roughness, and runoff generation. The distribution of settlements and agricultural land along the river corridor is particularly relevant because these areas may be affected when increased river discharge exceeds channel capacity. In addition, the spatial arrangement of the main river and its tributaries influences surface-water connectivity and the concentration of runoff from the surrounding terrain.

The combination of topographic variation, drainage characteristics, land-cover diversity, and geological conditions provides an appropriate spatial context for assessing flood susceptibility using multiple environmental criteria. Steeper, higher terrain may direct runoff toward lower areas, while relatively flat terrain near the drainage network may facilitate water

accumulation under unfavorable conditions. Therefore, the study area was selected to represent spatial variations in the environmental characteristics that potentially control flood occurrence along the Klawing River. The analysis focuses on relative flood susceptibility and does not directly estimate flood probability, inundation depth, flow velocity, or flood return period.

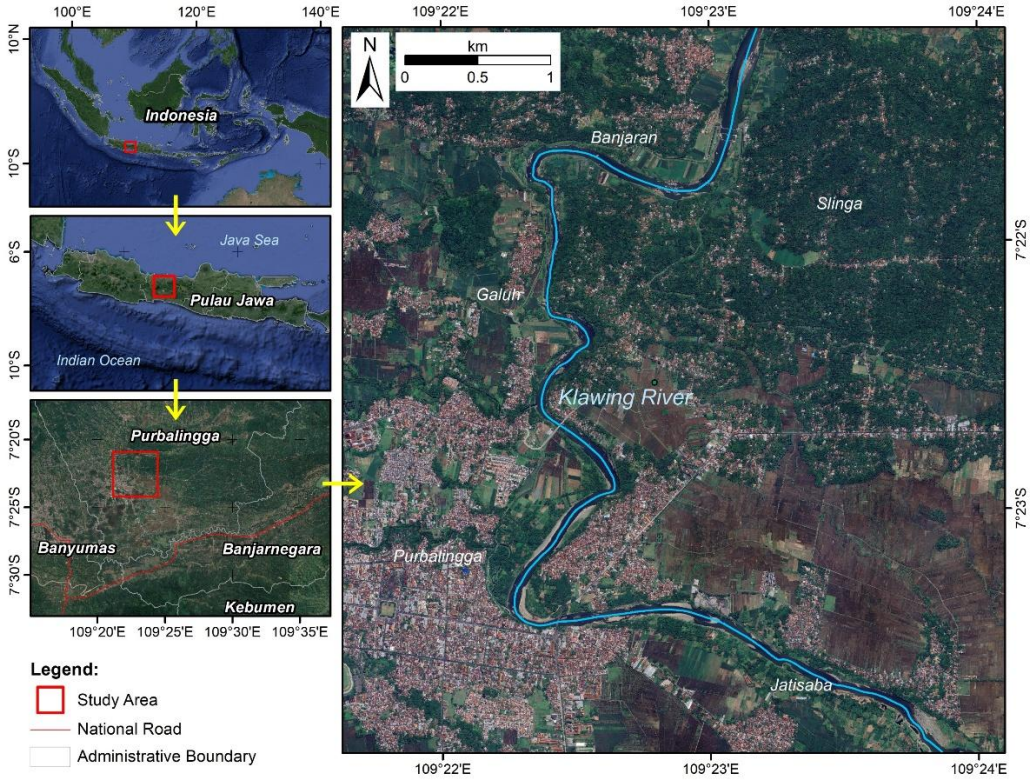

Figure 1. Location of the study area along the Klawing River, Purbalingga Regency

B. Data and Flood-Susceptibility Parameters

Eight conditioning factors were selected for the flood susceptibility assessment based on the framework proposed in previous research, with adjustments to reflect the physical characteristics of the study area and the availability of spatial data (Lee & Rezaie, 2022). The selected factors comprise slope, elevation, land cover, distance from the river, rainfall, lithology, Topographic Wetness Index (TWI), and river density. Collectively, these factors represent the main topographic, hydrological, climatic, geological, and land-surface conditions that may influence runoff generation, water accumulation, drainage connectivity, and the spatial distribution of flood susceptibility.

Slope and elevation were derived from DEMNAS provided by the Indonesian Geospatial Information Agency (BIG) at a spatial resolution of approximately 8.3 m. Slope represents the terrain gradient and influences the rate and direction of surface runoff, while elevation describes each location's relative topographic position. Land-cover data were obtained from the Indonesian Topographic Map, or Rupa Bumi Indonesia (RBI), at a scale of 1:50,000 and were used to represent spatial differences in infiltration and runoff characteristics. The RBI river network was also used to calculate distance from the river and river density. Distance from the river represents each location's proximity to the drainage network, while river density characterizes the concentration of river channels and potential surface-water connectivity in the surrounding area.

Annual rainfall data for 2025 were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) at a spatial resolution of approximately 0.05°, or about 5 km. Lithological information was obtained from the Regional Geological Map of Indonesia at a scale of 1:100,000 (Djuri et al., 1996) to represent spatial differences in geological materials and their potential influence on infiltration and surface runoff. TWI was derived from DEMNAS to characterize the topographic tendency of water to accumulate at a particular location. Each conditioning factor was prepared as a spatial layer, classified according to its characteristics, and standardized into a common rating scale before integration into the GIS-based MCDA–AHP framework. Table 1 summarizes the data sources, spatial resolution or scale, and principal preparation procedure for each conditioning factor.

Table 1. Data sources and spatial preparation of flood-susceptibility conditioning factors

Conditioning factor	**Data source**	**Spatial resolution/scale**	**Spatial preparation**
Slope	DEMNAS, Indonesian Geospatial Information Agency (BIG)	8.3 m	Spatial analysis
Elevation	DEMNAS, BIG	8.3 m	Classification
Land cover	Indonesian Topographic Map (RBI), BIG	1:50,000	Reclassification
Distance from river	Indonesian Topographic Map (RBI), BIG	1:50,000	Euclidean distance analysis
Rainfall	CHIRPS Annual Rainfall 2025	~0.05° (~5 km)	Spatial analysis
Lithology	Regional Geological Map of Indonesia (Djuri et al., 1996)	1:100,000	Reclassification
Topographic Wetness Index (TWI)	DEMNAS, BIG	8.3 m	Spatial analysis
River density	Indonesian Topographic Map (RBI), BIG	1:50,000	Spatial analysis

C. GIS-Based MCDA Using AHP

Multi-Criteria Decision Analysis (MCDA) provides a structured framework for integrating multiple criteria in spatial decision-making, while the Analytic Hierarchy Process (AHP) is used to determine the relative importance of criteria through structured pairwise comparisons and ratio-scale weighting. AHP's hierarchical structure integrates quantitative and qualitative criteria into a consistent decision-making process, making it well suited for spatial flood susceptibility assessment involving multiple environmental factors (Saaty & Vargas, 2012; Shah & Ai, 2024). In the present study, AHP was implemented within a GIS-based MCDA framework to establish the relative weights of eight selected conditioning factors. The comparisons employed the nine-point fundamental scale, ranging from 1 (equal importance) to 9 (extreme importance), with reciprocal values assigned for reverse comparisons. The pairwise comparison procedure and weighting framework followed the methodology used in flood susceptibility assessment (Swain et al., 2020).

The pairwise comparison matrix was normalized by dividing each element by its column sum. The normalized matrix was used to derive the relative weight of each conditioning factor. The consistency of the resulting weights was assessed using the Consistency Index (*CI*) and Consistency Ratio (*CR*):

$$CR = CI \,/\, RI$$

$$CI = (\lambda_{max} - n) \,/\, (n - 1)$$

Here, *CR* is the consistency ratio, *CI* is the consistency index, *RI* is the random consistency index, λ_{max} is the maximum eigenvalue of the comparison matrix, and n is the number of criteria. A *CR* below 0.10 is considered acceptable consistency. Higher values indicate inconsistent pairwise judgments and necessitate reassessment of the assigned weights (Swain et al., 2020).

The standardized scores of the conditioning factors and their AHP-derived weights were integrated within the GIS-based MCDA framework to calculate the susceptibility composite score:

$$S = \Sigma(W_i X_i) \times \Pi(C_j)$$

Here, *S* is the susceptibility composite score, W_i is the weight assigned to factor *i*, X_i is the estimated score for factor *i*, and C_j is the constraint score ranging from 0 to 1 (Swain et al., 2020). The resulting susceptibility scores were classified into five categories (very low, low, moderate, high, and very high) to produce the final flood susceptibility zonation. The spatial distribution of the resulting zones was subsequently interpreted in relation to the selected conditioning factors.

The spatial integration was performed on a cell-by-cell basis, allowing each location to receive a composite score based on its standardized factor values and the corresponding AHP weights. Consequently, the final score reflects the cumulative contribution of the conditioning factors rather than the influence of any single variable. Higher composite scores indicate locations where factors associated with greater flood susceptibility occur simultaneously, whereas lower scores indicate less favorable combinations for flooding. This procedure produced a continuous susceptibility surface that served as the basis for classifying and mapping relative flood susceptibility across the study area.

D. Flood Susceptibility Zonation

The GIS-based MCDA generated a susceptibility composite score categorized into five levels: Very Low, Low, Moderate, High, and Very High. This classification delineated relative spatial differences in flood susceptibility throughout the study area. Higher composite scores indicate locations where conditioning factors associated with flood susceptibility occur simultaneously and have relatively high standardized scores or AHP weights. Conversely, lower composite scores indicate areas where factors contribute less to flood susceptibility.

The classified susceptibility layer was used to calculate the spatial extent of each category. The area of each susceptibility class was calculated in square kilometers and then converted to a percentage of the total study area. This calculation enabled a quantitative comparison of the proportions occupied by the Very Low, Low, Moderate, High, and Very High classes. The resulting values were summarized in tabular form and used together with the susceptibility map to describe the dominant classes and their spatial distribution.

The resulting zones were interpreted in relation to the spatial patterns of the eight conditioning factors. Particular attention was given to the influence of slope, elevation, land cover, and distance from the river because these factors received relatively high weights in the AHP analysis. Areas classified as High or Very High susceptibility were examined in relation to their proximity to the Klawing River and its tributaries, their topographic position, and the surrounding land-cover characteristics. Where these zones coincide with settlements and agricultural land, they were identified as priority areas for further field assessment, flood preparedness, and land-use management.

The resulting map shows relative flood susceptibility, not a direct measure of flood hazard or risk. The susceptibility classes indicate the spatial tendency toward flooding based on the environmental conditioning factors included in the model, but they do not represent flood frequency, probability, depth, duration, or flow velocity. In addition, flood risk depends not only on physical susceptibility but also on the exposure and vulnerability of communities,

infrastructure, agricultural land, and other elements at risk. Therefore, the susceptibility zonation serves as a spatial screening tool to support disaster risk reduction and provide a basis for more detailed hydrological, hydraulic, and flood-risk assessments along the Klawing River corridor.

III. RESULTS AND DISCUSSIONS

A. Result

AHP Weighting and Consistency

The eight flood-conditioning factors were coded as F1–F8 to simplify the presentation of the AHP and MCDA procedures. F1 represents slope, F2 elevation, F3 land cover, F4 distance from the river, F5 rainfall, F6 lithology, F7 TWI, and F8 river density. A pairwise comparison matrix was developed to assess the relative importance of these factors in the flood susceptibility analysis (Table 2). The comparisons used Saaty's relative importance scale, with reciprocal values assigned to reverse comparisons.

Table 3 presents the AHP-derived weights and ranking of the eight conditioning factors. F1 received the highest weight of 0.291 (29.1%), followed by F2 at 0.214 (21.4%) and F3 at 0.154 (15.4%). F4 and F5 contributed weights of 0.116 (11.6%) and 0.083 (8.3%), respectively, whereas F6, F7, and F8 received lower weights of 0.062 (6.2%), 0.048 (4.8%), and 0.032 (3.2%). Together, F1 and F2 accounted for 50.5% of the total weight, indicating the strong contribution of topographic factors to the composite susceptibility score.

Table 2. Pairwise comparison matrix of the eight flood conditioning factors

	F1	F2	F3	F4	F5	F6	F7	F8
F1	1	2	3	3	4	4	5	5
F2	1/2	1	2	3	3	4	4	5
F3	1/3	1/2	1	2	3	3	4	4
F4	1/3	1/3	1/2	1	2	3	3	4
F5	1/4	1/3	1/3	1/2	1	2	3	3
F6	1/4	1/4	1/3	1/3	1/2	1	2	3
F7	1/5	1/4	1/4	1/3	1/3	1/2	1	3
F8	1/5	1/5	1/4	1/4	1/3	1/3	1/3	1

Table 3. AHP-derived weights and ranking of flood conditioning factors

Code	Conditioning factor	Weight	Percentage	Rank
F1	Slope	0.291	29.10%	1
F2	Elevation	0.214	21.40%	2
F3	Land cover	0.154	15.40%	3
F4	Distance from river	0.116	11.60%	4
F5	Rainfall	0.083	8.30%	5
F6	Lithology	0.062	6.20%	6
F7	TWI	0.048	4.80%	7
F8	River density	0.032	3.20%	8

The weights decrease progressively from slope to river density, producing a clear hierarchy among the conditioning factors. The first four factors (slope, elevation, land cover, and distance from the river) collectively accounted for 77.5% of the total weight. The remaining 22.5% was distributed among rainfall, lithology, TWI, and river density.

Nevertheless, all eight factors were retained because the final susceptibility index reflects their combined spatial contribution rather than the effect of any single factor.

The consistency of the pairwise judgments was evaluated using the Consistency Ratio (CR). The calculation yielded a maximum eigenvalue (λ_{max}) of 8.576, a Consistency Index (CI) of 0.082, and a CR of 0.058 (5.8%). Because the CR is below the commonly accepted threshold of 0.10, the pairwise judgments demonstrate acceptable consistency. The resulting weights were therefore considered suitable for integration into the GIS-based MCDA framework.

Spatial Distribution of Conditioning Factors

The eight conditioning factors exhibit distinct spatial patterns across the 25 km² study area (Figure 2). Slope and elevation differ markedly between the Klawing River corridor and the surrounding hilly areas. Lower elevations are concentrated around the main river corridor and toward the southern part of the study area, whereas higher elevations occur primarily in the northern and peripheral areas. Slope variations generally correspond to these elevation patterns, with relatively gentle terrain in lower areas and steeper terrain toward the surrounding uplands.

Land cover consists mainly of settlements, agricultural areas, plantations, and open land. The spatial distribution of land cover adds variability to the susceptibility model because each land-cover type has different infiltration and runoff characteristics. The distance-from-river layer shows a gradual spatial transition from the Klawing River and its tributaries toward more distant locations, thereby distinguishing areas based on their relative proximity to the mapped drainage network.

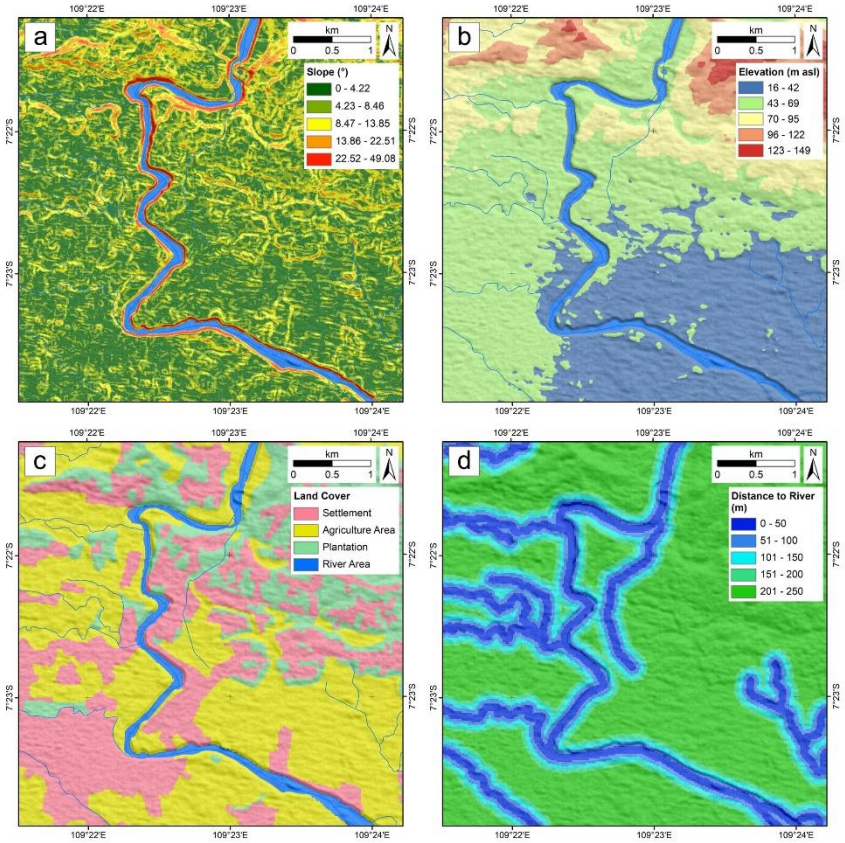

Figure 2. Spatial distribution of the eight flood conditioning factors used in the MCDA framework: (a) slope, (b) elevation, (c) land cover, (d) distance from river, (e) annual rainfall, (f) lithology, (g) topographic wetness index (TWI), and (h) river density.

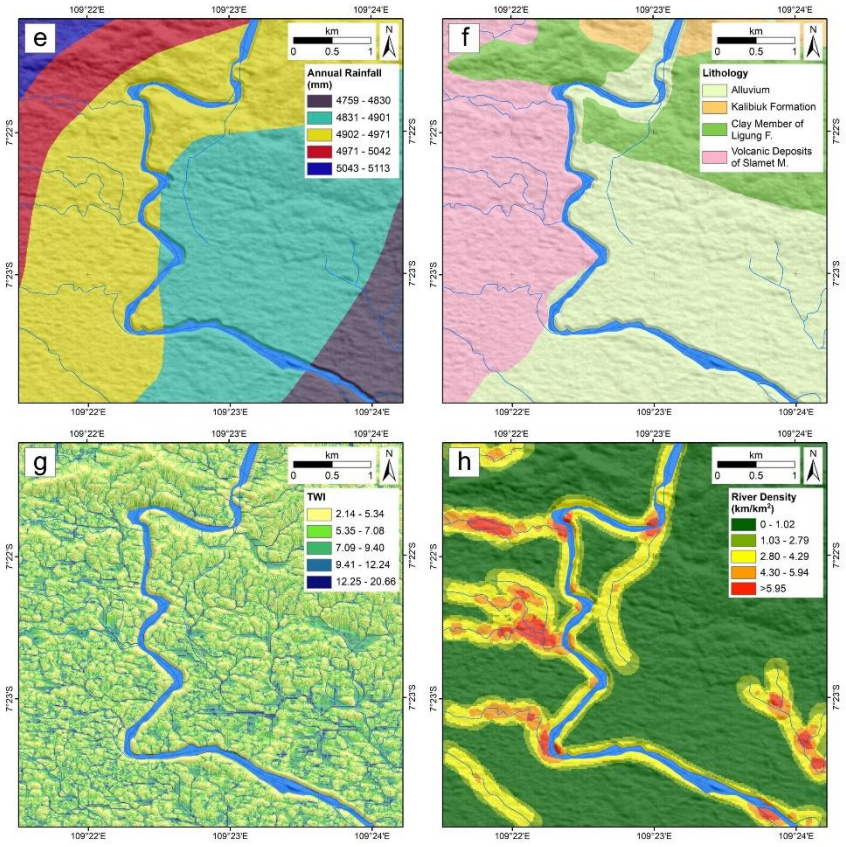

Figure 2. (continued)

Rainfall and lithology provide climatic and geological information that complements the topographic and land-surface factors. The rainfall layer captures broad spatial variations in annual precipitation across the study area. Meanwhile, the lithological layer distinguishes geological materials that may exhibit different infiltration and runoff characteristics, contributing to variations in the terrain's spatial response to rainfall.

TWI identifies relative differences in the topographic tendency for water accumulation, whereas the river-density layer represents variations in the concentration of mapped drainage channels. Although rainfall, lithology, TWI, and river density received lower individual AHP weights than slope and elevation, their standardized scores contributed to local variations in the composite susceptibility index. The final susceptibility pattern therefore reflects the combined spatial contribution of all eight conditioning factors rather than the influence of an individual factor.

Flood Susceptibility Zonation

The eight standardized conditioning factors were integrated using their respective AHP-derived weights to produce the flood susceptibility zonation shown in Figure 3a. The resulting composite scores were classified into five categories: Very Low, Low, Moderate, High, and Very High. Each category represents a different combination of the conditioning-factor scores and their relative contributions to the MCDA model.

The High susceptibility class is the dominant category, covering approximately 14.406 km², or 57.62% of the study area. The Moderate class occupies approximately 6.867 km² (27.47%), while the Very High class accounts for 1.217 km² (4.87%). The Low and Very Low classes cover approximately 2.465 km² (9.86%) and 0.045 km² (0.18%), respectively. The calculated areas total 25 km², corresponding to the full extent of the study area.

The combined High and Very High susceptibility classes cover approximately 15.623 km², equivalent to 62.49% of the study area. In contrast, the combined Very Low and Low classes account for only 2.510 km², or 10.04%. The remaining 27.47% falls within the Moderate class. These results show that susceptibility is concentrated in the upper categories, although the High class covers a much larger area than the Very High class.

The spatial arrangement of the susceptibility classes reflects the cumulative contribution of the eight conditioning factors. The resulting map shows where high standardized factor scores and larger AHP weights overlap within the study area. Field photographs in Figure 3b–c show the Klawing River channel and its surrounding riverbank environment, supporting the physical interpretation of the mapped river corridor.

Table 4. Spatial distribution of flood susceptibility classes

Flood susceptibility class	Score	Area (km²)	Area (%)
Very low	1.00–1.80	0.045	0.18
Low	>1.80–2.60	2.465	9.86
Moderate	>2.60–3.40	6.867	27.47
High	>3.40–4.20	14.406	57.62
Very high	>4.20–5.00	1.217	4.87
Total	1.00–1.80	25	100

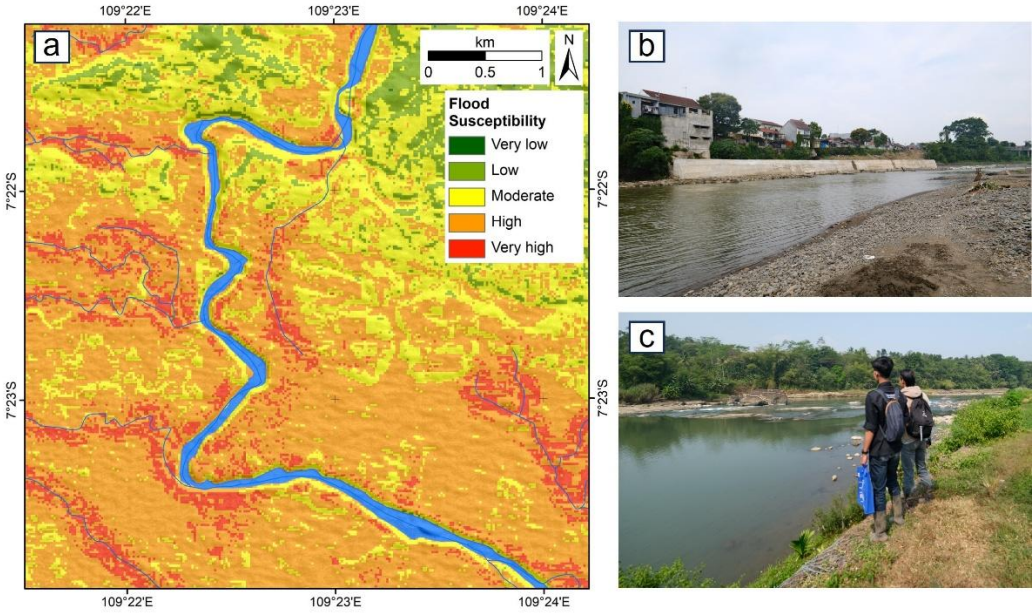

Figure 3. Flood susceptibility zonation and field observations along the Klawing River: (a) spatial distribution of flood susceptibility classes derived from the AHP–MCDA model, and (b–c) representative field conditions of the river channel and surrounding riverbank environment.

B. Discussion

Influence of Conditioning Factors on Flood Susceptibility

The spatial distribution of the susceptibility classes reflects the combined contributions of the eight AHP-weighted conditioning factors. Slope received the highest weight of 0.291, followed by elevation at 0.214, indicating that these topographic factors contributed most to the composite susceptibility score. Together, slope and elevation accounted for 50.5% of the total model weight. However, these weights represent relative importance within the AHP

framework and should not be interpreted as direct empirical measures of each factor's causal influence on flood occurrence.

The importance of slope and elevation aligns with the topographic configuration of the Klawing River corridor. Elevation determines an area's relative position within the surrounding terrain, while slope influences the direction and movement of surface runoff. Higher, steeper terrain may direct runoff toward lower parts of the study area, whereas relatively gentle, low-lying areas near the river corridor may facilitate water accumulation under unfavorable drainage conditions. Therefore, the combined spatial relationship between slope and elevation provides a more meaningful interpretation than either factor considered independently.

Land cover and distance from the river received weights of 0.154 and 0.116, respectively. Together with slope and elevation, these four factors accounted for 77.5% of the total weight. Land cover influences rainfall interception, infiltration, surface roughness, and runoff generation, while distance from the river reflects each location's proximity to the mapped drainage network. Areas where settlements, agricultural land, or open land coincide with relatively low terrain and short distances from the river may consequently receive higher composite susceptibility scores.

Rainfall, lithology, TWI, and river density collectively accounted for the remaining 22.5% of the total model weight. Although their individual contributions were smaller, these factors further differentiated the susceptibility scores by representing climatic input, geological characteristics, potential water accumulation, and drainage-network concentration. Including them allowed the model to capture spatial variation not captured by slope, elevation, land cover, and distance from the river alone. The final susceptibility pattern therefore reflects the cumulative interaction of all eight conditioning factors rather than the influence of a single dominant variable.

Integrating the eight factors resulted in High and Very High susceptibility classes covering 15.623 km², equivalent to 62.49% of the study area. This result indicates that environmental conditions associated with relatively high susceptibility scores are spatially extensive along the Klawing River corridor. Field photographs in Figure 3b–c provide contextual support for interpreting the river-channel and riverbank conditions represented in the spatial model. However, these observations should be regarded as supporting field evidence rather than independent quantitative validation of the susceptibility zonation.

Practical Implications for Disaster Risk Reduction

The High and Very High susceptibility classes can serve as preliminary priority areas for more detailed field investigations and flood-preparedness activities. These classes cover 62.49% of the study area and indicate locations where flooding-related conditioning factors combine in relatively unfavorable ways. Priority field activities may include documenting historical inundation, examining riverbank and drainage conditions, identifying potential flow obstructions, and evaluating the proximity of settlements and agricultural land to the Klawing River and its tributaries.

The susceptibility map may also support local preparedness planning by identifying areas that require more detailed monitoring, community awareness, and coordination among relevant stakeholders. Nevertheless, the map should not be used independently to establish evacuation routes, determine safe locations, or predict the timing and severity of future floods. Such operational decisions require additional information on flood depth, flow velocity, duration, accessibility, channel capacity, and the condition of local infrastructure.

For land-use management, areas classified as High or Very High susceptibility may be treated as preliminary screening zones before new development or substantial land-use changes are implemented. Site-specific investigations remain necessary to evaluate local terrain, drainage performance, historical flooding, riverbank stability, and the exposure of

planned infrastructure. The Moderate class, covering 27.47% of the study area, should also receive attention because changing rainfall, drainage, and land-cover conditions may alter its susceptibility. The zonation should therefore inform, rather than replace, detailed hydrological, hydraulic, and engineering assessments.

Study Limitations and Future Research

Several limitations should be considered when interpreting the susceptibility zonation. The spatial datasets used in the analysis vary in resolution and scale. DEMNAS has a spatial resolution of approximately 8.3 m, whereas CHIRPS rainfall data have a resolution of approximately 0.05°, or about 5 km. The lithological map was produced at a scale of 1:100,000, while the RBI land-cover and river-network data were obtained at a scale of 1:50,000. These differences may affect the level of spatial detail represented by each conditioning factor. In addition, annual rainfall for 2025 describes broad precipitation conditions but does not directly represent rainfall intensity, duration, antecedent rainfall, or individual flood-producing events.

The AHP weights depend on the pairwise judgments that determine the relative importance of the conditioning factors. Although the CR value of 0.058 indicates acceptable internal consistency, it does not demonstrate that the resulting weights are uniquely correct or that the model has high predictive accuracy. Furthermore, the susceptibility map was not quantitatively validated against an independent inventory of historical flood locations or mapped inundation boundaries. The field photographs provide supporting context but cannot be used to calculate model accuracy. The resulting classes therefore represent relative susceptibility rather than verified flood probability, inundation depth, flow velocity, duration, or return period.

Future research should incorporate historical flood inventories, observed inundation boundaries, or documented flood locations to quantitatively evaluate model performance. Event-based rainfall, maximum daily rainfall, river-discharge records, channel geometry, and drainage-capacity information could also improve the representation of flood-triggering processes. Integrating the susceptibility model with hydrological or hydraulic simulations would enable comparison with flood extent, depth, and velocity. Subsequent studies could also combine susceptibility or hazard information with population, buildings, roads, agricultural assets, and community vulnerability to develop a more comprehensive flood-risk assessment for the Klawing River corridor.

IV. CONCLUSION

The GIS-based multi-criteria decision analysis (MCDA) using the analytic hierarchy process (AHP) effectively mapped flood susceptibility in the Klawing River study area. Of the eight conditioning factors considered, slope and elevation received the highest AHP weights, together accounting for 50.5% of the total weighting. The consistency ratio of 0.058 indicates acceptable consistency. Susceptibility zonation shows that the High class dominates, covering 14.41 km² (57.62%), followed by Moderate (27.47%) and Very High (4.87%) classes. Together, the High and Very High zones cover 62.49% of the area. This pattern reflects the combined influence of topography, land surface, hydrology, climate, and geology, rather than any single factor. The zonation provides a framework for identifying priority areas for flood preparedness, disaster risk reduction, and land-use planning along the Klawing River.

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