Using of Analytical Hierarchy Process (AHP) in Disaster Management: A Review of Flooding and Landslide Susceptibility Mapping

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Abstract
This paper presents a comprehensive review of the application of the Analytical Hierarchy Process (AHP) in site suitability analysis, with a particular focus on disaster-prone areas such as flood and landslide zones. AHP, a multi-criteria decision analysis (MCDA) method, has been widely employed in spatial planning to evaluate and prioritize alternative sites based on a range of environmental, socio-economic, and regulatory criteria. Its strength lies in its structured hierarchical framework, the ability to incorporate both quantitative data and qualitative expert judgment, and its integration with Geographic Information Systems (GIS). The review systematically analyzes methodological approaches across numerous studies, highlighting best practices in criteria selection, pairwise comparison, consistency evaluation, and final suitability mapping. Key findings indicate that slope, lithology, and land use/land cover (LULC) are the most frequently prioritized factors in landslide susceptibility mapping, while flood susceptibility analysis consistently emphasizes rainfall intensity, proximity to rivers, and drainage density. This paper also explores sub-criteria weighting techniques such as straight ranking, reciprocal ranking, exponential ranking, and rank order centroid (ROC), evaluating their practicality in enhancing decision-making. A significant contribution of this review is its comparative synthesis of 20 landslide and 20 flood susceptibility studies across various global contexts. The results underscore the importance of context-specific criteria selection while advocating for standardized methodologies to enhance transparency and comparability. Despite its widespread use, AHP is not without limitations. Issues such as subjectivity in pairwise comparisons, sensitivity to inconsistencies, and methodological variability across studies may affect the robustness of results. The paper concludes with actionable recommendations to improve the consistency, reliability, and adaptability of AHP-based site suitability assessments, particularly in high-risk areas. This review thus serves as a valuable resource for researchers and practitioners aiming to leverage AHP for evidence-based and sustainable spatial decision-making.

Keywords: AHP, Analytical Hierarchy Process, Criteria Weight, Decision Making, MCDA, Pairwise Comparison Matrix, Consistency Ratio

1. Introduction

Site suitability analysis (SSA) has become an indispensable tool in spatial planning and decision-making, particularly in an era marked by rapid urbanization, environmental degradation, and increasing demand for land-based resources. The core objective of SSA is to identify the most appropriate locations for specific land uses or infrastructure projects based on multiple criteria. These criteria typically include environmental factors (e.g., slope, soil type, land cover), socio-economic indicators (e.g., population density, proximity to services), and regulatory constraints (e.g., zoning laws, protected areas). As spatial problems often involve trade-offs among these diverse and sometimes conflicting factors, the process of evaluating and prioritizing suitable sites is inherently complex and multi-dimensional. To address this complexity, the use of multi-criteria decision-making (MCDM) methods has gained significant traction. MCDM techniques are designed to support decision-makers in evaluating alternatives by considering multiple, and often competing, criteria.

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Among the various MCDM approaches available, the Analytical Hierarchy Process (AHP) has become one of the most popular tools for SSA. Introduced by Thomas L. Saaty in 1980, AHP provides a structured framework that simplifies complex decision problems by organizing them into a hierarchical model, allowing for systematic pairwise comparisons of criteria and alternatives. The method then synthesizes these comparisons into a set of relative weights or priorities that guide the final decision.

AHP's strength lies in its ability to integrate both qualitative and quantitative data, as well as subjective expert judgments, into a coherent decision-making model. This feature is particularly valuable in land suitability assessments, where decision-makers often rely on local knowledge and experience in addition to empirical data. Moreover, AHP's compatibility with Geographic Information Systems (GIS) has further expanded its utility. The integration of AHP with GIS has enabled spatially explicit multi-criteria evaluations, allowing for visual representation of suitable areas across landscapes, and supporting more transparent and evidence-based planning processes.

Since its inception, AHP has been applied across a wide range of disciplines and geographic contexts. In agriculture, it has been used to determine suitable lands for crop cultivation based on soil fertility, water availability [1][2][3] and [4], climate conditions [5][6] and [7]. In urban planning, AHP has supported the identification of optimal sites for housing [8][9] and [10], transportation infrastructure [11][12] and [13], and waste management facilities [14][15][16]and [17]. In environmental conservation, it has been employed to prioritize areas for protection based on biodiversity value and ecological sensitivity [18][19] and [20]. These varied applications demonstrate AHP's adaptability and robustness in addressing complex spatial problems.

However, the widespread use of AHP in SSA has also led to a diversity of methodologies, with significant variation in how criteria are selected, weighted, and validated. While this flexibility can be seen as a strength, it also poses challenges for consistency and comparability across studies. Additionally, concerns have been raised regarding the subjectivity inherent in pairwise comparisons, potential bias in expert judgments, and the method's sensitivity to inconsistencies in input data.

The primary objective of this study is to conduct a comprehensive review of the application of the AHP in disaster management as flooding and landslide prone areas. Recognizing the growing reliance on AHP as a decision-support tool in spatial planning, this review seeks to synthesize existing research to better understand the methodological practices and effectiveness of AHP-based approaches. A specific focus of the study is the identification and comparative analysis of criteria selection used in AHP-driven flooding and landslide prone areas analyses. Since the selection and prioritization of evaluation criteria significantly influence the outcomes of site suitability assessments, this study aims to highlight how criteria are chosen, categorized, and weighted in flooding and landslide prone areas. The objectives of the study are as follows:

1. To review the methodology of AHP calculation.
2. To summarize and categorize the criteria commonly used in AHP-based flooding and landslide susceptibility mapping.
3. To evaluate the strengths and limitations of AHP in supporting multi-criteria spatial decision-making.
4. To propose recommendations for improving criteria selection practices in future AHP applications within the context of flooding and landslide prone areas analysis.

By achieving these objectives, the study aims to provide valuable insights into best practices in the use of AHP for SSA and contribute to the development of more consistent and transparent spatial decision-making methodologies.

2. AHP Method

2.1 Criteria Selection

The effectiveness of the Analytic Hierarchy Process (AHP) hinges on the careful selection and structuring of decision criteria. Criteria serve as the foundation upon which alternatives are evaluated, and their appropriate selection ensures that the final decision is comprehensive, rational, and aligned with the decision-making objectives. The following principles and methodological considerations guide the selection of criteria in AHP:

Relevance to the Decision Problem: Criteria must be directly aligned with the overarching goal of the decision-making problem. Relevance ensures that each criterion contributes meaningfully to evaluating the alternatives. Irrelevant or tangential criteria may introduce noise into the analysis and obscure the true performance of alternatives [21].

- *Completeness*: A well-defined set of criteria should capture all significant dimensions of the decision problem. Incomplete criteria sets can lead to biased or narrow evaluations. Completeness does not imply an exhaustive list of all possible factors but rather a holistic representation of all essential aspects [22].

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- *Independence and Non-Redundancy*: To preserve the validity of pairwise comparisons and prevent double-counting, criteria should be as independent as possible. Interdependence between criteria can distort relative weightings and violate the AHP assumption that each criterion independently contributes to the goal [23].
- *Measurability and Operationalization*: Each criterion should be defined in measurable terms, enabling consistent and objective pairwise comparisons. Measurability can be either quantitative (e.g., cost in USD) or qualitative (e.g., customer satisfaction, assessed on a Likert scale), but must allow for a consistent judgment framework.
- *Mutual Exclusivity*: To avoid overlap in content and ensure clarity in the evaluation process, criteria must be mutually exclusive. Each should represent a distinct evaluative dimension.
- *Limited Number of Criteria*: While AHP can technically accommodate numerous criteria, practical limitations of human judgment suggest a manageable number, typically between 5 to 9 criteria is ideal [21] and [24]. A large number of criteria can overwhelm decision-makers and lead to inconsistency in pairwise comparisons. For an example, A decision matrix with 20 criteria requires 190 pairwise comparisons, which is cognitively demanding.
- *Stakeholder and Expert Involvement*: Criteria should reflect the perspectives of all relevant stakeholders. Engaging domain experts and stakeholders in the criteria selection process enhances the legitimacy and acceptability of the final decision. Methods such as Delphi technique [25], focus groups [26], or structured interviews [27] are commonly employed to gather input.

2.2 Hierarchical Structuring

AHP employs a multi-level hierarchical structure as illustrates in Figure 1, where the top level represents the overall goal, followed by intermediate levels of criteria and sub-criteria, and the bottom level represents suitability level. This hierarchy must be logically and functionally sound, with clear linkages between levels [28].

2.3 Fundamental Saaty Scale

In AHP, once the decision hierarchy is established and criteria are selected, the next step involves evaluating the relative importance of criteria and alternatives through pairwise comparisons [29]. This method allows decision-makers to systematically compare elements two at a time with respect to their contribution to a higher-level criterion or goal. To quantify the strength of preferences in these comparisons, AHP employs the fundamental Saaty scale, a 1 to 9 numerical scale developed by [30]. The scale presented in Table 1 translates qualitative judgments into quantitative values, enabling the construction of a pairwise comparison matrix from which priority vectors (weights) are derived through mathematical normalization. The assigned values from 1 to 9 to indicate the intensity of importance. A value of 1 indicates equal importance, while 9 indicates that one element is extremely more important than the other. Intermediate values represent varying degrees of preference, and reciprocal values (e.g., 1/3, 1/7) are used when the second element is preferred over the first.

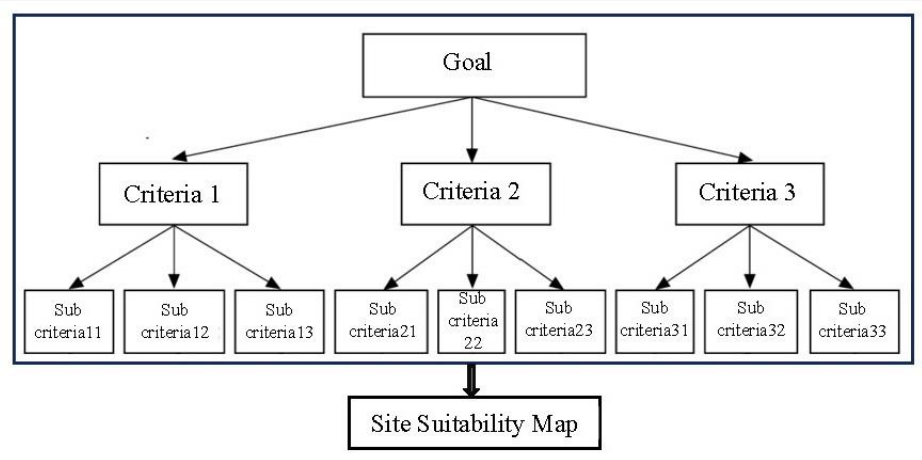

Figure 1: AHP hierarchy for site suitability analysis

Table 1: Fundamental Saaty scale used in AHP [30]

Intensity of importance	Definition
1	Equal importance
3	Moderate importance
5	Strong or essential importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values
Reciprocals	Values for inverse comparison

Table 2: Pairwise comparison matrix

Criteria	C1	C2	C3	C4	C5
C1	1	3	4	5	7
C2	1/3	1	2	3	5
C3	1/4	1/2	1	3	4
C4	1/5	1/3	1/3	1	3
C5	1/7	1/5	1/4	1/3	1
SUM	**1.926**	**5.033**	**7.583**	**12.333**	**20.000**

Table 3: Normalized pairwise comparison matrix

Criteria	C1	C2	C3	C4	C5	Eigenvector
C1	0.519	0.596	0.572	0.405	0.350	0.480
C2	0.173	0.199	0.264	0.243	0.250	0.226
C3	0.130	0.099	0.132	0.243	0.200	0.161
C4	0.104	0.066	0.044	0.081	0.150	0.089
C5	0.074	0.040	0.033	0.027	0.050	0.045
SUM	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

2.4 AHP Calculation

2.4.1 Pairwise comparison matrix

The pairwise comparison matrix is a core component of the AHP, enabling a structured and consistent approach to evaluating the relative importance of criteria or alternatives. After establishing the decision hierarchy and identifying relevant criteria, decision-makers compare each pair of criteria based on their contribution to the overall objective. These comparisons are captured in a square reciprocal matrix, often denoted as Equation 1.

$$A = [a_{ij}]$$

Equation 1

Where a_{ij} represents the relative importance of element i over element j.

The pairwise comparison matrix is of order $n \times n$, where n is the number of criteria. Each element a_{ij} reflects the decision-maker's judgment of the importance of criterion i compared to criterion j. The matrix has the following properties:

Reciprocal property defined in Equation 2.

$$a_{ji} = \frac{1}{a_{ij}} \text{ for all } i, j$$

Equation 2

Diagonal elements equal 1 as expressed in Equation 3.

$$a_{ii} = 1 \text{ for all } i$$

Equation 3

Pairwise comparisons matrix are made using the Saaty fundamental scale and number of criteria (n) = 5.

Once the pairwise comparison matrix is populated, as shown in Table 2, the priority weights (also referred to as eigenvector values or local weights) are derived by normalizing the matrix. This is done by dividing each element in the matrix by the sum of its corresponding column, resulting in a normalized matrix from which the average of each row is calculated to obtain the final priority weights. The AHP weights, or eigenvector values, are determined by calculating the average of the normalized values in each row of Table 3. According to Table 3, the criteria weights for C1, C2, C3, C4, and C5 are 0.480, 0.226, 0.161, 0.089, and 0.045, respectively. To ensure the accuracy of the calculations, the sum of each column in the normalized matrix should equal 1.00, as shown in the last row of Table 3. If the column totals deviate from 1.00, the computations should be re-examined for possible errors.

2.4.2 Consistency analysis

In the Analytic Hierarchy Process (AHP), consistency analysis is a critical step used to validate the reliability of the pairwise comparisons made by decision-makers. The goal is to ensure that the judgments are logically coherent; for instance, if Criterion C1 is preferred to Criterion C2, and Criterion C2 is preferred to Criterion C3, then Criterion C1 should reasonably be preferred to Criterion C3. This logical consistency is quantified using Consistency Ratio (CR) which is defined in Equation 4.

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

Equation 4

Where *CI* is consistency index determined from Equation 5.

The *CR* value of 0.10 or less is generally considered acceptable, indicating that the judgments are sufficiently consistent. If the CR exceeds this threshold, the decision-maker is advised to revisit and revise the pairwise comparisons to improve consistency and strengthen the validity of the resulting priority weights.

$$CI = \frac{\lambda_{\max} - n}{n-1}$$

Equation 5

Where λ_{max} is the principal eigenvalue of the pairwise comparison matrix which expressed in Equation 6.

$$\lambda_{\max} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{(A \cdot w)_i}{w_i}\right)$$

Equation 6

Where *A* is the pairwise comparison matrix, and *w* is the eigenvector, and w_i is the priority weight.

The Random Index (*RI*) is not calculated using a specific equation but is instead derived through empirical simulation. Its value depends on the number of criteria, as shown in Table 4. According to Tables 2 and 3, the λ of the criteria *C1* to C5 are determined as shown in Table 5. The λ_{max} is determined from the average of the λ in Table 5 which is 5.199, therefore, the CI is 0.050. For n = 5, RI is 1.12. Then the *CR* in this example is approximately 0.05 which is less than the threshold of 0.10. Therefore, weights assigned in the pairwise comparison matrix is consistent and the AHP derived weights can be further used in the suitability analysis. The value of λ_{max} is obtained by averaging the λ values in Table 5, resulting in 5.199. For a matrix of size $n = 5$, the corresponding Random Index (*RI*) is 1.12. Consequently, the Consistency Index (*CI*) is calculated as 0.050. This gives a Consistency Ratio (*CR*) of approximately 0.05, which is below the acceptable threshold of 0.10. Therefore, the weights assigned in the pairwise comparison matrix are considered consistent, and the AHP-derived weights can be reliably used in the suitability analysis.

2.5 Sub Criteria Weights

In site suitability analysis using the AHP, sub-criteria weights are essential for refining the evaluation of potential locations. Sub-criteria represent specific factors under broader criteria such as urban, vegetation, baresoil and water bodies under the main criterion "land use and land cover" These sub-criteria are evaluated using pairwise comparisons and in the previous section of “Ranking technique” to determine their relative importance within their category.

Table 4: Random Index [30]

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
R	0.0	0.0	0.5	0.9	1.1	1.2	1.3	1.4	1.4	1.4	1.5	1.4	1.5	1.5	1.5
I	0	0	8	0	2	4	2	1	5	9	1	8	6	7	8

Table 5: Determination of principal eigenvalue (λ_{max})

Criteria	**Calculation: $\lambda = (Aw)_i/w_i$**	**λ**
C1	([1 3 4 5 7] × [0.480 0.226 0.161 0.089 0.045]^T) / 0.480	5.335
C2	([1/3 1 2 3 5] × [0.480 0.226 0.161 0.089 0.045]^T) / 0.226	5.308
C3	([1/4 1/2 1 3 4] × [0.480 0.226 0.161 0.089 0.045]^T) / 0.161	5.221
C4	([1/5 1/3 1/3 1 3] × [0.480 0.226 0.161 0.089 0.045]^T) / 0.089	5.034
C5	([1/7 1/5 1/4 1/3 1] × [0.480 0.226 0.161 0.089 0.045]^T) / 0.445	5.099

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2.5.1 Straight ranking

The straight ranking technique (w_{RS}) is a simple method used in decision-making to prioritize alternatives or factors based on their perceived importance. In this approach, each criterion or option is directly assigned ranking number (i), typically starting with "1" for the most important or suitable, followed by "2," "3," and so on in descending order of importance [31]. There is no calculation of pairwise comparison. The rankings are based purely on expert judgment, stakeholder input, or practical considerations. While it lacks the analytical rigor of methods like AHP, the straight ranking technique is quick, easy to apply, and useful in situations where data is limited or a rapid assessment is needed. The straight ranking is expressed in Equation 7.

$$w_{RS} = \frac{n+1-i}{\sum_{i=1}^{n} i} = \frac{2(n+1-i)}{n(n+1)}$$

Equation 7

2.5.2 Reciprocal ranking

The reciprocal ranking technique (w_{RR}) is a semi-quantitative method used to assign relative weights to criteria or alternatives based on their rank order [31]. In this approach, each criterion is first ranked (e.g., 1 for the most important, 2 for the next, and so on), and then a weight is calculated as the reciprocal of its rank (i.e., 1/rank). For example, if a criterion is ranked 1st, its weight is 1/1 = 1.0; if it's ranked 2nd, the weight is 1/2 = 0.5, and so on. These reciprocal values are then normalized by dividing each by the total sum of all reciprocals, producing final weights that add up to 1. This technique is more refined than straight ranking, as it provides proportional weights while remaining simple to apply without complex comparisons. The reciprocal ranking is expressed in Equation 8.

$$w_{RR} = \frac{1/i}{\sum_{i=1}^{n}(1/i)}$$

Equation 8

2.5.3 Exponential ranking

The exponential ranking technique (w_{ER}) is a method used to assign weights to ranked criteria or alternatives by applying an exponential function to emphasize the differences in importance. Exponential ranking is particularly useful when it is important to strongly differentiate between higher and lower ranked factors. In this approach, each criterion is ranked (with rank 1 being the most important) as the other ranking techniques, and a weight is assigned using an exponential as defined in Equation 9 [32].

$$w_{RR} = \frac{(n+1-i)^P}{\sum_{i=1}^{n}(n+1-i)^P}$$

Equation 9

Where P is power function number.

2.5.4 Rank Order Centroid (ROC)

The Rank Order Centroid (w_{ROC}) method is a simple and efficient technique used to derive approximate weights from a ranked list of criteria when precise pairwise comparisons are not feasible. It is particularly useful in decision-making scenarios like multi-criteria analysis, where stakeholders may find it easier to rank criteria in order of importance rather than assign exact numerical values. In ROC, weights are calculated by averaging the reciprocal values of the ranks, giving higher-ranked criteria more influence. Equation 10 is used to calculate the w_{ROC} [33].

$$w_{ROC} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{i}$$

Equation 10

This approach ensures a reasonable approximation of relative importance while maintaining simplicity and transparency. ROC is especially valuable when expert judgment is limited or when rapid estimation of weights is needed without complex computations. An example of applying a ranking technique to determine sub-criteria weights under the main criterion "Slope" in the suitability analysis for locating a new industrial park is presented in Table 6. The slope is classified into five classes based on slope angle, with flatter areas considered more suitable for industrial development. The power function of 2 is used in exponential ranking.

Table 6: The computation of sub-criteria weights using ranking techniques

Slope	Rank	[1]	[2]	[3] = [1]^2	w_{RS}	w_{RR}	w_{ER}	w_{ROC}
(°)	(i)	n + 1 - i	1/i	(n + 1 – i)^2	[1] / Sum[1]	[2] / Sum[2]	[3] /Sum[3]	Sum[2]$_i$ /n
0-10	1	5	1/1	25	0.333	0.438	0.455	[1+ 1/2 + 1/3 + 1/4 + 1/5] / 5 = 0.457
11-20	2	4	1/2	16	0.267	0.219	0.291	[1/2 + 1/3 +1/4 + 1/5] /5 = 0.257
21-30	3	3	1/3	9	0.200	0.146	0.164	[1/3 + 1/4 +1/5] /5 = 0.157
31-40	4	2	1/4	4	0.133	0.109	0.073	[1/4 + 1/5] / 5 = 0.090
> 40	5	1	1/5	1	0.067	0.088	0.018	[1/5] / 5 = 0.040
Sum	**15**	**15**	**2.238**	**55.000**	**1.000**	**1.000**	**1.000**	**1.000**

The sub-criteria weights, known as local weights, reflect how significant each sub-criterion is compared to others in the same group. These are then multiplied by the weight of their parent criterion to calculate a global weight, which reflects their overall influence on site suitability. By incorporating sub-criteria weights, AHP ensures a more accurate and realistic assessment, aligning the analysis with expert judgment and practical priorities.

2.6 Final Score Determination

The determination of resulting map using the Analytic Hierarchy Process (AHP) involves a structured decision making approach where multiple criteria are considered and weighted according to their relative importance. Once the AHP weights for each criterion are established through pairwise comparisons and consistency checks, they are applied to standardized spatial data layers representing those criteria. The final score is computed as a weighted linear combination of the criterion scores. Equation 10 is generally used for calculating the final score of the resulting map (F).

$$F = \sum_{i=1}^{n} w_i s_i C_i$$

Equation 10

Where w_i represents the AHP-derived weight for the i^{th} criterion, s_i is the sub-criteria weight for the i^{th} criterion at a given location, C_i is the main criteria, and n is the total number of criteria. This process enables objective comparison of different areas based on multiple influencing factors, aiding in optimal site selection for specific land use or development purposes.

3. Applications of AHP

The AHP is widely applied in spatial analysis across various fields, including marketing and business [34][35][36][37][38] and [39], healthcare [40][41][42][43][44][45][46] and [47], engineering [48][49][50] and [51] agriculture [52] and [53], site selection for landfill [54][55][56] and [57], and environmental management [58][59] and [60] . The following sections explore the integration of AHP into flooding and landslide prone areas studies.

3.1 Landslide Susceptibility Mapping

Landslide susceptibility refers to the likelihood or probability that a landslide will occur in a specific area based on the presence of certain contributing factors, but without considering the timing or frequency of such events [61]. The AHP is a widely used decision-making tool in landslide susceptibility mapping, helping to identify and prioritize areas at risk by considering multiple contributing factors such as slope, soil type, land use, rainfall, and proximity to fault lines. In these studies, experts assign weights to each factor based on their relative importance in influencing landslide occurrence, typically through pairwise comparisons. This systematic approach allows for a more objective evaluation of complex, multi-criteria problems. An overview of the publications that have utilized AHP to delineate landslide susceptibility zones is presented in Table 7. The review of 20 recent landslide susceptibility mapping (LSM) studies reveals consistent prioritization of certain geophysical and environmental factors, notably slope, lithology, and LULC, alongside varying emphasis on topographic, hydrologic, and anthropogenic variables depending on regional context. The summarized overview of the most frequently prioritized criteria are as follows:

Slope was identified as a critical determinant in 16 out of the 20 studies reviewed, ranking as the most important factor in 12 cases. Slope is commonly derived from digital elevation model (DEM) [82] and [83]. Its role in influencing gravitational forces and slope stability processes makes it a universally recognized variable in landslide modeling frameworks. Steeper slopes are generally associated with increased susceptibility due to higher shear stress and reduced stability.

Lithology was included in 18 studies and ranked among the top five factors. The nature of rock and soil types directly affects both the mechanical strength and weathering susceptibility of the ground material, which in turn governs slope behavior. Weak, highly weathered, or fractured lithologies are particularly prone to failure under triggering conditions such as rainfall or seismic activity.

LULC was considered in 15 studies, typically ranked between second and eighth in overall importance. Human-induced changes to land cover, especially deforestation, urbanization, and agriculture significantly alter surface hydrology and increase erosion, thereby enhancing landslide susceptibility. These impacts underscore the critical role of LULC in anthropogenically modified environments [84].

Topographic factors were widely incorporated across studies. Elevation (12 studies) was used to infer drainage conditions and potential water accumulation zones. Aspect (16 studies) influences sunlight exposure and soil moisture retention, both of which are relevant to vegetation cover and weathering. Curvature (15 studies), particularly plan and profile curvature, was found to control the direction and concentration of surface runoff, affecting erosion and deposition patterns.

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Table 7: Overview of criteria in AHP for landslide susceptibility mapping

No.	Study area	Priority of criteria	Reference
1.	Great Xi'an Region, China	1.) Slope, 2.) Elevation 3.) River density, 4.) LULC 5.) Curvature, 6.) Soil type, 7.) Lithology, 8.) Aspect	[62]
2.	Van Yen District, Yen Bai Province, Vietnam	1.) Distance from road, 2.) LULC 3.) Slope, 4.) Lithology, 5.) Rainfall intensity, 6.) Aspect, 7.) Profile curvature, 8.) Distance to fault, 9.) Plan curvature, 10.) Topographic wetness index; TWI, 11.) Distance to river	[63]
3.	Choke mountain, northwestern Ethiopia	1.) Slope, 2.) Elevation, 3.) Distance to drainage 4.) Distance to road 5.) Lithology, 6.) Profile curvature 7.) Plan curvature, 8.) NDVI, 9) Aspect	[64]
4.	Oum Er Rbia high basin, Morocco	1.) Lithology, 2.) Slope 3.) LULC, 4.) Distance to roads, 5.) Distance to drainage, 6.) Distance to faults, 7.) Elevation, 8.) Aspect	[65]
5.	A Highway Road Section in Constantine, Algeria	1.) Slope, 2.) Lithology, 3.) Internal friction angle, 4.) Cohesion 5.) LULC 6.) Aspect 7.) Distance from faults, 8.) Distance from streams	[66]
6.	North Bandung Region, Indonesia	1.) Rainfall, 2.) Slope, 3.) Lineament distance 4.) Aspect, 5.) Drainage distance, 6.) Curvature, 7.) Drainage density, 8.) TWI, 9.) Elevation	[67]
7.	Chen-Yu-Lan Watershed, Taiwan.	1.) Geology 2.) LULC, 3.) Aspect 4.) Slope 5.) Drainage density	[68]
8.	Yunxian County, Southwest China	1.) LULC, 2.) Landslide density, 3.) Lithology, 4.) Distance from road, 5.) Distance from river 6.) Distance from faults, 7.) NDVI, 8.) Slope 9.) Relative relief, 10.) Curvature, 11.) Accept	[69]
9.	North Branch of Argentino Lake, Argentina	1.) Slope, 2.) Geomorphology, 3.) Aspect, 4.) Lithology 5.) Plan curvature, 6.) Distance to faults	[70]
10.	Khao Yai National Park, Thailand	1.) Slope, 2.) Precipitation, 3.) Distance from road 4.) Elevation, 5.) Distance from drainage, 6.) Lithology 7.) Aspect, 8.) LULC, 9.) Curvature, 10.) TWI	[71]
11	Northwest of Alborz province, Iran	1.) Slope, 2.) Precipitation, 3.) Lithology, 4.) Aspect 5.) LULC, 6.) Distance to fault 7.) Curvature 8.) Distance to river, 9.) Distance to road	[72]
12	National Highway 5 in India	1.) Distance from road 2.) Lithology, 3.) Geology 4.) Drainage density, 5.) Fault density, 6.) Slope 7.) TWI, 8.) Curvature, 9.) Relative relief, 10.) Aspect	[73]
13	Inegöl Forest Management Directorate in İnegöl district of Bursa province, located in the Marmara region of Türkiye	1.) Lithology, 2.) Slope, 3.) Curvature, 4.) Precipitation 5.) Aspect, 6.) Distance from faults, 7.) Distance from river, 8.) Distance from road, 9.) LULC, 10.) Soil type, 11.) Elevation, 12.) NDVI	[74]
14	Bafoussam-Dschang region, Western Cameroon	1.) Slope, 2.) LULC, 3.) Lithology, 4.) Flow density 5.) Soil type, 6.) Curvature, 7.) Elevation, 8.) Aspect	[75]
15	Meghalay, India	1.) Slope, 2.) Rainfall, 3.) Distance from road, 4.) Lithology 5.) LULC 6.) Elevation, 7.) NDVI, 8.) Geomorphology, 9.) TWI, 10.) Aspect, 11.) Plan curvature, 12.) Soil texture, 13.) Distance from river, 14.) SPI, 15.) Distance from faults	[76]
16	Reggio Calabria metropolitan city, Calabria region in the south of Italy,	1.) Slope, 2.) Rainfall, 3.) Distance from road 4.) LULC, 5.) Elevation, 6.) Geology, 7.) Distance from river	[77]
17	Great East region, Aube department, Northeastern France.	1.) Lithology, 2.) Slope, 3.) Elevation, 4.) Precipitation 5.) Distance from road, 6.) Distance from drainage 7.) Density of quarry, 8.) Distance from fault	[78]
18	The Japanese archipelago	1.) Slope type, 2.) Geology, 3.) Elevation, 4.) Slope angle 5.) Flow accumulation, 6.) Vegetation	[79]
19	Astore region, Pakistan	1.) Slope, 2.) Geology, 3.) Soil type, 4.) LULC 5.) Distance from stream, 6.) Plan curvature, 7.) SPI 8.) TWI, 9.) Aspect	[80]
20	A Lesser Himalayan Road Corridor, India	1.) Slope, 2.) Rainfall, 3.) Lithology, 4.) NDVI 5.) Aspect, 6.) Distance from road, 7.) LULC 8.) Distance from drainage, 9.) Distance from fault 10.) Altitude, 11.) Soil type, 12.) Seismicity 13.) TWI, 14.) SPI	[81]

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Hydrologic conditions play a key role in slope instability. Distance to rivers and drainage networks was considered in 14 studies, serving as a proxy for saturation and erosional processes. Rainfall intensity, though included in only 8 studies, was found to be a critical trigger in tropical, where short-duration, high-intensity precipitation events frequently initiate landslides.

Human activities were represented through variables such as distance to roads (13 studies), with road construction often contributing to cut-and-fill imbalances and drainage disruption, thus destabilizing slopes. Quarry density, while included in only one study (France), highlighted localized blasting effects and the need to consider unique industrial influences.

Regional differences were apparent in the prioritization of certain factors. In tropical climates such as Vietnam and Thailand, rainfall and the Topographic Wetness Index (TWI) were emphasized due to the prevalence of precipitation-triggered landslides. In contrast, studies conducted in mountainous areas like the Himalayas and the Alps prioritized seismicity and relative relief, reflecting the role of tectonic activity and terrain ruggedness. In urban environments, such as Constantine, Algeria, proximity to roads and soil cohesion were more influential, indicating the compounded effects of infrastructure development and soil engineering properties.
Several studies also introduced unique or locally significant variables. Soil texture was assessed in Meghalaya, India, recognizing its role in infiltration and cohesion. The Stream Power Index (SPI) was applied in watersheds with high fluvial activity, and the Normalized Difference Vegetation Index (NDVI) was utilized in Ethiopia and China to monitor vegetation cover and associated root reinforcement effects.

The synthesis of 20 landslide susceptibility studies underscores the universal significance of slope and lithology, reaffirming their foundational role in LSM. Nevertheless, the variability in factor selection across regions reflects the necessity of context-specific modeling approaches. Incorporating both globally recognized and locally relevant variables enhances the precision and applicability of susceptibility assessments, thereby improving hazard mitigation strategies.

3.2 Flood Susceptibility Mapping

Flood susceptibility mapping is a critical component of disaster risk reduction, providing spatial insights that inform land use planning, infrastructure development, and emergency preparedness. There are several models for flood mapping and modelling, for instance, Flash Flood Potential Index (FFPI) [85], hydrological model [86], machine learning algorithms [87], and UN-SPIDER flood mapping recommendation [88]. Among the various techniques, the AHP has emerged as a widely adopted method due to its straightforward ability to systematically integrate expert judgment with spatial data. This review presents a synthesis of recent studies that have applied AHP for flood susceptibility mapping, with a focus on the selection and weighting of contributing factors. To facilitate comparative analysis, the findings are organized in Table 8, highlighting the criteria used in each study. A review of 20 international case studies employing the Analytic Hierarchy Process (AHP) for flood susceptibility mapping reveals a consistent prioritization of hydrological, topographical, and land use-related factors. The analysis of the priority rankings in Table 8 demonstrates both global patterns and context-specific variations in the selection and weighting of flood susceptibility criteria. The summarized overview of the most frequently prioritized criteria are as follows:

Hydrological factors:

- *Rainfall intensity and precipitation:* Rainfall intensity is among the most frequently prioritized criteria, ranked as the first or second most important factor in numerous studies (e.g., Bangladesh, Indonesia, Pakistan, Cameroon). Its dominant role reflects the direct influence of extreme precipitation events on flood generation, particularly in monsoon-affected and tropical regions. Precipitation, often considered alongside rainfall intensity, further underscores the importance of climatic inputs in flood susceptibility.
- *Distance from river/ drainage and drainage density:* Proximity to rivers or drainage networks is consistently ranked as a top priority (e.g., Nowshera, Lower Teesta basin, Haripur, Wadi Hanifah). This criterion reflects the increased flood risk for areas located near watercourses, where overflow and inundation are more likely. Drainage density, which quantifies the closeness of stream channels, is also commonly prioritized, indicating the role of catchment hydrology in flood propagation.

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Table 8: Overview of criteria in AHP for flood susceptibility mapping

No.	Study area	Priority of criteria	Reference
1.	Maran District, Pahang - Malaysia	1.) Soil type, 2.) Rainfall intensity, 3.) Slope angle, 4.) LULC	[89]
2.	Nowshera district, Peshawar division, Khyber Pakhtunkhwa province, Pakistan	1.) Distance from river, 2.) Elevation, 3.) Height above nearest drainage, 4.) Slope, 5.) TWI, 6.) Drainage density, 7.) Rainfall intensity, 8.) NDVI, 9.) LULC 10.) Distance from road, 11.) Curvature, 12) Soil type	[90]
3.	Subbasins of Kali River, Karnataka and Goa, India	1.) Elevation, 2.) Slope, 3.) Distance from river 4.) Rainfall intensity, 5.) Flow accumulation, 6.) Stream density, 7.) Soil type, 8.) Water ratio index 9.) LULC, 10.) TWI, 11.) SPI	[91]
4.	Hoan Kiem district, Hanoi, Vietnam	1.) LULC, 2.) NDVI, 3.) Sewer line length per capita, 4.) Slope	[92]
5.	Hanoi, Vietnam	1.) LULC, 2.) Distance from road, 3.) Distance from river 4.) TWI, 5.) NDVI, 6.) Precipitation, 7.) Elevation, 8.) Slope 9.) Drainage density	[93]
6.	watershed of wadi Cheliff-Ghrib outh-west of Algiers Algeria	1.) Elevation, 2.) Slope, 3.) Drainage density, 4.) Distance to river, 5.) TWI, 6.) MNDWI 7.) Rainfall intensity, 8.) NDVI, 9.) Lithology	[94]
7.	Greater Bandung area Cimahi city, West Java, Indonesia,	1.) Slope, 2.) TWI, 3.) LULC, 4.) Precipitation, 5.) Elevation 6.) Distance from road, 7.) NDVI, 8.) Distance from river	[95]
8.	Busu River Basin, Papua New Guinea	1.) Surface runoff, 2.) Distance from river, 3.) Elevation 4.) Slope, 5.) LULC, 6.) Flow accumulation, 7.) Soil texture 8.) Drainage density, 9.) Lithology	[96]
9.	Lower Yom Basin, Sukhothai Province, Thailand	1.) Rainfall intensity, 2.) Slope, 3.) Drainage density, 4.) LULC, 5.) Elevation, 6.) Soil type	[97]
10.	Lower Teesta basin, Bangladesh	1.) Distance from river, 2.) Elevation, 3.) TWI, 4.) Precipitation, 5.) Drainage density, 6.) Soil type, 7.) Slope, 8.) LULC, 9.) NDVI, 10.) Distance from road	[98]
11	Saqqez City, the north of Kurdistan Iran	1.) Slope length, 2.) Distance from river, 3.) Aspect 4.) Elevation, 5.) Slope, 6.) Rainfall intensity, 7.) Curvature 8.) TWI, 9.) Geology, 10.) LULC	[99]
12	East Aceh Regency, Indonesia	1.) Rainfall intensity, 2.) Slope, 3.) Elevation 4.) Flow accumulation	[100]
13	Haripur District, Khyber Pakhtunkhwa region, Pakistan.	1.) Rainfall intensity, 2.) Distance from river, 3.) Slope 4.) elevation, 5.) LULC, 6.) TWI, 7.) Soil type, 8.) NDVI 9.) Curvature	[9101]
14	Ain Smara, Constantine Algeria	1.) TWI, 2.) Precipitation, 3.) Drainage density, 4.) Distance from river, 5.) Elevation, 6.) Slope, 7.) Lithology 8.) LULC, 9.) NDVI, 10.) Distance from road	[102]
15	Bangladesh	1.) Rainfall intensity, 2.) Slope, 3.) Elevation 4.) Drainage density 5.) Flood depth 6.) LULC, 7.) Geology 8.) Flood duration, 9.) Soil type	[103]
16	Mfoundi Watershed, Yaoundé in the South-Cameroon Plateau, Cameroon	1.) LULC, 2.) Elevation, 3.) Geology, 4.) Rainfall intensity 5.) Drainage density, 6.) Distance from river, 7.) Slope 8.) Hydraulic conductivity, 9.) TWI, 10.) Groundwater table	[104]
17	Northeast Haor region, Bangladesh	1.) Rainfall intensity, 2.) Elevation, 3.) Slope 4.) Distance from river, 5.) Aspect, 6.) Drainage density 7.) TWI, 8.) LULC, 9.) Lithology, 10.) NDVI, 11.) Soil type	[105]
18	Davidson county, Tennessee USA.	1.) Soil type, 2.) LULC, 3.) TWI, 4.) Slope, 5.) Elevation 6.) Drainage density, 7.) NDVI, 8.) Distance from river 9.) Rainfall intensity, 10.) Distance from road	[106]
19	Wadi Hanifah drainage basin Riyadh region, Saudi Arabia.	1.) Distance to drainage, 2.) Elevation, 3.) LULC, 4.) Runoff 5.) Slope, 6.) Curvature, 7.) Geology, 8.) Soil type 9.) Drainage density, 10.) TWI	[107]
20	Punjab Province. Pakistan	1.) Drainage density, 2.) TWI, 3.) Precipitation 4.) Rainfall intensity, 5.) Elevation, 6.) Slope, 7.) LULC 8.) NDVI, 9.) Distance from river, 10.) Distance from road 11.) Soil type	[108]

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- *Topographic Wetness Index (TWI) and flow accumulation:* TWI and flow accumulation are frequently included among the top criteria (e.g., Punjab, Davidson County, Greater Bandung). These indices capture the spatial distribution of soil moisture and potential surface runoff, which are critical in identifying flood-prone zones.

Topographical Factors:

- *Elevation and slope:* Elevation is a key determinant of flood susceptibility, especially in low-lying regions (e.g., Bangladesh, Vietnam, Algeria). Lower elevations are more prone to inundation [109]. Slope is also prioritized in most studies, with lower slope gradients associated with higher flood retention and slower runoff, thus increasing susceptibility.
- *Curvature and aspect:* Curvature (plan/profile) and aspect are occasionally considered, reflecting their influence on water flow paths and microclimatic conditions that may affect soil moisture and runoff.

Land Use and Anthropogenic Factors:

- *Land Use/Land Cover (LULC):* LULC is a dominant anthropogenic criterion, ranked as the first or second priority in several urban and peri-urban studies (e.g., Hanoi, Hoan Kiem, Cameroon). Urbanization, deforestation, and agricultural practices significantly alter surface runoff characteristics and infiltration capacity, thereby affecting flood risk.
- *Distance from Road and Sewer Infrastructure:* Distance from road and the presence of sewer infrastructure are included in several studies (e.g., Hanoi, Greater Bandung), highlighting the impact of built environments and drainage systems on flood dynamics.

Soil and Geological Factors:

- *Soil Type and Lithology:* Soil type is prioritized in many studies (e.g., Maran, Busu River, Davidson County), reflecting its role in infiltration and water retention. Lithology and geology are also considered, particularly in regions where substrate permeability influences flood behavior.

Vegetation and Remote Sensing Indices:

- *NDVI (Normalized Difference Vegetation Index):* NDVI is incorporated as a supporting criterion in several studies, providing information on vegetation cover, which can mitigate flood risk through enhanced infiltration and evapotranspiration.

Regional and Contextual Variations:

- While hydrological and topographical factors are universally prioritized, the relative importance of criteria varies with local environmental and socio-economic conditions. For example, rainfall intensity and TWI are more critical in tropical and monsoon regions, while urban infrastructure and LULC are emphasized in densely populated or rapidly urbanizing areas.

summary, flood susceptibility mapping using AHP consistently prioritizes rainfall intensity, proximity to rivers, drainage density, elevation, slope, and LULC as the most influential criteria. The integration of hydrological, topographical, and anthropogenic factors enables comprehensive and context-sensitive flood risk assessments. The observed regional variations in criteria ranking underscore the need for site-specific calibration of AHP models to enhance the accuracy and relevance of flood susceptibility maps.

4. Conclusion

The Analytical Hierarchy Process (AHP) has emerged as a leading methodological tool in site suitability analysis, particularly in disaster management contexts involving landslides and floods. This review illustrates the method’s strengths in organizing complex spatial decision problems, integrating diverse types of data, and enabling structured expert input. Through its hierarchical framework, AHP allows decision-makers to decompose multifaceted challenges into a coherent structure of goals, criteria, and sub-criteria, thereby facilitating more informed and transparent evaluations. The extensive application of AHP across varied geographic regions and decision-making contexts affirms its flexibility and adaptability. In landslide susceptibility mapping, the review found that slope, lithology, and land use/land cover (LULC) are the most consistently prioritized criteria, which aligns with the physical mechanics of slope failure. For flood susceptibility mapping, hydrological parameters, especially rainfall intensity, proximity to rivers, and drainage density dominate the criteria rankings.

Topographical and anthropogenic factors such as elevation, slope, LULC, and NDVI also contribute significantly to susceptibility modeling.

The review also assessed four key sub-criteria weighting methods straight ranking, reciprocal ranking, exponential ranking, and rank order centroid. These techniques offer practical alternatives to traditional pairwise comparisons, especially in cases where data limitations or time constraints make full AHP implementation challenging. However, the choice of ranking method can influence the final outcome, highlighting the need for careful methodological selection.

One of the main challenges associated with AHP is its sensitivity to subjective judgment and inconsistency in pairwise comparisons. While the consistency ratio (CR) provides a mechanism to quantify and control inconsistency, the reliability of AHP still depends heavily on the expertise and objectivity of those performing the evaluations. Moreover, there is considerable variation in how AHP is applied across studies from the selection of criteria to the integration with GIS which can affect the comparability and reproducibility of results. In summary, AHP remains a robust and valuable decision-support tool for spatial planning in disaster-prone regions. When used thoughtfully, it provides a transparent framework for evaluating complex decisions involving multiple criteria. However, to fully realize its potential, researchers and practitioners should strive for methodological standardization, integrate stakeholder perspectives, and complement AHP with other decision-making or modeling approaches where appropriate. This review contributes to advancing best practices in AHP-based site suitability analysis and offers guidance for future applications aimed at reducing risk and enhancing sustainable land use planning.

5. Limitations of AHP

Despite its strengths, the AHP has several limitations that affect its application in flood susceptibility mapping. The method's reliance on expert judgment in pairwise comparisons introduces a degree of subjectivity, which can lead to biased or inconsistent weight assignments, especially when dealing with a large number of criteria. Additionally, the lack of standardized criteria across studies limits the generalizability of results to different geographic or climatic contexts. AHP is also highly dependent on the quality and availability of input data, posing challenges in data-scarce regions, particularly in developing countries. Moreover, its traditional static framework does not account for temporal changes in environmental or socio-economic conditions, such as evolving climate patterns or land use dynamics, potentially reducing its long-term applicability.

6. Recommendation

To enhance the effectiveness and reliability of AHP-based studies in disaster risk and site suitability assessment, several key recommendations are proposed. First, the standardization of criteria selection methods is essential to ensure consistency and comparability across different case studies and geographic regions. Active stakeholder involvement, particularly from local communities and domain experts should be integrated throughout the decision-making process to align selected criteria with on-the-ground realities and enhance the legitimacy of outcomes. Addressing uncertainty is equally important; incorporating techniques such as sensitivity analysis or fuzzy AHP can help assess the impact of variability in expert judgments on final results. The adoption of hybrid approaches that combine AHP with complementary tools such as machine learning, or hydrological modeling can also improve analytical depth by integrating both expert knowledge and empirical data. Finally, building local capacity through training programs and practical toolkits can empower planners and policymakers to effectively apply AHP in disaster risk reduction and spatial planning initiatives.

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