Flood Vulnerability Mapping of the Kosi River Basin using a Multi-Criteria Decision-Making Approach

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ABSTRACT

The research presented in this study introduces a novel methodology for delineating flood-prone regions within the Kosi River Basin, utilizing a multi-criteria decision-making approach. This method integrates multi-criteria analysis, Geographical Information Systems (GIS), and Remote Sensing (RS). The specific process involves the creation of flood susceptibility maps based on five crucial factors: rainfall, land use/cover, slope, drainage density, and distance from the river. Expert judgments were incorporated and translated into weighted values to ascertain the relative significance of each factor in determining flood susceptibility. Weight calculations were performed using the Fuzzy Analytic Hierarchy Process (FAHP). The findings of this study indicate that across all 10 districts in the region, a varying degree of land area is classified as high-risk, with Madhubani displaying the highest percentage of land area categorized as of very high-risk. Key challenges include data accuracy and model generalization, with potential applications in other flood-prone areas. This approach not only improves the precision of flood susceptibility mapping, but also offers valuable insights for disaster management and planning in areas with limited data availability.

Keywords-GIS; remote sensing; rainfall; land use; land cover; Kosi river basin

I. INTRODUCTION

Floods are among the most destructive natural disasters, affecting approximately 170 million people worldwide annually and contributing to more than 60% of deaths related to such occurrences [1-3]. Investigating floods on a large scale poses significant challenges because of their susceptibility to local variables, such as rainfall patterns, terrain slopes, hydroclimatic conditions, soil characteristics, and Land Use/Land Cover (LULC) [4, 5]. Furthermore, the magnitude of flooding in a particular area can vary substantially owing to the influences of climatic fluctuations, alterations in land use, deforestation, and other human-induced interferences [6-8]. In recent years, the frequency and intensity of floods have been exacerbated by climate change, posing greater risks to human life, infrastructure, and ecosystems [6, 9, 10]. Understanding the complex interplay of natural and anthropogenic factors driving flood events is crucial for implementing effective mitigation strategies and adaptive measures to minimize their adverse impacts [11]. In this context, advanced methodologies that integrate Remote Sensing (RS), Geographic Information Systems (GIS), and Multi-Criteria Decision-Making (MCDM) tools offer promising avenues for comprehensive flood risk assessment and management at regional and global scales.

Flood risk and vulnerability assessments play a crucial role in providing decision-makers with informative maps to guide various aspects of disaster management, including potential transportation disruptions, cost-benefit analyses, the extent of floods, and the fragility of critical infrastructure [12, 13]. MCDM has emerged as a suitable tool for offering a versatile perspective on flood risk, incorporating demographic, socioeconomic, and geophysical attributes to produce complete flood risk assessments. In the Kosi Basin, where the occurrence of flooding has increased in recent decades, flood risk management has become an ongoing process aimed at preventing deaths and minimizing financial losses [14]. Assessing current risk levels is crucial for prioritizing vulnerable areas and implementing appropriate mitigation measures.

The Fuzzy Analytical Hierarchy Process (FAHP) is a promising approach for addressing the inherent uncertainty and lack of precision often encountered in decision-making contexts. Through its ability to facilitate decision-making amid uncertainty, the FAHP adeptly accommodates imprecise factors and criteria by expressing them as fuzzy numbers [15]. Unlike conventional Analytic Hierarchy Process (AHP) methods, FAHP employs a fuzzy decision matrix featuring fuzzy numbers, which enables the derivation of precise weights from coherent and incoherent fuzzy comparison matrices [16].

Researchers frequently employ regulatory maps for flood risk assessment, even though data-driven techniques have been shown to be effective in creating flood maps with limited resources [17]. Existing flood vulnerability mapping methodologies for the Kosi River Basin lack a comprehensive and integrated approach that simultaneously considers multiple criteria. Previous studies have often focused on individual factors without adequately addressing the complex interactions among different variables influencing flood susceptibility.

The primary objective of this study is to introduce a novel methodology to define flood-prone regions within the Kosi River Basin. Specifically, its goal was to integrate various techniques, such as multi-criteria analysis, GIS, and RS, to develop comprehensive flood susceptibility maps. By incorporating key factors, including rainfall, LULC, slope, drainage density, and distance from the river, the decision-makers are provided with informative maps that can guide effective flood risk management strategies. Using MCDM techniques, a comprehensive flood risk mapping can be performed to provide a comprehensive understanding of flood risk in the Kosi Basin.

II. STUDY AREA

The geographical coordinates of the Kosi River Basin were delineated, spanning from latitude 25° 21.0’ to 26° 21.6’ N and longitude 86° 31.8’ to 87° 35.4’ E (Figure 1). Originating in Tibet, the Kosi River traverses Nepal before entering Bihar, India near Bhimnagar, and eventually converges with the Ganga River near Kurshela. The river in Bihar spans more than 261 km, covering 10 districts, including Supaul, Saharsa, Madhepura, and Katihar. Located in the Bihar plains, the basin has a maximum elevation of 91 m and slopes ranging from 0° to 35°.

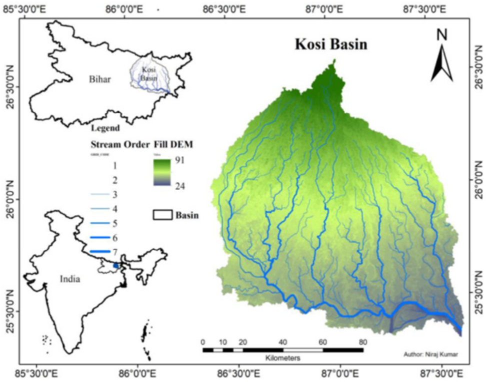

Fig. 1. Location map of the study area.

III. METHOLOGY

A. Analytic Hierarchy Process

The AHP, developed by the author in [18], is a methodology designed to tackle complex issues that encompass numerous criteria. It uses mathematical techniques to assess decisions by considering the preferences of individuals or groups within a specific context guided by the chosen variables. AHP bridges the gap between the necessity for practical solutions and the rigor of scientific decision making, offering a way to merge qualitative and quantitative assessments [19]. This combination facilitates an efficient and effective strategy for navigating complex dilemmas. The AHP method is implemented through a five-step process that includes defining the issue and pinpointing relevant factors, assigning values to these factors using the AHP scale, constructing a pairwise comparison matrix (Table I), determining the relative importance of each factor, and assessing the Consistency Ratio (CR) to ensure the reliability of the analysis.

TABLE I. PAIRWISE COMPARISON OF FACTORS INFLUENCING FLOODS

Factors	LULC	Rainfall	Drainage density	Slope	Road density
LULC	1	0.5	0.5	1	0.5
Rainfall	2	1	2	3	1
Drainage density	2	0.5	1	2	1
Slope	1	0.33	0.5	1	0.33
Road density	2	1	1	3	1

λ_{max}=5.06, CI=0.01, RI=1.12, CR=0.013

Pairwise Comparison Matrix: This matrix uses numerical values based on the AHP scale to show the relative importance of the elements (see Table I). Equation (1) was used to create the pairwise comparison matrix:

$$A = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{pmatrix} \quad (1)$$

Two factors were compared in (1). A value between 1 and 9 should be assigned if a factor value in the row has a higher weight than another factor in the column. Conversely, if a factor in the column has a lower weight than another, its value should be assigned between 1/2 and 1/9, and the cross parameters should naturally be equal to 1.

Evaluation of Consistency: The CR was calculated to ensure the consistency of the comparisons. According to [20], the matrix is deemed consistent if the Consistency Index (*CI*) value is zero. Additionally, a pairwise comparison matrix exhibiting a CR of less than 0.1 indicates a decent degree of consistency, whereas a CR of more than 0.1 suggests inconsistent evaluations. Equation (3) indicates that the *CR* value is the product of the CI value and the Random Index (*RI*) value.

$$CI = {}^{\lambda_{max} - n}/_{n - 1} \quad (2)$$

$$CR = {}^{CI}/_{RI} \quad (3)$$

where λ_{max} denotes the largest eigenvalue acquired from the pairwise matrix and n signifies the count of parameters [21]. Furthermore, *RI* represents a random index that varies according to the matrix dimensions (Table II). This study opted for a value of 1.12 for *RI* based on the proposed parameter count.

TABLE II. RI VALUES FOR EACH n [18]

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45

B. *Fuzzy Analytic Hierarchy Process*

The Fuzzy Analytic Hierarchy Process (FAHP) was executed when the CR was less than or equal to 0.10. The computation and evaluation entailed a fusion of the AHP technique and fuzzy logic, accomplished through the pair-wise comparison method of AHP using Triangular Fuzzy Numbers (TFNs), as delineated in Table III [22]. The attributes of TFNs are evidenced in Figure 2. Priority weighting for each factor was adopted [23].

TABLE III. TRIANGULAR FUZZY NUMBERS FOR PAIRWISE COMPARISON

Interpretation	**AHP scale**	**TFN scale**
Equally important	1	(1, 1, 1)
Moderately important	3	(1, 1.5, 2)
Important	5	(2, 2.5, 3)
Highly important	7	(3, 3.5, 4)
Extremely important	9	(4, 4.5, 4.5)

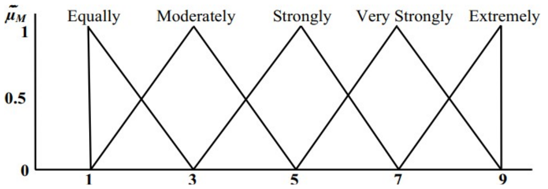

Fig. 2. Linguistic variables for the importance weight of each criterion.

To compute the fuzzified pairwise comparison matrix, consider a set of objects $X = \{x_1, x_2,\ldots,x_n$, and a goal set $U = \{u_1, u_2,\ldots,u_m\}$. Each object undergoes an analysis with respect to each goal g_i. Consequently, for each object m extent analysis values can be obtained denoted as $M_{gi1}, M_{gi2},\ldots,M_{gim}$; where i ranges from 1 to n, and all M_{gij} (where $j = 1, 2,\ldots,m$) are TFNs. Subsequently, a pairwise comparison matrix is formulated based on the fuzzy process using (4).

$$\left(M_{gi}^{j}\right)_{n\times m} = \begin{bmatrix} M_{g1}^{1} & M_{g1}^{2} & \cdots & M_{g1}^{m} \\ M_{g2}^{1} & M_{g2}^{2} & \cdots & M_{g2}^{m} \\ \vdots & \vdots & \vdots & \vdots \\ M_{gn}^{1} & M_{gn}^{2} & \cdots & M_{gn}^{m} \end{bmatrix} =$$

$$\begin{bmatrix} (1,1,1) & \left(l_{1_2}, m_{1_2}, u_{1_2}\right) & \cdots & \left(l_{1_m}, m_{1_m}, u_{1_m}\right) \\ \left(l_{2_1}, m_{2_1}, u_{2_1}\right) & (1,1,1) & \cdots & \left(l_{2_m}, m_{2_m}, u_{2_m}\right) \\ \vdots & \vdots & \vdots & \vdots \\ \left(\frac{1}{u_{n_1}}, \frac{1}{m_{n_1}}, \frac{1}{l_{n_1}},\right) & \left(\frac{1}{u_{n_2}}, \frac{1}{m_{n_2}}, \frac{1}{l_{n_2}},\right) & \cdots & (1,1,1) \end{bmatrix} \quad (4)$$

To compute the fuzzy synthetic extent concerning the *i*th alternative, the calculation can be performed employing (5):

$$S_i = \sum_{j=1}^{m} M_{g_i}^{j} \times \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} \quad (5)$$

Si is the synthetic extent value of the pairwise comparison, and $\sum_{j=1}^{m} M_{g_i}^{j}$ is the summation of the TFNs, which can be expressed as:

$$\sum_{j=1}^{m} M_{g_i}^{j} = \left[\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j,\right]^{-1} \quad (6)$$

and:

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} l_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} u_i},\right) \quad (7)$$

Estimation of the degree of possibility: $S_i \geq S_j$ when $S_i = (l_i, m_i, u_i)$ and $S_j = (l_j, m_j, u_j)$, where $i = 1, 2, \ldots, m$ and $i \neq j$, can be expressed as in (8):

$$V(S_i \geq S_j) = \begin{cases} 1 & \text{if } m_i \geq m_j \\ 0 & \text{if } l_i \geq u_i \\ \frac{l_j - u_i}{(m_i - u_i) - (m_j - l_j)} & \end{cases} \quad (8)$$

For S_i being greater than S_j, this can be expressed as in (9):

$$S_i \geq S_j \middle| j = 1,2,\ldots,m; i \neq j) = min\, V(S_i \geq S_j \middle| j = 1,2,\ldots,m; i \neq j) \quad (9)$$

Equations (10)-(12) were used to calculate the weight vector and normalize the non-fuzzy weight vector:

Assuming that:

$$w_i' = min\, V(S_i \geq S_j | j = 1,2,\ldots,m; i \neq j) \quad (10)$$

then, the weight vector is given by:

$$w_i = \frac{w_i'}{\sum_{i=1}^{n} w_i'} \quad (11)$$

and the normalized weight vector is:

$$W = (w_1, w_2, \ldots, w_n)^T \quad (12)$$

where w_i is a non-fuzzy number that is the weight of each factor. More information about the FAHP method can be found in previous studies [24, 25].

Table IV comprehensively portrays the fuzzy judgment matrices for all the factors (LULC, rainfall, drainage density, slope, and road density) that were considered for the FAHP method.

TABLE IV. FUZZY JUDGMENT MATRICES FOR VARIOUS FACTORS IN THE FAHP METHOD

Factors	**Land use**	**Rainfall**	**Drainage density**	**Slope**	**Road density**
LULC	(1, 1, 1)	(0.67, 1, 2)	(0.67, 1, 2)	(1, 1, 1)	(0.67, 1, 2)
Rainfall	(0.5, 1, 1.5)	(1, 1, 1)	(0.5, 1, 1.5)	(1, 1.5, 2)	(1, 1, 1)
Drainage density	(0.5, 1, 1.5)	(0.67, 1, 2)	(1, 1, 1)	(0.5, 1, 1.5)	(1, 1, 1)
Slope	(1, 1, 1)	(0.5, 0.67, 1)	(0.67, 1, 2)	(1, 1, 1)	(0.5, 0.67,1)
Road density	(0.5, 1, 1.5)	(1, 1, 1)	(1, 1, 1)	(1, 1.5, 2)	(1, 1, 1)

C. *Flood Hazard Index*

The creation of a flood risk map involves utilizing the raster calculator feature within GIS applications and employing the raster overlay technique. This method incorporates factor weights derived from the FAHP. The Flood Hazard Index (*FHI*), calculated according to (13), was used for these calculations. Upon completion, the resulting data were segmented into five distinct hazard levels, ranging from very low to very high, facilitating the generation of a map that is straightforward to interpret.

$$FHI = \sum_{I=1}^{N} r_i \times w_i \qquad (13)$$

where r_i is the rating of the factor at each point, w_i is the weight of each factor, and N is the number of criteria used. Figure 3 presents the flowchart of the methodology deployed in this study.

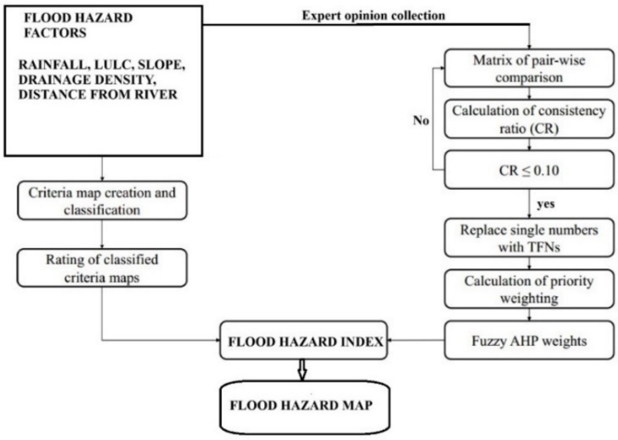

Fig. 3. Flowchart of the methodology.

IV. RESULTS AND DISCUSSION

A. Thematic Layers

In the present study, five thematic layers were developed. Rainfall, LULC, drainage density, slope, and road density maps were generated (Figures 4-8).

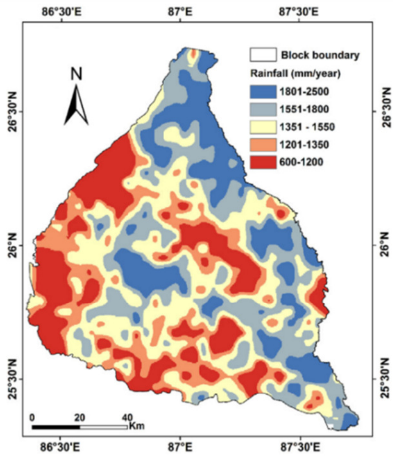

Fig. 4. Rainfall map of the study area.

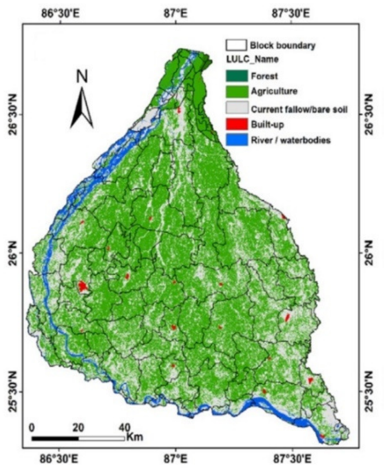

Fig. 5. LULC map of the study area.

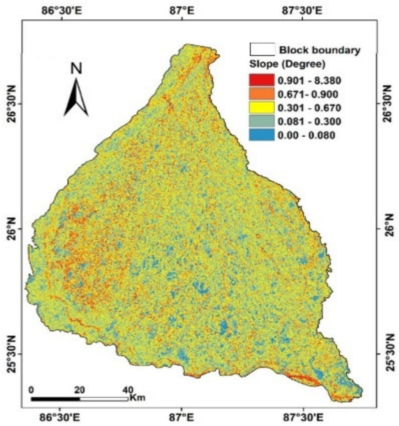

Fig. 6. Slope map of the study area.

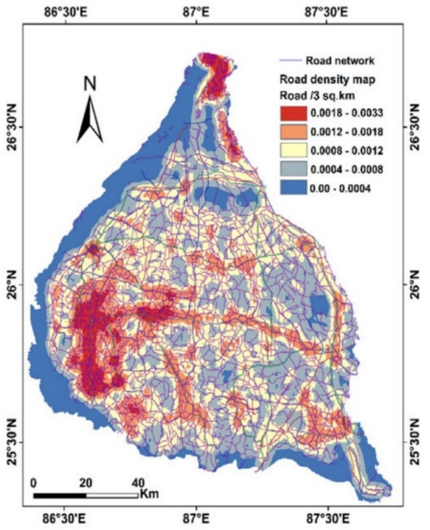

Fig. 7. Road density map of the study area.

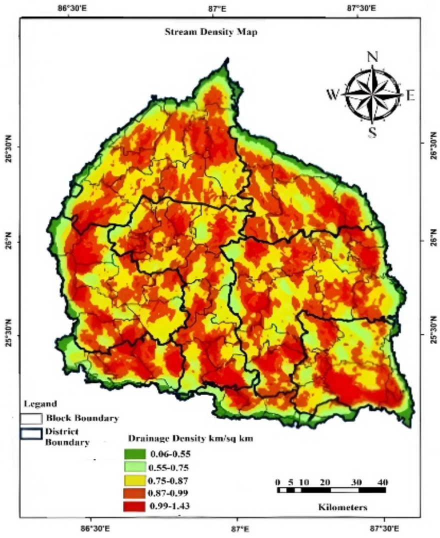

Fig. 8. Drainage density map of the study area.

Table V presents a set of factors and their corresponding FAHP weights designed for use in flood hazard mapping. These weights represent the relative importance of each factor in determining the flood hazards within a given geographic area. These factors include rainfall, LULC, drainage density, slope, and road density. Assigning these weights is crucial for accurately assessing the flood risk, with higher weights indicating greater significance. For instance, the rainfall factor had a weight of 0.25, signifying its substantial impact on the flood hazard assessment, followed by road density with a weight of 0.22. Each weight was normalized to ensure that its sum was equal to 1, facilitating a comprehensive assessment of flood susceptibility based on multiple contributing factors.

TABLE V. WEIGHTS OF DIFFERENT FACTORS USED IN FAHP

Factors	Fuzzy AHP weight	Fuzzy AHP weight (%)
Rainfall	0.25	25
LULC	0.18	18
Drainage density	0.20	20
Slope	0.15	15
Road density	0.22	22

B. Flood Hazard Mapping

In this study, a risk map was generated using a simple method that involved multiplying categorized flood hazard maps with the Raster Calculator tool in the ArcGIS software environment. Subsequently, the resultant map was classified into five main categories (Very Low, Low, Moderate, High, and Very High) putting into service the Reclassify tool (Figure 9). To determine the areas within different risk classes, the Tabulate Area (Zonal) tool was employed to calculate the district and block areas. The results of this investigation revealed a spectrum of land risks in the 10 districts surveyed, Madhubani exhibiting the highest proportion of land designated as very high risk. Flood risks in high-risk areas such as Madhubani have profound socioeconomic impacts on local communities. Recurrent flooding exacerbates poverty by destroying homes, personal property, and local infrastructure, leading to costly rebuilding efforts that many residents cannot afford. Floods disrupt essential services, such as education and healthcare, causing schools to close and limiting the access to medical facilities during and after flood events. This disruption has long-term effects on the community health and educational outcomes.

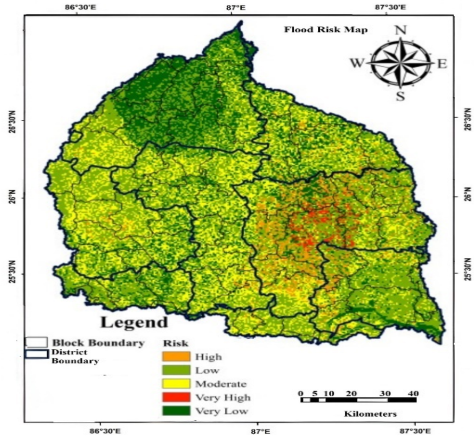

Fig. 9. Flood hazard map of the study area.

Critical infrastructure, including roads and bridges, is often damaged or destroyed by floods, which isolate communities and hinder economic activities. Agricultural productivity, a primary source of livelihood for many in Madhubani, is severely affected by floods washing away crops, erosion of fertile soil, and damage to irrigation systems. This loss of agricultural output leads to food insecurity and reduced incomes for farming households, further entrenching economic instability. Purnia and Madhepura also showed substantial areas being classified as of high risk. Conversely, regions such as Supaul boast significant expanses being marked as of very low risk, indicating comparatively safer environments. Araria, Munger, and Supaul stand out for their extensive and low-risk areas. Notable concentrations of high-risk areas include Raniganj in Araria district as well as Krityanand Nagar, Damdaha, Barhara, Bhawanipur, and Banmankhi in the Purnia region. In the Supaul district, the Supaul region also registers significant land being classified as of high-risk.

V. CONCLUSIONS

This study presents a practical approach for flood risk mapping in the Kosi River Basin area by combining the Fuzzy Analytical Hierarchy Process (FAHP) and Geographic Information Systems (GIS). This integrated method provides important information for decision makers and policymakers to analyze and manage flood events in the region. This facilitates the evaluation of the effectiveness of the drainage network infrastructure and identifies the necessary developments to reduce flood risks. Consistency ratios were computed during the decision-making process to maintain the credibility of the approach and findings. This methodology shows potential for use in various flood-prone areas with scarce data and mapping resources. Significantly, certain areas highlighted on the map presented high hazard risks, even without previous inundation occurrences, owing to the influence of other significant factors. Utilizing high-resolution imagery and Digital Elevation Models (DEMs) enhances mapping accuracy and efficiency. The results of this study emphasize the effectiveness of integrating FAHP and GIS techniques, providing decision-makers with a robust tool for assessing flood risk. These methodologies enable the coherent and effective use of spatial data, helping in informed decision-making processes.

However, several limitations must be considered. First, the accuracy of this study's results was contingent on the quality and resolution of the input data. Any inaccuracies in the input datasets can propagate through the model, potentially affecting the reliability of flood susceptibility maps. Second, although the proposed model has been proven effective in the study area, its generalization to other regions with different hydrological and climatic conditions may pose challenges. Variations in local geography, climate patterns, and land use practices could impact the applicability of the model and require region-specific adjustments.

REFERENCES

[1] A. Dixit, "Floods and Vulnerability: Need to Rethink Flood Management," *Natural Hazards*, vol. 28, no. 1, pp. 155–179, Jan. 2003, https://doi.org/10.1023/A:1021134218121.

[2] J. F. León-Cruz, D. Romero, and H. I. Rodríguez-García, "Spatial and Temporal Changes in Social Vulnerability to Natural Hazards in Mexico," *ISPRS International Journal of Geo-Information*, vol. 13, no. 3, Mar. 2024, Art. no. 66, https://doi.org/10.3390/ijgi13030066.

[3] A. Maulana, M. Tumpu, I. P. Indriani, and I. Utama, "Flood Sedimentology for Future Floods Mitigation in North Luwu, Sulawesi, Indonesia," *Civil Engineering Journal*, vol. 9, no. 4, pp. 906–914, Apr. 2023, https://doi.org/10.28991/CEJ-2023-09-04-011.

[4] B. M. Leta, D. Adugna, and A. A. Wondim, "Comprehensive investigation of flood-resilient neighborhoods: the case of Adama City, Ethiopia," *Applied Water Science*, vol. 14, no. 2, Jan. 2024, Art. no. 14, https://doi.org/10.1007/s13201-023-02053-7.

[5] L. Tarasova, B. Ahrens, A. Hoff, and U. Lall, "The Value of Large-Scale Climatic Indices for Monthly Forecasting Severity of Widespread Flooding Using Dilated Convolutional Neural Networks," *Earth's Future*, vol. 12, no. 2, 2024, Art. no. e2023EF003680, https://doi.org/10.1029/2023EF003680.

[6] S. Rajkhowa and J. Sarma, "Climate change and flood risk, global climate change," in *Global Climate Change*, S. Singh, P. Singh, S. Rangabhashiyam, and K. K. Srivastava, Eds. Elsevier, 2021, pp. 321–339.

[7] K. Loumi and A. Redjem, "Integration of GIS and Hierarchical Multi-Criteria Analysis for Mapping Flood Vulnerability: The Case Study of M'sila, Algeria," *Engineering, Technology & Applied Science Research*, vol. 11, no. 4, pp. 7381–7385, Aug. 2021, https://doi.org/10.48084/etasr.4266.

[8] P. Guayjarernpanishk, P. Bussababodhin, and M. Chiangpradit, "The Partial L-Moment of the Four Kappa Distribution," *Emerging Science Journal*, vol. 7, no. 4, pp. 1116–1125, Jul. 2023, https://doi.org/10.28991/ESJ-2023-07-04-06.

[9] Z. W. Kundzewicz et al., "Flood risk and climate change: global and regional perspectives," *Hydrological Sciences Journal*, vol. 59, no. 1, pp. 1–28, Jan. 2014, https://doi.org/10.1080/02626667.2013.857411.

[10] I. Arianti, M. Rafani, N. Fitriani, and Nizar, "Spatial Modeling of Flood-Vulnerability as Basic Data for Flood Mitigation," *Civil Engineering Journal*, vol. 9, no. 4, pp. 787–798, Apr. 2023, https://doi.org/10.28991/CEJ-2023-09-04-02.

[11] C. Raymond et al., "Understanding and managing connected extreme events," *Nature Climate Change*, vol. 10, no. 7, pp. 611–621, Jul. 2020, https://doi.org/10.1038/s41558-020-0790-4.

[12] T. D. C. Luu, "Flood risk analysis and spatial flood risk assessment for Vietnam," Ph.D dissertation, University of Newcastle, Australia, 2018.

[13] A. Hallil and A. Redjem, "Assessment of Urban Vulnerability to Flooding Using Multi-Criteria Analysis: The Case Study of El Bayadh City, Algeria," *Engineering, Technology & Applied Science Research*, vol. 12, no. 2, pp. 8467–8472, Apr. 2022, https://doi.org/10.48084/etasr.4828.

[14] O. Singh and M. Kumar, "Flood occurrences, damages, and management challenges in India: a geographical perspective," *Arabian Journal of Geosciences*, vol. 10, no. 5, Feb. 2017, Art. no. 102, https://doi.org/10.1007/s12517-017-2895-2.

[15] P.-H. Nguyen, L.-A. T. Nguyen, H.-A. T. Pham, and M.-A. T. Pham, "Breaking ground in ESG assessment: Integrated DEA and MCDM framework with spherical fuzzy sets for Vietnam's wire and cable sector," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 9, no. 3, Sep. 2023, Art. no. 100136, https://doi.org/10.1016/j.joitmc.2023.100136.

[16] H. Cheemakurthy and K. Garme, "Fuzzy AHP-Based Design Performance Index for Evaluation of Ferries," *Sustainability*, vol. 14, no. 6, Jan. 2022, Art. no. 3680, https://doi.org/10.3390/su14063680.

[17] R. B. Mudashiru, N. Sabtu, I. Abustan, and W. Balogun, "Flood hazard mapping methods: A review," *Journal of Hydrology*, vol. 603, Dec. 2021, Art. no. 126846, https://doi.org/10.1016/j.jhydrol.2021.126846.

[18] T. Saaty, "The analytic hierarchy process (AHP) for decision making," presented at the Kobe, Japan, 1980, vol. 1, Art. no. 69.

[19] T. Eldamaty, A. G. Ahmed, and M. M. Helal, "GIS-Based Multi Criteria Analysis for Solar Power Plant Site Selection Support in Mecca," *Engineering, Technology & Applied Science Research*, vol. 13, no. 3, pp. 10963–10968, Jun. 2023, https://doi.org/10.48084/etasr.5927.

[20] M. S. Dwi Putra, S. Andryana, Fauziah, and A. Gunaryati, "Fuzzy Analytical Hierarchy Process Method to Determine the Quality of Gemstones," *Advances in Fuzzy Systems*, no. 1, 2018, Art. no. 9094380, https://doi.org/10.1155/2018/9094380.

[21] J. Malczewski, *GIS and Multicriteria Decision Analysis*. Wiley, New York, 1999.

[22] D. E. Asuquo and F. E. Onuodu, "A Fuzzy AHP Model for Selection of University Academic Staff," *International Journal of Computer Applications*, vol. 141, no. 1, pp. 19–26, May 2016, https://doi.org/10.5120/ijca2016908969.

[23] P. Thamsatitdej, M. Jongpaiboon, P. Samaranayake, and T. Laosirihongthong, "Green supply chain management, triple bottom line, and organizational theory - prioritization with fuzzy AHP method," in *2015 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Singapore, Dec. 2015, pp. 1588–1592, https://doi.org/10.1109/IEEM.2015.7385915.

[24] R. SN. Mahmudah, D. I. Putri, A. G. Abdullah, M. A. Shafii, D. L. Hakim, and T. Setiadipura, "Developing a Multi-Criteria Decision-Making model for nuclear power plant location selection using Fuzzy Analytic Hierarchy Process and Fuzzy VIKOR methods focused on socio-economic factors," *Cleaner Engineering and Technology*, vol. 19, Apr. 2024, Art. no. 100737, https://doi.org/10.1016/j.clet.2024.100737.

[25] E. Mokhtari, B. Abdelkebir, A. Djenaoui, and N. E. H. Hamdani, "Integrated analytic hierarchy process and fuzzy analytic hierarchy process for Sahel watershed flood susceptibility assessment, Algeria," *Water Practice and Technology*, vol. 19, no. 2, pp. 453–475, Jan. 2024, https://doi.org/10.2166/wpt.2024.012.