Comparative Analysis of Flood Risk Zoning and Susceptibility Assessment for the Western Corn Belt Plains using Geospatial Techniques

S M Samiul Islam[1,2] * and Ibrahim Demir[3,4]

[1] IIHR Hydroscience and Engineering, University of Iowa, Iowa City, US.
[2] Civil and Environmental Engineering, University of Iowa, Iowa City, US.
[3] Department of River-Coastal Science and Eng, Tulane University, New Orleans, LA, USA
[4] Bywater Institute, Tulane University, New Orleans, LA, USA

Abstract

Flooding is among the most destructive natural hazards, causing severe socioeconomic and environmental impacts. Accurate flood susceptibility assessment is critical for effective mitigation and sustainable resource planning. This study integrates Geographic Information Systems (GIS), Remote Sensing (RS), and multi-criteria decision-making (MCDM) methods to evaluate flood vulnerability across four Iowa sub-basins: Middle Cedar, Lower Cedar, Middle Iowa, and Lower Iowa. Three approaches—Analytic Hierarchy Process (AHP), Fuzzy AHP (FAHP), and Equal Weighting (EW)—were applied to compare the influence of geophysical and socioeconomic factors. Key parameters included elevation, slope, land use/land cover (LULC), soil type, precipitation, river proximity, and low-income households. High-resolution (30-meter) datasets from SRTM DEM, Landsat-8, and TRMM precipitation sources were processed to develop composite flood susceptibility indices within a GIS framework. Results reveal significant spatial variability, with high-risk zones concentrated in low-lying areas near major rivers and socio-economically vulnerable urban regions. The Middle Cedar sub-basin exhibited the highest susceptibility, while Lower Cedar and Middle Iowa showed lower risk levels. FAHP demonstrated greater sensitivity in capturing risk variations compared to AHP and EW models. The findings underscore the importance of integrating physical and socioeconomic factors into flood assessments. They also highlight the need for targeted interventions, such as enhancing drainage infrastructure, equitable resource distribution, and supporting vulnerable populations. This study delivers a robust, scalable approach for flood susceptibility mapping, offering valuable insights for policymakers, urban planners, and disaster management authorities to enhance community resilience and guide flood mitigation strategies in Iowa and similarly flood-prone regions.

Keywords: Flood susceptibility, Iowa sub-basins, GIS and remote sensing, Multi-Criteria Analysis, and Flood risk assessment.

1. Introduction

Flooding is a devastating disaster, impacting millions and resulting in significant economic, social, and environmental repercussions (Jonkman, 2005; Vojinovic, 2015). In the United States, floods have persistently been among the most expensive disasters, with damages surpassing $11 billion throughout the 1990-2009 period (Wing et al., 2022; Yildirim et al., 2022). Furthermore, floods damage towns, displace inhabitants, and cause fatalities, leading to enduring social and economic difficulties (Jha et al., 2011; Alabbad et al., 2023). Despite significant investments surpassing $80 billion in flood management and mitigation by federal and state governments over the last twenty years, flood dangers continue, with the frequency and intensity of these occurrences anticipated to rise owing to climate change and urbanization (Jha et al., 2011; Louw et al., 2019). Such challenges highlight the essential requirement for efficient risk evaluation and management solutions for flooding and droughts to alleviate effects on at-risk populations (Islam et al., 2024).

Flooding happens due to a complex interaction of natural and human-driven factors (Di Baldassarre et al., 2013; Merz et al., 2014). Extreme rainfall, river overflow, and underdeveloped drainage systems are crucial physical triggers of floods (Douben, 2006; Merz et al., 2021; Schumacher, 2017; Seo et al., 2019). Elevation, slope, and proximity to water bodies intensify flood susceptibility since low-lying and steep terrain are more prone to water accumulation or channeling (Das, 2020; Gonzlez-Arqueros et al., 2018; Swain et al., 2020). Human activities, including land use and cover alterations, soil degradation, deforestation, and socioeconomic vulnerabilities, substantially increase flood risks by modifying natural water flow and diminishing the resilience of impacted regions (Li et al., 2020; Mullick et al., 2019). In addition, densely populated areas with a significant presence of low-income families are especially susceptible since constrained resources frequently hinder disaster planning and recovery initiatives (Satterthwaite, 2011).

Flood susceptibility has been addressed through a variety of approaches, from structural interventions like building levees, dams, and drainage systems to non-structural ones like public education campaigns, policy-based land use regulations, and early warning systems (Kumar et al., 2021). However, the effectiveness of structural and non-structural solutions still depends on identifying and mapping flood-prone locations (Grant et al., 2024). By giving policymakers, urban planners, and community leaders a scientific foundation for decision-making, flood susceptibility mapping helps them prioritize mitigation initiatives, distribute resources efficiently, and improve disaster preparation (Rehman et al., 2019; Rodrguez-Espndola et al., 2018).

Different approaches and techniques have been utilized to evaluate flood hazards. Most research on flood risk is based on climatic and hydrological elements that influence the probability of flooding (Cea & Costabile, 2022; Kundzewicz et al., 2014; Steinschneider et al., 2015). Hydrological models are frequently employed to forecast the extent of floods and their possible effects on people and infrastructure (Johnston & Smakhtin, 2014; Mujumdar & Kumar, 2012; Rozalis et al., 2010). These models incorporate data such as rainfall, land use, soil properties, and other variables to simulate how water behaves during a flooding event. The results from these models can help identify areas vulnerable to flooding and evaluate the possible effects of floods on buildings and infrastructure (Alabbad et al., 2024). Although modeling is generally a robust tool, it depends on statistical data and does not account for other significant factors like exposure impact and land use (Kopp et al., 2019; Van Westen, 2013).

While sophisticated methods, such as machine learning algorithms and hydrological modeling, have been applied to environmental and flood risk assessment (Bayar et al., 2009; Krajewski et al., 2021), these techniques often require extensive data and computational resources (Agliamzanov et al., 2020), making them less accessible for practical applications in resource-limited settings. Consequently, the MCDA approach remains preferred for its balance between robustness and feasibility (De Montis et al., 2000; Wahlster et al., 2015; Zheng et al., 2016). The MCDA approach considers various criteria and objectives when evaluating the risk of flooding. It also entails recognizing different factors associated with flood risk, including the frequency, severity, and duration of floods, and assigning weights based on their significance. MCDA method has emerged as one of the most widely used techniques for flood risk mapping due to its adaptability, simplicity, and effectiveness (Abdullah et al., 2021; De Brito & Evers, 2016).

MCDA combines spatial datasets, such as digital elevation models (DEMs), precipitation patterns, soil type, and socioeconomic data, to identify regions at varying levels of flood susceptibility. Using the MCDA approach, decision-makers can discern the most pressing flood hazards and prioritize measures to mitigate flood risk (Dutta & Deka, 2024; Levy et al., 2007). It has been successfully employed in diverse geographical contexts, ranging from urban flood management in developed countries to coastal vulnerability assessments in regions worldwide. Geographic Information Systems (GIS) and Remote Sensing (RS) technologies are other tools widely used for different kinds of hazard analysis (Li et al., 2023; Sit et al., 2021). Advances in Geographic Information Systems (GIS) and Remote Sensing (RS) technologies have revolutionized flood risk assessment by providing tools and technologies to integrate and analyze spatial data (Eniolorunda, 2014; Munawar et al., 2022; Li and Demir, 2024). GIS-based approaches efficiently generate flood susceptibility maps, incorporating multiple physical, climatic, and socioeconomic factors into a comprehensive analysis (Deroliya et al., 2022; Hussain et al., 2021; Xu et al., 2019).

The Analytic Hierarchy Process is another widely recognized technique that provides a rigorous methodology for quantifying the weights of decision-making criteria (Bernasconi et al., 2010; Saaty & Vargas, 2012). As a structured, hierarchical approach to multi-criteria analysis, AHP facilitates the organization, evaluation, and synthesis of complex judgments (Wind & Saaty, 1980). This methodology has been extensively applied in water resource management and hydrology, particularly in tasks such as delineating recharge zones and assessing flood risk (Chen et al., 2016; Jha et al., 2014; Malczewski, 1999; Ozsahin et al., 2021). Despite its effectiveness, AHP is inherently subjective, as it heavily relies on expert judgment, introducing ambiguity into the decision-making process (Vargas, 1990).

To mitigate this subjectivity, the Fuzzy Analytic Hierarchy Process integrates fuzzy logic with AHP, thereby enhancing decision-making under conditions of uncertainty. FAHP has been widely employed to assess and prioritize factors contributing to flood exposure risk, particularly in arid regions (Kahraman et al., 2003; Saaty, 1996; Wang et al., 2020; Alabbad & Demir, 2024). While fuzzy logic provides a mathematical framework for managing imprecision and uncertainty, AHP is a robust multi-criteria decision-making tool for evaluating and ranking alternatives (Buckley, 1985; Zadeh, 1965). By combining these two methodologies, FAHP offers a more refined and comprehensive assessment of flood exposure risk (Lee et al., 2012). Given its ability to accommodate uncertainty, FAHP has emerged as a critical tool for prioritizing flood risk factors in hydrological studies (Ali & Ahmad, 2020; Y. Chen et al., 2013; Saaty, 2008).

The fuzzy extension of AHP enables decision-making in uncertain environments by representing imprecise criteria through fuzzy numbers. Unlike traditional AHP, which relies on exact numerical comparisons, FAHP employs a fuzzy judgment matrix that accommodates inconsistencies in expert assessments. This technique derives crisp weight values from both consistent and inconsistent fuzzy comparison matrices, eliminating the need for additional aggregation and ranking operations (Mikhailov, 2003).

Recent studies have leveraged fuzzy logic to evaluate flood exposure risk in arid regions by incorporating geospatial and environmental factors, such as topography, land use, and soil type (Mendoza & Martins, 2006). In these assessments, the AHP framework was utilized to determine the relative weights of contributing datasets, which were subsequently used to compute fuzzy values. This methodological approach integrates qualitative decision-making techniques, such as AHP, with soft computing methodologies, such as fuzzy logic (Bellman & Zadeh, 1970).

In this study, flood risk is quantified based on two primary components: exposure impact and the probability of occurrence. The probability of occurrence is estimated using the Fuzzy Analytic Hierarchy Process and fuzzy logic, allowing for a comparative analysis of their efficacy. The proposed framework is applied to a case study in four sub-basins of Iowa: Middle and Lower Cedar Rapids and Middle and Lower Iowa sub-basins. These regions have had many catastrophic floods in recent decades, notably in 1993, 2008, and 2019, which resulted in extensive devastation and required substantial federal assistance (Longenecker Iii, 2019). This investigation applies GIS and RS technologies to generate precise flood susceptibility maps to examine the cumulative impact of several parameters, including elevation, slope, proximity to water bodies, land use and land cover (LULC), soil type, and socioeconomic vulnerabilities.

The study uses a 30-meter resolution across all datasets, allowing a micro-level analysis that yields practical insights for localized flood control and planning. This study's findings enhance the field of flood risk assessment by providing a reproducible and scalable approach for high-resolution flood susceptibility mapping. This methodology might improve urban planning, infrastructure development, and disaster management techniques in Iowa and other locations with analogous flood-related issues. The research integrates physical, meteorological, and socioeconomic data into a cohesive framework, emphasizing the interrelation of elements affecting flood threats and the necessity of comprehensive measures to bolster community resilience.

2. Materials and Methods

Flood hazard is inherently characterized as an adverse event and is quantitatively assessed through the cross-product of its probability and associated impact (Kirk, 1991). It is formally defined as the likelihood of a flood with adverse consequences (Ostrom & Wilhelmsen, 2019). The probability of occurrence is determined by evaluating various factors influencing flood events, while the impact is assessed based on land use and land cover characteristics (Avand & Moradi, 2021).

The probability of flood hazard is influenced by various hydrogeological factors, with precipitation intensity and duration, along with topography being the primary determinants in flood analysis. The slope of an area is also crucial for the susceptibility of flooding, which identifies areas where surface runoff is likely to converge during precipitation events (Kazakis et al., 2015; Msabi & Makonyo, 2021; Vojtek & Vojteková, 2019). Additional critical factors include land cover, soil type, surface runoff, and distance to water bodies (Diakakis et al., 2016). Due to low income, people hardly maintain their property, which exposes their vulnerability to a greater risk (Satterthwaite, 2011; Tanir et al., 2024). This study also considered the mean household income level to quantify the flood susceptibility spectrum.

Saaty (1987) introduced the Analytic Hierarchy Process as a systematic approach for multi-criteria decision-making (Saaty, 1987; Saaty, 1977; 1978). This method provides a structured framework for evaluating multiple criteria, comparing them in pairs, and incorporating expert judgment to achieve a specific objective. The AHP assigns weight to each criterion, facilitating a rational decision-making process. Since its development, the AHP has been widely applied to various fields, including water quality assessment, ecological studies, groundwater recharge analysis, and vulnerability evaluation (Munpa et al., 2022; Ouma & Tateishi, 2014; Sutadian et al., 2017; Zhang et al., 2014).

Despite its effectiveness in decision-making, the AHP does not account for uncertainties inherent in the numerous variables involved. The Fuzzy Analytic Hierarchy Process was introduced to address this limitation, allowing for a broader range of values in the evaluation process. Zadeh (1965) proposed Fuzzy Logic (FL) as an alternative to the classical Boolean (0–1) approach, providing greater flexibility in parameter assessment. Unlike traditional binary logic, fuzzy logic employs membership functions to represent degrees of truth rather than absolute true or false values. While FL is designed to manage uncertainty, the FAHP is specifically tailored to enhance decision-making in multi-criteria analyses. The FAHP extends the AHP methodology by incorporating fuzzification, replacing conventional verbal assessments with weighted pairwise comparisons.

This study applies FAHP, AHP, and equal weighting methods to assess flood hazard in the corn belt of the Midwest (Iowa), as illustrated in Figure 1. Key factors influencing flood probability include elevation, slope, precipitation, land use and land cover, soil type, distance from adjacent rivers or waterbodies, and income level. Flow accumulation inherently accounts for land slope by determining the direction of runoff based on topography. Soil type plays a crucial role in runoff and infiltration processes, as different soil compositions exhibit varying infiltration capacities.

Land cover further influences runoff characteristics, while precipitation serves as a fundamental driver of flood events, with higher rainfall intensities increasing the likelihood of flash floods. Higher elevations are generally less prone to flooding, making elevation an essential factor in flood hazard assessment.

2.1. Study Area

The research covers four sub-basins in Iowa: The Middle and Lower Cedar Rapids sub-basins and the Middle and Lower Iowa sub-basins, areas susceptible to frequent flooding and considerable socioeconomic repercussions. The sub-basins in eastern Iowa differ in size, with the Middle Cedar being the largest at 2,416 square miles and the Lower Cedar the smallest at 1,098 square miles (Figure 1). They comprise an intricate system of streams and rivers that contribute to larger water bodies, like the Mississippi River. Low-lying regions adjacent to these water bodies are more susceptible to intense precipitation and seasonal snowmelt, increasing flood hazards.

The humid continental climate of Iowa intensifies floods in these regions, with storms and elevated precipitation reaching its peak in spring and summer (Andresen et al., 2012). Agricultural practices, a primary land use in the sub-basins, exacerbate surface runoff due to intensive plowing and diminished plant cover (Bilotta et al., 2007; Wang & Li, 2019). Urban regions such as Cedar Rapids contribute impermeable surfaces, augmenting runoff during precipitation events. The depletion of natural flood buffers, like forests and wetlands, exacerbates these vulnerabilities, rendering the region increasingly prone to severe and extensive flooding.

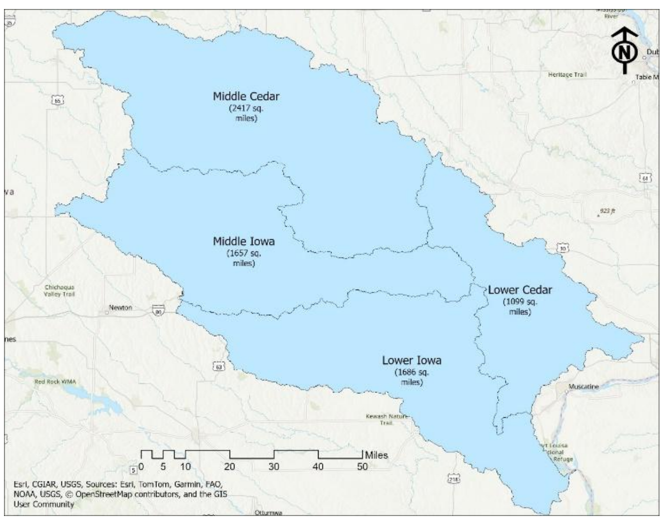

Figure 1. Study area map (name of sub-basin and area are in parenthesis).

The American Community Survey states that a substantial proportion of the population is classified as moderate to low-income, and the sub-basins exhibit socioeconomic diversity. Affordable housing is frequently located in flood-prone regions, exacerbating potential hazards due to these communities' limited resources and inadequate infrastructure. The necessity of confronting these issues was underscored by the devastating floods of 1993, 2008, and 2019, which resulted in extensive devastation and relocation. The study provides a comprehensive flood susceptibility analysis for these sub-basins to assist policymakers, planners, and community leaders formulate effective mitigation solutions (Yildirim et al., 2023). Additionally, it provides a reproducible technique for similar locations.

2.2. Data and Methods

This study used a GIS and Remote Sensing-based multi-criteria analysis (MCDA) framework to develop flood susceptibility maps for the Middle and Lower Cedar Rapids and Middle and Lower Iowa subbasins in Iowa. The technique used numerous physical, hydrological, and economic variables to assess flood susceptibility at a 30-meter spatial resolution. The investigation followed a systematic procedure encompassing data collecting, preprocessing, factor categorization, and flood susceptibility modeling.

2.2.1. AHP Method in Flood Susceptibility Analysis

The Analytic Hierarchy Process was developed to address complex decision-making problems involving multiple criteria (Saaty, 1987). This methodology employs a mathematical framework to evaluate decisions by incorporating the preferences of decision-makers or expert groups within a specific domain based on predefined factors. AHP effectively bridges the gap between practical requirements and scientific decision-making by integrating qualitative and quantitative analyses, enhancing decision-making efficiency and effectiveness in complex scenarios (Yang et al., 2018). The implementation of the AHP method follows five key stages: (1) defining the problem and identifying relevant parameters, (2) assigning parameter ratings using the AHP scale, (3) constructing a pairwise comparison matrix, (4) calculating the relative weights of each parameter, and (5) assessing the consistency ratio (CR) to ensure the reliability of the evaluation.

The pairwise comparison matrix represents the relative significance of numerical values based on the AHP scale (Table 1). This matrix is constructed using a standardized mathematical approach to compare criteria in relation to one another systematically. The formulation for generating the pairwise comparison matrix is given by Equation (1).

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{n1} \end{pmatrix} \quad \text{Eq. 1}$$

Equation 1 facilitates a comparative analysis between two factors. If the value of a factor in each row holds greater significance than the corresponding factor in the column, it is assigned a value ranging from 1 to 9. Conversely, if the factor in the row is less important than the one in the column, it is assigned a reciprocal value between $1/2$ and $1/9$. Additionally, the diagonal elements of the comparison matrix are inherently equal to 1. Based on the scale interpretation outlined in Table 1, comparison matrices were established for all the parameters, structured according to the relative importance of the parameters (Tables 2 and 3). After that, the normalization of the matrix is required by applying the following Eq.2 and Eq.3:

$$b_{ij} = \frac{a_i}{\sum_{i=1}^{n} a_{ij}} \qquad \text{Eq. 2}$$

$$A = \begin{pmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ b_{n1} & b_{n2} & \cdots & b_{nm} \end{pmatrix} \qquad \text{Eq. 3}$$

Table 1. Pairwise comparison matrices for all the parameters in the AHP

Parameters	Elevation	River Distance	Precip.	LULC	Soil Type	Slope	HH - Low Income
Elevation	1	2	3	2	2	3	4
River Distance	0.5	1	2	1	1	2	3
Precipitation	0.33	0.5	1	1	0.5	1	2
LULC	0.5	1	1	1	0.5	1	2
Soil Type	0.5	1	2	2	1	2	3
Slope	0.33	0.5	1	1	0.5	1	2
Low Income HH	0.25	0.33	0.5	0.5	0.33	0.5	1
	λmax = 6.069; **CI** = 0.0138; **RI** (for n = 7) = 1.24; **CR** = 0.0111						

Table 2. Random index value (RI) by (R. W. Saaty, 1987)

N	1	2	3	4	5	6	7	8
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41

To find the weight of each parameter, the average of each row is estimated in the normalized pairwise comparison matrix using Eq. 4 in the following:

$$W_i = \frac{\sum_{j=1}^{n} b_{ij}}{n} \ and \ \sum_{i=0}^{n} W_i = 1 \qquad \text{Eq. 4}$$

Here, the number of factors is shown by 'n.' After that, the consistency ratio (CR) is quantified to evaluate the consistency of the comparison. The consistency ratio (CR) is computed to assess the reliability of the pairwise comparisons. A zero consistency index (CI) value indicates a perfectly consistent matrix (Dwi Putra et al., 2018). Furthermore, if the CR value is less than 0.1, the pairwise comparison matrix exhibits an acceptable level of consistency. Conversely, a CR value exceeding 0.1 suggests inconsistencies in the assessments. The CR is determined as the ratio of the consistency index (CI) to the random index (RI), as expressed in Eq. 5 and 6 in the following:

$$CI = \frac{\lambda \max - n}{n - 1} \quad \text{Eq. 5}$$

$$CR = \frac{Consitency\ Index(CI)}{RandomIndex(RI)} \quad \text{Eq. 6}$$

2.2.2. Fuzzy AHP in Flood Susceptibility Analysis

In the Analytic Hierarchy Process, assigning numerical values to parameters is inherently subjective, as it relies on human judgment and preference. Consequently, representing these values precisely with crisp numbers is challenging. The fuzzy set theory was introduced to address this, providing a more practical approach incorporating uncertainty and minimizing errors in human judgment (Ahmed et al., 2018; Zadeh, 1965). Recently, several Fuzzy AHP methodologies have been developed, including those proposed by several scholars (Buckley, 1985; Chang, 1996). Among these methods, Fuzzy Extent Analysis, introduced by Chang (1996), has been recognized as particularly suitable for risk assessment applications (Radionovs & Uzhga-Rebrov, 2017).

This study employs the FAHP approach to identify flood susceptibility zones by following a structured process. The methodology consists of five key stages: first, the Fuzzy Judgment Matrix is developed; second, the Fuzzy Synthetic Extent Value (Si) is calculated; third, the Magnitude of Si is determined; fourth, the Factor Weights are computed; and finally, the Final Weight Factors are normalized. The Fuzzy Judgment Matrix is constructed by integrating the pairwise comparison matrix with Triangular Fuzzy Numbers (TFN), a fundamental concept in fuzzy set theory. A TFN is represented as (l, m, u), where l denotes the lower bound (minimum value), m represents the most likely (middle) value, and u signifies the upper bound (maximum value) of the fuzzy set. The fuzzy judgment matrices corresponding to the seven selected parameters are shown in Table 3. After defining the triangular fuzzy numbers, the fuzzy judgment matrix is established to facilitate further analysis in flood susceptibility assessment.

$$\tilde{A} = \begin{bmatrix} \breve{1} & \breve{a}_{12} & \dots & \breve{a}_{1n} \\ \breve{a}_{21} & \breve{1} & \dots & \breve{a}_{2n} \\ \dots & \dots & \breve{1} & \dots \\ \breve{a}_{n1} & \breve{a}_{n2} & \dots & \breve{1} \end{bmatrix} \quad \text{Eq. 7}$$

The computation of the magnitude of S_i is performed by calculating $S_1 = (l_1; m_1; u_1)$ and $S_2 = (l_2; m_2; u_2)$, where $S_1 \geq S_2$ is expressed by the following Eq. 8:

$$V\ (S_1 \geq S_2)$$

$$V = \left\{ \begin{array}{c} 1\ if\ m_1 \geq m_2 \\ O\ if\ l_2 \geq u_1 \\ \frac{l_2 - u_1}{(m_1 - u_1) - (m_2 - l_2)}\ otherwise \end{array} \right\} \quad \text{Eq. 8}$$

The FAHP-derived weights for each parameter are determined using Equation (9), which quantifies the magnitude of a convex fuzzy number. This calculation is based on the degree of possibility associated with the fuzzy number derived from 'k,' providing a structured approach to assessing the relative importance of parameters in the decision-making process.

$$V(S \geq S_1, S_2, \ldots S_k) = V(S \geq S_1) \text{ and } (S \geq S_2) \text{ and } (S \geq S_k) \qquad \text{Eq. 9}$$
$$V = \min V(S \geq S_i),\ i = 1, 2, \ldots, k$$

The weights of the factors (W′) are determined using Equations (10) and (11), which provide a mathematical framework for calculating the relative significance of each factor in the analysis.

$$d'(Ai) = \min V(Si \geq Sk), for\ k = 1, 2, \ldots, n;\ k \neq i \qquad \text{Eq. 10}$$
$$W' = \left(d'(A1), d'(A2), \ldots, d'(An)\right) \qquad \text{Eq. 11}$$

In the final stage, the computed parameter weights are normalized to derive a non-fuzzy numerical value, ensuring consistency in the decision-making process. This normalization process is performed using Eq. 12, expressed as:

$$W(A_i) = \frac{d'(A_i)}{\sum W'} \qquad \text{Eq. 12}$$

Table 3. Fuzzy judgment matrix for geophysical and socioeconomic parameters in the FAHP method.

Parameters	**DEM (Elevation)**	**River Distance**	**Precip.**	**LULC**	**Soil Type**	**Slope**	**Drainage Density**	**HH - Low Income**
DEM (Elevation)	(1, 1, 1)	(2, 3, 4)	(2, 3, 4)	(3, 4, 5)	(2, 3, 4)	(3, 4, 5)	(2, 3, 4)	(4, 5, 6)
River Distance	(0.25, 0.33, 0.5)	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(2, 3, 4)
Precipitation	(0.25, 0.33, 0.5)	(0.33, 0.5, 1)	(1, 1, 1)	(1, 2, 3)	(0.5, 1, 2)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)
LULC	(0.2, 0.25, 0.33)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(1, 1, 1)	(0.33, 0.5, 1)	(0.5, 1, 2)	(0.5, 1, 2)	(1, 2, 3)
Soil Type	(0.25, 0.33, 0.5)	(0.33, 0.5, 1)	(0.5, 1, 2)	(1, 2, 3)	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)	(2, 3, 4)
Slope	(0.2, 0.25, 0.33)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.5, 1, 2)	(0.33, 0.5, 1)	(1, 1, 1)	(1, 2, 3)	(2, 3, 4)
Drainage Density	(0.25, 0.33, 0.5)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.5, 1, 2)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(1, 1, 1)	(2, 3, 4)
Low-income HH	(0.17, 0.2, 0.25)	(0.25, 0.33, 0.5)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.25, 0.33, 0.5)	(0.25, 0.33, 0.5)	(0.25, 0.33, 0.5)	(1, 1, 1)

2.2.3. Data Collection

This study combines various geospatial datasets to assess the factors affecting the target phenomenon. The chosen datasets, classified into characteristic, forcing, and socioeconomic factors, are sourced from publicly available materials, guaranteeing spatial and temporal consistency.

2.2.3.1. Characteristics Factors

Topographic and land surface features are essential for environmental analysis. This study uses elevation data sourced from the Shuttle Radar Topography Mission (SRTM)-based Digital Elevation Model (DEM) with a resolution of 30 meters (USGS Earth Explorer, https://earthexplorer.usgs.gov). We calculate DEM-derived parameters, like slope, to evaluate terrain variations that affect hydrological processes and land stability. Land use and land cover (LULC) data were obtained from Landsat-8 multi-spectral images captured on March 23, 2024, offering a spatial resolution of 30 meters. This dataset reveals changes in land surfaces and their potential effects on environmental processes. The imagery was retrieved from the USGS Earth Explorer (https://earthexplorer.usgs.gov). Soil characteristics were integrated using FAO-based soil data, initially in vector format, then converted to raster to ensure compatibility with geospatial analysis workflows (FAO Soils Portal, https://www.fao.org/soils-portal/data-hub/en). These soil properties impact water retention, permeability, and the overall stability of land, making them critical factors in environmental modeling.

2.2.3.2. Environmental Forcing Factors

External factors such as rainfall and proximity to rivers affect the environmental and hydrological dynamics of the study area. Precipitation data were sourced from the Tropical Rainfall Measuring Mission (TRMM) and the TRMM Multi-satellite Precipitation Analysis (TMPA) from 2000 to 2022. These datasets offer high-resolution, satellite-derived precipitation estimates crucial for understanding climate variability and hydrological reactions (NASA DISC, https://disc.gsfc.nasa.gov/datasets/TRMM_3B42_Daily_7). The proximity to river networks was evaluated by creating a distance-to-river map for Iowa using stream-line shapefiles. This dataset, obtained from Iowa's Geodata Portal (https://geodata.iowa.gov), was processed through spatial analysis methods to assess hydrological connectivity and the risk of flooding.

2.2.3.3. Socioeconomic Factors

Understanding socio-environmental dynamics requires integrating demographic and economic data. This study assessed socioeconomic vulnerability through the proportion of low-income populations, sourced from the 2024 American Community Survey (ACS) 1-year estimates at the census tract-group level. This dataset offers insights into economic disparities and their spatial distribution (US Census Bureau, https://www.census.gov). All datasets underwent preprocessing, including standardization of coordinate systems, resampling, and reclassification, to ensure compatibility and integration within the geospatial framework. These multi-source datasets comprehensively assess the study region's environmental, hydrological, and socioeconomic interactions.

Table 4. Summary of datasets categorized into characteristics, environmental forcing, and socioeconomic factors, including sources and spatial resolutions.

Data Type	**Factors**	**Source**
Characteristics Factors	Elevation	The SRTM-based Digital Elevation Model (DEM) has a resolution of 30 meters. Data source: https://earthexplorer.usgs.gov/
	Land Use	30m resolution Landsat-8 multi-spectral imagery of June 23, 2024. Data source: https://earthexplorer.usgs.gov/
	Soil Type	FAO-based soil data was downloaded from https://www.fao.org/soils-portal/data-hub/en/ Moreover, it converted from a shapefile into a raster file.
	Slope	The slope was calculated from the DEM file.
Environmental Forcing Factors	Daily Rainfall	TRMM and TMPA-based mean daily precipitation data for the 2000-2022 period. Source: https://disc.gsfc.nasa.gov/datasets/TRMM_3B42_Daily_7/
	Distance from River	A stream-line shapefile for Iowa was used, and a distance map was produced to calculate the proximity to rivers. Source: https://geodata.iowa.gov/
Socioeconomic Factors	Low-Income HH	American Community Survey data of 2019 (5-year estimation) for census tract-group level. Source: https://www.census.gov/data.html

2.2.4. Data processing

Each dataset was preprocessed to ensure compatibility and consistency across spatial and temporal scales. To make the analysis compatible, all datasets were converted into raster files with a uniform 30-meter spatial resolution using GIS software. Feature-based data, such as soil type and census block group-based income level information, were rasterized to match the resolution. The Euclidean Distance tool in GIS was applied to calculate proximity to rivers, and slope data were derived from the SRTM DEM.

All parameters were resampled to a 30 × 30-meter grid using ArcGIS, ensuring uniformity across all data layers. Following the resampling process, each layer was classified into five flood risk categories using the work of Cikmaz et al. (2023), where 1 represents very low risk, 2 indicates low risk, 3 corresponds to moderate risk, 4 signifies high risk, and 5 represents very high risk, as outlined in Table 5. Since different indicators contribute variably to flood risk, AHP-derived weights were assigned to each parameter to generate a flood susceptibility map. The same procedure was subsequently applied using FAHP-derived weights instead of AHP weights. Seven flood risk maps were generated, based on AHP and the FAHP approach, enabling a comparative analysis of the two methodologies.

Table 5. Classification of the flood susceptibility parameters (Cikmaz et al., 2023)

Parameters	**Unit**	**Classes and Susceptibility Levels**				
		1 (Very Low)	**2 (Low)**	**3 (Moderate)**	**4 (High)**	**5 (Very High)**
Elevation	Meter	269-284	254-269	239-254	224-239	209-224
Land Use	-	Wetlands	open space/barren	cropland	developed	water bodies
Soil Type	-	loam sand / sandy clay loam	silty clay loam / organic silt loam	sand	clay loam	sandy loam
Slope	Degree	>15	8 - 15	4 - 8	2 - 4	0 - 2
Mean precipitation	mm	>125	110 - 125	87 - 110	62 - 87	<62
Distance from River	Meter	>1800	1200 - 1800	800 - 1200	500 - 800	0 – 500
Low-Income HH (annual)	USD	>$85,719	$85,719	$71,433	$57,146	<$42,860

For flood susceptibility calculation using both AHP and FAHP, the subsequent weights of each parameter are assigned according to their importance. The assigned weights for each parameter were initially obtained from Cikmaz et al. (2023), who applied the methodology approach in similar geographical areas. However, slight modifications were made to account for elevation, and income category as the geographical feature is slightly different from that to suit the context of this study better.

Table 6. Weights of geophysical and vulnerability parameters used in AHP and FAHP.

Type of Factors	**Parameters**	**AHP Weight**	**FAHP Weight**
Characteristics	Elevation	0.3	0.22
	Land Use	0.12	0.2
	Soil Type	0.21	0.2
	Slope	0.1	0.17
Environmental Forcing	Mean Precipitation	0.23	0.23
	Distance from River	0.26	0.21
Socioeconomic	Low-Income HH (annual)	0.07	0.14

2.2.5. Multi-Criteria Based Susceptibility

Flood susceptibility maps were produced by categorizing all characteristics into five classifications, from 1 (minimal susceptibility) to 5 (maximum susceptibility). Classification methods encompassed natural breaks for height and slope, designating higher altitudes and steeper slopes as less prone to floods. Proximity to rivers was inversely categorized, with regions nearer to water bodies allocated elevated susceptibility ratings. LULC categories, including loam soils and urbanized terrain, were deemed more susceptible to floods, while rocky soils were categorized as less susceptible. A raster calculator combined all categorized variables into a composite flood susceptibility index. A schematic diagram to combine the variables is shown in Figure 2. In contrast to other research, like the study of Franci et al., 2016, which utilized differential weighting for components, this study allocated weights based on Cikmaz et al. (2023) to all variables to guarantee a balanced evaluation and mitigate bias.

To illustrate the integration of multiple flood susceptibility factors, a schematic diagram was developed using a 3D GIS-based approach. This visualization combines key influencing factors, including elevation (DEM), household income, river distance, precipitation, land use land cover (LULC), soil type, and slope, each represented as distinct thematic layers. The stacked representation ensures a clear distinction between factors while maintaining their spatial relationships. Each layer contributes uniquely to the flood susceptibility assessment, with DEM providing topographic context, while hydrological and environmental factors influence runoff and flood extent. The multi-layered visualization effectively conveys how these parameters interact spatially, aiding in decision-making for flood risk assessment.

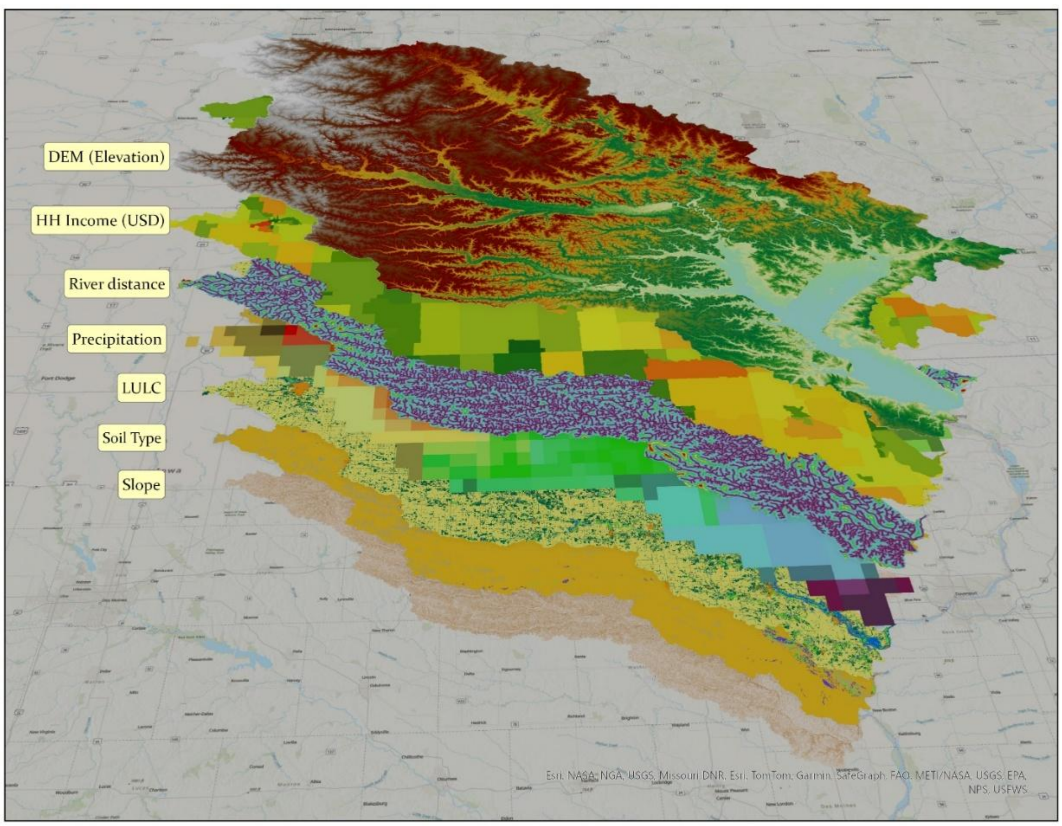

Figure 2. A schematic figure showing the combination method

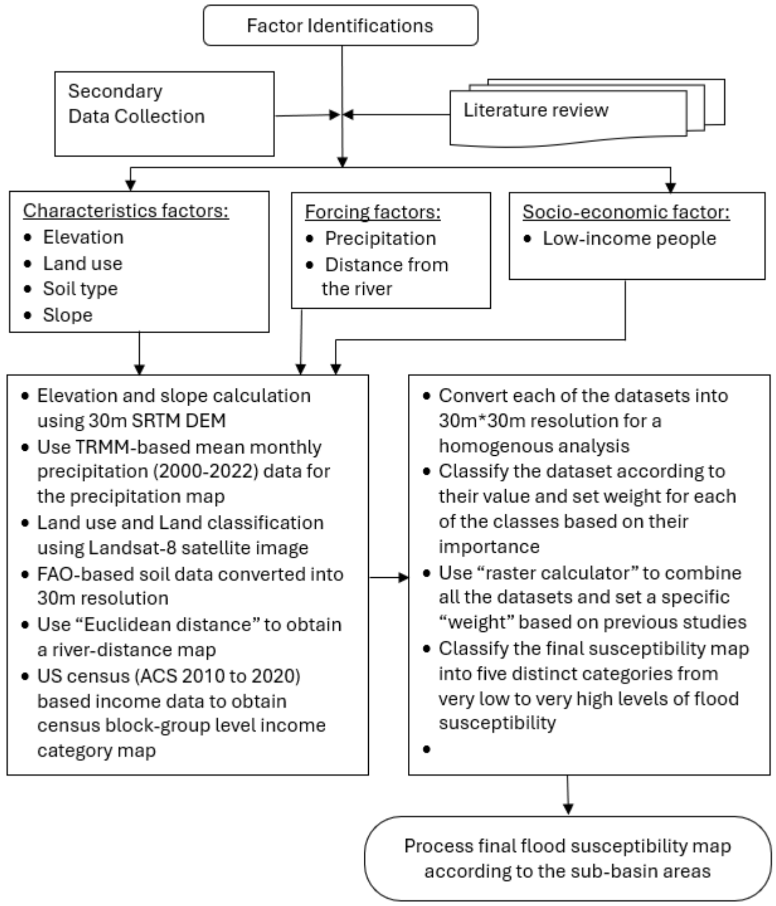

Figure 3. Methodology and workflow process.

3. Results and Discussion

The outcomes of this study are presented in the following sections, detailing the results obtained from the Fuzzy Analytic Hierarchy Process, the FAHP with equal weighting, and the fuzzy logic methodology.

3.1. Flood Susceptibility Analysis using AHP

The Analytic Hierarchy Process model was employed to assess each parameter's weight and verify the consistency ratio, given that this approach relies on expert judgment to determine the relative significance for all three types of flood susceptibility factors. Upon verification, the final weight factors for AHP and FAHP were calculated, as presented in Table 6. For characteristics and forcing parameters using AHP, elevation exhibited the highest relative weight of 0.30, followed by distance from the river and soil type, with weights of 0.26 and 0.21, respectively. Land use and slope were assigned lower influence levels, with weight values of 0.12 and 0.10, respectively. In terms of socioeconomic indicators, i.e., low-income households had the lowest influence, with a weight of 0.07, followed by a slope at 0.10.

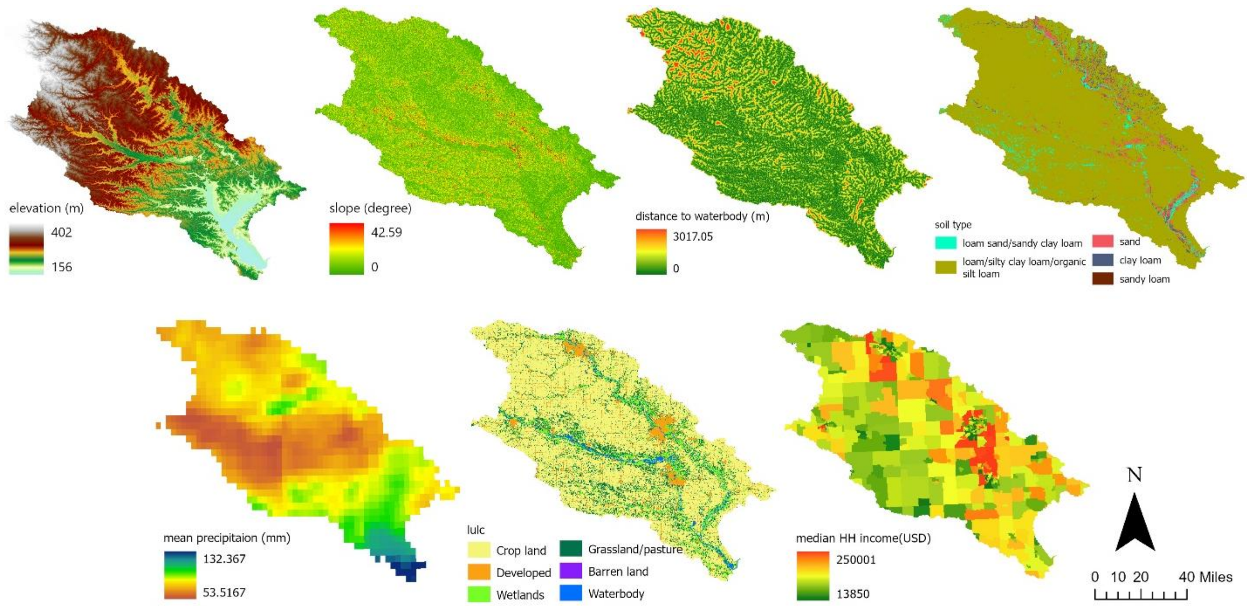

Figure 4. All the Indicators of flood susceptibility mapping.

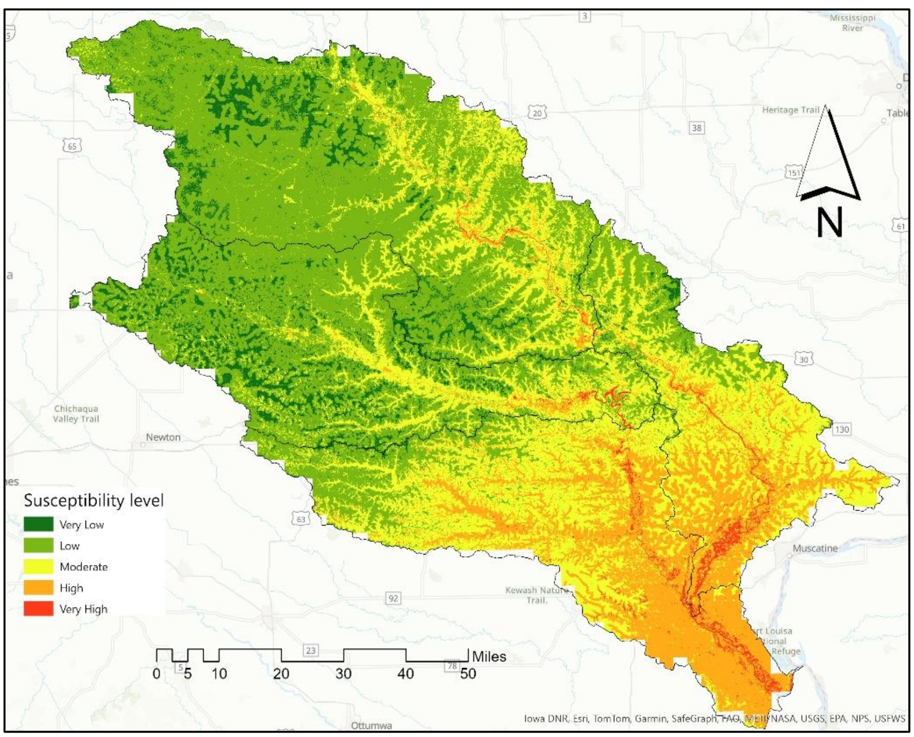

Figure 5. Spatial distribution of flood susceptibility using the AHP method.

3.2. Flood Susceptibility Analysis using Fuzzy AHP

In the FAHP model, the most influential geophysical parameters based on their weights were elevation (0.22), distance from the river (0.21), soil type (0.20), and land use (0.20), while slope had the lowest weight among the geophysical parameters at 0.17. For vulnerability factors, low-income households remained the most significant factor, with a weight of 0.26, followed by road network density (0.22) and mean precipitation (0.20). The weights assigned to land use and soil type were identical in the FAHP model, whereas low-income household weight remained the lowest among the susceptibility indicators. Additionally, the FAHP method demonstrated a narrower range of weight variations across the parameters than AHP.

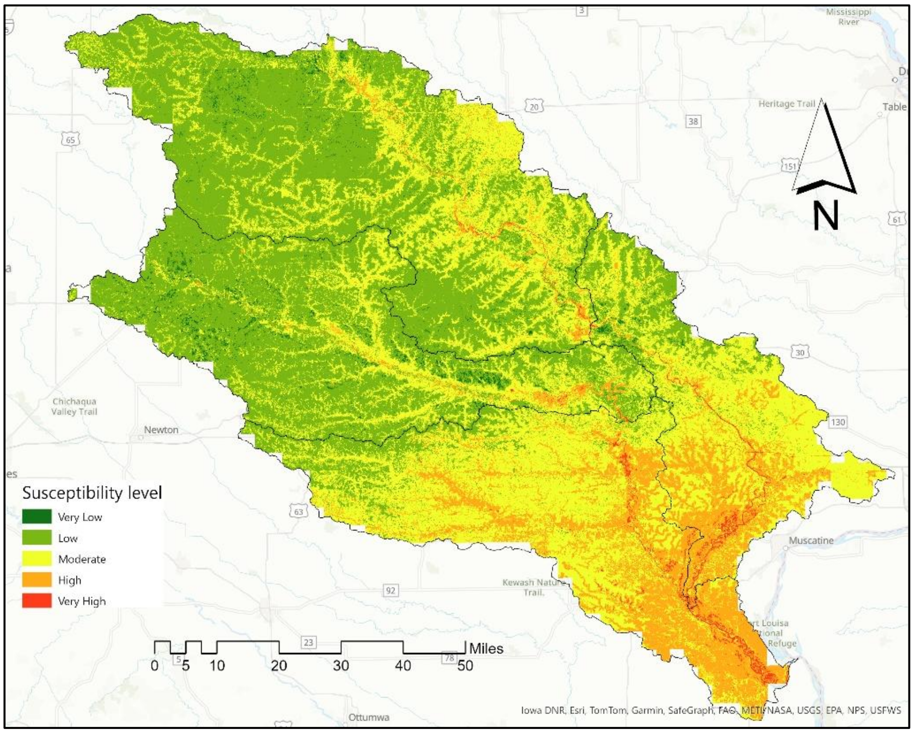

Figure 6. Spatial distribution of flood susceptibility using the FAHP method.

3.3. Equal Weights Analysis

The previous analysis applied the fuzzy analytic hierarchy process and AHP using the relative importance of various pairwise parameters contributing to flood susceptibility, as outlined in Table 6. The assigned weights were based on peer-reviewed studies from scientific literature. An alternative analysis was conducted to evaluate the impact of weighting on the flood susceptibility map in which all parameters were assigned equal weights. Given that seven parameters were considered, each was assigned a weight of 0.2 to maintain uniformity.

The resulting flood susceptibility map, presented in Figure 7, demonstrates the effects of equal weighting on flood risk distribution. While the low-risk zones closely resemble those generated using FAHP and AHP, notable differences emerge in high-risk areas. In all cases, high-risk zones are concentrated within built-up areas; however, the equal-weighted map exhibits a broader extent of high-risk zones than the FAHP model. This discrepancy likely arises because the equal-weight approach does not differentiate between the significance of various parameters. Consequently, the FAHP model proves to be more precise, as it effectively distinguishes between different levels of exposure and impact. Nonetheless, for low-risk areas, the results from the equal-weight analysis remain consistent with those derived from the FAHP and AHP methods, as discussed in the subsequent section.

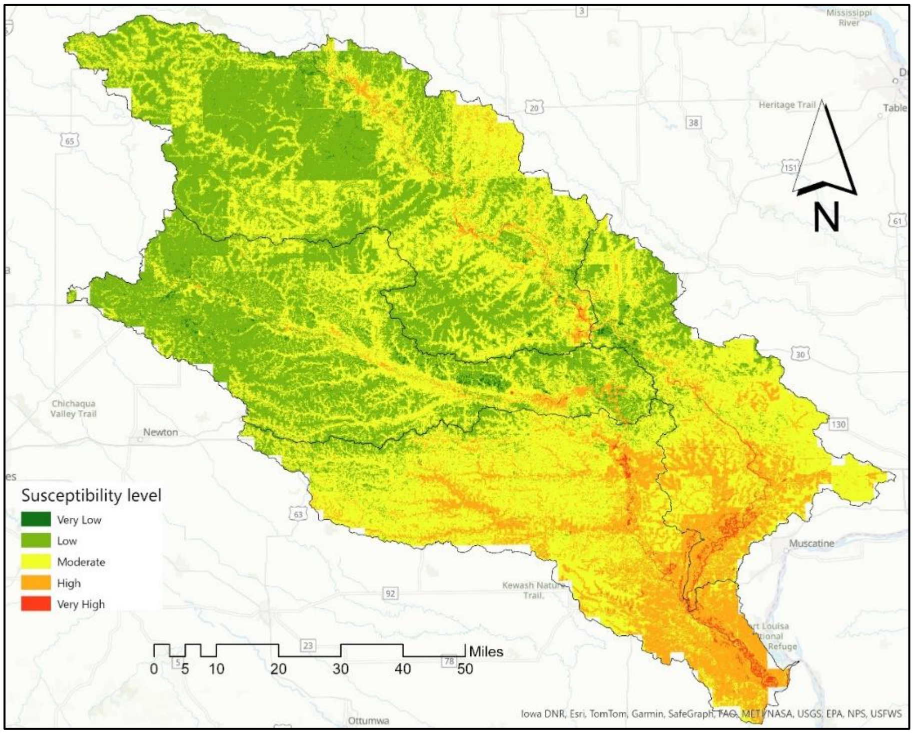

Figure 7. Spatial distribution of flood susceptibility using the Equal Weighting method.

3.4. Spatial Comparison Among the Methods

A comparative analysis of three decision-making methods - Analytic Hierarchy Process (AHP), Fuzzy AHP (FAHP), and Equal Weighting (EW) was conducted to assess the statistical variation across four subbasins within the Iowa-Cedar River Basin: Middle Cedar, Lower Cedar, Middle Iowa, and Lower Iowa. Table 7 and Figure 8 present the mean and standard deviation (Std) values for each method for the subbasins. The results show that FAHP consistently produced higher mean values across all subbasins than AHP and EW. For example, FAHP yielded mean values of 3.70, 4.37, 3.63, and 4.52 in the Middle Cedar, Lower Cedar, Middle Iowa, and Lower Iowa subbasins. These values exceeded AHP (3.28–4.29) and EW (2.75–3.35), indicating FAHP's greater sensitivity in capturing variations among subbasins.

Table 7. Statistical comparison of AHP, FAHP, and equal weighting methods across subbasins.

Subbasin	Mean AHP	Std AHP	Mean FAHP	Std FAHP	Mean EW	Std EW
Middle Cedar	3.28	0.49	3.70	0.45	2.79	0.33
Lower Cedar	4.17	0.66	4.37	0.60	3.23	0.43
Middle Iowa	3.25	0.53	3.63	0.47	2.75	0.34
Lower Iowa	4.29	0.64	4.52	0.56	3.35	0.38

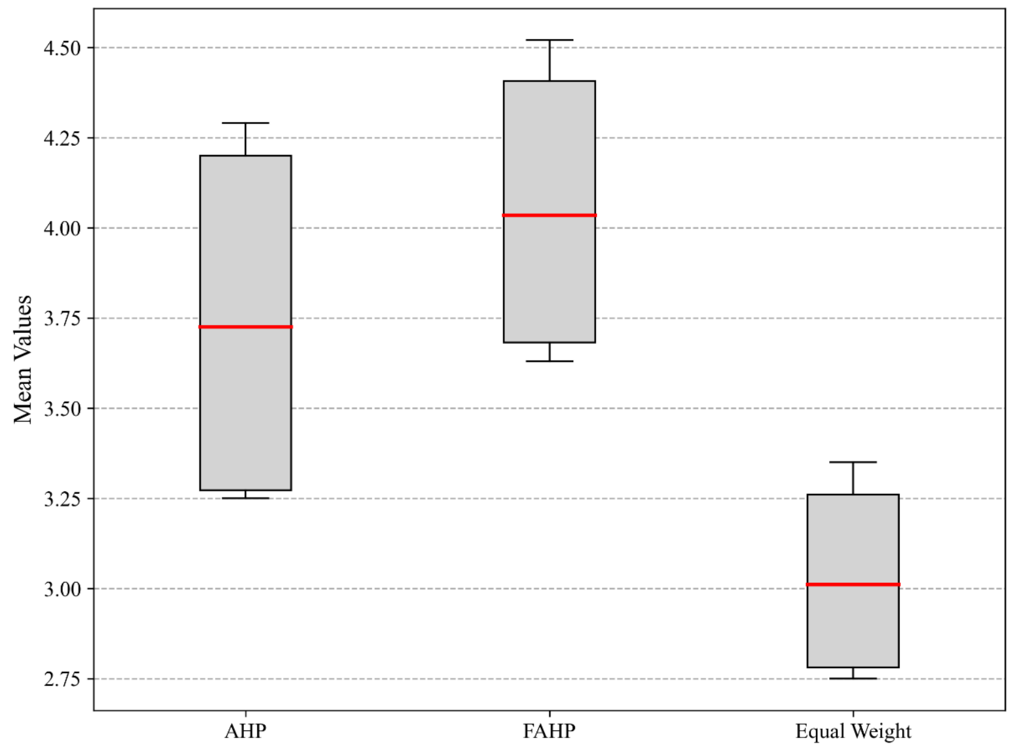

Figure 8. Mean values among three different methods.

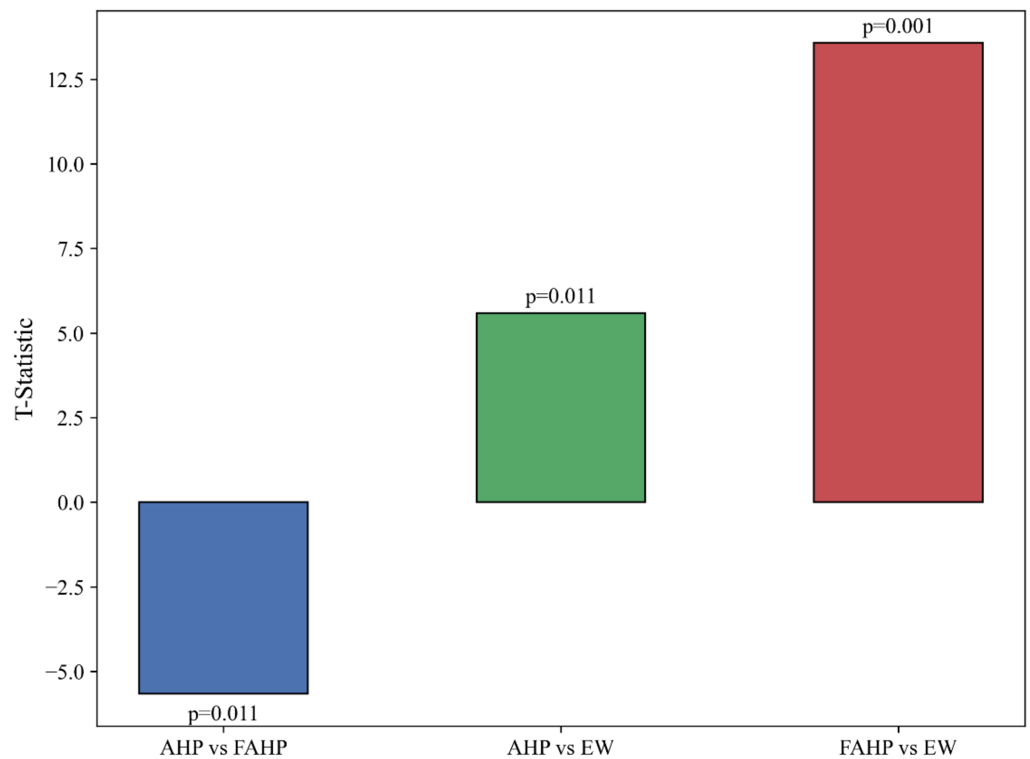

Figure 9. Paired T-Test results between methods.

Overall, the FAHP method demonstrated greater sensitivity in capturing variations across the subbasins, as reflected in the consistently higher mean values. In contrast, the equal weighting approach yielded the lowest mean scores across all subbasins, highlighting the potential underestimation of critical factors when uniform weights are assigned. The standard deviation values across methods remained relatively stable, suggesting that while the central tendency varied, the data spread within each subbasin was comparable.

Paired t-tests revealed significant differences between the methods. The comparison between AHP and FAHP and FAHP and Equal Weighted methods showed statistically significant differences ($p < 0.05$), while the difference between AHP and Equal Weight was also notable. These results confirm that the choice of method influences the mean values assigned to the subbasins.

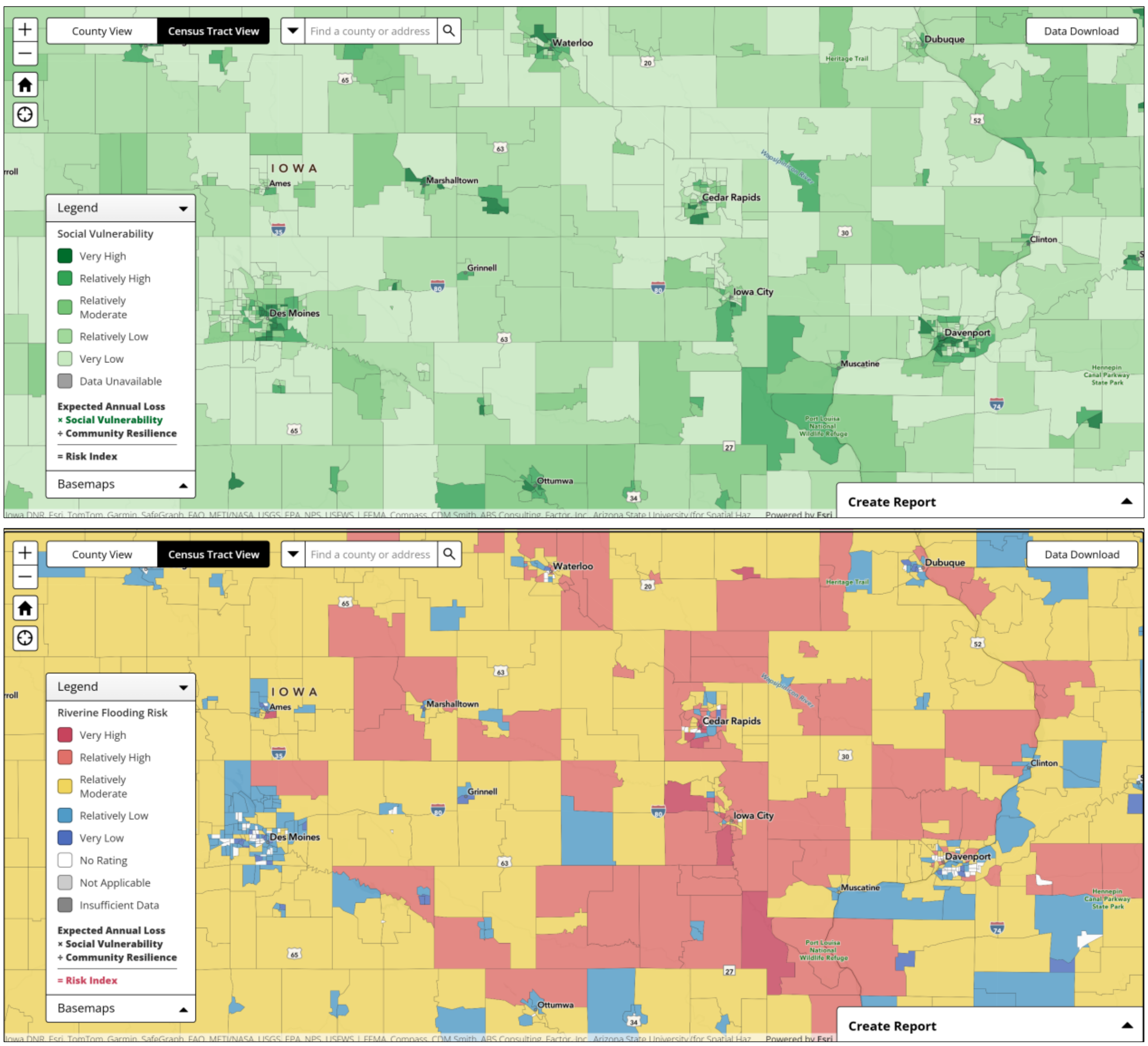

Figure 10. Riverine flood risk map at National Risk Index (NRI) outlook at census tract level (FEMA, 2025).

3.5. Comparison with National Risk Index (NRI) Map

Figure 8 presents the risk index and social vulnerability associated with riverine flooding. The National Risk Index (NRI), developed by FEMA, utilizes hydraulic and vulnerability models to assist decision-makers in implementing more effective and equitable mitigation strategies. However, the highest resolution in the NRI analysis is limited to the census tract level. In contrast, this study generated flood risk maps at a finer spatial resolution of 30 meters without relying on complex hydraulic modeling. The results obtained in this study align with the NRI outputs, as both highlight elevated flood risk levels, particularly in the study area's Lower Iowa and Lower Cedar basin regions.

4. Conclusion

This study provides a comprehensive flood susceptibility assessment for the Iowa-Cedar River Basin, integrating geophysical, forcing, and socioeconomic parameters within a multi-criteria decision-making framework using GIS and remote sensing techniques. Three distinct approaches—the Analytic Hierarchy Process, Fuzzy AHP, and Equal Weighting—were applied to generate high-resolution (30-meter) spatial flood susceptibility maps, offering critical insights into the spatial variability of flood risk across four sub-basins: Middle Cedar, Lower Cedar, Middle Iowa, and Lower Iowa.

The results underscore the complex interplay of physical and socioeconomic drivers of flood risk, with elevation, proximity to rivers, and soil type emerging as the most influential geophysical parameters. Among the vulnerability indicators, low-income households showed the highest influence on flood susceptibility, particularly in the FAHP model. These findings affirm the significance of environmental and social factors in flood risk evaluation.

Statistical comparisons revealed that the FAHP method demonstrated superior sensitivity in capturing variations among the sub-basins, producing higher mean susceptibility scores than AHP and Equal Weighting. This highlights the methodological strength of incorporating fuzzy logic to represent uncertainties inherent in expert judgments better. Moreover, the paired t-tests confirmed statistically significant differences between methods, emphasizing the critical impact of weighting schemes on flood risk assessment outcomes.

Spatial analysis indicates that high-risk zones are predominantly located in low-lying urban areas adjacent to major water bodies, particularly the Mississippi River and Cedar River corridors. Urban centers like Cedar Rapids are notably vulnerable due to dense populations and impervious surfaces, exacerbating runoff and flood hazards. Socio-economically vulnerable populations in these regions face heightened risks, underscoring the need for equitable and targeted flood mitigation strategies.

The findings have direct implications for policy and planning. High-risk areas identified in this study should be prioritized for interventions such as enhancing drainage infrastructure, implementing flood control measures, and strengthening early warning systems. Addressing socioeconomic disparities through subsidized flood insurance programs, community education, and relocation assistance can significantly reduce vulnerability. Ensuring that socially disadvantaged populations are included in disaster preparedness and response planning is essential to promoting equity and resilience.

From a methodological perspective, this research demonstrates the effectiveness of GIS-based MCDM approaches for flood risk evaluation. The system's adaptability, reproducibility, and cost-effectiveness make it suitable for application in other regions facing similar flood-related challenges. 30-meter resolution data enabled detailed micro-level mapping; however, future research could benefit from incorporating higher-resolution datasets and dynamic, real-time hydrological models to enhance predictive accuracy further.

The consistency between this study's outputs and the National Risk Index (NRI) developed by FEMA further validates the robustness of the methodology. While the NRI operates at the census tract level, this study advances flood risk mapping by delivering fine-scale (30 m) spatial outputs, offering granular insights critical for resource prioritization, infrastructure development, and land-use planning.

By integrating physical and socioeconomic dimensions of flood risk into a robust decision-making framework, this research provides a scientific foundation to support disaster preparedness, resilience planning, and climate adaptation strategies. These findings directly apply to water resource managers, urban planners, civil engineers, and policymakers, aiding in developing targeted, data-driven interventions that enhance community resilience against escalating flood risks driven by climate change and urban expansion.

5. References

Abdullah, M. F., Siraj, S., & Hodgett, R. E. (2021). An overview of multi-criteria decision analysis (MCDA) application in managing water-related disaster events: analyzing 20 years of literature for flood and drought events. *Water, 13* (10), 1358.

Agliamzanov, R., Sit, M., & Demir, I. (2020). Hydrology@ Home: a distributed volunteer computing framework for hydrological research and applications. *Journal of Hydroinformatics, 22*(2), 235-248.

Ahmed, A. I. A., Khan, S., Gani, A., Ab Hamid, S. H., & Guizani, M. (2018). *Entropy-based fuzzy AHP model for trustworthy service provider selection in Internet of Things.* Paper presented at the 2018 IEEE 43rd Conference on Local Computer Networks (LCN).

Alabbad, Y., Yildirim, E., & Demir, I. (2023). A web-based analytical urban flood damage and loss estimation framework. *Environmental Modelling & Software, 163,* 105670.

Alabbad, Y., Mount, J., Campbell, A. M., & Demir, I. (2024). A web-based decision support framework for optimizing road network accessibility and emergency facility allocation during flooding. *Urban Informatics, 3*(1), 10.

Alabbad, Y., & Demir, I. (2024). Geo-spatial analysis of built-environment exposure to flooding: Iowa case study. *Discover Water, 4*(1), 28.

Ali, S. A., & Ahmad, A. (2020). Suitability analysis for municipal landfill site selection using fuzzy analytic hierarchy process and geospatial technique. *Environmental Earth Sciences, 79*(10), 227.

Andresen, J., Hilberg, S., Kunkel, K., & Center, M. R. C. (2012). Historical climate and climate trends in the Midwestern USA. *US National Climate Assessment Midwest Technical Input Report*, 1-18.

Avand, M., & Moradi, H. (2021). Using machine learning models, remote sensing, and GIS to investigate the effects of changing climates and land uses on flood probability. *Journal of hydrology, 595*, 125663.

Bayar, S., Demir, I., & Engin, G. O. (2009). Modeling leaching behavior of solidified wastes using back-propagation neural networks. *Ecotoxicology and environmental safety*, *72*(3), 843-850.

Bellman, R. E., & Zadeh, L. A. (1970). Decision-making in a fuzzy environment. *Management science, 17*(4), B-141-B-164.

Bernasconi, M., Choirat, C., & Seri, R. (2010). The analytic hierarchy process and the theory of measurement. *Management science, 56*(4), 699-711.

Bilotta, G. S., Brazier, R. E., & Haygarth, P. M. (2007). The impacts of grazing animals on the quality of soils, vegetation, and surface waters in intensively managed grasslands. *Advances in agronomy, 94*, 237-280.

Buckley, J. J. (1985). Fuzzy hierarchical analysis. *Fuzzy sets and systems, 17*(3), 233-247.

Cea, L., & Costabile, P. (2022). Flood risk in urban areas: Modelling, management and adaptation to climate change. A review. Hydrology, 9(3), 50.

Chang, D.-Y. (1996). Applications of the extent analysis method on fuzzy AHP. *European journal of operational research, 95*(3), 649-655.

Chen, W., Li, W., Chai, H., Hou, E., Li, X., & Ding, X. (2016). GIS-based landslide susceptibility mapping using analytical hierarchy process (AHP) and certainty factor (CF) models for the Baozhong region of Baoji City, China. *Environmental Earth Sciences, 75*, 1-14.

Chen, Y., Yu, J., & Khan, S. (2013). The spatial framework for weight sensitivity analysis in AHP-based multi-criteria decision making. *Environmental modelling & software, 48*, 129-140.

Cikmaz, B. A., Yildirim, E., & Demir, I. (2023). Flood susceptibility mapping using fuzzy analytical hierarchy process for Cedar Rapids, Iowa. *International journal of river basin management*, 1-13.

Das, S. (2020). Flood susceptibility mapping of the Western Ghat coastal belt using multi-source geospatial data and analytical hierarchy process (AHP). Remote Sensing Applications: Society and Environment, 20, 100379.

De Brito, M. M., & Evers, M. (2016). Multi-criteria decision-making for flood risk management: a survey of the current state of the art. Natural Hazards and Earth System Sciences, 16(4), 1019-1033.

De Montis, A., De Toro, P., Droste-Franke, B., Omann, I., Stagl, S., & others. (2000). *Criteria for quality assessment of MCDA methods*.

Deroliya, P., Ghosh, M., Mohanty, M. P., Ghosh, S., Rao, K. H. V. D., & Karmakar, S. (2022). A novel flood risk mapping approach with machine learning considering geomorphic and socioeconomic vulnerability dimensions. *Science of the Total Environment, 851*, 158002.

Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Salinas, J. L., & Blschl, G. (2013). Socio-hydrology: conceptualising human-flood interactions. *Hydrology and Earth System Sciences, 17*(8), 3295-3303.

Diakakis, M., Deligiannakis, G., Pallikarakis, A., & Skordoulis, M. (2016). Factors controlling the spatial distribution of flash flooding in the complex environment of a metropolitan urban area. The case of Athens 2013 flash flood event. *International Journal of Disaster Risk Reduction, 18*, 171-180.

Douben, K.-J. (2006). Characteristics of river floods and flooding: a global overview, 1985-2003. *Irrigation and Drainage: The journal of the International Commission on Irrigation and Drainage, 55*(S1), S9-S21.

Dutta, P., & Deka, S. (2024). A novel approach to flood risk assessment: Synergizing with geospatial based MCDM-AHP model, multicollinearity, and sensitivity analysis in the Lower Brahmaputra Floodplain, Assam. *Journal of Cleaner Production, 467*, 142985.

Dwi Putra, M. S., Andryana, S., Fauziah, & Gunaryati, A. (2018). Fuzzy analytical hierarchy process method to determine the quality of gemstones. *Advances in fuzzy systems, 2018*(1), 9094380.

Eniolorunda, N. (2014). Climate change analysis and adaptation: the role of remote sensing (Rs) and geographical information system (GIS). *International Journal of Computational Engineering Research, 4*(1), 41-51.

Franci, F., Bitelli, G., Mandanici, E., Hadjimitsis, D., & Agapiou, A. (2016). Satellite remote sensing and GIS-based multi-criteria analysis for flood hazard mapping. *Natural Hazards, 83*, 31-51.

González-Arqueros, M. L., Mendoza, M. E., Bocco, G., & Castillo, B. S. (2018). Flood susceptibility in rural settlements in remote zones: The case of a mountainous basin in the Sierra-Costa region of Michoacán, Mexico. Journal of environmental management, 223, 685-693.

Grant, C. A., Alabbad, Y., Yildirim, E., & Demir, I. (2024). Comprehensive Assessment of Flood Risk and Vulnerability for Essential Facilities: Iowa Case Study. Urban Science, 8(3), 145.

Hussain, M., Tayyab, M., Zhang, J., Shah, A. A., Ullah, K., Mehmood, U., & Al-Shaibah, B. (2021). GIS-based multi-criteria approach for flood vulnerability assessment and mapping in district Shangla: Khyber Pakhtunkhwa, Pakistan. *Sustainability, 13*(6), 3126.

Jha, A., Lamond, J., Bloch, R., Bhattacharya, N., Lopez, A., Papachristodoulou, N., . . . Barker, R. (2011). Five feet high and rising: cities and flooding in the 21st century. *World Bank Policy Research Working Paper*(5648).

Islam, S. S., Yeşilköy, S., Baydaroğlu, Ö., Yıldırım, E., & Demir, I. (2024). State-level multidimensional agricultural drought susceptibility and risk assessment for agriculturally prominent areas. *International Journal of River Basin Management*, 1-18.

Jha, M. K., Chowdary, V., Kulkarni, Y., & Mal, B. C. (2014). Rainwater harvesting planning using geospatial techniques and multi-criteria decision analysis. *Resources, Conservation and Recycling, 83*, 96-111.

Johnston, R., & Smakhtin, V. (2014). Hydrological modeling of large river basins: how much is enough? *Water resources management, 28*, 2695-2730.

Jonkman, S. N. (2005). Global perspectives on loss of human life caused by floods. *Natural Hazards, 34*(2), 151-175.

Kahraman, C., Cebeci, U., & Ulukan, Z. (2003). Multi-criteria supplier selection using fuzzy AHP. *Logistics information management, 16*(6), 382-394.

Kazakis, N., Kougias, I., & Patsialis, T. (2015). Assessment of flood hazard areas at a regional scale using an index-based approach and Analytical Hierarchy Process: Application in Rhodope–Evros region, Greece. *Science of the Total Environment, 538*, 555-563.

Kirk, R. (1991). River-beach interaction on mixed sand and gravel coasts: a geomorphic model for water resource planning. *Applied Geography, 11*(4), 267-287.

Kopp, R. E., Gilmore, E. A., Little, C. M., Lorenzo-Trueba, J., Ramenzoni, V. C., & Sweet, W. V. (2019). Usable science for managing the risks of sea-level rise. *Earth's future, 7*(12), 1235-1269.

Krajewski, W. F., Ghimire, G. R., Demir, I., & Mantilla, R. (2021). Real-time streamflow forecasting: AI vs. Hydrologic insights. *Journal of Hydrology X, 13*, 100110.

Kumar, N., Liu, X., Narayanasamydamodaran, S., & Pandey, K. K. (2021). A systematic review comparing urban flood management practices in India to China's sponge city program. *Sustainability, 13*(11), 6346.

Kundzewicz, Z. W., Kanae, S., Seneviratne, S. I., Handmer, J., Nicholls, N., Peduzzi, P., . . . others. (2014). Flood risk and climate change: global and regional perspectives. *Hydrological Sciences Journal, 59*(1), 1-28.

Lee, S., Kim, W., Kim, Y. M., & Oh, K. J. (2012). Using AHP to determine intangible priority factors for technology transfer adoption. *Expert Systems with Applications, 39*(7), 6388-6395.

Levy, J. K., Hartmann, J., Li, K. W., An, Y., & Asgary, A. (2007). Multi-criteria decision support systems for flood hazard mitigation and emergency response in urban watersheds 1. *JAWRA Journal of the American Water Resources Association, 43*(2), 346-358.

Li, S., Wang, Z., Lai, C., & Lin, G. (2020). Quantitative assessment of the relative impacts of climate change and human activity on flood susceptibility based on a cloud model. *Journal of hydrology, 588*, 125051.

Li, Z., Duque, F. Q., Grout, T., Bates, B., & Demir, I. (2023). Comparative analysis of performance and mechanisms of flood inundation map generation using Height Above Nearest Drainage. *Environmental Modelling & Software, 159*, 105565.

Li, Z., & Demir, I. (2024). Better localized predictions with Out-of-Scope information and Explainable AI: One-Shot SAR backscatter nowcast framework with data from neighboring region. *ISPRS Journal of Photogrammetry and Remote Sensing, 207*, 92-103.

Longenecker Iii, H. E. (2019). *Evaluating the effects of induced development on flood hazards and losses in US communities with levees.*

Louw, E., Olanrewaju, C. C., Olanrewaju, O. A., & Chitakira, M. (2019). Impacts of flood disasters in Nigeria: A critical evaluation of health implications and management. Jàmbá: Journal of Disaster Risk Studies, 11(1), 1-9.

Malczewski, J. (1999). *GIS and multi-criteria decision analysis*: John wiley & sons.

Mendoza, G. A., & Martins, H. (2006). Multi-criteria decision analysis in natural resource management: A critical review of methods and new modelling paradigms. *Forest ecology and management, 230*(1-3), 1-22.

Merz, B., Aerts, J. C. J. H., Arnbjerg-Nielsen, K., Baldi, M., Becker, A., Bichet, A., ... & Nied, M. (2014). Floods and climate: emerging perspectives for flood risk assessment and management. Natural Hazards and Earth System Sciences, 14(7), 1921-1942.

Merz, B., Blöschl, G., Vorogushyn, S., Dottori, F., Aerts, J. C., Bates, P., ... & Macdonald, E. (2021). Causes, impacts and patterns of disastrous river floods. Nature Reviews Earth & Environment, 2(9), 592-609.

Mikhailov, L. (2003). Deriving priorities from fuzzy pairwise comparison judgements. *Fuzzy sets and systems, 134*(3), 365-385.

Msabi, M. M., & Makonyo, M. (2021). Flood susceptibility mapping using GIS and multi-criteria decision analysis: A case of Dodoma region, central Tanzania. *Remote Sensing Applications: Society and Environment, 21*, 100445.

Mujumdar, P., & Kumar, D. N. (2012). *Floods in a changing climate: hydrologic modeling*: Cambridge University Press.

Mullick, M. R. A., Tanim, A. H., & Islam, S. M. S. (2019). Coastal vulnerability analysis of Bangladesh coast using fuzzy logic based geospatial techniques. *Ocean & coastal management, 174*, 154-169.

Munawar, H. S., Hammad, A. W. A., & Waller, S. T. (2022). Remote sensing methods for flood prediction: A review. *Sensors, 22*(3), 960.

Munpa, P., Kittipongvises, S., Phetrak, A., Sirichokchatchawan, W., Taneepanichskul, N., Lohwacharin, J., & Polprasert, C. (2022). Climatic and hydrological factors affecting the assessment of flood hazards and resilience using modified UNDRR indicators: Ayutthaya, Thailand. *Water, 14*(10), 1603.

Ostrom, L. T., & Wilhelmsen, C. A. (2019). *Risk assessment: tools, techniques, and their applications*: John Wiley & Sons.

Ouma, Y. O., & Tateishi, R. (2014). Urban flood vulnerability and risk mapping using integrated multi-parametric AHP and GIS: methodological overview and case study assessment. *Water, 6*(6), 1515-1545.

Radionovs, A., & Uzhga-Rebrov, O. (2017). *Comparison of different fuzzy ahp methodologies in risk assessment.* Paper presented at the Environment. Technologies. Resources. Proceedings of the International Scientific and Practical Conference.

Rehman, J., Sohaib, O., Asif, M., & Pradhan, B. (2019). Applying systems thinking to flood disaster management for a sustainable development. *International Journal of Disaster Risk Reduction, 36*, 101101.

Rodrguez-Espndola, O., Albores, P., & Brewster, C. (2018). Disaster preparedness in humanitarian logistics: A collaborative approach for resource management in floods. *European Journal of Operational Research, 264*(3), 978-993.

Rozalis, S., Morin, E., Yair, Y., & Price, C. (2010). Flash flood prediction using an uncalibrated hydrological model and radar rainfall data in a Mediterranean watershed under changing hydrological conditions. *Journal of hydrology, 394*(1-2), 245-255.

Saaty, R. W. (1987). The analytic hierarchy process—what it is and how it is used. *Mathematical modelling, 9*(3-5), 161-176.

Saaty, T. L. (1977). A scaling method for priorities in hierarchical structures. *Journal of mathematical psychology, 15*(3), 234-281.

Saaty, T. L. (1978). Exploring the interface between hierarchies, multiple objectives and fuzzy sets. *Fuzzy sets and systems, 1*(1), 57-68.

Saaty, T. L. (1996). *Decision making with dependence and feedback: The analytic network process* (Vol. 4922): RWS Publ. Pittsburgh, PA, USA.

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International journal of services sciences, 1*(1), 83-98.

Saaty, T. L., & Vargas, L. G. (2012). *Models, methods, concepts & applications of the analytic hierarchy process* (Vol. 175): Springer Science & Business Media.

Satterthwaite, D. (2011). What role for low-income communities in urban areas in disaster risk reduction. Documento informativo elaborado para el Informe de evaluación global sobre la reducción del riesgo de desastres.

Schumacher, R. S. (2017). Heavy rainfall and flash flooding.

Seo, B. C., Keem, M., Hammond, R., Demir, I., & Krajewski, W. F. (2019). A pilot infrastructure for searching rainfall metadata and generating rainfall product using the big data of NEXRAD. *Environmental modelling & software*, *117*, 69-75.

Sit, M., Langel, R. J., Thompson, D., Cwiertny, D. M., & Demir, I. (2021). Web-based data analytics framework for well forecasting and groundwater quality. *Science of the Total Environment*, *761*, 144121.

Steinschneider, S., Wi, S., & Brown, C. (2015). The integrated effects of climate and hydrologic uncertainty on future flood risk assessments. *Hydrological Processes, 29*(12), 2823-2839.

Sutadian, A. D., Muttil, N., Yilmaz, A. G., & Perera, B. (2017). Using the Analytic Hierarchy Process to identify parameter weights for developing a water quality index. *Ecological indicators, 75*, 220-233.

Swain, K. C., Singha, C., & Nayak, L. (2020). Flood susceptibility mapping through the GIS-AHP technique using the cloud. *ISPRS International Journal of Geo-Information, 9*(12), 720.

Tanir, T., Yildirim, E., Ferreira, C. M., & Demir, I. (2024). Social vulnerability and climate risk assessment for agricultural communities in the United States. *Science of The Total Environment*, *908*, 168346.

Uzun Ozsahin, D., Ahmed, M., & Uzun, B. (2021). Analytical Hierarchy Process (AHP). *Application of Multi-Criteria Decision Analysis in Environmental and Civil Engineering*, 17-24.

Van Westen, C. J. (2013). Remote sensing and GIS for natural hazards assessment and disaster risk management. *Treatise on geomorphology, 3*(15), 259-298.

Vargas, L. G. (1990). An overview of the analytic hierarchy process and its applications. *European journal of operational research, 48*(1), 2-8.

Vojinovic, Z. (2015). *Flood risk: the holistic perspective*: IWA Publishing.

Vojtek, M., & Vojteková, J. (2019). Flood susceptibility mapping on a national scale in Slovakia using the analytical hierarchy process. *Water, 11*(2), 364.

Wahlster, P., Goetghebeur, M., Kriza, C., Niederlnder, C., Kolominsky-Rabas, P., & National Leading-Edge Cluster Medical Technologies 'Medical Valley, E. (2015). Balancing costs and benefits at different stages of medical innovation: a systematic review of Multi-criteria decision analysis (MCDA). *BMC health services research, 15*, 1-12.

Wang, Y., Xu, L., & Solangi, Y. A. (2020). Strategic renewable energy resources selection for Pakistan: Based on SWOT-Fuzzy AHP approach. *Sustainable Cities and Society, 52*, 101861.

Wang, Z.-H., & Li, S.-X. (2019). Nitrate N loss by leaching and surface runoff in agricultural land: A global issue (a review). *Advances in agronomy*, *156*, 159-217.

Wind, Y., & Saaty, T. L. (1980). Marketing applications of the analytic hierarchy process. *Management science, 26*(7), 641-658.

Wing, O. E., Lehman, W., Bates, P. D., Sampson, C. C., Quinn, N., Smith, A. M., ... & Kousky, C. (2022). Inequitable patterns of US flood risk in the Anthropocene. Nature Climate Change, 12(2), 156-162.

Xu, H., Muste, M., & Demir, I. (2019). Web-based geospatial platform for the analysis and forecasting of sedimentation at culverts. *Journal of Hydroinformatics*, *21*(6), 1064-1081.

Yang, W., Xu, K., Lian, J., Bin, L., & Ma, C. (2018). Multiple flood vulnerability assessment approach based on fuzzy comprehensive evaluation method and coordinated development degree model. *Journal of environmental management, 213*, 440-450.

Yildirim, E., Just, C., & Demir, I. (2022). Flood risk assessment and quantification at the community and property level in the State of Iowa. *International journal of disaster risk reduction*, *77*, 103106.

Yildirim, E., Alabbad, Y., & Demir, I. (2023). Non-structural flood mitigation optimization at community scale: Middle Cedar Case Study. *Journal of environmental management*, *346*, 119025.

Zadeh, L. A. (1965). Fuzzy sets. *Information and control, 8*(3), 338-353.

Zhang, Z., Lu, W., Zhao, Y., & Song, W. (2014). Development tendency analysis and evaluation of the water ecological carrying capacity in the Siping area of Jilin Province in China based on system dynamics and analytic hierarchy process. *Ecological modelling, 275*, 9-21.

Zheng, J., Egger, C., & Lienert, J. (2016). A scenario-based MCDA framework for wastewater infrastructure planning under uncertainty. *Journal of environmental management*, *183*, 895-908.