

Article

Assessment of Flood Risk Using Remote Sensing and GIS Techniques Based on the Analytic Hierarchy Process (AHP) and Fuzzy AHP (FAHP) in the R'Dom Watershed (Meknes, Morocco)

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Highlights

What are the main findings?

- The comparison between AHP and Fuzzy AHP highlighted differences in spatial classification and predictive performance for flood susceptibility mapping.
- Integration of 17 conditioning factors using remote sensing and GIS identified high- to very high-flood-risk zones.

What are the implications of the main findings?

- The Fuzzy AHP methodology provides reliable flood risk assessment for data-scarce watersheds facing climate change challenges.

Abstract

Flooding is one of the most damaging natural hazards worldwide, particularly in data-scarce watersheds where long-term hydrometeorological records are limited. This study focuses on the R'Dom watershed in the Meknes region, Morocco, and aims to improve flood susceptibility and relative flood risk assessment by integrating remote sensing, Geographic Information Systems (GIS), and multi-criteria decision-making (MCDM) approaches. The Analytic Hierarchy Process (AHP) and Fuzzy Analytic Hierarchy Process (Fuzzy AHP/FAHP) were applied to evaluate flood hazard, vulnerability, and overall risk using seventeen conditioning factors, including topographic, hydrological, geological, land-cover, socio-economic, and infrastructure-related variables. The Flood Hazard Index (FHI), Flood Vulnerability Index (FVI), and Flood Risk Index (FRI) were calculated to produce flood susceptibility, vulnerability, and relative flood risk maps. Model validation was performed using a point-based flood inventory dataset composed of 900 locations, including 450 flood and 450 non-flood points, compiled from historical flood information,



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field observations, local information, official reports, and satellite-based interpretation. The dataset was divided into 70% for training and 30% for testing, and model performance was assessed using receiver operating characteristic–area under the curve (ROC-AUC) analysis. The AHP and Fuzzy AHP models showed good to excellent predictive performance, with testing AUC values ranging from 0.767 to 0.935. The AHP-based models achieved the highest testing performance, while Fuzzy AHP remained useful for representing uncertainty in expert judgment and gradual spatial transitions. The final flood risk map indicates that approximately 18.78% of the study area, corresponding to 240.62 km², is classified as having a high to very high flood risk, mainly around the Meknes conurbation and locally near the El Hajeb region. These results provide a practical decision-support tool for identifying priority areas for flood mitigation, land-use planning, and watershed management. However, the proposed GIS–MCDA approach produces relative flood susceptibility and risk classes and does not replace hydrological or hydraulic modeling for estimating flood depth, discharge, inundation extent, or return-period-based flood hazard.

Keywords: R'Dom watershed; Meknes; flood susceptibility; relative flood risk; flood vulnerability; AHP; Fuzzy AHP; GIS; remote sensing; MCDA

1. Introduction

Floods are among the most frequent, destructive, and deadly natural disasters worldwide [1]. Over recent decades, they have accounted for nearly half of all fatalities caused by natural hazards and about one-third of global economic losses [2,3]. In Morocco, floods, droughts, and earthquakes are among the most significant natural risks in terms of human and economic impacts. Flooding represents a major threat, particularly in vulnerable areas affected by rapid urbanization, climate variability, and intense localized rainfall.

As in other Mediterranean countries, Morocco is increasingly affected by recurrent and intense floods in the context of climate change [4]. Major events, such as the 2014 Guelmim floods, the 1995 Ourika Valley floods, and recurrent urban flooding in cities such as Tangier, Casablanca, Agadir, Tetouan, Taza, Fez, Meknes, and Mohammedia, highlight the high vulnerability of both urban and mountain watersheds [5]. Climate change projections also indicate increasing rainfall intensity and irregularity, which may favor flash flood generation in semi-arid basins.

Rapid urbanization has modified natural drainage systems, increased impervious surfaces, and exposed growing populations to flood risk, particularly in expanding metropolitan areas such as Meknes and Fez [6]. Although Morocco has developed several risk management initiatives, including the flood risk program launched by the Ministry of Water in 2003 and the National Atlas of Major Risks in 2008, many Moroccan cities continue to experience flooding during the rainy season [7].

Flood risk assessment is essential for disaster management, land-use planning, and decision-making. Traditional approaches rely on historical flood records, hydrological and hydraulic modeling, and flood hazard maps [8,9]. However, in data-scarce regions, these approaches are often limited by the lack of long-term hydrometeorological records. Remote sensing and Geographic Information Systems (GIS) provide useful tools for spatial flood susceptibility and risk assessment, particularly when combined with multi-criteria decision-making methods such as AHP and Fuzzy AHP [10,11].

The advancement of remote sensing and GIS has improved flood susceptibility assessment by enabling the integration of multi-criteria decision-making (MCDM) and machine learning (ML) models [12]. Several approaches have been applied in flood susceptibility

modeling, including frequency ratio [13], weights-of-evidence [14], logistic regression [15], AHP [16], fuzzy logic [17], evidential belief function [18], artificial neural networks [19], decision trees [20], and support vector machines [21]. These methods rely on geospatial datasets to identify flood-prone areas across different environmental contexts [22].

Recent studies have continued to demonstrate the relevance of GIS–MCDA and remote-sensing-based approaches for flood susceptibility and risk mapping, particularly in data-scarce environments. For example, Ashfaq et al. [23] used GIS-based AHP and frequency ratio models for flood susceptibility assessment, while Santosh et al. [24] applied a FAHP–GIS approach to account for uncertainty in flood hazard assessment. Similarly, Nazir et al. [11] integrated remote sensing, GIS, and AHP for flood vulnerability and risk mapping in an urban context.

Although machine learning approaches often show strong predictive performance in data-rich environments, their application may be limited by insufficient training datasets and incomplete flood inventories [25]. This limitation is particularly relevant in Morocco, where detailed historical flood databases remain unavailable for many watersheds. In contrast, MCDM methods provide a structured framework for integrating multiple criteria and expert knowledge, making them suitable for data-limited environments [26].

The AHP methodology, originally proposed by Saaty [27], is a widely used MCDM technique based on pairwise comparison matrices. It allows the relative importance of conditioning factors to be assessed in a structured and transparent way [27]. AHP has been widely applied in flood hazard and risk assessment because it can combine qualitative expert judgment and quantitative spatial information. However, conventional AHP relies on crisp pairwise comparisons and may be affected by inconsistencies and expert subjectivity [28].

To address these limitations, the Fuzzy Analytic Hierarchy Process (FAHP) integrates AHP with fuzzy set theory to better represent uncertainty and imprecision in expert judgment [29]. More recent studies have also highlighted the usefulness of FAHP–GIS approaches for representing uncertainty in expert-based flood hazard and susceptibility assessment, especially where hydrological observations are limited.

AHP is particularly useful in data-scarce watersheds because it provides a structured framework for integrating heterogeneous conditioning factors when hydrological records are incomplete or unavailable. However, the influence of flood-related factors such as rainfall, slope, distance to rivers, land use, and drainage density is often gradual rather than sharply defined. FAHP addresses this limitation by using triangular fuzzy numbers, allowing uncertainty in expert judgments to be represented more realistically. Therefore, comparing AHP and FAHP under the same spatial and environmental conditions is relevant for assessing how uncertainty treatment influences flood susceptibility and relative risk mapping in data-scarce basins such as the R'Dom watershed.

Machine learning and Artificial Intelligence (AI)-driven models are also increasingly being used to predict flood events by analyzing complex datasets, including rainfall, soil moisture, and topography. Light Detection and Ranging (LiDAR) technology can further improve flood modeling by providing high-resolution topographic data [30,31]. However, in many semi-arid and data-scarce watersheds, such datasets remain limited or unavailable.

The R'Dom watershed in the Meknes region is an important case study for flood risk assessment in Morocco [32]. It supports agricultural activities and urban development, while its semi-arid climate, irregular rainfall, and downstream urban expansion increase its exposure to flash floods. Effective flood assessment is therefore essential for regional planning and risk reduction.

AHP and Fuzzy AHP have been widely applied in flood susceptibility mapping, and several studies have shown their usefulness for producing reliable flood-prone area classifi-

cations [33,34]. Nevertheless, their performance remains context-dependent, particularly in semi-arid and data-constrained environments where hydrological records are incomplete.

The AHP, first introduced by Saaty in 1977 [35], remains a valuable tool for multi-criteria decision-making. It enables the systematic evaluation and ranking of multiple criteria in flood hazard and risk assessment [36]. In this study, Fuzzy AHP is used in addition to AHP to better account for uncertainty in expert judgment and to express preferences with greater flexibility [37]. Thus, this study combines AHP and Fuzzy AHP approaches with field-based knowledge, which strengthens the relevance of the adopted methodology and improves the spatial mapping of flood risk.

To the best of our knowledge, no previous study has developed an integrated GIS–MCDA framework combining flood hazard, vulnerability, and relative risk assessment using both AHP and Fuzzy AHP specifically for the R'Dom watershed. The novelty of this study therefore does not lie in comparing AHP and Fuzzy AHP. Rather, it lies in developing an integrated flood susceptibility and relative flood risk assessment framework for a semi-arid and data-scarce Moroccan watershed.

This framework combines physical flood conditioning factors, socio-economic vulnerability indicators, expert-based weighting, fuzzy uncertainty representation, and flood inventory-based validation. By integrating seventeen conditioning and vulnerability factors within a unified GIS–MCDA framework, the study provides operational flood susceptibility and relative risk maps that can support decision-making, land-use planning, and flood mitigation strategies in the R'Dom watershed and similar data-limited basins.

The objective of this research is to develop an integrated GIS-based approach for assessing flood susceptibility, vulnerability, and relative flood risk in the R'Dom watershed using AHP and Fuzzy AHP. The results aim to support flood risk management and provide a transferable methodological framework for similar semi-arid and data-scarce environments.

2. Material and Methods

2.1. Study Area

The study area falls within the Saïss Basin, a wide plain located between the Rif Mountains to the north and the Middle Atlas range to the south in Morocco. It occupies around 20 km in the west–east direction and 65 km in the north–south direction, comprising a total surface area of nearly 1290 km² [38,39]. The site is part of the R'Dom watershed, which spans two administrative communes: Meknes in the north and El Hajeb in the south. Geographically, the region lies between longitudes 5.10° and 5.38°W and latitudes 33.30° and 34.02°N, as illustrated in Figure 1.

The climate in this region is classified as Mediterranean, characterized by hot, dry summers and relatively mild, wet winters. More specifically, the watershed displays semi-arid climatic conditions, with an average annual rainfall of 474.4 mm. The dry season extends from May to mid-September. Approximately 44% of annual rainfall is recorded in winter, compared to 25% during spring [40]. The mean annual temperature is 17.6 °C, with January being the coldest month and August the warmest [41,42].

The R'Dom River flows through a variety of agricultural [32] and urban zones, notably the city of Meknes and the town of Boufakrane. From a hydrological perspective, the watershed's drainage network is dominated by the R'Dom River and its principal streams: Boufakrane, Ouislane, Chajara, and Ishak. The morphometric characteristics of the watershed are summarized in the following Table 1.

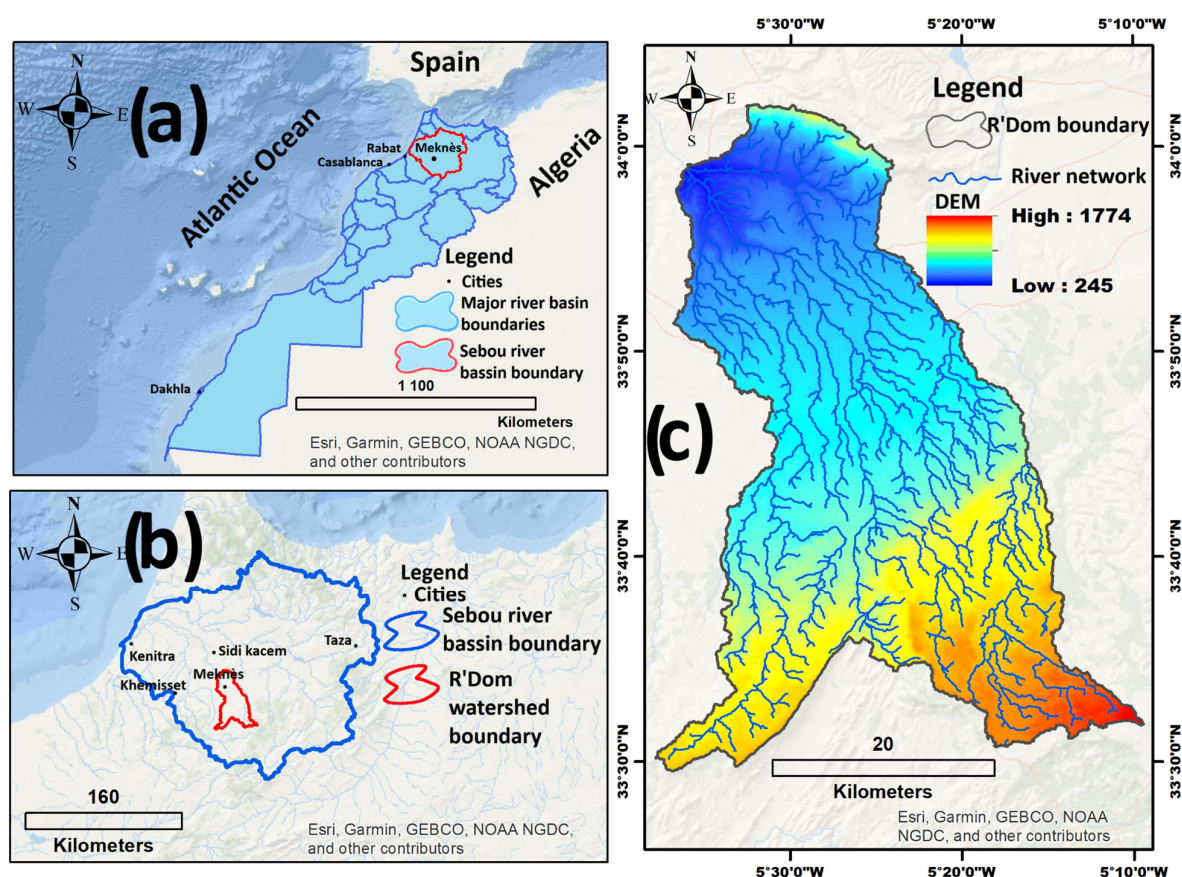


Figure 1. (a) Morocco and major river basin boundaries; (b) location of the Sebou Basin; and (c) digital elevation model of the R'Dom watershed. Coordinate system: WGS 84/UTM Zone 30N.

Table 1. Summary of morphometric indices for the R'Dom River Basin.

Parameters	Values
Area	1290.58 km ²
Perimeter	250.15 km
Gravelius Compactness Index (KG)	1.96
Maximum Altitude	1775 m
Minimum Altitude	245 m
Average Altitude	864.3 m
Equivalent Rectangle Length (Le)	114.72 km
Equivalent Rectangle Width (le)	11.25 km
Longest River Network (L)	77,351 m
Average Slope	1.98%
Concentration Time (Tc) (*)	22.67 h

(*) The concentration time (Tc) represents the average value obtained by applying five empirical methods: the Kirpich, Californian, Spanish, Turazza, and Ventura methods [43].

From a geological perspective, the study area comprises a wide array of geological formations ranging from the Paleozoic to the Quaternary. The oldest units of Paleozoic age are composed of schists that form the Hercynian basement [39]. This basement is unconformably overlain by secondary formations, including Triassic red clays and Jurassic carbonate deposits (limestones and dolomitic limestones of the Lower and Middle Lias).

These are, in turn, covered by grey and sandy marls from the Upper Miocene (Tortonian and Messinian). The Plio-Quaternary formations are represented by ochre sands, lacustrine limestones, loamy and fluvial Quaternary deposits (alluvium), and in some places conglomerates [44]. At the surface, especially in the southern part of the study area, volcanic features in the form of basaltic lava flows can occasionally be observed (as illustrated in the lithostratigraphic log or geological cross-section).

This geological diversity, marked by varying degrees of permeability, leads to significant heterogeneity in soil types, which in turn has a substantial impact on surface water runoff and flow dynamics [45]. Figure 2a provides geological facies of the R'Dom watershed, and Figure 2b indicates a general south-to-north geological cross-section of the study area (Figure 2).

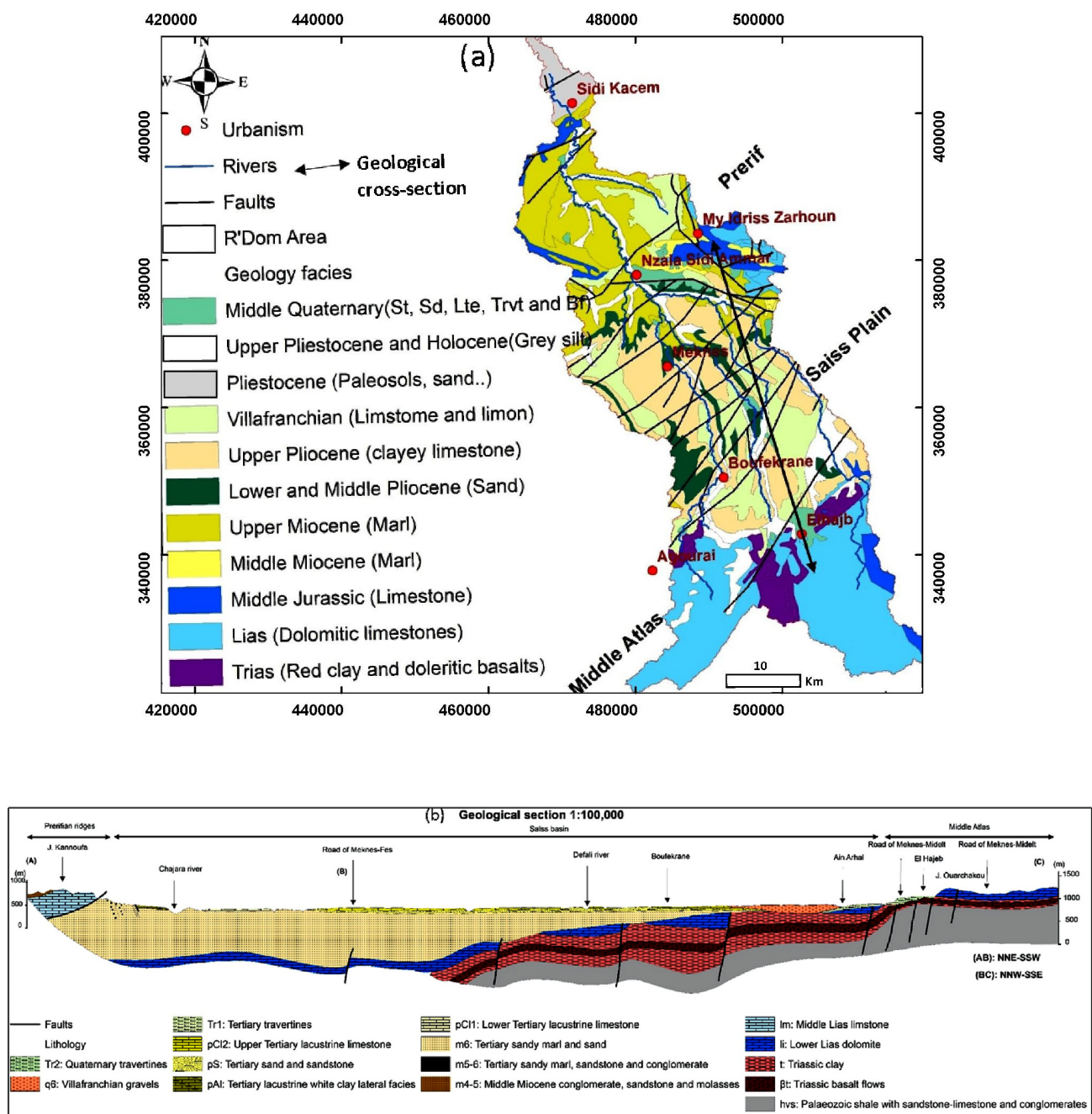


Figure 2. (a) Geological map of the watershed. (b) General geological cross-section of the study area (adapted from the El Hajeb geological map, scale 1:100,000).

From a hydrological standpoint, the R'Dom watershed is characterized by a dense river network, although the water flow remains generally low, particularly during the extended dry season. Hydrogeologically, the area is characterized by two major aquifer systems: a deep aquifer dating back to the Lias period and a shallower aquifer formed during the Plio-Quaternary era [46,47]. Agriculture represents the main livelihood for the local communities, with the landscape dominated by rainfed cereal farming, sunflower production, and the cultivation of onions and olive trees [47]. Forested areas are also present, especially in the southern part of the basin.

2.2. Data Used

2.2.1. Selection of Flood Conditioning Factors

The 17 factors selected for this study, as presented in Tables 2 and 3, include 13 variables related to flood hazard and 4 linked to flood vulnerability. Each of these factors is discussed in detail in the following subsections.

Table 2. Overview of the 13 data types, characteristics, and sources used for the flood hazard map.

No.	Factor	Description	Max–Min	Resolution/Scale	Source and Range
1	Elevation (DEM)	Elevation is one of the key criteria in identifying flood-prone areas. Lower-elevation areas are more likely to experience flooding.	Average = 864 Max = 1774 Min = 245	30 × 30 m	topographic data version 2 (https://earthexplorer.usgs.gov/) (accessed on 15 May 2024), 2011
2	Slope	Slope controls runoff and flow velocity. Flat areas accelerate the potential for flood occurrence.	Average = 4.9 Max = 55.7 Min = 0	30 × 30 m	topographic data (https://earthexplorer.usgs.gov/) (accessed on 15 May 2024), 2011
3	Curvature	Describes the surface geomorphology with three classes: convex, concave, and flat.	Average = −7.5 Max = 11 Min = −13.67	30 × 30 m	topographic data version 2 (https://earthexplorer.usgs.gov/) (accessed on 15 May 2024), 2011
4	Distance from Stream	Distance to the nearest stream affects flood exposure. The closer the point, the higher the flood risk.	Average = 370 Max = 2578.8 Min = 0	30 × 30 m	topographic data version 2 (https://earthexplorer.usgs.gov/) (accessed on 15 May 2024), 2011
5	TRI (Terrain Ruggedness Index)	Captures elevation variation around each pixel. Low TRI values correspond to higher flood susceptibility.	Average = 0.496 Max = 0.854 Min = 0.118	30 × 30 m	topographic data version 2 (https://earthexplorer.usgs.gov/) (accessed on 15 May 2024), 2011
6	Rainfall	Rainfall directly influences river discharge. High rainfall in short periods can trigger flash floods, especially in semi-arid areas.	Average = 549 Max = 602 Min = 510	Climate stations	Sebou Hydraulic Basin Agency (SHBA) rainfall station data, 1 September 2013–31 August 2020, complemented by WorldClim data, World Climate Website, https://worldclim.org/ (accessed on 15 May 2024)
7	Drainage Density	Higher drainage density indicates more surface runoff and hence higher flood risk.	Average = 0.89 Max = 2.01 Min = 0.0	30 × 30 m	topographic data version 2 (https://earthexplorer.usgs.gov/) (accessed on 15 May 2024), 2011
8	SPI (Stream Power Index)	Represents the erosive power of flow within the catchment. High SPI values indicate strong flood potential.	Average = −5.11 Max = 10.72 Min = −13.81	30 × 30 m	topographic data version 2 (https://earthexplorer.usgs.gov/) (accessed on 15 May 2024), 2011
9	Geology (Lithology)	Rock types and formations greatly affect flood initiation and intensity.	5 classes	1:1,000,000 & 1:50,000	Geological map of Morocco Service Géologique du Maroc
10	TWI (Topographic Wetness Index)	Identifies areas likely to accumulate surface runoff.	Average = 7.62 Max = 23.99 Min = 3.02	30 × 30 m	topographic data version 2 (https://earthexplorer.usgs.gov/) (accessed on 15 May 2024), 2011
11	MNDWI	Modified NDWI highlights zones of water accumulation critical for flood mapping.	Average = −0.255 Max = 0.233 Min = −0.451	30 × 30 m	Landsat-9 OLI (https://earthexplorer.usgs.gov/) (accessed on 16 May 2024), 2021–2024
12	Hydraulic Soil Group (HSG)	Incorporates parameters like permeability, thickness, infiltration, and soil moisture to assess runoff behavior.	2 classes (C and D)	1:250,000	HYSOGs250m; FAO Digital Soil Map of the World (accessed on 20 May 2024)
13	NDVI	NDVI evaluates vegetation coverage. Dense vegetation tends to reduce surface runoff and flood susceptibility.	Average = 0.163 Max = 0.56 Min = −0.13	30 × 30 m	Landsat-9 OLI (https://earthexplorer.usgs.gov/) (accessed on 16 May 2024), 2021–2024

Note: The “Range” column indicates the observed minimum and maximum values or the classification intervals used for reclassifying each flood hazard conditioning factor within the study area.

Table 3. Overview of the 4 data types, characteristics, and sources used for the flood vulnerability map.

No.	Factor	Description	Max–Min/Classes	Resolution/Scale	Source and Range
14	Built-Up Area	Mapping built-up areas is essential for assessing infrastructure vulnerability.	2 classes	10 × 10 m	ESRI, https://livingatlas.arcgis.com/landcoverexplorer (accessed on 17 May 2024), 2018
15	Population Density	Higher population density corresponds to greater vulnerability.	Average = 4.80 Max = 221 Min = 0.013	30 arc-seconds (~1 km ²)	WorldPop Hub, https://hub.worldpop.org/ (accessed on 20 May 2024), 2000–2020
16	Distance to Access	Distance to roads or infrastructure impacts emergency access and evacuation potential.	Average = 486.9 Max = 4322.6 Min = 0	5 × 5 m	GeoFabrik, https://geofabrik.de/ (accessed on 17 May 2024), 2024
17	Land Use/Land Cover (LULC)	Influences hydrological processes such as runoff, infiltration, and sediment transport.	5 classes	10 × 10 m	Sentinel-2, ESRI; https://livingatlas.arcgis.com/landcoverexplorer (accessed on 17 May 2024); 2024

Note: The “Range” column indicates the observed value range or classification intervals used for reclassifying each flood vulnerability factor within the study area.

One of the main challenges in multi-criteria flood risk assessment is the integration of diverse factors into a single, coherent index. To facilitate their management, integration, and processing within a Geographic Information System (GIS), a comprehensive set of thematic layers was developed based on the selected criteria [48,49]. ArcGIS 10.8 (Esri, Redlands, CA, USA) software was used to generate thematic maps corresponding to each factor. All variables were converted into raster layers with a pixel size of 30 × 30 m, using the UTM projection (Zone 30N) and Morocco’s official LCC projection (Zone 1).

2.2.2. Input Data

The use of remote sensing technologies for generating flood hazard and vulnerability maps is generally recognized as an effective approach [50]. The assessment factors were selected based on an optimized set of well-defined criteria.

Tables 2 and 3 present an overview of the primary and secondary data employed in this study, including a brief description of each dataset, its spatial resolution, and the corresponding source.

2.2.3. Flood Inventory Map

A flood inventory is essentially a detailed record of past flood events within a specific region, compiled from various reliable sources [23,51]. Building such a database is a crucial step in understanding how flood-related factors correlate with actual flood occurrences. The quality and completeness of this historical data play a key role in ensuring that flood susceptibility maps are both accurate and dependable.

In this study, the inventory map was created by gathering geospatial data from 450 flood-affected sites and 450 unaffected locations. This information was collected through a mix of fieldwork, direct observation, and official reports provided by the Ministry of Equipment, Transport, Logistics, and Water [4]. Additional records were obtained from the Sebou Hydraulic Basin Agency (SHBA) [46] and satellite data made available by the NASA Earth Observatory, with a particular focus on flood events that have impacted Morocco [52].

The inventory points were distributed across the watershed to represent the main flood-prone and non-flood-prone areas, including river corridors, low-slope zones, agricultural areas, and urbanized sectors. The flood points were checked against available historical flood information and local observations to ensure their consistency with known flood-affected areas.

Flood points were selected from locations with documented flood occurrence, particularly along river corridors, low-lying areas, flood-prone zones, and areas characterized by low permeability or unfavorable geomorphological conditions. Non-flood points were selected

from locations with no known flood occurrence, generally situated in higher-elevation areas, farther from river channels, or in zones less favorable to flood accumulation. This selection aimed to represent both flood-prone and non-flood-prone conditions across the watershed.

The flood inventory used in this study consists of discrete flood and non-flood locations. It does not include information on flood depth, inundation extent, flood duration, flow velocity, discharge, or exceedance probability. Therefore, the inventory was used only to validate the spatial agreement between the predicted flood susceptibility classes and the observed occurrence of flood events. It should not be interpreted as a hydrological or hydraulic validation dataset.

For model development, the data points were randomly divided into 70% of locations used to train the model and the remaining 30% used for validation using the geostatistical tools available in ArcGIS (Figure 3). This type of data splitting is commonly used in flood susceptibility studies [23,53].

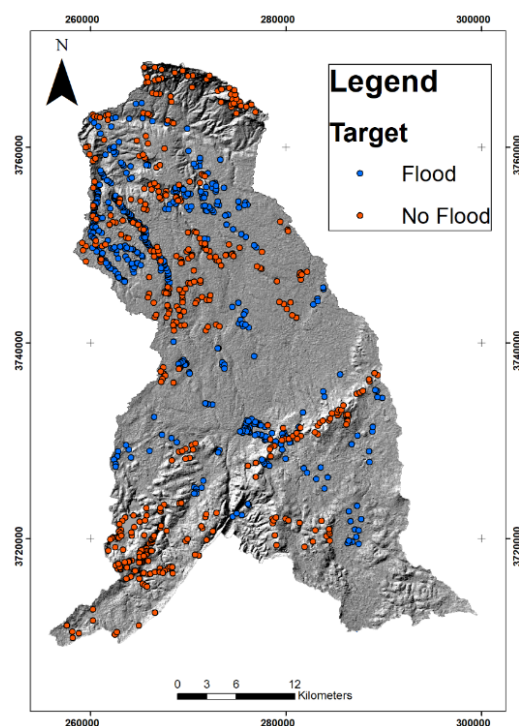


Figure 3. Spatial distribution of training and validation data points. Coordinate system: WGS 84/UTM Zone 30N. Base map source: ESRI World Topographic Map.

2.3. Methods

The methodology for the flood risk assessment adopted in this paper follows a three-step approach, as outlined below in the flowchart presented below.

Step 1: Data collection and processing: We collected and processed various types of data needed for flood risk analysis (Table 2). These included topographic data from satellite data, climate data from weather stations, geological maps, and population information. We identified 17 factors that influence flooding: 13 factors related to flood hazards (like elevation, slope, rainfall, and soil type) and 4 factors related to vulnerability (like population density and land use). All thematic maps were obtained after manual reclassification. A database of 900 locations where floods have occurred was gathered from government records, field surveys, and satellite observations. All data were converted to pixel size of 30×30 m grid format for consistent analysis.

Step 2: Analysis and modeling: We analyzed the flood data using two different methods: AHP (Analytic Hierarchy Process) and Fuzzy AHP. We divided our flood location

data into two groups: 70% for training the models and 30% for testing them later. We used expert knowledge to determine how important each factor is for causing floods, creating comparison matrices and calculating weights for each factor. Both AHP methods were then applied to combine all factors into flood hazard, vulnerability, and overall risk maps using Arc GIS software 10.8.

Step 3: Validation and map generation: In the final step, we tested how well our models perform using the validation data we set aside in Step 2. We calculated accuracy scores (AUC values) to measure how good each method is at predicting flood risk. We created final flood risk maps with five categories: very low-, low-, moderate-, high-, and very high-risk areas. All analysis was done using ArcGIS 10.8 software.

The flow chart presented in Figure 4 illustrates the sequential procedures and analytical models applied throughout the study. Both the Analytic Hierarchy Process (AHP) and Fuzzy AHP methods, under the multi-criteria decision analysis (MCDA) framework, were employed to generate flood hazard, vulnerability, and risk maps for the R'Dom watershed.

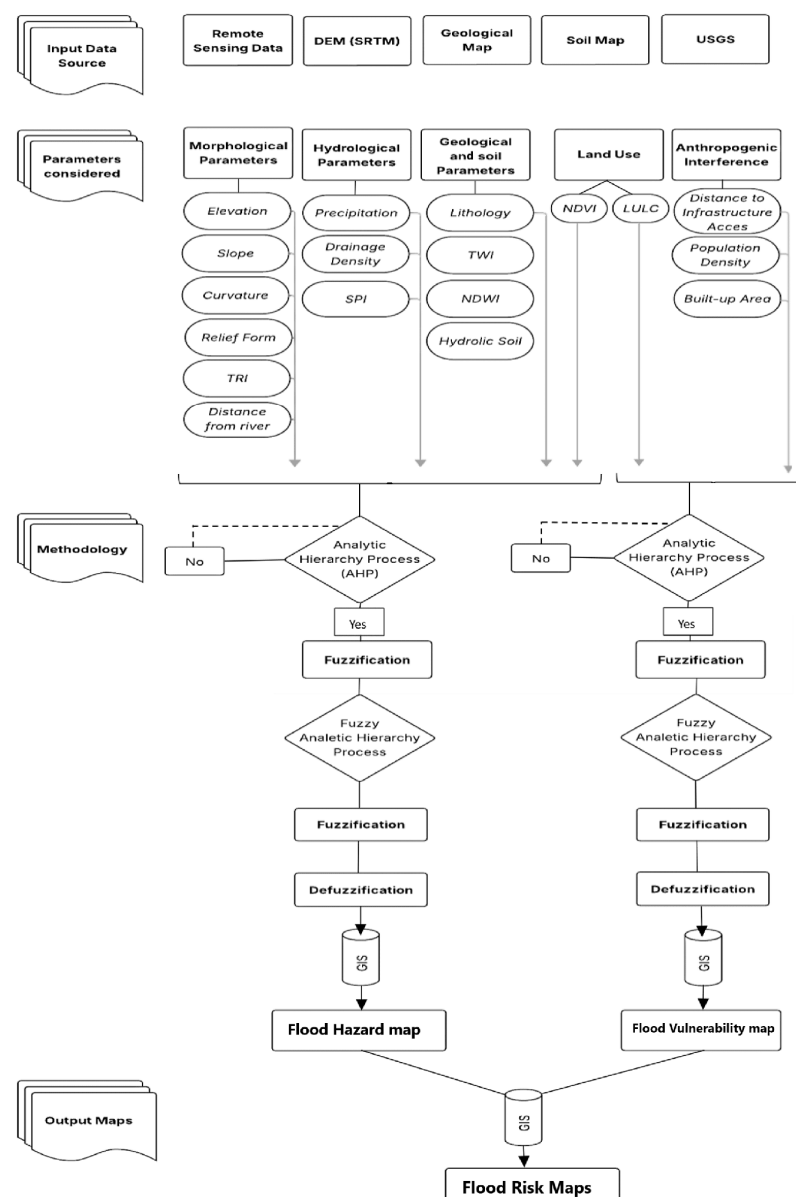


Figure 4. Methodological flow chart illustrating the use of AHP and Fuzzy AHP approaches for flood hazard, vulnerability, and risk mapping in the R'Dom watershed.

2.3.1. Multicollinearity Analysis

The following results of the multicollinearity analysis were obtained for the sake of checking the collinearity among the conditioning factors and as a reminder to maintain the consistency of the model. Multicollinearity analysis is a statistical technique that helps alert researchers when a regression model's independent variables are highly correlated with one another. This is quite significant; the identification of these issues is of vital importance to the healthiness of the model.

Multicollinearity among the conditioning factors was assessed using two diagnostic indices: the Variance Inflation Factor (VIF) and Tolerance (TOL). Factors were considered suitable for further analysis when $TOL > 0.1$ and $VIF < 10$ [24]. These two indices, TOL and VIF, can be calculated using the following equations:

$$VIF = \frac{1}{TOL}, \quad (1)$$

$$TOL = 1 - R^2, \quad (2)$$

where R^2 is the coefficient of determination of regression on all other independent variables.

2.3.2. Analytic Hierarchy Process (AHP) Model

The Analytic Hierarchy Process (AHP), introduced by Saaty, is a widely used multi-criteria decision-making method that allows complex problems to be structured into a hierarchy of criteria and alternatives [27,35]. It has been extensively applied in environmental planning, natural hazard assessment, and flood susceptibility mapping because it can integrate both qualitative expert judgment and quantitative spatial information [54,55].

In this study, AHP was used to derive the relative weights of the selected flood conditioning factors [56]. The method began with the construction of pairwise comparison matrices, in which the relative importance of each factor was evaluated using Saaty's 1–9 scale [57]. A total of eight experts participated in the weighting process. The expert panel included hydrologists, geomorphologists, GIS/remote sensing specialists, and flood risk management practitioners, each with more than ten years of professional or research experience in watershed hydrology and flood-related studies in Morocco.

Each expert independently completed the pairwise comparison matrices. The individual judgments were then aggregated using the geometric mean method, which is commonly recommended in group AHP applications because it preserves the reciprocal properties of the comparison matrix and reduces individual bias. In this study, the AHP structure was defined using two main hierarchical levels: the objective and the criteria. For the hazard/susceptibility component, the objective was to produce a relative flood susceptibility map, and the criteria corresponded to the selected flood conditioning factors. For the vulnerability component, the objective was to produce a flood vulnerability map, and the criteria corresponded to population density, buildings, distance to infrastructure, and LULC. The subclasses of each criterion were not treated as independent AHP subcriteria; they were reclassified and assigned ranks from 1 to 5 according to their expected contribution to flood susceptibility or vulnerability. The aggregated matrix was normalized by dividing each element by the sum of its corresponding column, and the priority weight of each criterion was obtained by calculating the average value of each row.

The consistency of the pairwise comparisons was evaluated using the Consistency Ratio (CR). A CR value lower than 0.10 indicates acceptable consistency, whereas a CR value higher than 0.10 requires revision of the pairwise comparison matrix [54]. The CR was calculated as follows:

$$CR = \frac{CI}{RI} \quad (3)$$

where CI is the Consistency Index and RI is the Random Index, which is a function of the number of criteria being compared, n (cf. Saaty [35]; see Table 4).

Table 4. Saaty’s scale of relative importance [35,58].

Importance Scale	Level of Preference	Explanation
1	Same and equal importance	When both contribute equally
3	One factor’s moderate importance relative to another	Experience and judgment slightly favor one factor over another
5	Strong or vital importance	One factor is strongly favored over another by experience and judgment
7	Very strong and high importance	When a factor is highly preferred and its domination is shown in actuality
9	Extreme importance	The most robust order of affirmation is found in the evidence supporting one factor over another
2, 4, 6, 8	Values in the middle of two adjacent judgments	When a compromise is necessary

The RI values applied in this analysis are the ones associated with the conventional Saaty scale (cf. Table 5) [35]. The Consistency Index (CI) was calculated using the equation defined by Saaty (Equation (3)). According to widely accepted standards, a Consistency Ratio (CR) greater than 10% suggests inconsistencies in the pairwise comparisons, requiring further review. In contrast, CR values below this threshold are typically deemed acceptable for decision-making purposes.

Table 5. Random Index (RI).

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.58

This approach provides a structured and transparent method for evaluating the relative importance of each factor, ultimately contributing to improved accuracy and credibility in the resulting flood hazard maps.

In this context, the Consistency Index (CI) is derived from the principal eigenvalue, γ_{max} , of the pairwise comparison matrix. The Consistency Index (CI) is calculated as follows:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (4)$$

where n is the number of factors being compared in the matrix and γ_{max} is the principal eigenvalue of the pairwise comparison matrix.

After deriving the AHP weights, the subclasses of each reclassified factor were assigned influence scores ranging from 1 to 5 according to their expected contribution to flood susceptibility or vulnerability. A score of 1 indicates very low influence, while a score of 5 indicates very high influence. The weighted overlay technique was then applied in ArcGIS to integrate the standardized raster layers and generate the flood hazard/susceptibility and vulnerability indices. Similar GIS-based weighted overlay approaches have been widely used in flood susceptibility and risk assessment studies [59].

To improve readability and avoid repetition, the detailed AHP pairwise comparison matrices for hazard and vulnerability factors are presented later in the Results section together with the final weighting and consistency analysis.

Flood Hazard Index (FHI–AHP-Based)

Based on the FHI values obtained via the AHP methodology, the flood hazard/susceptibility map was generated. This map identifies areas with different levels of susceptibility to flooding, ranging from very low to very high. By integrating the selected conditioning factors through the weighted overlay approach, the FHI provides a spatial representation of zones that are more prone to flood occurrence within the study area.

$$FHI_{AHP} = \sum_{i=1}^n X_i \times W_i, \quad (5)$$

Flood Vulnerability Index (FVI–AHP-Based)

The Flood Vulnerability Index (FVI) is defined as the degree of exposure and impact of flood hazards on human populations, built environments, and socio-environmental systems. It follows the same weighting methodology applied to the hazard index, with its equation being as follows:

$$FVI_{AHP} = \sum_{i=1}^n X_i \times W_i, \quad (6)$$

In the above equations, FHI_{AHP} and FVI_{AHP} refer to the Flood Risk Index and the Flood Vulnerability Index, calculated using the AHP method; n is the number of contributing factors; X_i is the standardized ranked value of the factor class; and W_i is the weight of the factors.

The FHI and FVI values were then categorized into very low, low, moderate, high, and very high flood susceptibility using the natural breaks classification method. This was considered to have been successfully applied in determining flood-prone areas based on past research works, when applied within the AHP approach [15,60].

Flood Risk Map (FRM) according to the AHP approach

A flood risk map is generated by combining two core components: vulnerability and hazard. Our conceptual model is broadly applicable to all types of natural hazard [60,61] and is represented mathematically in Equation (7) as follows:

$$FRM_{AHP} = FHM_{AHP} \times FVM_{AHP}, \quad (7)$$

where FRM_{AHP} is the flood risk map based on AHP, FHM_{AHP} is the flood hazard map based on AHP, and FVM_{AHP} is the flood vulnerability map based on AHP.

Our resulting FHI and FVI values were subjected to the natural breaks classification technique to generate a five-susceptibility-level-based classification—very low, low, moderate, high, and very high. It has been shown that the classification technique employed in this study is particularly well-suited for flood susceptibility mapping based on AHP [15].

2.3.3. Fuzzy Analytic Hierarchy Process (FAHP)

Although AHP is highly appreciated for its thoughtful and efficient work, the major disadvantage is that the method is based on an exact numerical evaluation as it is perhaps the method that is most sensitive to subjective expert bias [35,62]. To eliminate this disadvantage, it was proposed to add fuzzy logic to the structure, which would make it possible to consider the element of uncertainty regarding the expression of mistaken or indefinite preferences. As a result, the structure used is the FAHP.

By integrating fuzzy logic, a fuzzy-based approach allows the obtainment of a flexible and more realistic interpretation of expert judgments that is particularly attractive in the case of complex decision-making situations like the flood susceptibility analysis (Table 6).

Table 6. Triangular fuzzy scale for AHP, adapted from [62].

AHP (Saaty's Scale)	Linguistic Terms	Fuzzy Triangular Scale
1	Equally important	(1,1,1)
3	Weakly important	(2,3,4)
5	Fairly important	(4,5,6)
7	Strongly important	(6,7,8)
9	Absolutely important	(9,9,9)
2	Intermediate value for interphase evaluation	(1,2,3)
4	Intermediate value for interphase evaluation	(3,4,5)
6	Intermediate value for interphase evaluation	(5,6,7)
8	Intermediate value for interphase evaluation	(7,8,9)

After the AHP comparison matrix is transformed into a fuzzy matrix, the geometric mean of the fuzzy numbers can be calculated through Equation (8).

$$t_i = \left(\prod_{j=1}^n \tilde{a}_{ij} \right)^{\frac{1}{Z}}, \quad (8)$$

where t_i denotes the fuzzy geometric mean of the fuzzy values, $\tilde{a}_{ij}$ is the fuzzy preference of criterion i with respect to criterion j , and Z is the number of decision-makers involved in the evaluation.

Subsequently, the fuzzy weight for each criterion is computed using the following equation:

$$Wi = \frac{t_i}{\sum_{i=1}^n t_i}, \quad (9)$$

where Wi is the normalized fuzzy weight of criterion i .

The following step, defuzzification, refers to the conversion of fuzzy weights to crisp weights that can be quantitatively compared. This is done as follows:

$$Mi = \frac{W_{ia} + W_{ib} + W_{ic}}{3}, \quad (10)$$

where Mi is the defuzzified (crisp) value and $W_{ia} + W_{ib} + W_{ic}$ represents the components of the fuzzy weight assigned to criterion i (i.e., the lower, middle, and upper bounds of the triangular fuzzy number).

The following step is the normalization of these crisp values using the following formula:

$$Ni = \frac{M_i}{\sum_{j=1}^n M_j}, \quad (11)$$

where Ni represents the final normalized weight of criterion i .

The incorporation of fuzzy logic into the AHP framework results in a more flexible and realistic representation of the factors controlling flood susceptibility [35].

It also allows uncertainty and subjectivity in expert judgments to be better considered. In the present study, the FAHP procedure started from the AHP pairwise comparison matrices, which were first checked for consistency using the Consistency Ratio ($CR < 0.10$). The crisp comparison values were then converted into triangular fuzzy numbers, allowing a more nuanced representation of expert preferences. Following the defuzzification step, the

final normalized weights were reintegrated into the GIS environment through a weighted overlay model. This process enabled the production of flood hazard/susceptibility, vulnerability, and risk maps, each classified into five relative classes.

To improve readability and avoid repetition, the detailed triangular fuzzy comparison matrices for hazard and vulnerability factors are presented later in the Results section together with the final weighting results.

2.3.4. Validation of the Models

Validating the generated flood susceptibility maps is a critical step to ensure the effectiveness and practical relevance of the applied models [63]. The Flood Hazard Index (FHI) used in this study should be interpreted as a relative flood susceptibility index rather than a probabilistic flood hazard measure. It does not represent flood exceedance probability, return period, water depth, flow velocity, discharge, or inundation extent. Due to the lack of long-term hydrological records, rainfall intensity–duration–frequency curves, and hydraulic flood observations for the R'Dom watershed, the validation was based on binary flood/non-flood inventory points. Therefore, the ROC-AUC validation evaluated the spatial agreement between predicted susceptibility classes and observed flood occurrence locations, but it did not validate flood magnitude, flood depth, flood extent, or flood frequency. Several methods are available to assess the accuracy and reliability of such results. In this study, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was used. This statistical and mathematical approach has been widely and successfully employed in natural hazard modeling and mapping, particularly in flood susceptibility assessment, due to its rational, consistent, and easily interpretable methodology [63].

For the validation process, a total of 900 flood inventory points (compiled from heterogeneous and indirect sources, including remote sensing interpretation, field surveys, and local reports) were compared against the flood hazard, vulnerability, and risk maps to produce AUC-ROC curves for both models (AHP and Fuzzy AHP), enabling an evaluation of their predictive accuracy and a comparative analysis of their performance. The validation was based on an internal split of the available flood inventory into training and testing subsets. No fully independent external validation dataset was available for the study area. Therefore, the reported ROC-AUC values should be interpreted as an internal assessment of model discrimination capacity rather than as an external validation of predictive performance. The ROC curve [64] is constructed by plotting the true positive rate (sensitivity) on the Y-axis against the false positive rate (1-specificity) on the X-axis, and the AUC is calculated as shown in Equation (12) [65].

$$AUC = \frac{\sum TP \times \sum TN}{(P + N)}, \quad (12)$$

In this context, the AUC refers to the Area Under the ROC Curve. TP (true positive) indicates the number of flood points correctly identified by the model, while TN (true negative) represents the number of non-flood points accurately classified as such. The variable P corresponds to the number of pixels classified as flood-prone, and N denotes those classified as non-flood areas. The AUC value ranges from 0 to 1, with higher values indicating better model performance. According to [66], the qualitative interpretation of AUC values is as follows: 0.5–0.6 (poor), 0.6–0.7 (moderate), 0.7–0.8 (good), 0.8–0.9 (very good), and 0.9–1.0 (excellent) [67].

3. Results

3.1. Independent Analysis of the Conditioning Factors

The results of the multicollinearity analysis conducted on the 17 flood conditioning factors are summarized in Table 7. This analysis was performed using the R 4.5.3 software environment [68]. The Tolerance (TOL) values for all factors were found to be below 1.0, and the corresponding Variance Inflation Factor (VIF) values were all less than 8.5. No conditioning factor was removed from the analysis because all VIF values remained below the commonly accepted threshold of 10 and all TOL values were greater than 0.1, confirming an acceptable level of independence among the selected factors. Consequently, all 17 conditioning factors were retained for flood hazard, vulnerability, and risk modeling.

Table 7. Multicollinearity analysis of the flood conditioning factors.

Flood Conditioning Factors	Collinearity Statistics	
	TOL	VIF
Elevation	0.118	8.5
Slope	0.337	2.9
Curvature	0.693	1.4
Distance from River	0.500	2.0
TRI	0.864	1.1
Rainfall	0.121	8.2
Drainage Density	0.458	2.1
SPI	0.312	3.2
Lithology	0.869	1.1
TWI	0.321	3.1
MNDWI	0.586	1.70
HSG	0.823	1.2
NDVI	0.633	1.6
LULC	0.304	3.3
Distance to Infrastructure	0.487	2.0
Population Density	0.611	1.6
Built-Up Area	0.269	3.7

In addition, the potential redundancy between the Built-Up area layer and the built-up class included in the LULC dataset was examined through the multicollinearity analysis. The obtained VIF values for LULC and Built-Up Area remained below the commonly accepted threshold of 10, while their TOL values were higher than 0.1. This indicates that the two variables do not introduce critical redundancy into the model and can be retained as complementary indicators, with LULC representing land-cover characteristics and Built-Up Area representing exposed physical assets.

3.2. Analysis of Flood Conditioning Factors

3.2.1. Analysis of the Flood Hazard Conditioning Factors

Rainfall

Rainfall is a direct driver of flood events [69]. Rainfall maps were generated using Inverse Distance Weighted (IDW) interpolation of climatic station data in ArcGIS 10.8. The spatial distribution of rainfall gauging stations and the IDW-interpolated mean annual rainfall map are presented in Figure 5. Rainfall values ranged from 510 mm to 602 mm and were divided into five classes using the natural breaks classification method available in

ArcGIS software. The most dominant class, accounting for 36.38%, includes areas receiving less than 510 mm of rainfall annually (Figure 5).

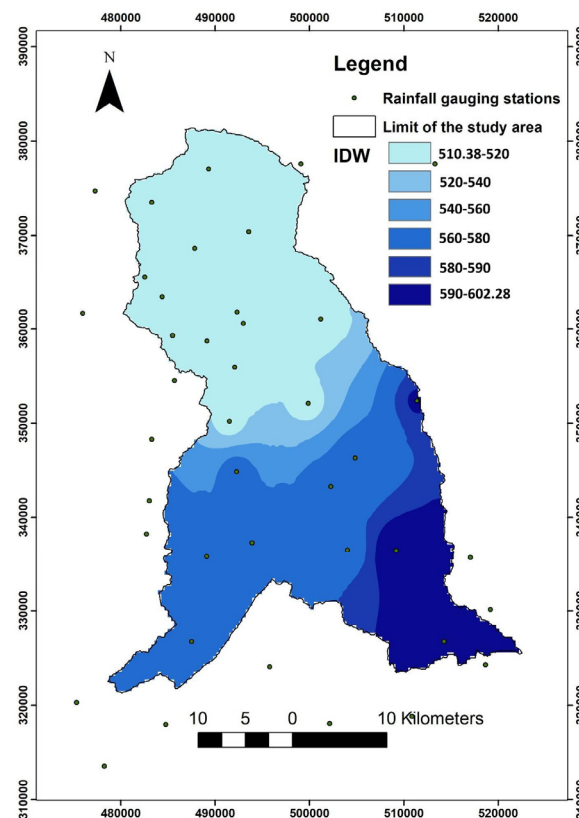


Figure 5. Rainfall gauging stations and IDW-interpolated mean annual rainfall distribution in the study area.

The rainfall layer used in this study represents the multi-year mean annual rainfall derived from Sebou Hydraulic Basin Agency (SHBA) rainfall station data for the period from 1 September 2013 to 31 August 2020, complemented by WorldClim data. It does not correspond to an extreme precipitation index or short-duration rainfall intensity. The objective was to represent the spatial variability of average rainfall conditions across the R'Dom watershed, which is relevant for regional-scale flood susceptibility mapping in a data-scarce context. Although rainfall intensity would be more appropriate for event-based flood hazard assessment, reliable intensity–duration–frequency data were not available for the whole watershed.

Elevation

Elevation represents a key factor influencing flood occurrence; lower elevations are more prone to flooding due to increased river discharge and rapid water accumulation [67]. The elevation map for the study area, derived from a Digital Elevation Model (DEM), shows altitudes ranging from 245 to 1774 m. As depicted in Figure 6, high-altitude regions such as the Middle Atlas plateau are located in the southern part of the watershed, whereas low-altitude areas are mostly found in the north. Elevation was classified into five hypsometric classes: >1200 m, 1200–1000 m, 1000–600 m, 600–300 m, and <300 m. The dominant class, representing 43.88% of the area, corresponds to elevations between 600 and 1000 m.

Slope

Flatter terrains are more susceptible to flooding than steep slopes, as water flows more slowly, tends to stagnate, and accumulates over time [70]. The slope map, derived

using percentages from the DEM, ranges from 0% to 55.7%. As shown in Figure 6, steep slopes are mainly located in the high-altitude mountainous areas in the south and northeast, while flatter slopes are found in the central part of the study area (Meknes Plateau). Using the natural breaks method, slope was classified into five categories: 0–3%, 3–6%, 6–12%, 12–21%, and >21%. Slopes in the range of 6–12% are the most widespread, covering 33.43% of the area.

Curvature

Topographic curvature describes the shape of the land surface [71]. Positive values indicate convex surfaces, negative values indicate concave surfaces, and values near zero indicate flat terrain [70]. Flat curvatures are most flood-prone, followed by concave and convex surfaces. Using the curvature tool in ArcGIS, curvature values ranging from −13.67 to +11 were obtained and automatically classified into three categories, <0, =0, and >0, as shown in Figure 6. Concave surfaces are dominant, covering 58.34% of the total area.

Distance from River

Proximity to rivers is a significant factor in flood susceptibility. Areas closer to rivers have a higher risk of flooding compared to those further away. However, the critical distance threshold can vary depending on river size [67]. In the study area, the major rivers, the Boufakrane, Ouislane, and Bou Ishak, flow from south to north. Localities near these rivers are considered more vulnerable. As illustrated in Figure 6, river distance was classified into five intervals using the manual classification method: 0–200 m, 200–400 m, 400–600 m, 600–800 m, and >800 m. Areas within 200 m account for only 8.57%, while those beyond 800 m cover 33.38%.

Terrain Ruggedness Index (TRI)

The TRI, developed by [69], quantifies terrain variation by comparing the elevation of a pixel with its surrounding neighbors. TRI values in the study area range from 0.118 to 0.854, as shown in Figure 6. Using the Euclidean Distance tool available in ArcGIS software, the index was generated and reclassified into five categories: >0.7, 0.7–0.6, 0.6–0.5, 0.5–0.4, and <0.4.

Drainage Density

Drainage density, defined as the total stream length per unit area, is a critical factor influencing flood dynamics [72]. The drainage density map was classified into five categories using the natural breaks classification method available in ArcGIS software: <0.2, 0.2–0.6, 0.6–1.0, 1.0–1.4, and >1.4 (Figure 6).

Stream Power Index (SPI)

A high SPI value indicates areas with greater erosion and flood potential. SPI values in the study area range from −13.81 to +10.72 (Figure 6). The index was classified into two categories: negative SPI and positive SPI. The negative SPI class is dominant, covering 87.66% of the area.

Lithology and Permeability

Lithology significantly influences surface runoff, with impermeable formations leading to higher flood risk. Based on geological permeability, five lithological classes were defined automatically. The permeable class is the most prevalent, covering 61.11% of the study area (Figure 6).

Topographic Wetness Index (TWI)

TWI helps identify zones prone to saturation and overflow, making it an essential indicator of flood risk [73]. The TWI map was classified into two classes using the natural

breaks classification method available in ArcGIS software: $TWI < 6.55$ and $6.55\text{--}8.28$, representing 37.11% and 37.50% of the area, respectively (Figure 6).

Modified Normalized Difference Water Index (MNDWI)

MNDWI delineates surface water accumulation zones, which are key to assessing flood susceptibility. In this study, the MNDWI was calculated from Landsat 9 OLI imagery using the green and short-wave infrared bands according to the following equation:

$$MNDWI = \frac{(Green - SWIR1)}{(Green + SWIR1)}$$

For Landsat 9 OLI, the green band corresponds to Band 3 and the SWIR1 band corresponds to Band 6. The index was then classified into five categories using the natural breaks classification method available in ArcGIS software. The class with MNDWI values < -0.25 dominates the region, accounting for 58.90% of the area (Figure 6).

Hydraulic Soil Group (HSG)

Soil type influences infiltration and runoff. Using HYSOGs 250 m and SWAT data, soils were classified into two groups: Group CC (which dominates the region, covering 58.3% of the area) and Group D (Figure 6).

Normalized Difference Vegetation Index (NDVI)

Vegetation density, as measured by NDVI, affects flood risk by reducing runoff and enhancing infiltration [74]. NDVI values, derived from Landsat 9 satellite imagery using bands (Band 4: Red; Band 5: NIR), range from -0.13 to 0.56 in this study area (Figure 6). These were reclassified into five classes. The class with NDVI values between 0.1 and 0.2 is dominant, covering 71.35% of the area.

3.2.2. Analysis of Flood Vulnerability Conditioning Factors

Land Use/Land Cover (LULC)

LULC significantly affects flood dynamics by influencing surface runoff [51]. The LULC map was extracted from Sentinel-2B satellite images with a 10 m spatial resolution. The classified LULC categories are: agriculture (61.19%), grassland (20%), built-up areas (7.83%), forest (10.98%), and water bodies (0.34%). As shown in Figure 6, many built-up areas are located near rivers, increasing their flood vulnerability.

Distance to Road Access

Road networks and their surrounding slopes can exacerbate flood impacts by increasing impermeable surfaces and altering natural flow paths [55]. The Euclidean distance from roads was calculated using ArcGIS and classified into five categories using the natural breaks classification method available in ArcGIS software: $0\text{--}200$ m, $200\text{--}400$ m, $400\text{--}600$ m, $600\text{--}800$ m, and >800 m. The closest distance class ($0\text{--}200$ m) dominates, covering 45.64% of the area (Figure 6).

Population Density

High-population density areas are generally more exposed to flood risk due to infrastructure concentration and disrupted drainage. Population density ranges from 0.13 to 221 inhabitants/ km^2 in the study area. The lowest density class (<10 inhabitants/ km^2) is predominant, representing 92.33% of the area (Figure 6). The WorldPop population density layer was used as provided by the original dataset and was not asymmetrically downscaled to built-up areas. This limitation may introduce uncertainty in the spatial representation of the exposed population and should be improved in future studies using detailed census data or asymmetric population mapping.

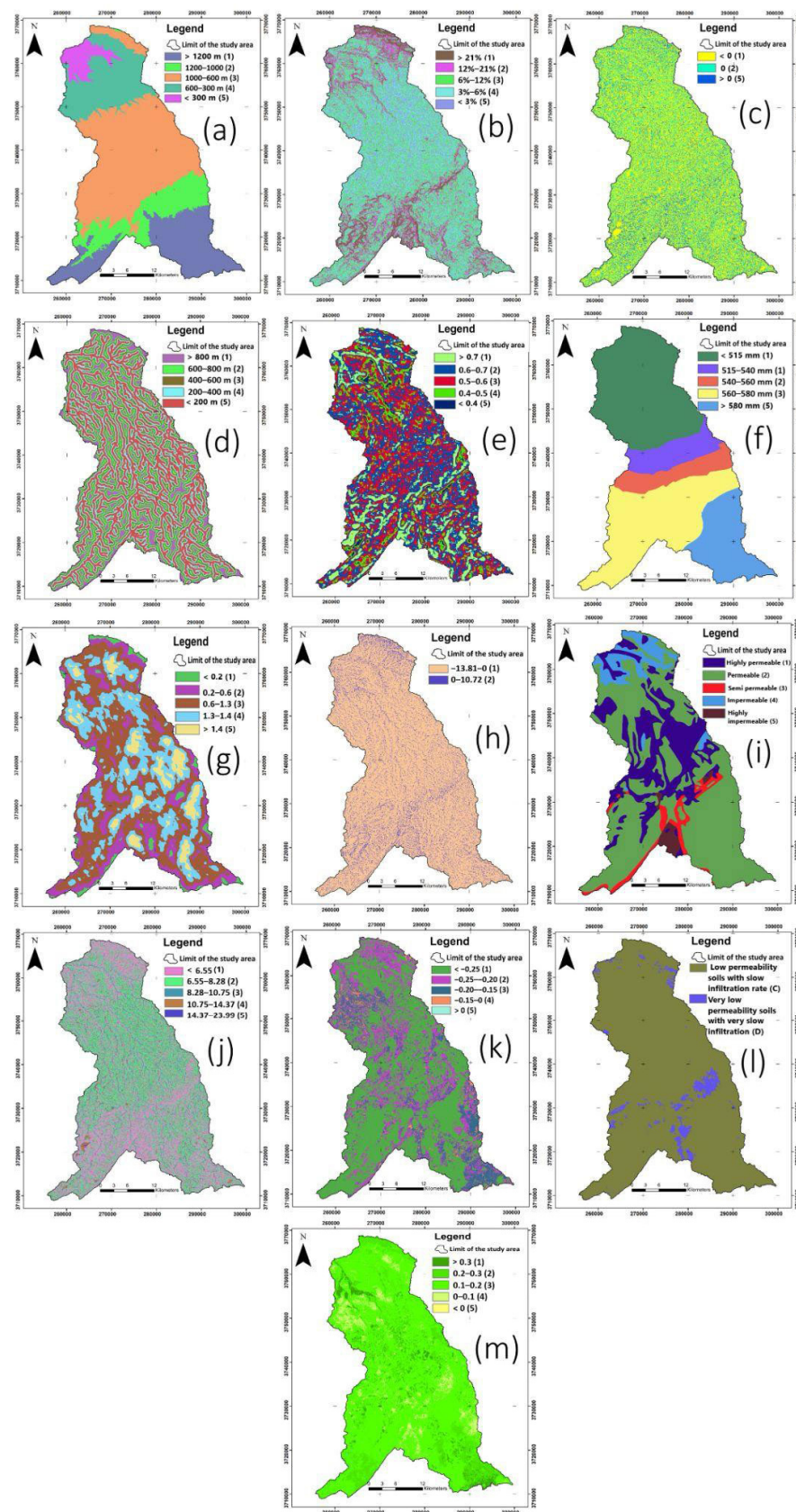


Figure 6. Cont.

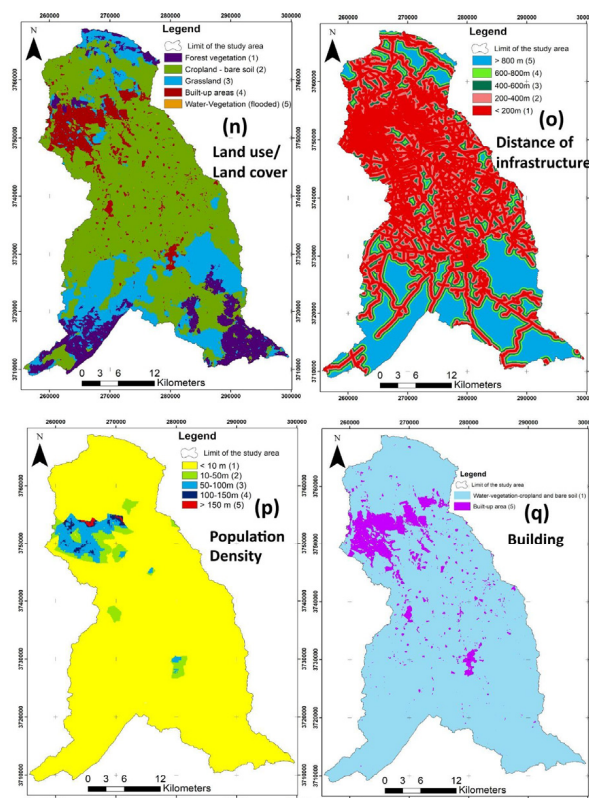


Figure 6. Flood hazard conditioning factors (a–m): (a) Elevation, (b) Slope, (c) Curvature, (d) Distance from River, (e) Terrain Ruggedness Index (TRI), (f) Rainfall, (g) Drainage Density, (h) Stream Power Index (SPI), (i) Lithology, (j) Topographic Wetness Index (TWI), (k) Modified Normalized Difference Water Index (MNDWI), (l) Hydrologic Soil Group (HSG), (m) Normalized Difference Vegetation Index (NDVI). Flood hazard conditioning factors (n–q): (n) Land Use/Land Cover (LULC), (o) Distance to Infrastructure, (p) Population Density, (q) Built-Up Area.

Built-Up Areas

Urbanization modifies watershed hydrology by increasing surface sealing and reducing infiltration [75], thereby intensifying surface runoff and flood risks. Built-up areas, derived from Sentinel-2B imagery, were reclassified into two categories: built-up and non-built-up. Built-up zones represent 7.84% of the total area and are mainly concentrated around Meknes, El Hajeb, and Boufakrane (Figure 6).

Both layers were kept because they capture different aspects: LULC built-up areas indicate impervious surfaces affecting runoff, while buildings represent exposed assets and vulnerability; they are complementary, not redundant.

The percentage distribution of the reclassified classes was calculated for both flood hazard and flood vulnerability factors. The results for the flood hazard conditioning factors are summarized in Table 8, while the corresponding results for the flood vulnerability factors are presented in Table 9.

Table 8. Percentage of classes for each hazard factor.

Classes	ELEV	SLOPE	CURV	DR	TRI	PREC	DD	SPI	LITHO	TWI	MNDWI	HSG	NDVI
Very Low	20.08	8.00	58.34	8.57	14.14	36.38	3.13	87.66	25.23	37.11	58.90	0.00	4.38
Low	14.15	16.61	25.36	11.12	38.39	8.71	18.07	0.00	61.11	37.50	25.51	95.30	17.12
Moderate	43.88	33.43	0.00	19.66	35.86	8.13	42.75	0.00	4.41	15.32	13.07	0.00	71.35
High	17.38	26.97	0.00	27.27	10.06	30.90	28.65	0.00	7.02	7.89	2.49	0.00	7.13
Very high	4.50	14.99	16.30	33.38	1.54	15.87	7.41	12.34	2.23	2.18	0.03	4.70	0.01

Table 9. Percentage of classes for each vulnerability factor.

Class	LULC	Distance to Infrastructure	Population Density	Built-Up
Very Low	10.99	19.56	92.63	92.16
Low	61.19	5.91	3.32	0.00
Moderate	19.95	10.30	3.33	0.00
High	7.84	18.59	0.57	0.00
Very high	0.03	45.64	0.15	7.84

3.3. Results of Pairwise Consistency

According to the results of the weighting process performed using both the AHP and Fuzzy AHP methods (Tables 10–13), the CR obtained for the AHP model was 0.064. Since this value is below the commonly accepted threshold of 0.1, it indicates that the pairwise comparisons were consistent, and the factor weighting is considered reliable. Using the Fuzzy AHP approach, new weights were recalculated for each parameter to better capture uncertainty and imprecision in the decision-making process. As shown in Tables 10–14, rainfall, slope, distance to river, and drainage density emerged as the most influential factors in the context of flood hazard assessment.

Table 10. AHP pairwise comparison matrix of 13 selected hazard flood conditioning factors for this study.

	Rf	SI	DR	DD	TRI	TWI	MNDWI	SPI	HSG	El	Lt	NDVI	Cu
Rf	1	3	5	5	6	6	6	6	6	5	8	8	8
SI	1/3	1	3	4	4	5	5	5	3	4	7	7	6
DR	1/5	1/3	1	2	3	4	4	4	3	3	6	6	4
DD	1/5	1/4	1/2	1	2	3	3	3	3	3	5	5	4
TRI	1/6	1/4	1/3	1/2	1	2	2	2	2	2	3	3	2
TWI	1/6	1/5	1/4	1/3	1/2	1	2	2	2	2	3	3	2
MNDWI	1/6	1/5	1/4	1/3	1/2	1/2	1	3	3	2	2	2	2
SPI	1/6	1/5	1/4	1/3	1/2	1/2	1/3	1	2	2	2	2	2
HSG	1/6	1/3	1/3	1/3	1/2	1/2	1/3	1/2	1	1	1	1	1
El	1/5	1/4	1/3	1/3	1/2	1/2	1/2	1/2	1	1	2	2	2
Lt	1/8	1/7	1/6	1/5	1/3	1/3	1/2	1/2	1	1/2	1	1	1
NDVI	1/8	1/7	1/6	1/5	1/3	1/3	1/2	1/2	1	1/2	1	1	1
Cu	1/8	1/6	1/4	1/4	1/2	1/2	1/2	1/2	1	1/2	1	1	1

Rf: Rainfall; DR: Distance from the River; Elev: Digital Elevation; SI: Slope; TWI: Topographic Wetness Index; LULC: Land Use/Land Cover; DD: Drainage Density; MNDWI: Modified Normalized Difference Water Index, So: Soil; Lt: Lithology; Cu: Curvature.

Table 11. AHP pairwise comparison matrix of 4 selected vulnerability flood conditioning factors for this study.

	Built-Up Area	Population Density	Distance to Infrastructure	LULC
Built-Up Area	1	1/2	3	4
Population Density	2	1	4	5
Distance to Infrastructure	1/3	1/4	1	2
LULC	1/4	1/5	1/2	1

Table 12. Triangular fuzzy numbers (hazard factors).

	Rf	SI	DR	DD	TRI	TWI	MNDWI	SPI	HSG	El	Lt	NDVI	Cu
Rf	1,1,1	2,3,4	4,5,6	4,5,6	5,6,7	5,6,7	5,6,7	5,6,7	5,6,7	4,5,6	7,8,9	7,8,9	7,8,9
SI	1/4,1/3,1/2	1,1,1	2,3,4	3,4,5	3,4,5	4,5,6	4,5,6	4,5,6	2,3,4	3,4,5	6,7,8	6,7,8	5,6,7
DR	1/6,1/5,1/4	1/4,1/3,1/2	1,1,1	1,2,3	2,3,4	3,4,5	3,4,5	3,4,5	2,3,4	2,3,4	5,6,7	5,6,7	3,4,5
DD	1/6,1/5,1/4	1/5,1/4,1/3	1/3,1/2,1	1,1,1	1,2,3	2,3,4	2,3,4	2,3,4	2,3,4	2,3,4	4,5,6	4,5,6	3,4,5
TRI	1/7,1/6,1/5	1/5,1/4,1/3	1/4,1/3,1/2	1/3,1/2,1	1,1,1	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	2,3,4	2,3,4	1,2,3
TWI	1/7,1/6,1/5	1/6,1/5,1/4	1/5,1/4,1/3	1/4,1/3,1/2	1/3,1/2,1	1,1,1	1,2,3	1,2,3	1,2,3	1,2,3	2,3,4	2,3,4	1,2,3
MNDWI	1/7,1/6,1/5	1/6,1/5,1/4	1/5,1/4,1/3	1/4,1/3,1/2	1/3,1/2,1	1/3,1/2,1	1,1,1	2,3,4	2,3,4	1,2,3	1,2,3	1,2,3	1,2,3
SPI	1/7,1/6,1/5	1/6,1/5,1/4	1/5,1/4,1/3	1/4,1/3,1/2	1/3,1/2,1	1/3,1/2,1	1/4,1/3,1/2	1,1,1	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3
HSG	1/7,1/6,1/5	1/4,1/3,1/2	1/4,1/3,1/2	1/4,1/3,1/2	1/3,1/2,1	1/3,1/2,1	1/4,1/3,1/2	1/3,1/2,1	1,1,1	1,1,1	1,1,1	1,1,1	1,1,1
El	1/6,1/5,1/4	1/5,1/4,1/3	1/4,1/3,1/2	1/4,1/3,1/2	1/3,1/2,1	1/3,1/2,1	1/3,1/2,1	1/3,1/2,1	1,1,1	1,1,1	1,2,3	1,2,3	1,2,3
Lt	1/9,1/8,1/7	1/8,1/7,1/6	1/7,1/6,1/5	1/6,1/5,1/4	1/4,1/3,1/2	1/4,1/3,1/2	1/3,1/2,1	1/3,1/2,1	1,1,1	1/3,1/2,1	1,1,1	1,1,1	1,1,1
NDVI	1/9,1/8,1/7	1/8,1/7,1/6	1/7,1/6,1/5	1/6,1/5,1/4	1/4,1/3,1/2	1/4,1/3,1/2	1/3,1/2,1	1/3,1/2,1	1,1,1	1/3,1/2,1	1,1,1	1,1,1	1,1,1
Cu	1/9,1/8,1/7	1/7,1/6,1/5	1/5,1/4,1/3	1/5,1/4,1/3	1/3,1/2,1	1/3,1/2,1	1/3,1/2,1	1/3,1/2,1	1,1,1	1/3,1/2,1	1,1,1	1,1,1	1,1,1

Table 13. Triangular fuzzy numbers (vulnerability factors).

	Built-Up Area	Population	Distance to Infrastructure	LULC
Built-Up Area	1,1,1	1/3,1/2,1	2,3,4	3,4,5
Population Density	1,2,3	1,1,1	3,4,5	4,5,6
Distance to Infrastructure	1/4,1/3,1/2	1/5,1/4,1/3	1,1,1	1,2,3
LULC	1/5,1/4,1/3	1/6,1/5,1/4	1/3,1/2,1	1,1,1

Table 14. Flood conditioning factors, their classes, flood susceptibility, assigned ranks of each class, and calculated factors: AHP weights and Fuzzy AHP normalized weights.

	Parameter	Class	Flood Susceptibility	AHP Weight	Fuzzy AHP Normalized Weight	Class Rank
Hazard Factors	Elevation	>1200 m	Very Low	3.53	3.35	1
		1200–1000 m	Low			2
		1000–600 m	Moderate			3
		600–300 m	High			4
		<300 m	Very high			5
	Slope	>21	Very Low	17.84	18.57	1
		12–21	Low			2
		6–12	Moderate			3
		3–6	High			4
		<3	Very high			5
	Curvature	<0	Very Low	2.43	2.36	1
		0	Low			2
		>0	Very high			5
	Distance from River	>800 m	Very Low	12.02	12.04	1
		600–800 m	Low			2
		400–600 m	Moderate			3
		200–400 m	High			4
		<200 m	Very high			5
	TRI	>0.7	Very Low	5.99	5.81	1
		0.6–0.7	Low			2
		0.5–0.6	Moderate			3
		0.4–0.5	High			4
		<0.4	Very high			5
	Rainfall	<515 mm	Very Low	27.22	28.36	1
		515–540 mm	Low			2
		540–560 mm	Moderate			3
		560–580 mm	High			4
		>580 mm	Very high			5
	Drainage Density	<0.2	Very Low	9.43	9.14	1
		0.2–0.6	Low			2
		0.6–1	Moderate			3
		1–1.4	High			4
		>1.4	Very high			5
	SPI	1	Very Low	3.98	3.67	1
		5	Very high			5

Table 14. Cont.

	Parameter	Class	Flood Susceptibility	AHP Weight	Fuzzy AHP Normalized Weight	Class Rank
Hazard Factors	Lithology	Very Permeable	Very Low	2.20	2.09	1
		Permeable	Low			2
		Semi-Permeable	Moderate			3
		Impermeable	High			4
		Very Impermeable	Very high			5
	TWI	<6.55	Very Low	5.27	4.99	1
		6.55–8.28	Low			2
		8.28–10.75	Moderate			3
		10.75–14.37	High			4
		14.37–23.99	Very high			5
	MNDVI	<−0.25	Very Low	4.98	4.64	1
		−0.05	Low			2
		−0.05	Moderate			3
		−0.15	High			4
		<0	Very high			5
	HSG	C	Low	2.92	2.87	2
		D	Very high			5
	NDVI	>0.3	Very Low	2.20	2.09	1
		0.2–0.3	Low			2
		0.1–0.2	Moderate			3
		0–0.1	High			4
		<0	Very high			5
Vulnerability factors	LULC	Vegetation (Forest)	Very Low	7.86	7.78	1
		Cultivated–Bare Soil	Low			2
		Grassland	Moderate			3
		Built-Up Area	High			4
		Water–Vegetation (Flooded)	Very high			5
	Distance from Infrastructure	>800 m	Very high	12.64	12.48	5
		600–800 m	High			4
		400–600 m	Moderate			3
		200–400 m	Low			2
		<200 m	Very Low			1
	Population Density	<10 inhabitants/km ²	Very Low	30.54	49.18	1
		10–50 inhabitants/km ²	Low			2
		50–100 inhabitants/km ²	Moderate			3
		100–150 inhabitants/km ²	High			4
		>150 inhabitants/km ²	Very high			5
	Built-Up Area	Water, Vegetation, Cropland and Bare Soil	Very Low	48.96	30.56	1
		Built-Up Area	Very high			5

3.4. Flood Hazard Map (AHP and Fuzzy AHP)

The flood hazard maps generated using both the AHP and Fuzzy AHP methods are presented in Figure 7. Both maps indicate that areas with high and very high flood hazards are primarily located in the southern part of the watershed, as well as in the north-central region near the main rivers, particularly Boufakrane River and its tributaries. More than 50% of the study area, approximately 652.9 km², is classified as having a very high flood hazard according to the AHP-based map (Table 15). The use of the Fuzzy AHP method provided a more nuanced delineation of hazard classes. The Fuzzy AHP-based hazard map shows that only 19.47% of the area, equivalent to 249.6 km², falls within the very high hazard category. Moreover, this method results in a broader distribution of the moderate hazard class, reflecting its ability to capture uncertainty and gradual transitions more effectively. Traditional AHP operates on crisp set theory using binary logic, where evaluation criteria are assigned precise weights derived from pairwise comparison matrices [27]. This deterministic methodology requires definitive categorical classifications, even when dealing with areas where multiple criteria present conflicting or unclear signals. Consequently, AHP tends toward more conservative risk assessments, classifying uncertain boundary conditions as high-risk areas to maintain decision-making principles. In contrast, FAHP addresses these limitations by incorporating fuzzy set theory, which allows for gradual transitions between risk categories rather than forcing binary classifications [29]. This approach better captures the inherent uncertainty present in natural systems and expert judgment, resulting in more nuanced spatial risk differentiation. Areas with ambiguous characteristics receive intermediate risk scores that reflect their actual level of uncertainty, rather than being forced into extreme categorical assignments. This methodological distinction explains why FAHP produces a more refined identification of truly high-risk areas, concentrating extreme classifications in locations where multiple criteria clearly indicate elevated flood potential.

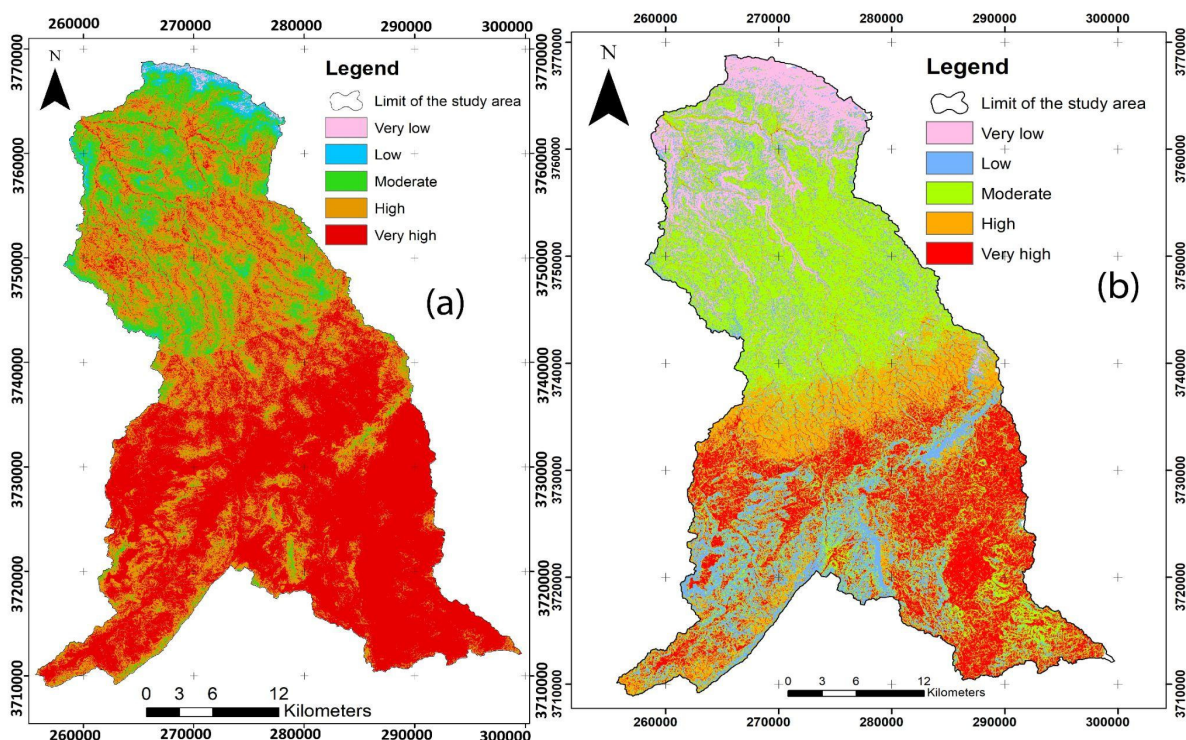


Figure 7. Spatial distribution of flood hazard/susceptibility classes across the study area: (a) AHP-based map and (b) Fuzzy AHP-based map.

Table 15. Area coverage of AHP and Fuzzy AHP flood hazard classes in km² and as a percentage.

Hazard Class	FHI _{AHP}		FHI _{Fuzzy AHP}	
	Area in km ²	Area in %	Area in km ²	Area in %
Very Low	4.2102	0.33	119.04	9.29
Low	19.5318	1.52	232.60	18.15
Moderate	164.1411	12.79	426.36	33.27
High	442.7172	34.49	254.09	19.82
Very High	652.9707	50.87	249.60	19.47

To further examine the difference between the AHP and Fuzzy AHP hazard maps, a spatial comparison was conducted between the two classifications. The largest discrepancy was observed in the “Very High” hazard class, which covered 50.87% of the watershed using AHP and 19.47% using Fuzzy AHP. This difference is mainly related to the methodological characteristics of the two approaches. AHP is based on crisp weights and discrete class boundaries, which may lead to sharper transitions between classes and a larger assignment of pixels to the highest hazard category. In contrast, Fuzzy AHP incorporates uncertainty in expert judgment through triangular fuzzy numbers and produces smoother transitions between hazard classes. As a result, Fuzzy AHP provides a more gradual spatial representation of flood susceptibility and reduces the over-concentration of pixels in the extreme hazard class.

Despite this difference, both models show spatial agreement in identifying the main flood-prone zones, particularly along the river corridors, low-slope areas, and the north-central part of the watershed near the Meknes agglomeration. The main differences occur in transitional zones where flood conditioning factors have intermediate values.

3.5. Flood Vulnerability Map (AHP and Fuzzy AHP)

The flood vulnerability map (Figure 8 and Table 16) was developed based on Flood Vulnerability Index (FVI) scores obtained through indicator classification and the application of the AHP method. The map delineates five vulnerability classes, ranging from very low to very high flood vulnerability. Unlike the Flood Hazard Index (FHI), which focuses primarily on physical characteristics, this FVI analysis emphasizes socio-economic and demographic factors, including population density, proximity to road access, land use and land cover (LULC), and built-up areas. The CR value obtained for the AHP analysis was 0.01, confirming the reliability of the pairwise comparisons (i.e., CR < 0.1). Based on the assigned weights, population density emerged as the most influential factor (49.18), followed by built-up areas (30.56), distance to access routes (12.48), and LULC (7.78).

Table 16. Area coverage of flood vulnerability classes derived from the Analytic Hierarchy Process (AHP) and Fuzzy Analytic Hierarchy Process (Fuzzy AHP), expressed in km² and as a percentage.

Vulnerability Class	FVI _{AHP}		FVI _{Fuzzy AHP}	
	Area in km ²	Area in %	Area in km ²	Area in %
Very Low	427.0122	33.12	428.112	33.21
Low	722.4579	56.04	432.055	33.51
Moderate	35.8821	2.78	316.718	24.57
High	62.9577	4.88	10.923	0.85
Very High	40.9491	3.18	101.453	7.86

Comparison of Flood Risk Index (FRI) classification results using AHP and Fuzzy AHP methods. The table shows the area (in km² and as a percentage) covered by each vulnerability class.

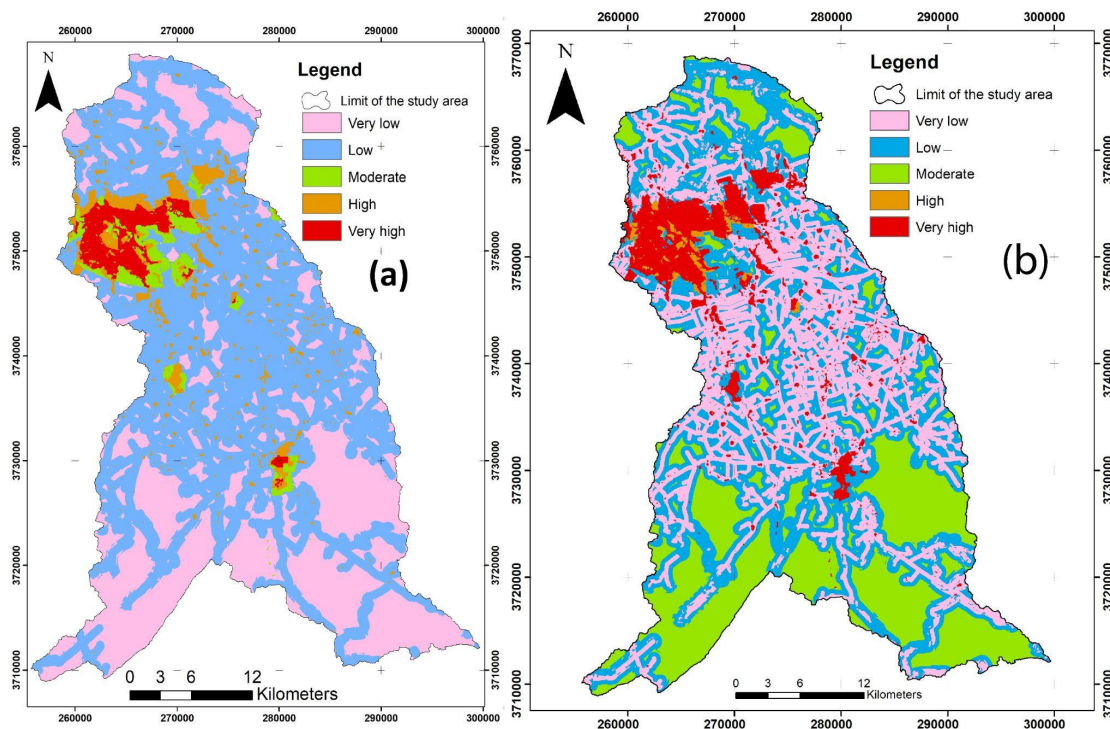


Figure 8. Spatial distribution of flood vulnerability intensity in the R'Dom watershed: (a) based on the Analytic Hierarchy Process (AHP) and (b) based on the Fuzzy Analytic Hierarchy Process (Fuzzy AHP).

Both AHP and FAHP methods have significant limitations. The need for expert judgment in creating comparison matrices introduces subjectivity, despite consistency checks ($CR < 0.1$) ensuring mathematical validity [76].

The quality of expert knowledge directly affects model reliability, especially in regions with limited local water expertise or poor records of past flood events. Combining different expert opinions, while improving reliability, may hide significant differences in professional judgment that reflect legitimate variations in technical interpretation or risk perception. These differences, though statistically combined through established methods, represent underlying uncertainties that go beyond the mathematical formulation of the analysis.

FVI scores indicating high to very high flood vulnerability are primarily concentrated in the urban areas of Meknes, Boufakrane, and El Hajeb. The vulnerability map produced using the Fuzzy AHP method further highlights elevated vulnerability in and around urban zones, particularly those with a high population density. As illustrated in both maps (Figure 8a,b), areas with high and very high vulnerability account for more than 8% of the study area, equivalent to nearly 100 km².

Moderate-vulnerability zones (Table 16) are more accurately represented using the Fuzzy AHP method, covering 24.57% of the area, or approximately 316.72 km². Areas classified as having very low vulnerability are similarly estimated by both the AHP and Fuzzy AHP methods, comprising approximately 33% of the study area, or around 428 km².

3.6. Flood Risk Map (AHP and Fuzzy AHP)

The flood risk map (Figure 9a,b and Table 17), based on Flood Risk Index (FRI) scores derived from the previously calculated Flood Hazard Index (FHI) and Flood Vulnerability Index (FVI), classifies the study area into five risk levels, ranging from very low to very high. Areas with high to very high flood risk within the R'Dom watershed are located where both hazard and vulnerability are, particularly in urban areas with high population

density, low slopes, close proximity to rivers, and high drainage density. Both maps show that the Meknes agglomeration is especially exposed to high and very high flood risk.

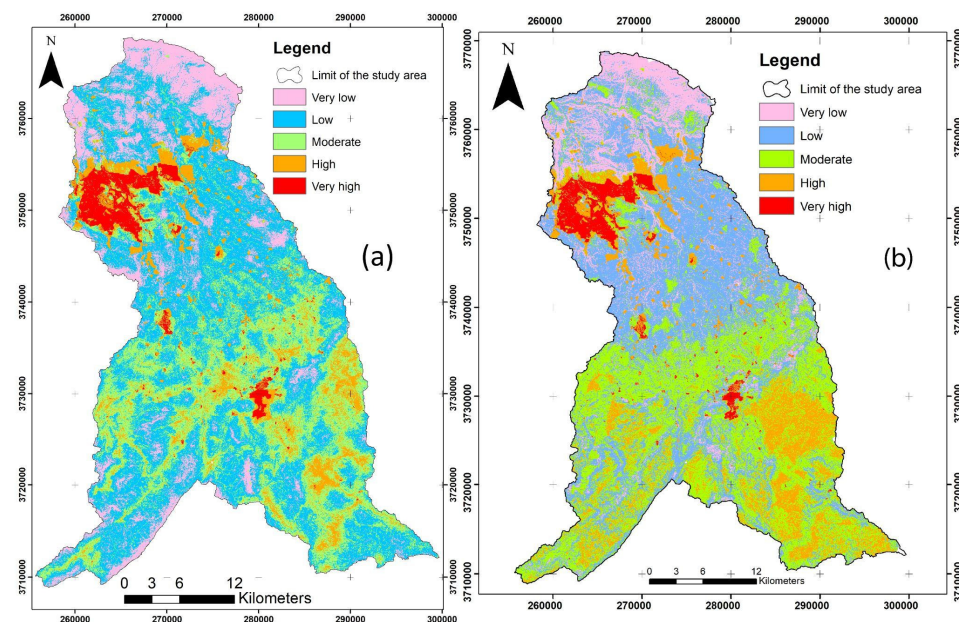


Figure 9. The final flood risk maps of the R'Dom watershed are based on the Flood Risk Index (FRI): (a) Analytic Hierarchy Process (AHP)-based FRI and (b) Fuzzy Analytic Hierarchy Process (Fuzzy AHP)-based FRI.

Table 17. Area coverage of AHP and Fuzzy AHP flood risk classes in km² and as a percentage.

Hazard Class	FRI _{AHP}		FRI _{Fuzzy AHP}	
	Area in km ²	Area in %	Area in km ²	Area in %
Very Low	193.916	15.11	150.559	11.75
Low	539.367	42.02	485.680	37.89
Moderate	368.145	28.68	404.811	31.58
High	134.279	10.46	195.167	15.23
Very High	47.815	3.73	45.454	3.55

Comparison of Flood Risk Index (FRI) classification results using AHP and Fuzzy AHP methods. The table shows the area (in km² and as a percentage) covered by each hazard class.

As illustrated in Figure 9a,b and detailed in Table 17, high- to very high-risk zones cover 14.19% of the area (182.1 km²) in the FRI_{AHP} map and 18.78% (240.62 km²) in the FRI_{Fuzzy AHP} map. These zones are primarily located in the north-central region and to a lesser extent in the southern part of the watershed.

Moderate-risk zones cover 368.14 km² in the FRI_{AHP} map and 404.8 km² in the FRI_{Fuzzy AHP} map, mostly concentrated in the southern portion of the study area.

Areas classified as very low and low flood risk, based on the Fuzzy AHP method, represent 150.5 km² and 485.68 km², respectively. These zones are distributed throughout the watershed and are characterized by steep slopes, dense vegetation cover or cultivated land, and low population density.

Figure 10 illustrates a comparison of the different levels of the FHI, FVI, and FRI indices based on both the AHP and Fuzzy AHP methods. The AHP method tends to overestimate areas classified as having a very high flood hazard, as well as those with moderate vulnerability. However, the flood risk scores obtained from both FRI_{AHP} and FRI_{Fuzzy AHP} are largely similar, indicating overall consistency in final risk outcomes despite methodological differences.

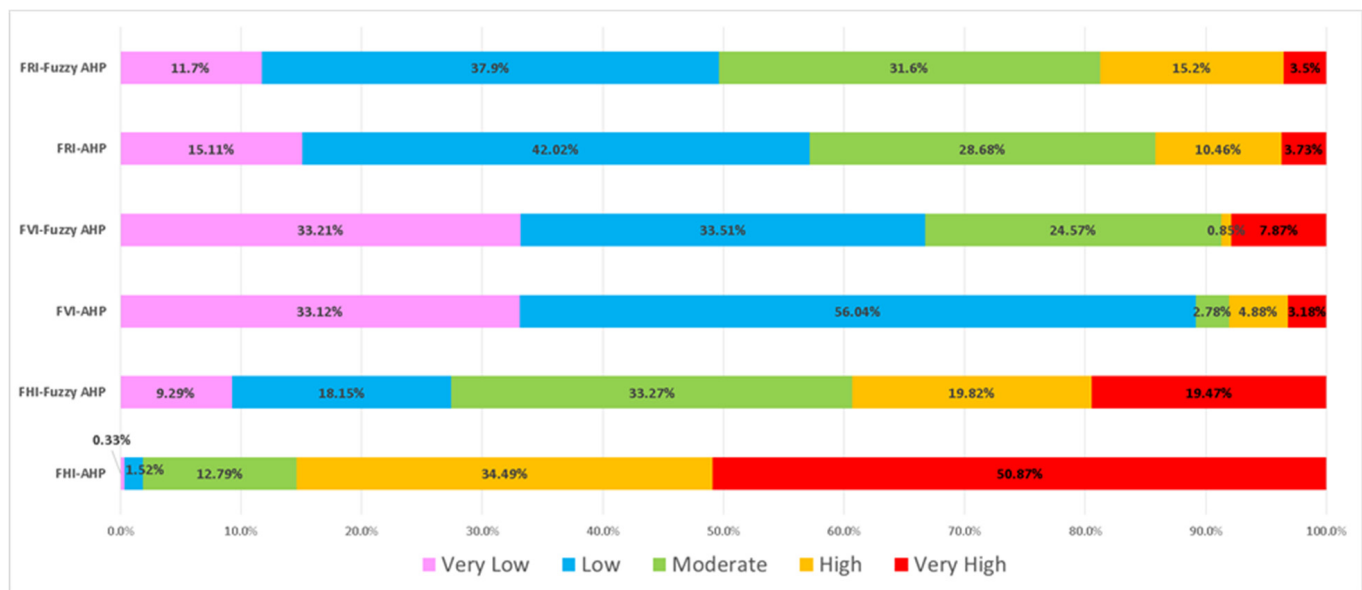


Figure 10. Percentage of spatial distribution of different Flood Hazard Index (FHI), Flood Vulnerability Index (FVI), and Flood Risk Index (FRI) classes based AHP and Fuzzy AHP.

3.7. Exploratory Relationship Between Flood Conditioning Factors and FHI Values

To examine the relationship between individual flood conditioning factors and the resulting flood susceptibility patterns, an exploratory analysis was conducted between the selected factors and the normalized Flood Hazard Index (FHI) values (Figure 11). The FHI values were normalized to a scale ranging from 0 to 1. A set of 900 points was then used to extract both FHI values and the corresponding values of the conditioning factors across the study area. Scatter plots were used to visualize general trends between continuous variables and FHI values. For categorical variables, such as LULC and lithology/permeability classes, the average FHI values were calculated for each class and represented using bar charts.

This analysis should not be interpreted as a statistical validation of the model. Since the FHI is a relative index derived from a weighted overlay of multiple criteria, no single conditioning factor is expected to explain the spatial distribution of flood susceptibility alone. The low regression coefficients observed in several scatter plots indicate that flood susceptibility results from the combined influence of multiple factors rather than from one isolated variable.

For the AHP-based FHI, the exploratory analysis shows that slope, distance from rivers, rainfall, drainage density, and Topographic Wetness Index (TWI) present clearer trends with the FHI values compared with the other factors. Similarly, for the Fuzzy AHP-based FHI, drainage density, distance from rivers, rainfall, and slope show the most visible relationships with the index values. These results are consistent with the spatial patterns observed in the flood hazard/susceptibility maps.

For the AHP-based FHI, the exploratory analysis shown in Figure 11 indicates that slope, distance from rivers, rainfall, drainage density, and Topographic Wetness Index (TWI) present clearer trends with the FHI values compared with the other factors. Similarly, for the Fuzzy AHP-based FHI, the exploratory analysis shown in Figure 12 indicates that drainage density, distance from rivers, rainfall, and slope show the most visible relationships with the index values. These results are consistent with the spatial patterns observed in the flood hazard/susceptibility maps.

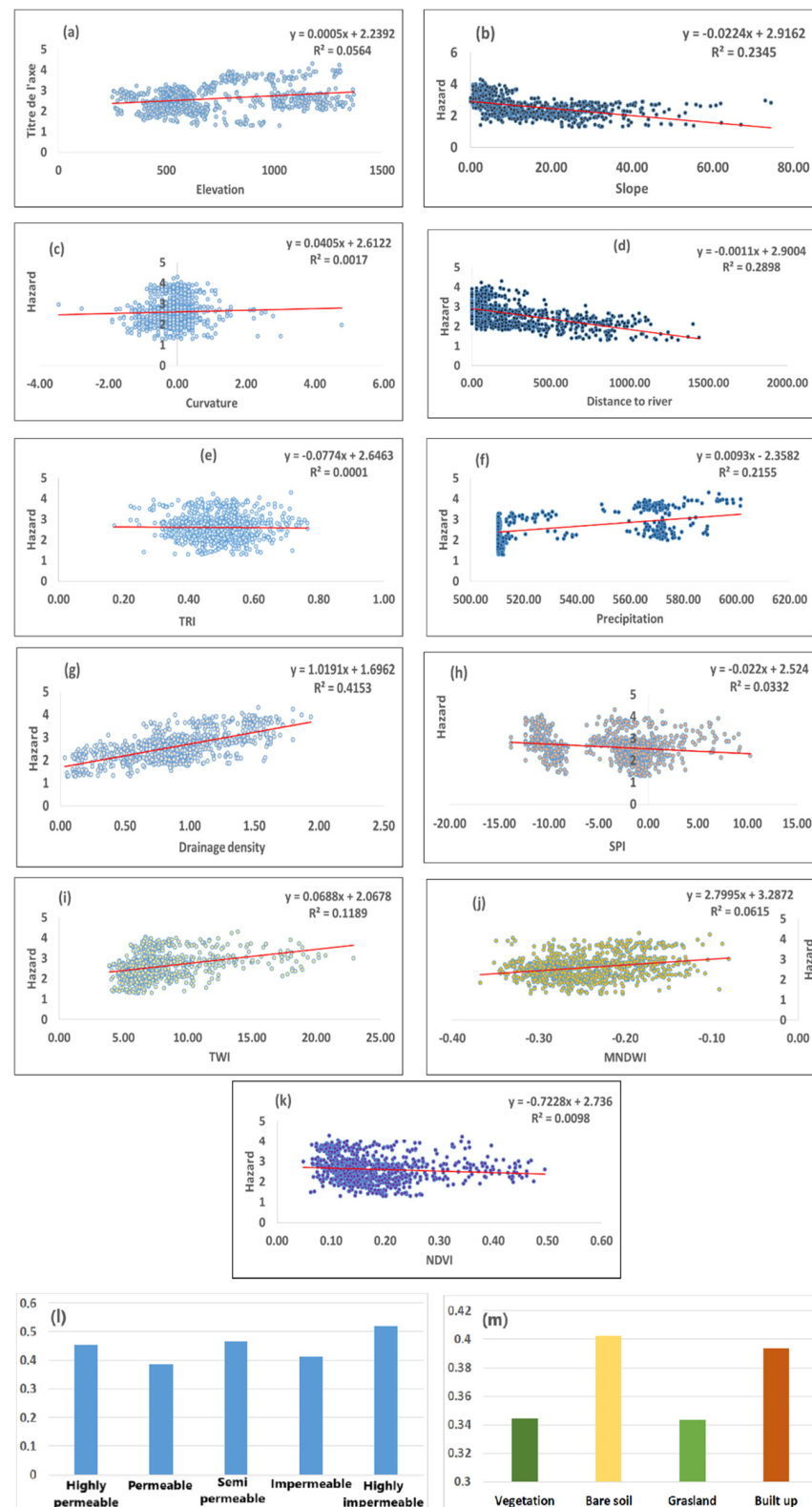


Figure 11. Exploratory relationships between flood conditioning factors and AHP-based Flood Hazard Index (FHI) values. Scatter plots (a–k) illustrate the exploratory relationships between selected continuous conditioning factors and normalized FHI values. Bar graphs (l,m) show the mean normalized FHI values for categorical variables, including Land Use/Land Cover (LULC) and soil permeability classes. Circles/dots represent individual data points, red lines indicate the fitted linear regression trends, and colors are used to distinguish the different variables or categorical classes shown in each subplot.

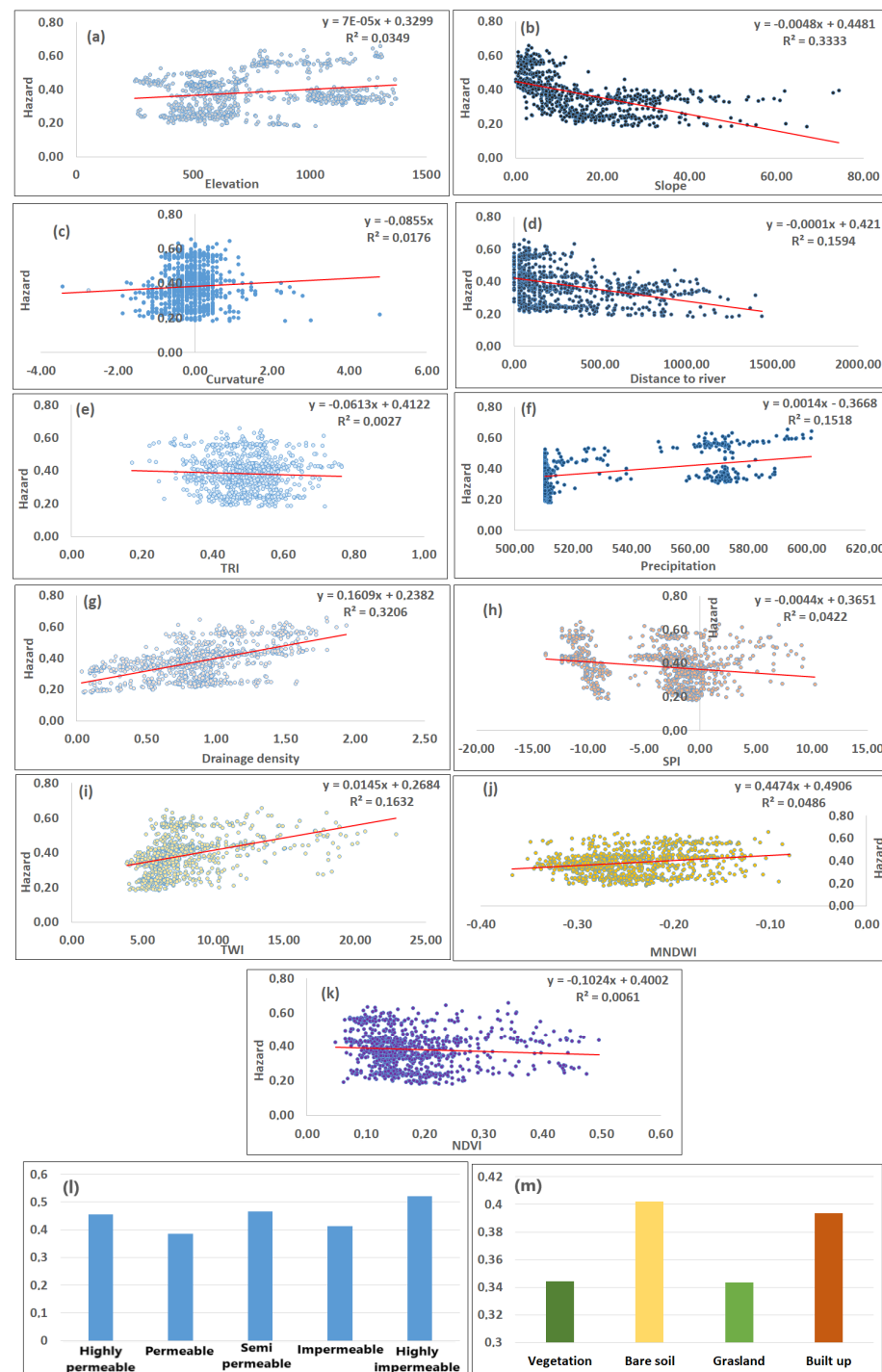


Figure 12. Exploratory relationships between flood conditioning factors and Fuzzy AHP-based Flood Hazard Index (FHI) values. Scatter plots (a–k) illustrate the exploratory relationships between selected continuous conditioning factors and normalized FHI values. Bar graphs (l,m) show the mean normalized FHI values for categorical variables, including Land Use/Land Cover (LULC) and soil permeability classes. Circles/dots represent individual data points, red lines indicate the fitted linear regression trends, and colors are used to distinguish the different variables or categorical classes shown in each subplot.

A visual comparison with the flood conditioning factor maps confirms these general trends. Areas classified as having a high or very high flood susceptibility are generally associated with flat terrain, proximity to rivers, high drainage density, and low-permeability or built-up surfaces. However, these patterns should be interpreted as exploratory rela-

tionships rather than direct causal correlations because the final FHI values were obtained through the combined weighted contribution of all selected conditioning factors.

3.8. Evaluating the Performance and Validation of Different Models

For the present work, the flood inventory map was created by gathering information on 450 flooded and 450 non-flooded locations. The 900 inventory points, comprising 450 flood and 450 non-flood locations, were randomly divided into a training dataset (70%, 630 points) and a testing dataset (30%, 270 points) (Figure 13).

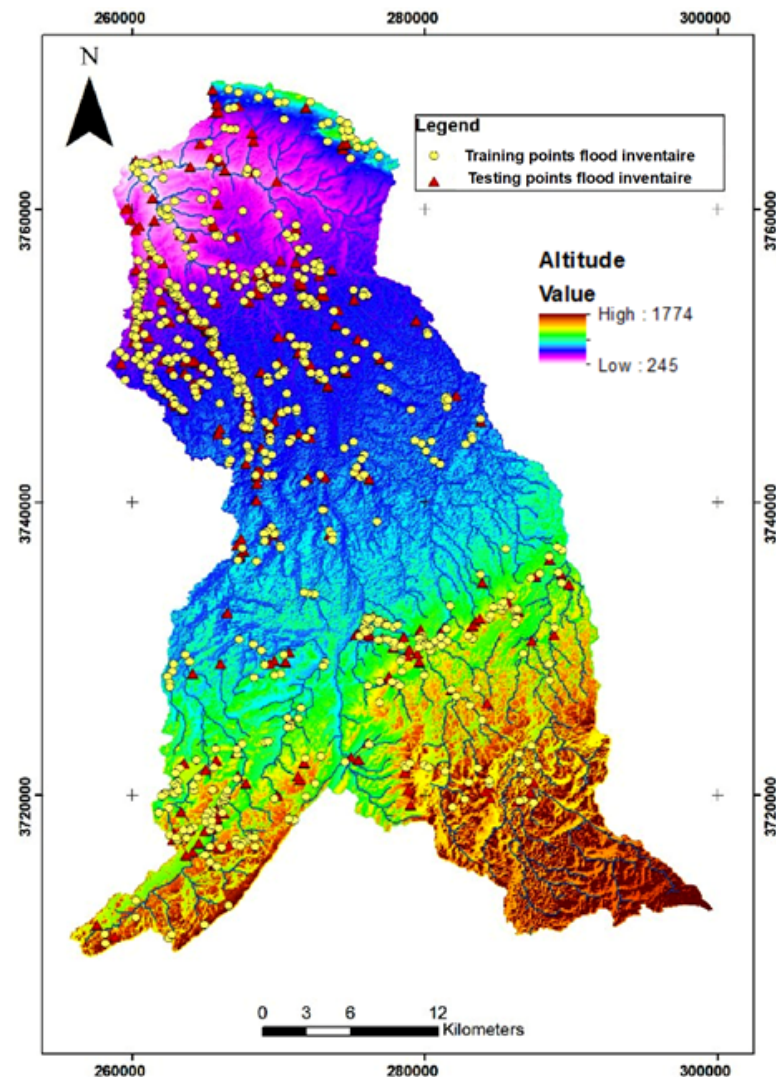


Figure 13. Random division of the flood inventory dataset into training (70%, 630 points) and testing (30%, 270 points) datasets.

All models demonstrated strong performance based on the training dataset, with AUC values ranging from 0.835 (FRI using Fuzzy AHP) to 0.922 (FHI using Fuzzy AHP), indicating very good to excellent fitting performance. For the testing dataset, ROC-AUC values ranged from 0.767 (FHI using Fuzzy AHP) to 0.905 (FHI using AHP), reflecting good to excellent predictive capability in assessing flood hazard and risk. These results confirm the overall robustness of both AHP- and Fuzzy AHP-based models, while showing that the AHP-based flood hazard model achieved the highest predictive accuracy for the testing dataset (Figure 14 and Table 18).

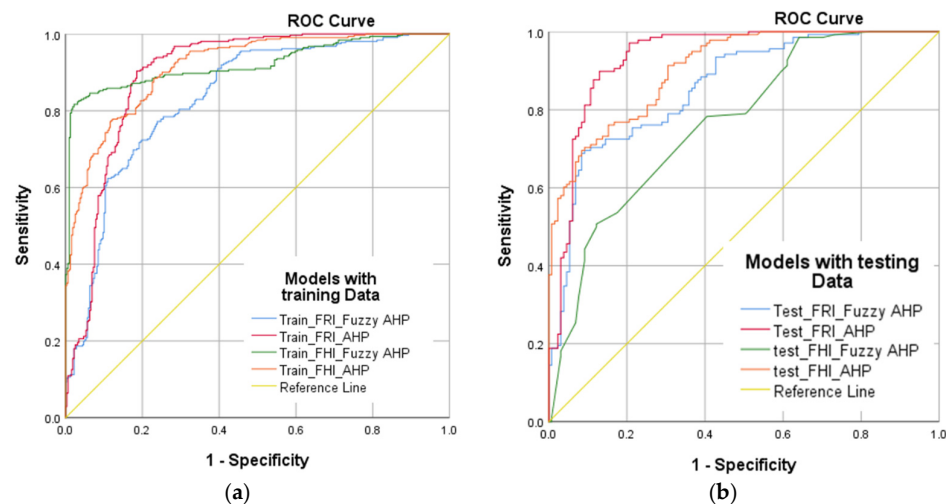


Figure 14. Plots representing the ROC success curves for AHP and Fuzzy AHP obtained using training points (a) and prediction curves obtained using testing points (b).

Table 18. Area Under the Curve (AUC) values of models applied to the training dataset.

Models	AUC Value	Std. Error	Asymptotic Sig.	Asymptotic 95 Confidence Interval	
				Lower Bound	Upper Bound
FRI_FuzzyAHP	0.835	0.016	0.000	0.803	0.866
FRI_AHP	0.896	0.013	0.000	0.870	0.922
FHI_FuzzyAHP	0.922	0.012	0.000	0.899	0.945
FHI_AHP	0.915	0.011	0.000	0.894	0.936

AUC = Area Under the ROC Curve; Std. Error = Standard error of the AUC; Asymptotic Sig. = Statistical significance (p -value); 95 Confidence Interval = Lower and upper bounds indicating the precision of AUC estimation.

For the testing dataset, the AHP-based flood hazard model achieved the highest AUC value (0.905), whereas the Fuzzy AHP-based flood hazard model obtained an AUC value of 0.767 (Table 19). These results indicate that the AHP approach showed stronger predictive accuracy for unseen testing data in this case study. However, the differences between AHP and Fuzzy AHP remain mainly related to their treatment of uncertainty in expert judgment. While AHP relies on crisp pairwise comparisons, Fuzzy AHP incorporates fuzzy logic to better represent uncertainty and gradual transitions between susceptibility classes. Therefore, although AHP achieved the highest testing AUC, Fuzzy AHP remains useful for producing a more flexible and uncertainty-aware representation of flood susceptibility patterns. In data-scarce basins such as the R'Dom watershed, where machine learning approaches may be constrained by limited training data, structured multi-criteria frameworks remain scientifically justified.

Table 19. Area Under the Curve (AUC) values of models applied to the testing dataset.

Models	AUC Value	Std. Error	Asymptotic Sig.	Asymptotic 95 Confidence Interval	
				Lower Bound	Upper Bound
Test_FRI_FuzzyAHP	0.857	0.022	0.000	0.813	0.901
Test_FRI_AHP	0.935	0.016	0.000	0.904	0.966
test_FHI_FuzzyAHP	0.767	0.028	0.000	0.711	0.823
test_FHI_AHP	0.905	0.017	0.000	0.872	0.938

AUC = Area Under the ROC Curve; Std. Error = Standard error of the AUC; Asymptotic Sig. = Statistical significance (p -value); 95 Confidence Interval = Lower and upper bounds indicating the precision of AUC estimation.

4. Discussion

4.1. Methodological Assessment and Comparative Analysis

The performance of MCDA approaches in flood risk assessment demonstrates significant variation across different studies, with methodological choices and regional adaptations playing crucial roles in determining effectiveness. Souissi et al. [77] applied conventional AHP in southeastern Tunisia's arid environments, utilizing eight conditioning factors focused on geological and hydrological parameters and achieving reliable results through deterministic approaches. Their validation approach relied on field observations, representing a different methodological framework from historical flood inventory validation. Senan et al. [78] conducted systematic comparisons between conventional AHP and Fuzzy AHP in India's Western Ghats, employing 20 conditioning factors and demonstrating superior performance of fuzzy approaches (F-AHP AUC: 0.943 vs. AHP AUC: 0.946) using 100 validation points with an emphasis on topographic factors and limited integration of climatic variability influences.

Kazakis et al. [79] implemented a regional-scale AHP methodology in Greece's Rhodope and Evros Prefectures in NE Greece, using seven conditioning factors with a strong emphasis on topographic characteristics. Their approach incorporated comprehensive geological information while employing equal weighting for some factor categories rather than systematic pairwise comparison, reflecting regional data availability and assessment objectives. Fernández and Lutz [80] employed an AHP methodology in Tucumoy Province in Argentina, using only five conditioning factors combining natural and anthropogenic variables, emphasizing the importance of factor selection and regional calibration within single-method frameworks.

Our study provides a comparison between AHP and Fuzzy AHP methodologies applied to identical datasets within the same environmental context, addressing methodological gaps where comparative evaluations are rarely conducted under controlled conditions. The validation framework employs 900 historical flood inventory points, while comparative studies utilized varying validation approaches, each appropriate for their respective study objectives and regional contexts.

The integrated analysis of flood hazard maps generated with the Analytic Hierarchy Process (AHP) and Fuzzy AHP reveals significant differences in the evaluation and spatial representation of flood risk across a watershed [81]. In the R'Dom watershed, both methods identified the southern region of the watershed and the north-central area near major rivers, particularly the Boufakrane River and its tributaries, as highly vulnerable to flooding. The AHP-based flood hazard map classifies over 50% (652.9 km²) of the study region as having a "very high" flood hazard, and the Fuzzy AHP technique achieves a more balanced hazard distribution, with just 19.47% (249.6 km²) classified as very high. This contrast demonstrates the importance of methodological choice in risk characterization and highlights the different spatial patterns that emerge from alternative MCDA approaches.

The flood vulnerability mapping, which uses both the AHP and Fuzzy AHP methods, proves useful in considering the socio-economic vulnerability to floods in the R'Dom watershed. This wide viewpoint improves understanding of flood risk by identifying communities and assets that are most vulnerable and least resilient to floods [82]. The AHP-based vulnerability map indicated that population density is the most important component, followed by built-up areas.

The AHP map effectively identifies vulnerability hotspots; however, its categorical structure may restrict its representation of transitional zones [83]. In contrast, the Fuzzy AHP technique provides a more accurate and detailed representation of the vulnerability map [78]. The results of this study using the Fuzzy AHP model show a moderate vulnerability class covering approximately 24.57% of the watershed compared to just 2.78%

in the AHP map. The results indicate that the Fuzzy AHP model is more sensitive to essential socio-economic factors in urban and semi-urban areas [84]. Both methods show nearly the same results for the “very low” vulnerability class, which covers about 33% of the total watershed, suggesting an area with minimal socio-economic exposure, typically corresponding to sparsely populated rural areas.

The flood risk maps created using the AHP and Fuzzy AHP methodologies incorporate both physical and socio-economic factors, merging the Flood Hazard Index (FHI) and Flood Vulnerability Index (FVI) into an inclusive Flood Risk Index (FRI). This analysis shows spatial flood risk patterns within the R'Dom watershed, where diverse topographic, hydrologic, and demographic conditions influence exposure levels [1]. The watershed area classified as high- to very high-flood-risk zones exists in the north-central and urbanized areas, which coincide with regions that have a high flood hazard and vulnerability. The results for the Fuzzy AHP flood risk map identify a greater extent of high- to very high-flood-risk areas around 18.78% of the watershed compared to 14.19% identified by the AHP map. Hence, Fuzzy AHP designates a larger area as belonging to the high-risk category (15.23%) than AHP (10.46%), suggesting that the conventional AHP method may underestimate the spatial extent of high-risk areas. The moderate risk category accounts for 31.58% in the Fuzzy AHP map and 28.68% in the AHP map, in the southern parts of the watershed where the flood hazard is moderate but socio-economic vulnerability is increasing because of urbanization. In the other case, low- and very low-risk zones are naturally associated with higher elevations, steep slopes, and rural or vegetated cover areas, leading to reduced flood exposure [85]. In the Fuzzy AHP results, these categories encompass 37.89% and 11.75% of the watershed area, respectively. In the other case, the AHP method estimates slightly higher proportions for these at 42.02% and 15.11%, reflecting AHP's tendency to provide a classification that is more decisive. The percentage distributions of FRI classes are similar, particularly in the very high and very low categories. However, AHP tends to overestimate very high- and moderate-vulnerability areas, which can distort decision-making and affect resource allocation [86].

The correlation analysis between the Flood Hazard Index (FHI) and various flood conditioning factors sheds light on the main drivers of flood susceptibility within the R'Dom watershed in a similar way to the study [87]. By normalizing the FHI values and comparing them against a sample of 900 points, the analysis identifies the physical and environmental factors that significantly affect flood hazard. The results for both AHP and Fuzzy AHP derived FHI value key factors: slope, distance from rivers, rainfall, drainage density, and Topographic Wetness Index (TWI) [88]. These variables showed the strongest correlations, proven by higher R-values in the scatter plots. In contrast, several other factors, such as elevation and aspect, displayed weak or negligible correlations. While these factors are often included in flood models, they may have localized or indirect effects within this watershed. This suggests that, although they influence hydrological processes, they are not the main predictors of flood hazard.

The analysis of categorical variables, especially Land Use/Land Cover (LULC) and soil permeability, supports the spatial trends noted in the hazard maps. The chart shows that built-up areas, bare soil, and regions with low permeability are consistently associated with higher average FHI values. These land-cover types impede infiltration and increase surface runoff, making them particularly vulnerable to flash flooding [89]. On the other hand, areas with dense vegetation or permeable soils have a lower flood hazard, serving as natural buffers against floodwaters [90]. The performance evaluation of the flood susceptibility and risk models used Receiver Operating Characteristic (ROC) curve analysis on a dataset that included 450 flooded and 450 non-flooded sample points. All models, including the Flood Hazard Index (FHI) and Flood Risk Index (FRI),

developed using the AHP and Fuzzy AHP methods demonstrated high accuracy in this watershed. In the training dataset, AUC values ranged from 0.835 for FRI-Fuzzy AHP to 0.922 for FHI-Fuzzy AHP, indicating performance levels from very good to excellent; this result is more effective than the result shown for the Assaka watershed in Morocco [91]. The validation results show differences between the training and testing datasets. In the training dataset, the FHI-Fuzzy AHP model achieved the highest AUC value (0.922), indicating excellent fitting performance. However, in the testing dataset, the AHP-based models generally showed higher AUC values than the Fuzzy AHP models. In particular, the FHI-AHP model achieved the highest testing AUC value (0.905), whereas the FHI-Fuzzy AHP model obtained an AUC value of 0.767. This indicates that, although Fuzzy AHP is useful for representing uncertainty in expert judgment and gradual spatial transitions, the AHP-based flood hazard model showed stronger predictive performance for unseen testing data in this case study. These differences highlight the importance of distinguishing between training performance and testing performance when comparing AHP and Fuzzy AHP models.

Certainly, the AHP and FAHP methods have limitations in terms of their use. However, our in-depth knowledge of the field and the availability of experimental data (for model validation) were the strengths of our study. Comparing the results obtained using other methods, such as machine learning algorithms, will be the focus of our future research.

4.2. Practical Applications and Management Implications

The identification of population density and building concentration in urban cores as key vulnerability drivers points to specific mitigation needs that can be addressed through globally proven approaches. The vulnerability analysis identified population density as the primary vulnerability driver in urban areas around Meknes, requiring globally applied mitigation strategies, including the implementation of community-based early warning systems following successful approaches like the Dutch “Room for the River” model adapted for semi-arid conditions [92], while community resilience building should establish neighborhood flood response teams following a Japanese approach, the “Jishu-bosai” disaster prevention model, where trained community leaders coordinate evacuation procedures and emergency response [93]. Our analysis shows concentrated building vulnerability in urban cores and expanding peri-urban areas, requiring evidence-based mitigation approaches, including flood-resistant building codes with elevated foundation requirements and systematic retrofitting of vulnerable buildings using proven techniques from European flood management programs that demonstrate cost-effective approaches for significantly reducing building damage [94]. Additionally, land-use analysis reveals extensive agricultural areas in flood-prone zones contributing to both hazard generation and vulnerability, requiring internationally proven agricultural mitigation measures, including conservation agriculture practices, through the implementation of no-till farming, cover cropping, and agroforestry, following successful programs in Brazil that increase soil infiltration capacity substantially while maintaining agricultural productivity [95]. Implementation of comprehensive watershed management approaches following successful models from the Rhine River [96] management program and initiatives should include strategic placement of retention areas, wetland restoration, and floodplain reconnection in areas our hazard analysis identifies as critical for flood flow management, while natural flood management approaches demonstrate significant flood peak reduction through landscape-scale interventions. This comprehensive mitigation framework addresses the specific vulnerability factors identified in our analysis while incorporating globally proven approaches adapted to the R'Dom watershed's semi-arid conditions and socio-economic context, providing multiple benefits beyond flood risk reduction, including environmental improvement, eco-

nomic development, and community resilience enhancement, that have been successfully implemented in comparable contexts, ensuring feasibility within Morocco's institutional and financial framework.

Through this study, and with the aim of mitigating the risk of flooding in the study area and especially near urban areas, several specific recommendations are made: align the flood susceptibility map obtained with the "no-build zones" urban extension and urban planning regulations and move from reaction to prevention; build water retention structures upstream of the Boufakrane River catchment area to the south of the town (in the rural commune of Ait Ouallal or the rural commune of Mejjat); create weirs or diversions upstream of the Bou Ishak River and the Boufakrane River; draw up a liquid sanitation plan adopting a separate system. These site-specific interventions complement the globally proven approaches by addressing the unique geographical and hydrological characteristics of the R'Dom watershed while maintaining consistency with international best practices in flood risk management.

4.3. Limitations and Future Improvements

Despite the usefulness of the GIS-MCDA approach for flood susceptibility and relative flood risk assessment in data-scarce watersheds, several limitations should be acknowledged. The flood susceptibility and risk maps produced in this study are relative index-based maps and do not represent probabilistic flood hazard maps based on return periods or exceedance probabilities. The flood inventory used for validation consists of discrete flood and non-flood points and does not include flood depth, inundation extent, flood duration, flow velocity, discharge, or exceedance probability. Therefore, ROC-AUC validation evaluates the spatial agreement between predicted susceptibility classes and observed flood occurrence locations, but it does not validate flood magnitude or flood frequency.

Another limitation concerns the rainfall and population datasets. Mean annual rainfall was used as a proxy for spatial rainfall variability because reliable rainfall intensity–duration–frequency data were not available for the whole watershed. However, rainfall intensity would be more appropriate for event-based flood hazard assessment, especially in semi-arid environments affected by flash floods. In addition, the WorldPop population density layer was used as provided and was not dasymetrically downscaled to built-up areas, which may have introduced uncertainty in the spatial representation of exposed populations. Finally, AHP and Fuzzy AHP rely partly on expert judgment; although consistency checks were applied and expert judgments were aggregated using the geometric mean method, subjectivity cannot be completely eliminated. Moreover, a formal sensitivity analysis of criterion weights was not performed in this study, which may limit the assessment of how variations in expert-derived weights influence the spatial distribution of flood susceptibility and risk classes.

Future research should integrate hydrological and hydraulic modeling, rainfall intensity data, SAR-derived flood extent maps, field-based flood depth observations, high-resolution DEMs, density population mapping using detailed census or building-level data, and systematic sensitivity analysis of criterion weights. In addition, the present study did not include a benchmark comparison with alternative statistical or machine learning models, such as frequency ratios, logistic regression, random forests, or support vector machines. This limits the ability to fully assess the relative performance of AHP and Fuzzy AHP compared with other modeling approaches.

5. Conclusions

This study implemented an integrated multi-criteria decision analysis approach employing both the AHP and FAHP methodologies to assess flood risk within the R'Dom watershed, utilizing remote sensing data and advanced geospatial tools. The multi-criteria analysis for mapping flood-prone areas involved integrating a hazard map based on 17 factors, including elevation, slope, curvature, distance to rivers, TRI, rainfall, drainage density, SPI, lithology, TWI, MNDWI, HSG, and NDVI, with a vulnerability map that considered LULC, distance to access roads, population density, and built-up areas. The AHP and Fuzzy AHP methods were used to assign weights to each factor. Consequently, two indices, FHI and FVI, were calculated and classified into five categories: very low, low, moderate, high, and very high.

The final FRI was computed using both AHP and Fuzzy AHP approaches to generate the flood risk map. This map indicates that 18.78% of the study area (i.e., 240.62 km²) is exposed to high to very high flood risk. These zones are mainly concentrated in the north-central part, around the Meknes agglomeration, and locally in the southern region of the watershed (El Hajeb area).

The flood risk and hazard maps were validated using a flood inventory dataset consisting of 900 historical flood and non-flood points through the generation of ROC-AUC curves. Using the training dataset, the models exhibited good to excellent AUC values. For the testing dataset, AUC values ranged from 0.767 to 0.905, with the AHP-based flood hazard model achieving the highest predictive accuracy. These results confirm the overall predictive capability of the AHP and Fuzzy AHP models, while showing that AHP performed better for the testing dataset.

Therefore, the flood zoning derived from this study can serve as a valuable tool for stakeholders involved in planning and implementing essential mitigation measures, helping reduce potential loss of life and property by future flood events.

Nevertheless, some limitations should be acknowledged. The produced maps are relative index-based susceptibility and risk maps and do not represent probabilistic flood hazard maps based on return periods or exceedance probabilities. The validation was based on a point-based flood inventory and did not include flood depth, inundation extent, discharge, or flow velocity. In addition, the use of mean annual rainfall, the spatial resolution of some input datasets, and the expert-based nature of AHP and Fuzzy AHP may have introduced uncertainty into the results. Future research should integrate hydrological and hydraulic modeling, rainfall intensity data, SAR-derived flood extent maps, high-resolution DEMs, and density population mapping to improve the physical interpretation and operational applicability of flood risk assessment.

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References

1. Pulvirenti, L.; Chini, M.; Pierdicca, N.; Guerriero, L.; Ferrazzoli, P. Flood Monitoring Using Multi-Temporal COSMO-SkyMed Data: Image Segmentation and Signature Interpretation. *Remote Sens. Environ.* **2011**, *115*, 990–1002. [CrossRef]
2. Gaurav, K.; Sinha, R.; Panda, P.K. The Indus Flood of 2010 in Pakistan: A Perspective Analysis Using Remote Sensing Data. *Nat. Hazards* **2011**, *59*, 1815–1826. [CrossRef]
3. US Department of Commerce; National Oceanic and Atmospheric Administration; National Weather Service. Great Flood of 1927. Available online: <https://www.weather.gov/ohx/greatfloodof1927> (accessed on 9 February 2025).
4. Ministry of Equipment, Transport, Logistics and Water. Available online: <https://www.equipement.gov.ma/Pages/Accueil.aspx> (accessed on 9 January 2025).
5. Organisation for Economic Co-operation and Development. *OECD Review of Risk Management Policies Morocco*; Organization for Economic Cooperation & Development: Paris, France, 2017.
6. Rhazi, A.; Essahlaoui, N.; Oumou, A.; Khrabcha, A.; Ijlil, S.; Alitane, A.; El Hafyani, M.; Ammari, Z.; Kassou, A.; Essahlaoui, A. Geomatics Applied to the Evaluation of Urban Growth in the City of Meknes, Morocco. In *Proceedings of the E3S Web of Conferences*; EDP Sciences: Les Ulis, France, 2025; Volume 607, p. 04023.
7. Erwann, M.-K.; Charles, S.; Axel, E.N.B.; Aditi, B.; Pierre, R.; Mohamed, M.; Olivier, M.; Laura Elizabeth, B.; Antonia, D.-B.; Julie, D. *Building Morocco's Resilience: Inputs for an Integrated Risk Management Strategy*; Groupe de la Banque Mondiale: Washington, DC, USA, 2014.
8. Haase, D. Participatory Modelling of Vulnerability and Adaptive Capacity in Flood Risk Management. *Nat. Hazards* **2013**, *67*, 77–97. [CrossRef]
9. Rehman, S.; Sahana, M.; Hong, H.; Sajjad, H.; Ahmed, B.B. A Systematic Review on Approaches and Methods Used for Flood Vulnerability Assessment: Framework for Future Research. *Nat. Hazards* **2019**, *96*, 975–998. [CrossRef]
10. Kerle, N. Disasters: Risk Assessment, Management, and Post-Disaster Studies Using Remote Sensing. In *Remote Sensing Handbook*; CRC Press: Boca Raton, FL, USA, 2024; Volume VI.
11. Nazir, M.F.; Atif, S.; Hussain, E. An Integrated Geographic Information System (GIS) and Analytical Hierarchy Process (AHP)-Based Approach for Drone-Optimized Large-Scale Flood Imaging. *Drone Syst. Appl.* **2025**, *13*, 1–18. [CrossRef]
12. Sharareh, R.S.; Borji, M.; Bagheri-Gavkosh, M.; Azimi, E.; Collins, T.W. A Novel Approach for Assessing Flood Risk with Machine Learning and Multi-Criteria Decision-Making Methods. *Appl. Geogr.* **2023**, *158*, 103035. [CrossRef]
13. Samanta, S.; Pal, D.K.; Palsamanta, B. Flood Susceptibility Analysis through Remote Sensing, GIS and Frequency Ratio Model. *Appl. Water Sci.* **2018**, *8*, 66. [CrossRef]
14. Tehrany, M.S.; Pradhan, B.; Jebur, M.N. Flood Susceptibility Mapping Using a Novel Ensemble Weights-of-Evidence and Support Vector Machine Models in GIS. *J. Hydrol.* **2014**, *512*, 332–343. [CrossRef]
15. Thai, T.H.; Thao, N.P.; Dieu, B.T. Assessment and Simulation of Impacts of Climate Change on Erosion and Water Flow by Using the Soil and Water Assessment Tool and GIS: Case Study in Upper Cau River Basin in Vietnam. *Vietnam J. Earth Sci.* **2017**, *39*, 376–392. [CrossRef]
16. Das, S. Flood Susceptibility Mapping of the Western Ghat Coastal Belt Using Multi-Source Geospatial Data and Analytical Hierarchy Process (AHP). *Remote Sens. Appl. Soc. Environ.* **2020**, *20*, 100379. [CrossRef]
17. Akay, H. Flood Hazards Susceptibility Mapping Using Statistical, Fuzzy Logic, and MCDM Methods. *Soft Comput.* **2021**, *25*, 9325–9346. [CrossRef]
18. Tien Bui, D.; Khosravi, K.; Shahabi, H.; Daggupati, P.; Adamowski, J.F.; Melesse, A.M.; Thai Pham, B.; Pourghasemi, H.R.; Mahmoudi, M.; Bahrami, S.; et al. Flood Spatial Modeling in Northern Iran Using Remote Sensing and GIS: A Comparison between Evidential Belief Functions and Its Ensemble with a Multivariate Logistic Regression Model. *Remote Sens.* **2019**, *11*, 1589. [CrossRef]
19. Nanda, K. A GIS-Based Artificial Neural Network Model for Flood Susceptibility Assessment. *Int. J. Environ. Res. Public Health* **2021**, *18*, 1072. Available online: <https://www.mdpi.com/1660-4601/18/3/1072> (accessed on 17 August 2025).
20. Tehrany, M.S.; Pradhan, B.; Jebur, M.N. Spatial Prediction of Flood Susceptible Areas Using Rule Based Decision Tree (DT) and a Novel Ensemble Bivariate and Multivariate Statistical Models in GIS. *J. Hydrol.* **2013**, *504*, 69–79. [CrossRef]

21. Choubin, B.; Moradi, E.; Golshan, M.; Adamowski, J.; Sajedi-Hosseini, F.; Mosavi, A. An Ensemble Prediction of Flood Susceptibility Using Multivariate Discriminant Analysis, Classification and Regression Trees, and Support Vector Machines. *Sci. Total Environ.* **2019**, *651*, 2087–2096. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Hitouri, S.; Mohajane, M.; Lahsaini, M.; Ali, S.A.; Setargie, T.A.; Tripathi, G.; D'Antonio, P.; Singh, S.K.; Varasano, A. Flood Susceptibility Mapping Using SAR Data and Machine Learning Algorithms in a Small Watershed in Northwestern Morocco. *Remote Sens.* **2024**, *16*, 858. [\[CrossRef\]](#)
23. Ashfaq, S.; Tufail, M.; Niaz, A.; Muhammad, S.; Alzahrani, H.; Tariq, A. Flood Susceptibility Assessment and Mapping Using GIS-Based Analytical Hierarchy Process and Frequency Ratio Models. *Glob. Planet. Change* **2025**, *251*, 104831. [\[CrossRef\]](#)
24. Santosh, M.; Arabameri, A.; Arora, A. Earth Fissure Susceptibility Mapping: Application of Random Subspace-based Novel Ensemble Approaches. *Geol. J.* **2024**, *59*, 1384–1400. [\[CrossRef\]](#)
25. Hakami, A. Strategies for Overcoming Data Scarcity, Imbalance, and Feature Selection Challenges in Machine Learning Models for Predictive Maintenance. *Sci. Rep.* **2024**, *14*, 9645. [\[CrossRef\]](#) [\[PubMed\]](#)
26. Kanani-Sadat, Y.; Arabsheibani, R.; Karimipour, F.; Nasser, M. A New Approach to Flood Susceptibility Assessment in Data-Scarce and Ungauged Regions Based on GIS-Based Hybrid Multi Criteria Decision-Making Method. *J. Hydrol.* **2019**, *572*, 17–31. [\[CrossRef\]](#)
27. Saaty, T.L. How to Make a Decision: The Analytic Hierarchy Process. *Eur. J. Oper. Res.* **1990**, *48*, 9–26. [\[CrossRef\]](#)
28. Kwong, C.K.; Bai, H. Determining the Importance Weights for the Customer Requirements in QFD Using a Fuzzy AHP with an Extent Analysis Approach. *IIE Trans.* **2003**, *35*, 619–626. [\[CrossRef\]](#)
29. Chan, H.K.; Sun, X.; Chung, S.-H. When Should Fuzzy Analytic Hierarchy Process Be Used Instead of Analytic Hierarchy Process? *Decis. Support Syst.* **2019**, *125*, 113114. [\[CrossRef\]](#)
30. Biazar, S.M.; Golmohammadi, G.; Nedhunuri, R.R.; Shaghghi, S.; Mohammadi, K. Artificial Intelligence in Hydrology: Advancements in Soil, Water Resource Management, and Sustainable Development. *Sustainability* **2025**, *17*, 2250. [\[CrossRef\]](#)
31. Zlopasa, O. AI-Driven Geospatial Tools for Flood Prediction and Comprehensive Environmental Assessments. 2024. Available online: https://www.researchgate.net/publication/384503187_AI-Driven_Geospatial_Tools_for_Flood_Prediction_and_Comprehensive_Environmental_Assessments (accessed on 21 June 2026).
32. Alitane, A.; Essahlaoui, A.; Van Griensven, A.; Yimer, E.A.; Essahlaoui, N.; Mohajane, M.; Chawanda, C.J.; Van Rompaey, A. Towards a Decision-Making Approach of Sustainable Water Resources Management Based on Hydrological Modeling: A Case Study in Central Morocco. *Sustainability* **2022**, *14*, 10848. [\[CrossRef\]](#)
33. Hammami, S.; Zouhri, L.; Souissi, D.; Souei, A.; Zghibi, A.; Marzougui, A.; Dlala, M. Application of the GIS Based Multi-Criteria Decision Analysis and Analytical Hierarchy Process (AHP) in the Flood Susceptibility Mapping (Tunisia). *Arab. J. Geosci.* **2019**, *12*, 653. [\[CrossRef\]](#)
34. Khaddari, A.; Jari, A.; Chakiri, S.; El Hadi, H.; Labriki, A.; Hajaj, S.; El Harti, A.; Goumghar, L.; Abioui, M. A Comparative Analysis of Analytical Hierarchy Process and Fuzzy Logic Modeling in Flood Susceptibility Mapping in the Assaka Watershed, Morocco. *J. Ecol. Eng.* **2023**, *24*, 62–83. [\[CrossRef\]](#)
35. Saaty, T.L. A Scaling Method for Priorities in Hierarchical Structures. *J. Math. Psychol.* **1977**, *15*, 234–281. [\[CrossRef\]](#)
36. Penki, R.; Basina, S.S.; Tanniru, S.R. Application of Geographical Information System-Based Analytical Hierarchy Process Modeling for Flood Susceptibility Mapping of Krishna District in Andhra Pradesh. *Environ. Sci. Pollut. Res. Int.* **2023**, *30*, 99062–99075. [\[CrossRef\]](#) [\[PubMed\]](#)
37. Emrouznejad, A.; Ho, W. *Fuzzy Analytic Hierarchy Process*, 1st ed.; Chapman and Hall/CRC: Boca Raton, FL, USA, 2017.
38. Essahlaoui, A.; Sahbi, H.; Bahi, L.; El-Yamine, N. Reconnaissance de La Structure Géologique Du Bassin de Saïss Occidental, Maroc, Par Sondages Électriques. *J. Afr. Earth Sci.* **2001**, *32*, 777–789. [\[CrossRef\]](#)
39. Essahlaoui, A.; Ouali, E.A. Détermination de la structure géologique de la partie Sud de la plaine du Saïss (bassin de Meknès-Fès, Maroc) par la méthode géoélectrique. *Bull. Eng. Geol. Environ.* **2003**, *62*, 155–166. [\[CrossRef\]](#)
40. El Hafyani, M.; Essahlaoui, N.; Essahlaoui, A.; Mohajane, M.; Van Rompaey, A. Generation of Climate Change Scenarios for Rainfall and Temperature Using SDSM in a Mediterranean Environment: A Case Study of Boufakrane River Watershed, Morocco. *J. Umm Al-Qura Univ. Appl. Sci.* **2023**, *9*, 436–448. [\[CrossRef\]](#)
41. Alitane, A.; Essahlaoui, A.; Yimer, E.A.; Ousmana, H.; Essahlaoui, N.; Oumou, A.; Hmadi, A.E.; Benyoussef, S.; Van Griensven, A. Hydrogeochemical Characterization and Statistical Approach to Assess the Quality of the Spring Water in the Meknes-El Hajeb Region, Morocco. *Model. Earth Syst. Environ.* **2024**, *10*, 6293–6308. [\[CrossRef\]](#)
42. Essahlaoui, A. *Méthodes Géophysiques Appliquées Aux Réservoirs d'eau Souterraine: Exemples d'application des Méthodes Électriques Aux Recherches Hydrogéologiques*; Éditions Universitaires Européennes: London, UK, 2011.
43. Essahlaoui, N.; El Ouali, A.; Rhazi, A.; Alitane, A.; Ijlil, S.; Mohajane, M.; Ammari, Z.; Oumou, A.; Khrabcha, A.; El Hafyani, M. Flood Risk Vulnerability Assessment Using GIS and Hydraulic Modeling, Case Study of the Fez River Watershed, Morocco. In *Proceedings of the E3S Web of Conferences*; EDP Sciences: Les Ulis, France, 2025; Volume 607, p. 04010.

44. Essahlaoui, A.; Sahbi, H.; El Yamine, N. Reconnaissance de La Structure Geologique de La Plaine Du Saiss (Bassin de Meknes-Fes, Maroc) Par La Methode Geoelectrique. *Afr. Geosci. Rev.* **2001**, *8*, 325–336.
45. Alitane, A.; Essahlaoui, A.; El Hafyani, M.; El Hmaidi, A.; El Ouali, A.; Kassou, A.; El Yousfi, Y.; van Griensven, A.; Chawanda, C.J.; Van Rompaey, A. Water Erosion Monitoring and Prediction in Response to the Effects of Climate Change Using RUSLE and SWAT Equations: Case of R'Dom Watershed in Morocco. *Land* **2022**, *11*, 93. [\[CrossRef\]](#)
46. ABHS. *Système Aquifère du Saiss*; ABHS: Fes, Morocco, 2016.
47. El Hafyani, M.; Essahlaoui, A.; Fung-Loy, K.; Hubbart, J.A.; Van Rompaey, A. Assessment of Agricultural Water Requirements for Semi-Arid Areas: A Case Study of the Boufakrane River Watershed (Morocco). *Appl. Sci.* **2021**, *11*, 10379. [\[CrossRef\]](#)
48. Eastman, J.R. Guide to GIS and Image Processing. In *Idrisi 32*; Clark University: Worcester, MA, USA, 1999; Volume 2, p. 170.
49. Hagos, Y.G.; Andualem, T.G.; Yibeltal, M.; Mengie, M.A. Flood Hazard Assessment and Mapping Using GIS Integrated with Multi-Criteria Decision Analysis in Upper Awash River Basin, Ethiopia. *Appl. Water Sci.* **2022**, *12*, 148. [\[CrossRef\]](#)
50. Althuwaynee, O.F.; Pradhan, B.; Park, H.-J.; Lee, J.H. A Novel Ensemble Bivariate Statistical Evidential Belief Function with Knowledge-Based Analytical Hierarchy Process and Multivariate Statistical Logistic Regression for Landslide Susceptibility Mapping. *Catena* **2014**, *114*, 21–36. [\[CrossRef\]](#)
51. Addis, A. GIS-Based Flood Susceptibility Mapping Using Frequency Ratio and Information Value Models in Upper Abay River Basin, Ethiopia. *Nat. Hazards Res.* **2023**, *3*, 247–256. [\[CrossRef\]](#)
52. Flooding in Morocco. Available online: <https://earthobservatory.nasa.gov/images/3005/flooding-in-morocco> (accessed on 9 June 2025).
53. Sarkar, D.; Mondal, P. Flood Vulnerability Mapping Using Frequency Ratio (FR) Model: A Case Study on Kulik River Basin, Indo-Bangladesh Barind Region. *Appl. Water Sci.* **2019**, *10*, 17. [\[CrossRef\]](#)
54. Pearman, A.D.; Phillips, L.D. *Multi-Criteria Analysis: A Manual*; Communities and Local Government: Leeds, UK, 2009.
55. Swain, K.C.; Singha, C.; Nayak, L. Flood Susceptibility Mapping through the GIS-AHP Technique Using the Cloud. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 720. [\[CrossRef\]](#)
56. Darwish, K. GIS-Based Multi-Criteria Decision Analysis for Flash Flood Hazard and Risk Assessment: A Case Study of the Eastern Minya Watershed, Egypt. In *Proceedings of the 7th International Electronic Conference on Water Sciences*; MDPI: Basel, Switzerland, 2023; p. 87.
57. Ramík, J. *Pairwise Comparisons Method: Theory and Applications in Decision Making*; Lecture Notes in Economics and Mathematical Systems; Springer International Publishing: Cham, Switzerland, 2020; Volume 690.
58. Saaty, T.L.; Vargas, L.G. Models, Methods, Concepts & Applications of the Analytic Hierarchy Process. In *International Series in Operations Research & Management Science*, 2nd ed.; Springer: New York, NY, USA, 2012.
59. Aydın, M.C.; Sevgi Birincioglu, E.; Büyüksaraç, A.; Işık, E. Earthquake Risk Assessment Using GIS-Based Analytical Hierarchy Process (AHP): The Case of Bitlis Province (Türkiye). *Int. J. Environ. Geoinform.* **2024**, *11*, 1–9. [\[CrossRef\]](#)
60. Yagoub, M.M. Spatio-Temporal and Hazard Mapping of Earthquake in UAE (1984–2012): Remote Sensing and GIS Application. *Geoenviron. Disasters* **2015**, *2*, 13. [\[CrossRef\]](#)
61. Ouma, Y.; Tateishi, R. Urban Flood Vulnerability and Risk Mapping Using Integrated Multi-Parametric AHP and GIS: Methodological Overview and Case Study Assessment. *Water* **2014**, *6*, 1515–1545. [\[CrossRef\]](#)
62. Jovčić, S.; Průša, P.; Samson, J.; Lazarević, D. A Fuzzy-AHP Approach to Evaluate the Criteria of Third-Party Logistics (3PL) Service Provider. *Int. J. TRAFFIC Transp. Eng.* **2019**, *9*, 280–289. [\[CrossRef\]](#) [\[PubMed\]](#)
63. Rahman, Z.U.; Ullah, W.; Bai, S.; Ullah, S.; Jan, M.A.; Khan, M.; Tayyab, M. GIS-Based Flood Susceptibility Mapping Using Bivariate Statistical Model in Swat River Basin, Eastern Hindukush Region, Pakistan. *Front. Environ. Sci.* **2023**, *11*, 1178540. [\[CrossRef\]](#)
64. Mukherjee, A.; Sarkar, S.; Chakraborty, M.; Duttgupta, S.; Bhattacharya, A.; Saha, D.; Bhattacharya, P.; Mitra, A.; Gupta, S. Occurrence, Predictors and Hazards of Elevated Groundwater Arsenic across India through Field Observations and Regional-Scale AI-Based Modeling. *Sci. Total Environ.* **2021**, *759*, 143511. [\[CrossRef\]](#) [\[PubMed\]](#)
65. Fatah, K.K.; Mustafa, Y.T.; Hassan, M.O. Flood Susceptibility Mapping Using an Analytic Hierarchy Process Model Based on Remote Sensing and GIS Approaches in Akré District, Kurdistan Region, Iraq. *Iraqi Geol. J.* **2022**, *55*, 123–151. [\[CrossRef\]](#)
66. Yesilnacar, E.; Topal, T. Landslide Susceptibility Mapping: A Comparison of Logistic Regression and Neural Networks Methods in a Medium Scale Study, Hendek Region (Turkey). *Eng. Geol.* **2005**, *79*, 251–266. [\[CrossRef\]](#)
67. Zzaman, R.U.; Nowreen, S.; Billah, M.; Islam, A.S. Flood Hazard Mapping of Sangu River Basin in Bangladesh Using Multi-Criteria Analysis of Hydro-Geomorphological Factors. *J. Flood Risk Manag.* **2021**, *14*, e12715. [\[CrossRef\]](#)
68. Salmerón-Gómez, R.; García-García, C.; García-Pérez, J. A Guide to Using the R Package “multiColl” for Detecting Multicollinearity. *Comput. Econ.* **2021**, *57*, 529–536. [\[CrossRef\]](#)
69. Avand, M.; Moradi, H.; Lasboyee, M.R. Spatial Modeling of Flood Probability Using Geo-Environmental Variables and Machine Learning Models, Case Study: Tajan Watershed, Iran. *Adv. Space Res.* **2021**, *67*, 3169–3186. [\[CrossRef\]](#)

70. Desalegn, H.; Mulu, A. Mapping Flood Inundation Areas Using GIS and HEC-RAS Model at Fetam River, Upper Abbay Basin, Ethiopia. *Sci. Afr.* **2021**, *12*, e00834. [\[CrossRef\]](#)
71. Tariq, A.; Shu, H.; Kuriqi, A.; Siddiqui, S.; Gagnon, A.S.; Lu, L.; Linh, N.T.T.; Pham, Q.B. Characterization of the 2014 Indus River Flood Using Hydraulic Simulations and Satellite Images. *Remote Sens.* **2021**, *13*, 2053. [\[CrossRef\]](#)
72. Onușluel Gül, G. Estimating Flood Exposure Potentials in Turkish Catchments through Index-Based Flood Mapping. *Nat. Hazards* **2013**, *69*, 403–423. [\[CrossRef\]](#)
73. Tang, J.; Liu, G.; Xie, Y.; Wu, Y.; Wang, D.; Gao, Y.; Meng, L. Effect of Topographic Variations and Tillage Methods on Gully Erosion in the Black Soil Region: A Case-study from Northeast China. *Land Degrad. Dev.* **2022**, *33*, 3786–3800. [\[CrossRef\]](#)
74. Ali, S.A.; Parvin, F.; Pham, Q.B.; Vojtek, M.; Vojteková, J.; Costache, R.; Linh, N.T.T.; Nguyen, H.Q.; Ahmad, A.; Ghorbani, M.A. GIS-Based Comparative Assessment of Flood Susceptibility Mapping Using Hybrid Multi-Criteria Decision-Making Approach, Naïve Bayes Tree, Bivariate Statistics and Logistic Regression: A Case of Topľa Basin, Slovakia. *Ecol. Indic.* **2020**, *117*, 106620. [\[CrossRef\]](#)
75. Arduino, G.; Reggiani, P.; Todini, E. Recent Advances in Flood Forecasting and Flood Risk Assessment. *Hydrol. Earth Syst. Sci.* **2005**, *9*, 280–284. [\[CrossRef\]](#)
76. Malczewski, J. *GIS and Multicriteria Decision Analysis*; John Wiley & Sons: New York, NY, USA, 1999.
77. Souissi, D.; Zouhri, L.; Hammami, S.; Msaddek, M.H.; Zghibi, A.; Dlala, M. GIS-Based MCDM–AHP Modeling for Flood Susceptibility Mapping of Arid Areas, Southeastern Tunisia. *Geocarto Int.* **2020**, *35*, 991–1017. [\[CrossRef\]](#)
78. Senan, C.P.C.; Ajin, R.S.; Danumah, J.H.; Costache, R.; Arabameri, A.; Rajaneesh, A.; Sajinkumar, K.S.; Kuriakose, S.L. Flood Vulnerability of a Few Areas in the Foothills of the Western Ghats: A Comparison of AHP and F-AHP Models. *Stoch. Environ. Res. Risk Assess.* **2023**, *37*, 527–556. [\[CrossRef\]](#) [\[PubMed\]](#)
79. Kazakis, N.; Kougias, I.; Patsialis, T. Assessment of Flood Hazard Areas at a Regional Scale Using an Index-Based Approach and Analytical Hierarchy Process: Application in Rhodope–Evros Region, Greece. *Sci. Total Environ.* **2015**, *538*, 555–563. [\[CrossRef\]](#) [\[PubMed\]](#)
80. Fernández, D.S.; Lutz, M.A. Urban Flood Hazard Zoning in Tucumán Province, Argentina, Using GIS and Multicriteria Decision Analysis. *Eng. Geol.* **2010**, *111*, 90–98. [\[CrossRef\]](#)
81. Maru, D.R.; Kumar, V.; Sharma, K.V.; Pham, Q.B.; Patel, A. Integrating GIS, MCDM, and Spatial Analysis for Comprehensive Flood Risk Assessment and Mapping in Uttarakhand, India. *Geol. J.* **2025**, *60*, 2263–2280. [\[CrossRef\]](#)
82. Membele, G.M.; Naidu, M.; Mutanga, O. Examining Flood Vulnerability Mapping Approaches in Developing Countries: A Scoping Review. *Int. J. Disaster Risk Reduct.* **2022**, *69*, 102766. [\[CrossRef\]](#)
83. Burayu, D.G.; Karuppannan, S.; Shuniye, G. Identifying Flood Vulnerable and Risk Areas Using the Integration of Analytical Hierarchy Process (AHP), GIS, and Remote Sensing: A Case Study of Southern Oromia Region. *Urban Clim.* **2023**, *51*, 101640. [\[CrossRef\]](#)
84. Dwivedi, C.S.; Pampattiwar, S.T.; Pandey, A.C.; Parida, B.R.; Mitra, D.; Kumar, N. Characterization of the Coastal Vulnerability in Different Geological Settings: A Comparative Study on Kerala and Tamil Nadu Coasts Using FuzzyAHP. *Sustainability* **2023**, *15*, 9543. [\[CrossRef\]](#)
85. Shah, S.M.H.; Mustaffa, Z.; Teo, F.Y.; Imam, M.A.H.; Yusof, K.W.; Al-Qadami, E.H.H. A Review of the Flood Hazard and Risk Management in the South Asian Region, Particularly Pakistan. *Sci. Afr.* **2020**, *10*, e00651. [\[CrossRef\]](#)
86. Sarmah, T.; Das, S.; Narendr, A.; Aithal, B.H. Assessing Human Vulnerability to Urban Flood Hazard Using the Analytic Hierarchy Process and Geographic Information System. *Int. J. Disaster Risk Reduct.* **2020**, *50*, 101659. [\[CrossRef\]](#)
87. Al-Kindi, K.M.; Alabri, Z. Investigating the Role of the Key Conditioning Factors in Flood Susceptibility Mapping Through Machine Learning Approaches. *Earth Syst. Environ.* **2024**, *8*, 63–81. [\[CrossRef\]](#)
88. Yilmaz, O.S. Flood Hazard Susceptibility Areas Mapping Using Analytical Hierarchical Process (AHP), Frequency Ratio (FR) and AHP-FR Ensemble Based on Geographic Information Systems (GIS): A Case Study for Kastamonu, Türkiye. *Acta Geophys.* **2022**, *70*, 2747–2769. [\[CrossRef\]](#)
89. Alshammari, E.; Rahman, A.A.; Rainis, R.; Seri, N.A.; Fuzi, N.F.A. The Impacts of Land Use Changes in Urban Hydrology, Runoff and Flooding: A Review. *Curr. Urban Stud.* **2023**, *11*, 120–141. [\[CrossRef\]](#)
90. Barnsley, I.; Spake, R.; Sheffield, J.; Leyland, J.; Sykes, T.; Sear, D. Exploring the Capability of Natural Flood Management Approaches in Groundwater-Dominated Chalk Streams. *Water* **2021**, *13*, 2212. [\[CrossRef\]](#)
91. Talha, S.; Akhssas, A.; Aarab, A.; Aabi, A.; Berkat, B. Enhancing Flash Flood Risk Prediction: A Case Study from the Assaka Watershed, Guelmim Region, Southwestern Morocco. *Ecol. Eng. Environ. Technol.* **2025**, *26*, 8–28. [\[CrossRef\]](#) [\[PubMed\]](#)
92. Bogdan, E.A. Making Room for Nature? Applying the Dutch Room for the River Approach to Flood Risk Management in Alberta, Canada. *ResearchGate* **2020**, *20*, 153–165. [\[CrossRef\]](#)
93. Bajek, R.; Matsuda, Y.; Okada, N. Japan’s Jishu-Bosai-Soshiki Community Activities: Analysis of Its Role in Participatory Community Disaster Risk Management. *Nat. Hazards J. Int. Soc. Prev. Mitig. Nat. Hazards* **2008**, *44*, 281–292.

94. Wang, L.; Cui, S.; Li, Y.; Huang, H.; Manandhar, B.; Nitivattananon, V.; Fang, X.; Huang, W. A Review of the Flood Management: From Flood Control to Flood Resilience. *Heliyon* **2022**, *8*, e11763. [[CrossRef](#)] [[PubMed](#)]
95. Skylar, C. A Comparative Review of Soil Carbon Sequestration Methods in Brazil's Agriculture. *Discussions* **2024**, *20*, 2. Available online: <https://commons.case.edu/discussions/vol20/iss1/2/> (accessed on 17 August 2025).
96. Hendrik, H. Towards Sustainable River Management of the Dutch Rhine River. *Water* **2020**, *12*, 1827. Available online: <https://www.mdpi.com/2073-4441/12/6/1827> (accessed on 17 August 2025).

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