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Research article

Integrating Multi-Source Geospatial Data and AHP for Flood Susceptibility Mapping in Ain Smara, Constantine, Algeria

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Abstract

Mapping flood susceptibility is essential for identifying flood-prone areas and informing flood risk management strategies. This study applies a multi-criteria decision-making approach to assess flood vulnerability in Ain Smara and its surrounding areas in Constantine, Algeria, which are highly susceptible to flooding. The analysis combines the Analytical Hierarchy Process (AHP), Geographic Information System (GIS), Remote Sensing (RS), and the Google Earth Engine (GEE) platform. Ten key flood-related criteria were selected, including the Topographic Wetness Index, Elevation, Slope, Precipitation, Land Cover/Land Use, Normalized Difference Vegetation Index (NDVI), Distance from Rivers, Distance from Roads, Drainage Density, and Lithology, along with more than 25 sub-criteria. A pairwise comparison matrix (PCM) was used to assign relative importance to each criterion based on its impact on flood susceptibility. The Topographic Wetness Index was identified as the most significant criterion, while Distance from Roads was deemed the least significant. The results reveal that approximately 4.00% of the area is classified as having high to very high flood susceptibility, particularly near the Rhumel River. Roughly 30% of the area has low to very low susceptibility, and the remaining 66% is categorised as moderately susceptible to flooding. Notably, most of the identified flood-prone zones correspond with areas that experienced flooding events in 2019, 2020, and 2021, predominantly within 1,000 meters of river courses. These findings demonstrate the GIS-AHP technique's effectiveness in generating reliable flood susceptibility maps, especially when numerous criteria are considered.

Keywords

Flood susceptibility; Geographic information system (GIS); Analytical hierarchy process (AHP); Google Earth Engine (GEE); Ain Smara.

1. Introduction

Floods rank among the most destructive natural disasters, leading to extensive damage to infrastructure, property, agricultural land, and even loss of life (Tekeli and Fouli, 2016; Das, 2020; Diakakis et al., 2020; Choudhury et al., 2022). Algeria has endured several severe flood events across various provinces, including Bab El Oued in 2001, Djanet in 2005, Ghardaïa in 2008, Djelfa in 2015, and multiple occurrences in Constantine from 2018 to 2023. These incidents have prompted researchers and government agencies to improve flood prediction models by incorporating advanced information systems, remote sensing, and the Analytical Hierarchy Process (AHP) (Tehrany et al., 2015; Terti et al., 2015; Das, 2020; Choudhury et al., 2022, Cvetkovic and Martinović, 2020). The recurrence of such events highlights the urgent need to adopt effective risk management strategies tailored to Algeria's diverse topography and climatic variability.

Flood risks can escalate quickly, especially in localized areas where sudden rises in water levels result from intense rainfall (Yang et al., 2020; Swain et al., 2020). The interplay of extreme weather patterns, urbanization, and inadequate infrastructure often exacerbates the severity of these events, necessitating robust predictive and preventive frameworks. Consequently, flood risk management has become a crucial research area, with flood susceptibility maps emerging as essential tools for decision-makers (Saharia et al., 2017; Pham et al., 2020; Lin et al., 2020; Papagiannaki et al., 2015, Perić and Cvetković, 2019). These maps are generated using both quantitative and qualitative methods that identify flood-prone areas by analyzing past flood events and environmental factors (Bui et al., 2019; Das, 2020; Choudhury et al., 2022).

Flood susceptibility is influenced by a mix of physical and human factors (Pappenberger et al., 2006; Lee et al., 2017; Chen et al., 2020). Comprehensive mapping requires assessing various factors, including topography, rainfall, land use, proximity to rivers, and drainage density (Tehrany et al., 2014; Swain et al., 2020). Properly identifying these elements is crucial for effective flood risk management and reducing potential damage (Wang et al., 2019b; Vafakhah et al., 2020; Swain et al., 2020; Das, 2020; Choudhury et al., 2022). The inclusion of advanced tools, such as remote sensing and GIS, further enhances the precision of these analyses, offering a scalable approach to assess flood risks across varied geographic settings.

Several methods exist for flood susceptibility mapping, such as multi-criteria decision analysis, logistic regression, and the frequency ratio method (Youssef et al., 2016; Das, 2020; Choudhury et al., 2022). Among these, AHP is recognized as a straightforward, adaptable method, especially when combined with remote sensing and Geographic Information Systems (GIS) (Razavi Termeh et al., 2018; Kanani-Sadat et al., 2019; Swa, 2020; Choudhury et al., 2022). This approach enables efficient spatial data management and analysis, facilitating the identification of flood-prone zones (Al-Juaidi et al., 2018; Chowdhuri et al., 2020; Shafapour Tehrany et al., 2019; Cao et al., 2020).

In Constantine, Algeria, the region's topography, seasonal rainfall, inadequate drainage, and presence of rivers such as Oued Rhumel and Oued Boumerzoug make it particularly vulnerable to flooding. This study applies the AHP method to map flood-prone areas within the urban agglomeration of Ain Smara and surrounding regions (Rebouh et al., 2021; Rebouh et al., 2024, Aktar et al., 2021). By assigning weights to various flood-inducing factors, the AHP method helps prioritize high-risk areas, serving as an invaluable tool for urban planners and disaster management authorities (Rahmati et al., 2016; Khosravi et al., 2016a; Sahana and Patel, 2019; Azareh et al., 2019; Kanani-Sadat et al., 2019; Kiani et al., 2019; Bouamrane et al., 2020; Mirzaei et al., 2021; Abedi et al., 2021; Prasad et al., 2021, Tout, 2023).

Overall, integrating AHP with GIS and remote sensing provides a robust platform for flood risk assessment, allowing for accurate and efficient mapping of flood-prone areas (Rahmati et al., 2016; Samanta et al., 2018; Ramesh and Iqbal, 2020; Siahkamari et al., 2018, Iftikhar and Iqbal, 2024). This approach supports the development of effective flood management strategies, helping to mitigate the impacts of future flood events in vulnerable regions like Constantine (Das, 2020; Dahri and Abida, 2017; Hammami et al., 2019; Joshi and Shahapure, 2020; Das and Gupta, 2021; Malik and Pal, 2021).

The main goal of this research is to develop a comprehensive flood susceptibility map for the Ain Smara region, Constantine, Algeria, by integrating multi-source geospatial data, such as Digital Elevation Models (DEMs), satellite imagery, and geological maps. The study employs the Analytical Hierarchy Process (AHP) to evaluate and prioritize key factors influencing flood susceptibility, including topography, precipitation, land use, and hydrology. The objective is to provide a scientifically grounded, spatially explicit map that can assist local authorities and urban planners in making informed decisions for flood risk management and disaster preparedness. Additionally, the research aims to assess the accuracy of the flood susceptibility map through validation techniques and explore uncertainties related to the AHP methodology and model outputs. Ultimately, the study seeks to improve flood risk assessment and offer a reliable framework for future geospatial flood susceptibility mapping in similar regions.

Study Area:

The study area is located in the central part of the high Constantine plains, within the North-Eastern region of Algeria's Maghrebian Mountain Range. Known as the South-West Constantinois, it extends across Constantine in the northeast, Oued Athmania in the northwest, Chelghoum Laid in the southwest, and Ain M'lila in the southeast (Chadi, 1991; Benabbas, 2006; Rebouh and Khiari, 2022).

The research area (Fig. 1) is situated in northeastern Algeria as part of the elevated Constantine plains. It includes the entire city of Ain Smara along with its surrounding areas (Derouiche, 2008; Rebouh and Khiari, 2022).

Among the most important data related to the study area is that it includes several prominent mountain ranges, such as Mount Fleten, Mount Ouled Salem, Massif of Chettaba, and Mount El Ouahch. The elevation range varies from 200 meters in low-lying areas to a maximum altitude of 1,400 meters in the mountainous regions. The slopes range from less than 10 degrees in flat areas to between 10 and 50 degrees in most other parts, with the steepest areas exceeding 50 degrees. The region's lithology is characterized by a dominance of claystones, followed by conglomerates, limestone, marlstone, and sandstone. Annual precipitation ranges between 300 mm and 450 mm, and the hydrological network features two major rivers: Oued Rhumel, which crosses the study area and drains into the Ain Smara Basin, and Oued Boumerzoug. Land use in the area includes agricultural lands, built-up areas, fallow lands (the most extensive), rivers, and forests. The study area includes three major cities: Constantine, El Khroub, and Ain Smara.

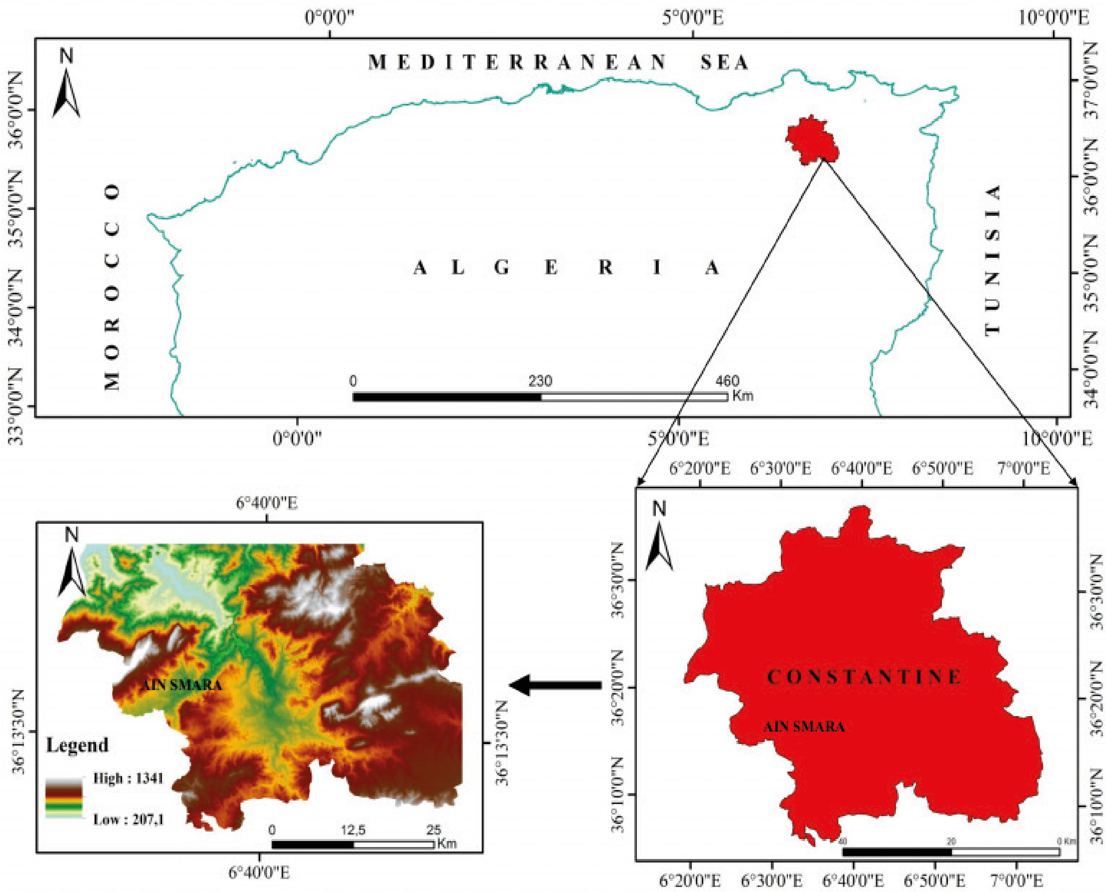

Figure 1. The location of the study area (https://earthexplorer.usgs.gov)

2. Methodology:

Data source selection

This study's primary achievement lies in generating a comprehensive set of multi-source geospatial thematic layers directly related to flood susceptibility (Khosvari et al., 2016b; Khosvari et al., 2019; Kanani-Sadat et al., 2019; Costache et al., 2019; Chakraborty and Mukhopadhyay, 2019; Souissi et al., 2020; Arabameri et al., 2020; Pham et al., 2020; Haque et al., 2021). Ten key factors influencing flood susceptibility were considered: Topographic Wetness Index, Elevation, Slope, Precipitation, Land Cover/Land Use, Normalized Difference Vegetation Index (NDVI), Distance from Rivers, Distance from Roads, Drainage Density, and Lithology. These factors were organized into a comprehensive database, supported by a high-quality Digital Elevation Model (DEM) with a spatial resolution of 30 × 30 m. Table 1 provides detailed data sources for these factors.

Geographic Information System (GIS) tools played a critical role in analyzing flood susceptibility. The study utilized software such as ArcGIS to generate thematic layers from data sources, including DEMs, satellite imagery, and geological maps. Key GIS techniques involved raster and vector analysis, spatial interpolation, and reclassification to refine flood risk zones. Layers like Topographic Wetness Index, Elevation, and Land Use were derived from DEMs and processed with spatial analysis tools. The Analytic Hierarchy Process (AHP) was applied for factor weighting, while Principal Component Analysis (PCA) further refined weight distribution to enhance accuracy.

Identifying key flood-conditioning factors is a crucial first step in developing an accurate flood map (Nachappa et al., 2020; Wang et al., 2020). According to Kia et al. (2012), the selection of these factors should account for their varying relevance over time. Extensive global studies (e.g., Tehrany et al., 2014; Hong et al., 2018; Choubin et al., 2019) have identified ten critical influencing factors, including the Topographic Wetness Index, Elevation, Slope, Precipitation, Land Cover/Land Use, NDVI, Distance from Rivers, Distance from Roads, Drainage Density, and Lithology (Pham et al., 2020).

The GIS-based mapping process involved collecting and preprocessing spatial data, such as topographic maps, satellite imagery, and land-use information. Data quality was ensured through cleaning, georeferencing, and standardization. Thematic layers were created for factors like Elevation, Slope, Land Use, and Hydrology, and integrated into a unified GIS environment. Spatial analysis techniques, including overlay analysis, buffering, and interpolation, were employed. The AHP method was used to assign weights and calculate susceptibility scores, with results visualized as flood susceptibility maps featuring clear symbology and legends. Validation was conducted using historical data and field observations, with accuracy assessed through statistical measures like ROC curves. Finally, maps were exported in user-friendly formats, ensuring practical utility for decision-makers in disaster management and urban planning.

Table.1 Data sources used in this study

Data	Description	Source (references)
Landsat 8 OLI	Downloaded	https://earthexplorer.usgs.gov
Aster GDEM (30m)	Downloaded	https://earthexplorer.usgs.gov
Slope angle	Derived from DEM 30 m	DEM 30 m
TWI	Derived from DEM 30 m	DEM 30 m
Elevation	Derived from DEM 30 m	DEM 30 m
NDVI	Image Sat LandSat Oli8	https://earthexplorer.usgs.gov
Drainage density	Derived from DEM 30 m	DEM 30 m
Lithology	Digitized from 1:200.000 geological map of Constantine	Geological map of Constantine (vila 1980)

Roads	Extracted	Google Earth
Rivers	Extracted	DEM 30 m
Precipitation	2019-2022	climate stations
Land cover/Land Use	Derived from Landsat 8 Oli image	Landsat 8 Oli image

Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP), introduced by Saaty (1980), is a powerful method for solving multi-criteria decision-making problems by assigning relative weights to various factors to meet a specific objective. AHP depends on subjective judgments and marginal factors, which are transformed into scores to evaluate each criterion (Chakraborty and Mukhopadhyay, 2019). This approach is particularly effective in risk management, as demonstrated in studies by Swain et al. (2020), Das (2020), and Choudhury et al. (2022).

The AHP method follows several steps: building a hierarchical structure, conducting pairwise comparisons, constructing a judgment matrix, calculating priority vectors, and validating consistency through the consistency index (CI) and consistency ratio (CR) (Handfield et al., 2002). After applying Principal Component Analysis (PCA) to the dataset, the weights were further refined and adjusted to better reflect the variance in the data. This resulted in a more accurate distribution of weights, ensuring that the most significant factors, such as the Topographic Wetness Index (TWI) and Elevation, received higher weights, while factors with lesser influence, such as Distance from Roads, were assigned lower weights. The integration of PCA enhanced the robustness and validity of the flood susceptibility model.

These steps are essential to verify the reliability of assigned weights, ensuring consistency in the analysis. The CR, in particular, is crucial as it assesses the coherence of the study by comparing each pair of criteria and highlighting any inconsistencies. In our hierarchical classification study, we checked the consistency of the weights using the random index values specified by Equation (01) (Table 3), which serves as a validation test. This equation calculates the CR, a key mathematical indicator that helps evaluate the robustness of the decision-making process by identifying any discrepancies. (1)

Eq: 01 $$CR = \frac{CI}{RI}$$

where (CI) is the coherence index calculated and (RI) is the random coherence index using Equation (2).

Eq: 02 $$CI = \frac{\lambda\max - 1}{n-1}$$

when (n) is the matrix's order and (max) is the matrix's dominant or main eigenvalue, which is determined from the matrix. According to Saaty, the consistency ratio must have an imprecision level of 10% or less. The foundation of this work's theory is the comparison of judgment with element weighting determined at random. Finally, using Equation (3), the acquisitive weights have been combined with the various triggered classes to create a single Flood susceptibility index.

Eq: 03 $$FSI = \sum_{i=1}^{n} Ri * Wi$$

Where (Wi) are the weights for each flood conditioning component and (Ri) are the rating classes for each layer.

Based on natural discontinuities, the resulting flood susceptibility map was divided into five classes (very low, low, moderate, high, and very high) to determine the class intervals.

Table.2 Fundamental scale of Saaty (1977)

Dominant values	Description	Explanation
1	Equal importance	Two factors contribute aqually
3	Moderate importance of one over other	Experience and judgment slightly or moderately favor one factor over another
5	Strong or essential prevalence	Experience and judgment is strongly favor over another
7	Very strong or demonstrated prevalence	An activity is strongly favor over another and its dominance is showed in practice
9	Extremely high prevalence	The evidence favoring one activity over another is of highest degree possible of an confirmation
2,4,6,8	Intermediate values	Used when comprises is needed

Table.3 Random index (RI) values of Saaty & Vargas (1991)

N	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Preparation of geospatial data

- Flood Inventory Map

Developing a flood inventory map is considered a foundational step in assessing flood vulnerability. Historical flood data from such maps can often be used to evaluate flood risks in other specific locations (Khosravi et al., 2018; Swain et al., 2020; Das, 2020; Choudhury et al., 2022). Although a flood inventory map for our study area is currently unavailable, we have identified flood-prone areas. Our goal, in collaboration with Algerian research institutes, is to create this essential map.

- Elevation

Elevation is considered the most significant determinant of flood susceptibility, as highlighted by several authors in various reviews (Pham et al., 2020). Water naturally flows from higher to lower elevations due to gravity, leading to stagnation and flooding in lower-lying areas (Nachappa et al., 2020). In our study area, which is specified in the title, the uneven distribution of elevation causes rapid water flow during unexpected downpours along the Oued Rhumel, Oued Boumerzoug, and Oued Seguen, directing water toward the interior flat areas of the lowlands and resulting in dangerous flooding (Swain et al., 2020; Das, 2020; Choudhury et al., 2022) (Fig. 2).

- Slope

The accumulation of water at any location is closely linked to the surface slope, with the slope directly influencing surface water runoff (Ngo et al., 2021). The strength and velocity of water movement are primarily determined by the topographical slope, while the infiltration process is typically controlled by the gradient of the terrain (Das, 2020; Choudhury et al., 2022). Areas with flat terrain or relatively gentle slopes are generally more prone to flooding, as water tends to stagnate there. The very steep and continuous regional slope runs along the escarpment at Djebel Felten, Massif du Chettaba, and the southern part of the study area. However, in the northern and northeastern regions, the slope is generally less than 10° (Fig. 3).

- Distance from drainage

Predick and Turner (2007) argue that the distance to the main river system is generally related to the factors that cause river flooding. Areas further from the drainage system are typically less prone to flooding (Pham et al., 2020). However, Pradhan (2009) observes that locations closer to drainage systems are more susceptible to flooding. There is no global consensus on the exact distance from a drainage system that makes an area more vulnerable to flooding; what can be said is that the distance varies based on the river's flow and how quickly it fills with water (Samanta et al., 2016). Large rivers can flood areas several kilometers wide, while smaller channels may only flood a few meters (Das, 2020; Choudhury et al., 2022). In particular, areas within 500 meters of the drainage line are most vulnerable to flooding. Some experts suggest that a distance of 100 meters serves as a threshold for flood susceptibility(Termeh et al., 2018). According to Das (2019a), the distance most likely to experience flooding is 500 meters. In our study area, we identified low-lying and flood-prone regions near the rivers (Fig. 4).

- Drainage density

According to the majority of morphometric studies, the most significant and impactful factor in regions at risk of river floods is drainage density (Choudhury et al., 2022). Drainage density is defined as the ratio of the total length of drainage segments in a watershed to its total area (Das and Pardeshi, 2018b). Ogden et al. (2011) explain that a high drainage density indicates two factors: a large amount of surface runoff and a greater length of drainage channels per unit area. Areas with a dense river system are more vulnerable to flooding due to the increased drainage density. In our study area, we observed a significant drainage density along the rivers (Fig. 5).

- Topographic Wetness Index (TWI)

The Topographic Wetness Index (TWI), derived from topographical data, is considered one of the most significant factors for assessing the impact of terrain features on hydrological processes, particularly flooding (Das, 2020). As the TWI value increases, so does the likelihood of flood risk. For this study, we created a map of the topographic wetness index, which is divided into five categories: very low (3.4 - 6.2), low (6.3 - 7.8), medium (7.9 - 10), high (11 - 13), and very high (14 - 27) (Fig. 6).

- Normalized difference vegetation index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a key graphical indicator that represents the spread of vegetation in a given area (Chen and Yu, 2011). In this context, vegetation cover plays a significant role in the infiltration capacity and management of surface water. Therefore, the NDVI can also be considered an important factor in identifying areas prone to flooding. This index is typically calculated using satellite imagery. The following equation is used to determine the NDVI:

$$NDVI = \frac{Pnir - Pr}{Pnir + Pr}$$

Where Pnir represents the reflectance in the form of infrared part and Pr represents the reflectance for red.

In this study, a normalized difference vegetation index map was broken down into 5 categories (Fig.7).

- Land use/land cover (LU/LC)

Yalcin et al. (2011) argue that an area's land use and land cover have a significant impact on various hydrological processes, including surface runoff, infiltration, and evapotranspiration. As such, these factors are considered essential for mapping flood susceptibility (Vignesh et al., 2021). The land uses in the research area include agricultural land, built-up areas, fallow land, rivers, and vegetation (Fig. 8).

- Distance from roads

The road system, which connects various locations, is a factor contributing with minimal impact to flooding susceptibility. People often migrate closer to roads for convenience and easier access to resources. However, during floods, roads become submerged, which disrupts connectivity between areas in flood-prone regions. Flooding primarily affects the population living near roadways. In our study area, the distance from highways was categorized into five groups, as shown in (Fig. 9).

- Lithology

The lithological diversity of a region has a significant impact on flooding (Svoboda, 1991). The variation in sedimentary surface hydrology can be attributed to differences in soil types (Oikonomidis et al., 2015). While geology does not directly affect flood vulnerability, it influences the characteristics of the river system. Generally, areas with more resistant rock types have lower drainage densities and are less prone to flooding (Kourgialas and Karatzas, 2011). The soil types in the study area mainly consist of clay, conglomerate, limestone, marl, and sandstone (Fig. 10).

- Rainfall

According to Hammami et al. (2019), rainfall intensity is one of the key climate factors directly influencing flood susceptibility. The risk of flooding increases with the amount of rainfall in a particular area (Marengo et al., 2021). A critical step in ensuring the accuracy of the flood susceptibility study is the creation of a precipitation map for the study area. This involves calculating the total amount of rainfall within a watershed, which is essential for determining runoff flow (Khaddari et al., 2022). In this study, a map of the maximum annual precipitation (Fig. 11) was created based on the highest total precipitation recorded over the year.

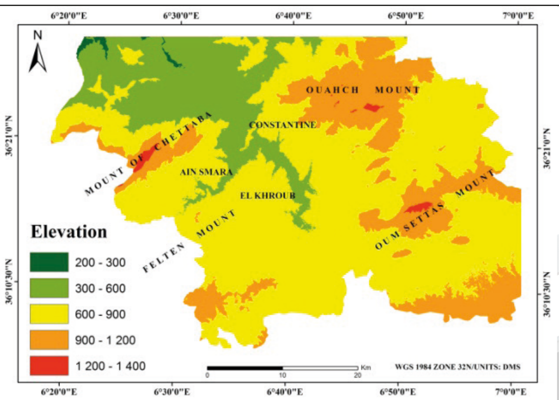

Figure 2. Elevation map of the Ain Smara area (DEM 30m https://earthexplorer.usgs.gov)

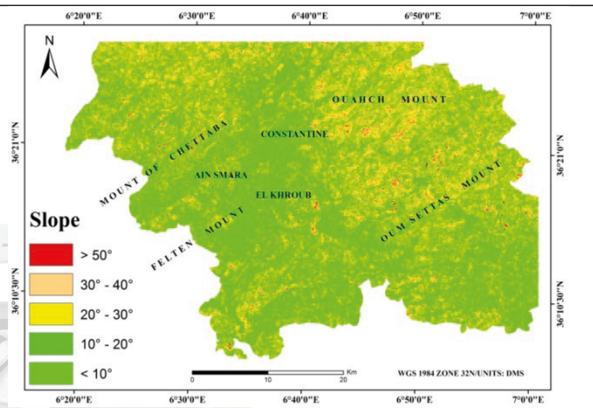

Figure 3. Slope map of the Ain Smara area (DEM 30m https://earthexplorer.usgs.gov)

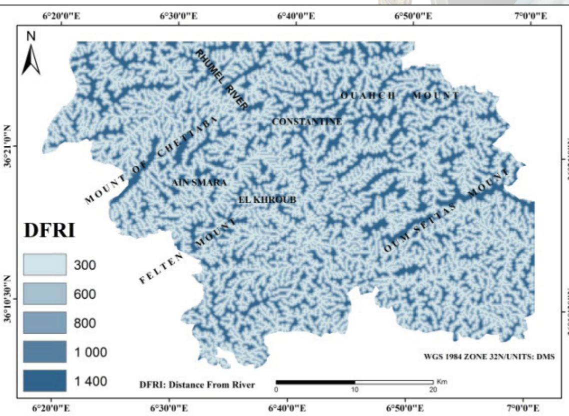

Figure 4. Distance from rivers map of the Ain Smara area (https://earthexplorer.usgs.gov)

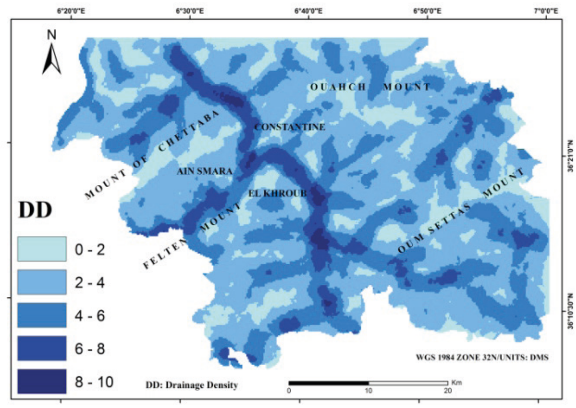

Figure 5. Drainage density map of the Ain Smara area (https://earthexplorer.usgs.gov)

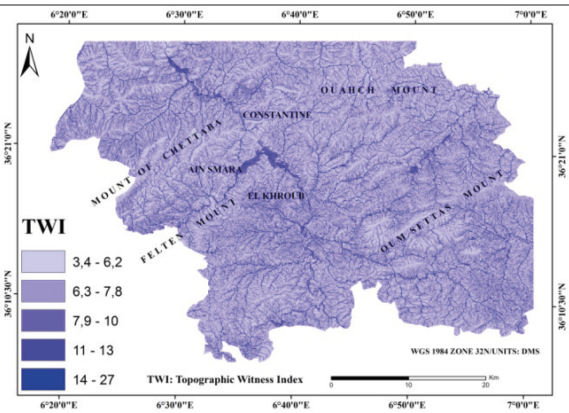

Figure 6. Topographic wetness index map of the Ain Smara (https://earthexplorer.usgs.gov) area

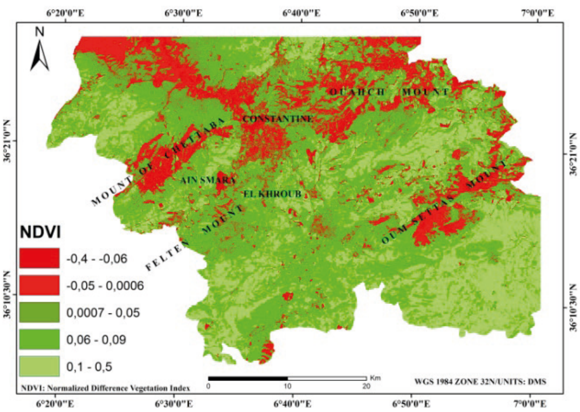

Figure 7. Normalized difference vegetation index map of the Ain Smara area

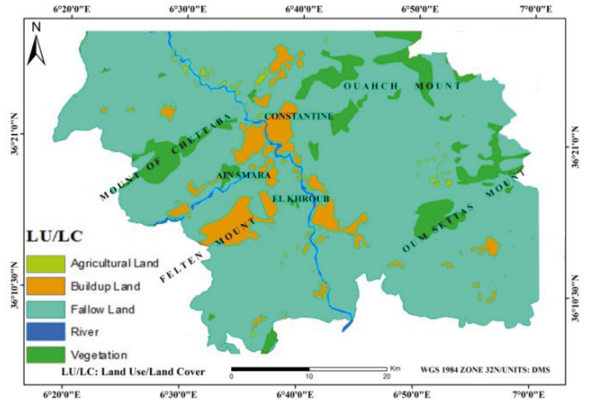

Figure 8. Land Use/ Land Cover map of the Ain Smara area (Image LandSat Oli8 from https://earthexplorer.usgs.gov)

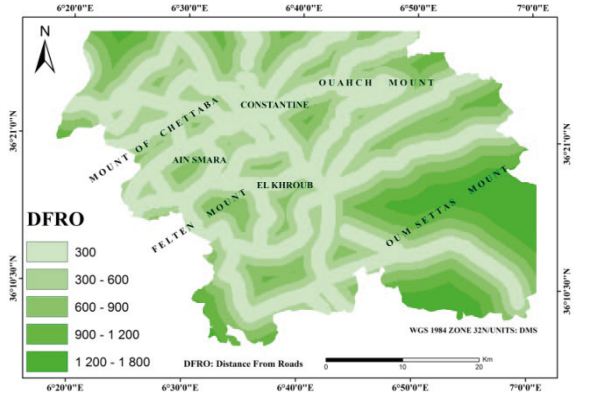

Figure 9. Distance from road map of the Ain Smara area (Open street maps)

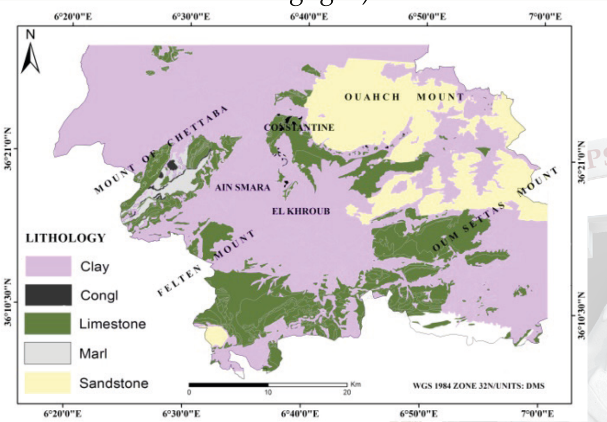

Figure 10. Lithology map of the Ain Smara area (Geological carte of Constantine 1/200000, Vila 1980)

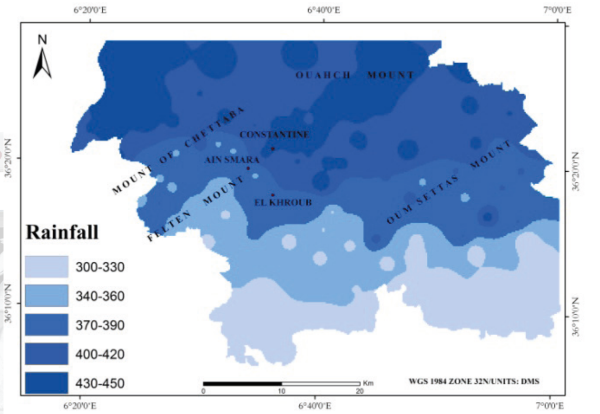

Figure 11. rainfall map of the Ain Smara area (Meteorological Station of Constantine 2019 to 2021)

3. Results and Discussion:

3.1.Results

- Flood susceptibility mapping

In this study, the values of various criteria were classified into five categories to create the flood-prone area map. Sub-criteria under each main criterion were used to generate the flood susceptibility map. To develop the final flood zoning map, the primary maps for each flood susceptibility criterion were integrated. After assessing each criterion, the significance of each was calculated using the Analytic Hierarchy Process (AHP) (Table 4). In this process, the values of each row and column were compared to generate a rating. The flood susceptibility map was constructed with a consistency ratio (CR) value of 0.05 (0.1, validated), using the weighted total of all contributing factors. The topographic wetness index criterion had the largest influence (13.78%), while the distance from highways had the smallest influence (5.59%) (Table 5).

Using actual flood data and topographical information from the study area, flood susceptibility maps for 25 sub-criteria were created through the AHP reclassification approach. Susceptibility maps based on key factors were also evaluated. The flood susceptibility map was divided into five categories based on the criteria, with approximately 4% of the total study area classified as high to very high flood susceptibility, located near the Oued Rhumel River. About 30% of the area was classified as very low to unlikely to flood, while the remaining 66% was considered to have moderate flood susceptibility (Fig. 12).

The study on flood susceptibility mapping in Ain Smara, Constantine, has some limitations, including reliance on available spatial data with varying accuracy, and the exclusion of dynamic factors like climate change and land-use changes. The scope of the study area may also limit its applicability to other regions. Additionally, the AHP method's subjectivity in assigning weights could influence results. Future research could incorporate real-time meteorological data, socio-economic factors, and expand criteria to account for climate change. Integrating machine learning with AHP could reduce subjectivity, and applying this approach to diverse regions could improve its generalizability and accuracy.

Table.4 Pairwise comparison matrix table

Matrix	TWI	Elevation	Slope	Precipitation	LULC	NDVI	Distance from river	Distance from road	Drainage density	Lithology	Weight
TWI	1	1	1	1	3	5	1	3	1	1	13,78%
Elevation	1	1	1	1	2	3	1	3	1	1	11,07%
Slope	1	1	1	1	3	1	1/2	1	1	1	9,90%
Precipitation	1	1	1	1	3	2	2	3	1	1	13,45%
LULC	1/3	1/2	1/3	1/3	1	1	1/3	3	1	1	6,62%
NDVI	1/5	1/3	1	1/2	1	1	1/5	1	1	1	5,87%
Distance from river	1	1	2	1/2	3	5	1	3	1	1	13,08%
Distance from road	1/3	1/3	1	1/3	1/3	1	1/3	1	1	1	5,59%
Drainage density	1	1	1	1	1	1	1	1	1	1	13,32%
Lithology	1	1	1	1	1	1	1	1	1	1	7,32%

Table.5 Flood susceptibility criteria and sub-criteria ranges for flood susceptibility assessment

Flood causative criterion	Unit	Class	Susceptibility class ranges and ratings	Susceptibility class ratings	Weight %
Topographic witness index (TWI)	Level	3,4 - 6,2	Very low	1	13.78
		6,3 - 7,8	Low	2	
		7,9 - 10	Moderate	3	
		11 - 13	High	4	
		14 - 27	Very High	5	
Elevation	m	200 - 300	Very High	5	11.07
		300 - 600	High	4	
		600 - 900	Moderate	3	
		900 - 1 200	Low	2	
		1 200 - 1 400	Very low	1	
Slope	Degree	<10°	Very High	5	9.90
		10°-20°	High	4	
		20°-30°	Moderate	3	
		30°-40°	Low	2	
		>50°	Very low	1	
Precipitation	mm/y	300 - 330	Very low	1	13.45
		340 - 360	Low	2	
		370 - 390	Moderate	3	
		400 - 420	High	4	
		430 - 450	Very High	5	

		River	Very High	5	
		Agricultural Land	High	4	
LU/LC	Level	Fallow Land	Moderate	3	6.62
		Buildup Land	Low	2	
		Vegetation	Very low	1	
		-0,4 - -0,06	Very High	5	
		-0,05 - 0,0006	High	4	
NDVI	Level	0,0007 - 0,05	Moderate	3	5.87
		0,06 - 0,09	Low	2	
		0,1 - 0,5	Very low	1	
		300	Very High	5	
		600	High	4	
Distance from river	m	800	Moderate	3	13.08
		1 000	Low	2	
		1 400	Very low	1	
		300	Very High	5	
		300 - 600	High	4	
Distance from road	m	600 - 900	Moderate	3	5.59
		900 - 1 200	Low	2	
		1 200 - 1 800	Very low	1	
		0 - 2	Very low	1	
		2 - 4	Low	2	
Drainage density	m/km	4 - 6	Moderate	3	13.32
		6 - 8	High	4	
		8 - 10	Very High	5	
		Clay	Very High	5	
		Marl	High	4	
Lithology	Level	Silt	Moderate	3	7.32
		Limestone	Low	2	
		Conglom-erate	Very low	1	

- Sentinel 1 Image Validation

In this study, Sentinel 1 data from before and after the 2019 floods were collected for the research area (Fig. 13). Using modified GEE code techniques, the VV and VH (dB) backscatter values for both pre- and post-flood conditions were evaluated. Heavy rainfall resulted in significant water accumulation in the Wadis, particularly in areas such as Oued Rhumel and Oued Boumerzoug.

The flood map for 2019, based on Sentinel 1 data, was compared with the flood susceptibility map created using the AHP method and Geographic Information System (GIS). The "Map Query" function was developed to compare areas with very high and high flood vulnerability (Fig. 14) against actual flooded locations. The resulting map indicated that areas with very high and high flood susceptibility were also affected by significant flooding. This finding highlights the usefulness of the susceptibility map as a flood warning system for identifying at-risk areas. However, the authenticity of the map could be questioned, as flooding predominantly affects regions with varying lithology, where water levels fluctuate during the rainy season.

- Flood zones near the river

A Geographic Information System (GIS) was used to analyze the location and distribution of flood-prone areas in the research region, specifically to assess the immediate effects of river flow. Our findings reveal that 65% of the areas identified as having extremely high or high flood susceptibility are situated closer to the rivers, while the remaining 35% of flood-prone areas are located further away (Fig. 15 and 16).

To assess the influence of each factor on the final flood susceptibility map, the "Map Query" method was employed. This approach helps validate and improve the applicability of the combined AHP and GIS methods, resulting in a more accurate and reliable flood susceptibility map for the study region.

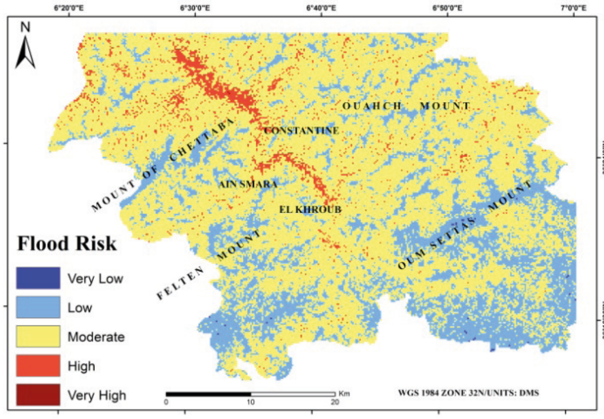

Fig. 12 Flood susceptibility map of the Ain Smara area

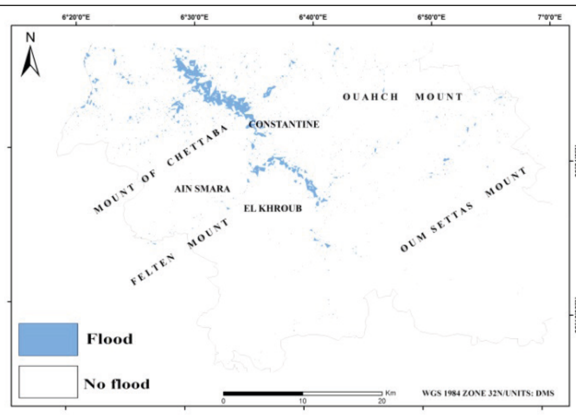

Fig. 13 Flooding in 2019 in the study area (Meteorological Station of Constantine 2019)

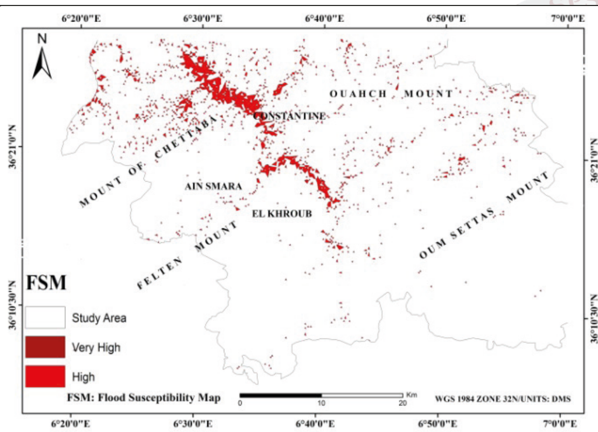

Fig. 14 Flood occurrence map in flood susceptible zones (under very high and high classes)

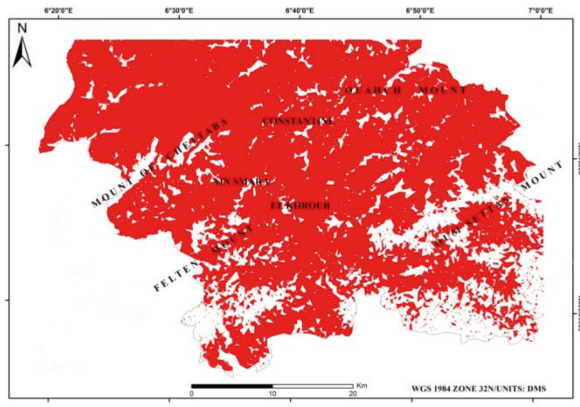

Fig. 15 Flood susceptible zone with respect to distance from river <600 m

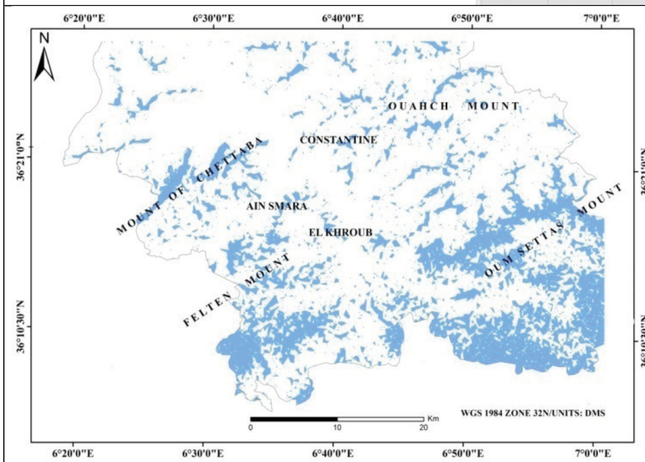

Fig. 16 Flood susceptible zone with respect to distance from river >600 m

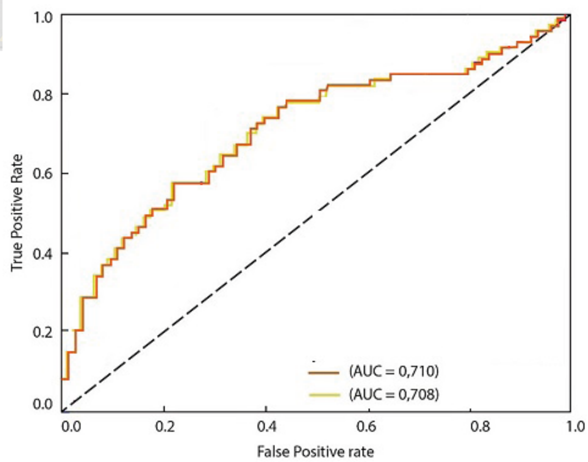

Fig. 17 Diagram for AUC and ROC analysis

3.2. Discussion

Our research area includes both plains and mountainous massifs, with well-known wadis such as Oued Rhumel, Oued Boumerzoug, and Oued Seguen. As previously established, areas near the wadis are the most vulnerable to flooding. Floods occur during the flood seasons due to the nature of Oued Rhumel, which necessitates frequent and rapid changes in its flow. The approach used in this study demonstrated that criteria such as the Topographic Wetness Index, Precipitation, and Drainage Density play a more significant role in determining flood-prone areas. In contrast, factors like lithology, slope, river distance, and elevation have a lesser impact compared to the first three.

The flooded areas in our study are typically characterized by their proximity to the wadis and very low slopes, similar to the findings of (Hitouri et al., 2024; Khaddari et al., 2023) and (Jemai et al., 2024), who obtained similar results. AHP is a method that calculates the weight of each criterion, relying on expert judgment worked on this study and the previous studies of (Das, 2020; Dahri and Abida, 2017; Hammami et al., 2019; Joshi and Shahapure, 2020; Das and Gupta, 2021; Malik and Pal, 2021) in the initial stages of allocating weights to the criteria, which can introduce some uncertainty (Swain et al., 2020). The key factors influencing the AHP approach in local and regional flood susceptibility studies include the Topographic Wetness Index, elevation, slope, precipitation, land cover/ land use, vegetation index (normalized difference), distance from the river, distance from the road, drainage density, and lithology.

To improve flood susceptibility mapping, modern techniques such as Bayesian Naive Alternating Decision Tree (AD Tree) (Swain et al., 2020), Random Forest (RF) (Das, 2020; Choudhury et al., 2022), and the frequency ratio and vector support model (Khaddari et al., 2022) can be employed.

In this study, the flood susceptibility map was validated using data extracted from Sentinel 1, showing a positive correlation between the 2019 flood zones and areas identified as very high and high susceptibility in the AHP-GIS map.

The study's strengths lie in its comprehensive methodology, combining AHP and GIS to assess flood susceptibility, allowing for the integration of multiple factors like the Topographic Wetness Index, Precipitation, and Drainage Density (Choudhury et al., 2022; Cvetkovic and Martinović, 2020; Perić and Cvetković, 2019). This approach is effective for the region's specific flood risks. By focusing on local geographic features, such as proximity to wadis and low-slope areas, the study provides highly relevant and actionable insights (Prasad et al., 2021; Iftikhar and Iqbal, 2024; Das, 2020; Dahri and Abida, 2017; Hammami et al., 2019; Joshi and Shahapure, 2020; Das and Gupta, 2021; Malik and Pal, 2021). The validation using Sentinel 1 data further strengthens the study's credibility, showing a positive correlation with actual flood zones. Additionally, the mention of advanced techniques like Random Forest and Bayesian Naive Alternating Decision Tree indicates the potential for improving the model's predictive accuracy in future work.

However, the study also has notable weaknesses. The reliance on expert judgment for weighting criteria introduces subjectivity, which could compromise the consistency and reproducibility of results (Hammami et al., 2019; Joshi and Shahapure, 2020; Das and Gupta, 2021; Malik and Pal, 2021). There is limited transparency regarding how these weights were determined, leaving the methodology open to questions (Choudhury et al., 2022; Cvetkovic and Martinović, 2020; Perić and Cvetković, 2019). The study also overlooks the temporal dimension of flood risk, failing to account for how factors like climate change or seasonal variations may influence flood patterns. While the findings are valuable for the specific region studied, their applicability to other areas with different geographical or climatic conditions is uncertain(Prasad et al., 2021; Iftikhar and Iqbal, 2024; Das and Gupta, 2021; Malik and Pal, 2021). Finally, while the study mentions advanced models, it does not provide a detailed comparison or evaluation of these techniques, which could offer opportunities for further refinement of flood susceptibility mapping.

The ROC and AUC curve is one of the most widely accepted performance assessment techniques for validating the AHP model. The AUC curve represents the combination of susceptibility and specificity, with the area under the curve (AUC) serving as a measure of model performance. AUC is a valuable tool for assessing the accuracy of flood modeling. Its value ranges from 0 to 1, with higher values indicating better model quality. A lower AUC value suggests insufficient adaptation of the model (Aleksova et al., 2024; Milevski et al., 2024.

In our study, the AUC value was 0.71, indicating a very good model. This result reflects the model's excellent ability to distinguish between the flood-prone and non-flood-prone areas within the data used to develop it. The AUC value also shows that the AHP model has been effectively modified to identify the flood susceptibility zone (Fig. 17).

4. Conclusions

Geologists, urban technology managers, and land developers must understand the importance of identifying flood-prone areas to effectively manage flood risks. This was achieved through the use of the AHP method, which helped develop a flood susceptibility map for Ain Smara and its surrounding urban agglomeration, considering ten influential factors. Expert estimates were used to determine the weights of these factors, and the most influential criteria for determining flood susceptibility were found to be the Topographic Wetness Index (TWI) (13.78%), precipitation (13.45%), drainage density (13.32%), and distance from the river (13.08%). In contrast, the least influential factors were distance from the road (5.59%), NDVI (5.87%), and land use/land cover (LU/LC) (6.62%).

This study's methodology, integrating multi-source geospatial data and the Analytical Hierarchy Process (AHP), offers several advantages. It provides a comprehensive and accurate flood susceptibility map by combining diverse datasets, utilizes GIS tools for detailed spatial analysis, and ensures a transparent weighting process through AHP. These methods enhance flood risk management by generating reliable maps for decision-makers. However, limitations include reliance on data quality and availability, potential subjectivity in AHP factor weighting, and the use of a 30x30 m DEM resolution, which may not capture fine-scale variations. Additionally, the model simplifies complex flood processes and may not fully account for dynamic environmental changes.

These flood influence criteria were combined to create a susceptibility map, which was then divided into five categories to describe the severity of flood vulnerability. According to the map, 1.13%, 2.87%, 66.00%, 28.35%, and 1.65% of the study area were classified as very high, high, medium, low, and very low flood susceptibility zones, respectively. The northern, northwest, and central regions of the study area were identified as being highly sensitive to unexpected floods, while the southern and eastern regions were classified as low or very low-susceptibility areas. This flood susceptibility map is considered an early warning system for flood-prone areas.

The accuracy of the model was verified using AUC curves, which showed a high accuracy (AUC = 0.71), confirming that the applied model is highly reliable. Given its consistent ability to accurately predict flood locations, this method is recommended for broader application in flood risk assessments and practical implications in the field of water management sectors.

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