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Comparison of the Fuzzy Analytic Hierarchy Process (F-AHP) and Fuzzy Logic for Flood Exposure Risk Assessment in Arid Regions

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Abstract: Flood risk assessment is an important tool for urban planning, land development, and hydrological analysis. The flood risks are very high in arid countries due to the nature of the rainfall resulting from thunderstorms and the land cover, which comprises mostly very dry arid soil. Several methods have been used to assess the flood risk, depending on various factors that affect the likelihood of occurrence. However, the selection of these factors and the weight assigned to them remain rather arbitrary. This study assesses the risk of flood occurrence in arid regions based on land cover, soil type, precipitation, elevation, and flow accumulation. Thematic maps of the aforementioned factors for the study area were prepared using GIS. The Fuzzy Analytic Hierarchy Process (F-AHP) was used to calculate the likelihood of the flood occurrence, and land use was used to assess the exposure impact. Using the likelihood map (i.e., probability) from the Fuzzy-AHP and an exposure map, the flood risk was assessed. This method was applied to Qatar as a case study. Results were compared with those produced by fuzzy logic. To explore the pairwise importance of the F-AHP, equal weight analysis was performed. The resulting risk map shows that the majority of urbanized areas in Qatar are within the high-risk zone, with some smaller parts within the very high flood-risk area. The majority of the country is within the low-risk zone. Some areas, especially land depressions, are located within the intermediate-risk category. Comparison of Fuzzy logic and the F-AHP showed that both have similarities in the low-risk and differences in the high-risk zones. This reveals that the F-AHP is probably more accurate than other methods as it accounts for higher variability.

Keywords: flood risk; fuzzy analytic hierarchy process; fuzzy logic; Qatar

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1. Introduction

Floods are natural hazards that can cause severe damage to communities and infrastructure. The situation is even worse in arid countries, where water resources are limited [1–3]. Arid climates prevail in many regions around the world where there is very little precipitation. However, when these dry regions receive rainfall, this can be very intense and cause flash floods, which can cause severe damage [4]. Rainfall in dry areas exhibits more spatial and temporal variability in terms of strength and duration [5]. Since high-intensity storms often only affect a limited portion of the catchment when causing floods in dry regions, these areas see far higher fluctuations in terms of floods from year to year and from location to location than do other regions [6].

Unsuitable urbanization and global climate change are two key contributors to the evolving nature of floods [7–9]. Globally, flood episodes are larger, occur more frequently and further afield [10]. In Morocco, for example, between 1995 and 2005, flood disasters significantly impacted more than 232,896 persons and resulted in more than USD 295 million in losses [10]. Over the past 20 years, there have been multiple devastating floods in the Gulf Cooperation Council countries (GCC). Due to growing urbanization and the hazard severity linked to climate change, the effects of floods on the Arabian Peninsula have drastically escalated during the past two decades [11]. During these 20 years, Riyadh and Jeddah, two of Saudi Arabia's biggest cities, were often hit by flash floods, which resulted in significant losses and expenses running into the billions of dollars [12,13]. A response to these hazards and an increase in the region's resilience are required in light of all these disturbing developments, and appropriate policies must be developed. To lessen future flood hazards, an integrated strategy to managing flood risk is needed, with an emphasis on lowering the vulnerability of society as a whole [14]. Assessing flood exposure risk in these areas is essential for effective flood management and disaster risk reduction [1].

Various methods and techniques have been used to assess flood hazards. The majority of studies on flood risk rely on climate and hydrological factors that affect the flood occurrence likelihood (i.e., [15–18]). Hydrological models are commonly used to predict the extent of flooding and the potential impacts of floods on people and infrastructure. These models use data such as rainfall, land use, soil characteristics, and other parameters to simulate the behavior of water during a flood event. The outputs of these models can be used to identify flood-prone areas and to assess the potential impacts of flooding on buildings and infrastructure. While modeling in general is a powerful tool, it relies on statistical data, and it fails to consider other important factors such as the exposure impact and land use.

The Multi-Criteria Decision Analysis (MCDA) is a decision-making approach that considers multiple criteria and objectives when assessing flood hazard risk. This method involves identifying different flood risk factors, such as flood frequency, severity, and duration, and then weighting them according to their relative importance. The MCDA approach can help decision makers identify the most critical flood hazards and prioritize actions to reduce flood risk. Geographical Information System (GIS) is another tool which has been widely used for flood hazard risk assessment. It provides a comprehensive approach to visualize and analyze flood-prone areas by including topography, land use, and hydrologic data. The GIS approach to flood hazard assessment involves identifying potential flood hazard zones and then overlaying them with other critical data, such as population density, critical infrastructure, and transportation networks. This information can then be used to develop effective flood mitigation strategies and emergency response plans. The GIS approach in general uses various factors that contribute to flood occurrence and utilizes thematic maps to estimate the flood risk (i.e., [19]). The challenge with these methods is the weights assigned to each factor map and the combination of these.

The analytic hierarchic process (AHP) approach provides a precise way for measuring the weights of choice criteria and is a systematic approach to multi-parameter analysis for structuring, organizing, and evaluating complicated judgments [20]. The AHP has been extensively used in various applications in water resources and hydrology, such as in the delineation of recharge zones and flood risk assessment [21–24]. While it is a great tool, the AHP can be subjective with ambiguity in the process because of its reliance on the expert's judgment. The Fuzzy Analytic Hierarchy Process (F-AHP) is a decision-making tool that has been widely used to assess and prioritize factors that contribute to flood exposure risk in arid areas [1,14,23]. The F-AHP is a combination of fuzzy logic and the Analytic Hierarchy Process (AHP) [23]. Fuzzy logic is a mathematical tool to cope with imprecision and uncertainty, while the AHP is a multi-criteria decision-making method that can be used to evaluate and prioritize alternatives [22,24]. The F-AHP combines the benefits of both methods to provide a more comprehensive and accurate assessment of flood exposure risk [24]. The F-AHP is a very useful decision-making tool that can be used to assess and prioritize factors that contribute to flood exposure risk in arid areas [20,22–24].

The fuzzy variant of the AHP enables decision making in uncertain situations where fuzzy numbers are used to represent the imprecise elements and criteria. Instead of using precise numerical values for the comparison ratios, the F-AHP technique employs a fuzzy judgment matrix with fuzzy numbers and produces crisp weights from consistent and inconsistent fuzzy comparison matrices, which removes the need for extra aggregating and ranking operations [23].

Previous studies have applied fuzzy logic to assess flood exposure risk in arid areas by considering various factors such as topography, land use, and soil type (e.g., [1]). The weight of each dataset was determined using the Analytical Hierarchy Process (AHP) approach, and the pertinent weight values were afterwards multiplied to produce fuzzy values. The quantitative approach makes use of qualitative analytical methods such as the Analytical Hierarchy Process as well as soft computing methods such as fuzzy logic.

This study utilizes the exposure impact and the probability of occurrence to calculate the flood risk. The probability of occurrence was calculated using two methods: the fuzzy Analytic Hierarchy Process (F-AHP) and fuzzy logic. The results of the F-AHP and fuzzy logic were compared using Qatar as a case study.

2. Materials and Methods

Risk is a negative event by definition, and it can be calculated using the cross-product of the probability of an event and its impact [25]. It is defined as the probability of a negative event with negative consequences [26]. The probability of occurrence is first calculated based on several factors affecting flood occurrence, and the impact is calculated using land use and land coverage.

The probability of flood occurrence depends on various hydrogeological factors. The main factor in flood analysis is the flow accumulation (or parameters related to it), which indicates areas where the surface runoff would go to in the case of precipitation [17,19,27]. Other important factors include land cover, soil type, elevation, surface runoff (or curve number), and rainfall intensity [28].

Saaty was the first to propose the Analytic Hierarchy Process (AHP) as a means to analyze and prioritize the multi-criteria decision-making process [29–31]. This method enables a rational framework for looking into various criteria, pairing them, and allowing the use of expert judgment to achieve a certain goal. The AHP provides a weight for each criterion in the decision-making process. Since its release, numerous studies have utilized the AHP approach for various decision-making problems such as water quality, ecology, recharge analysis, and vulnerability assessment, to name a few [15,32–36].

While the AHP is a great tool for the decision-making process, it fails to account for uncertainty in the many variables that are often required. As such, the F-AHP enables the consideration of a wider range of values in the process.

Zadeh [37] proposed the use of Fuzzy Logic (FL) instead of the classical 0–1 Boolean approach. This enables more flexibility when rating a certain factor or parameter. While fuzzy logic aims at coping with uncertainty, the F-AHP aims at helping the decision-making process when handling multi-criteria. The fuzzy logic uses a membership function for uncertain parameters to represent the partial truth instead of the classical (0,1) or true or false. On the other hand, the F-AHP uses a matrix of pairwise comparisons of each criterion to enable decision making, similar to the classical AHP but with the difference that it assigns weights to criteria and uses fuzzification instead of verbal appreciation.

This study utilizes the Fuzzy Analytic Hierarchy Process (F-AHP) approach to calculate flood risk in Qatar, as shown in Figure 1. The factors that affect the probability of occurrence of a flood are elevation, flow accumulation, precipitation, land cover, and soil type. Land slope is implicitly considered in flow accumulation, which calculates the direction in which flow occurs, following the topography. Soil type affects the runoff and infiltration as some soils have a higher infiltration capacity than others (Table 1), whereas land cover affects runoff. Precipitation is an important factor as it controls the amount of runoff over a period of time. As the precipitation increases, so does the probability of flash flood occurrence. In general, higher ground is less likely to experience floods; as such, elevation is considered.

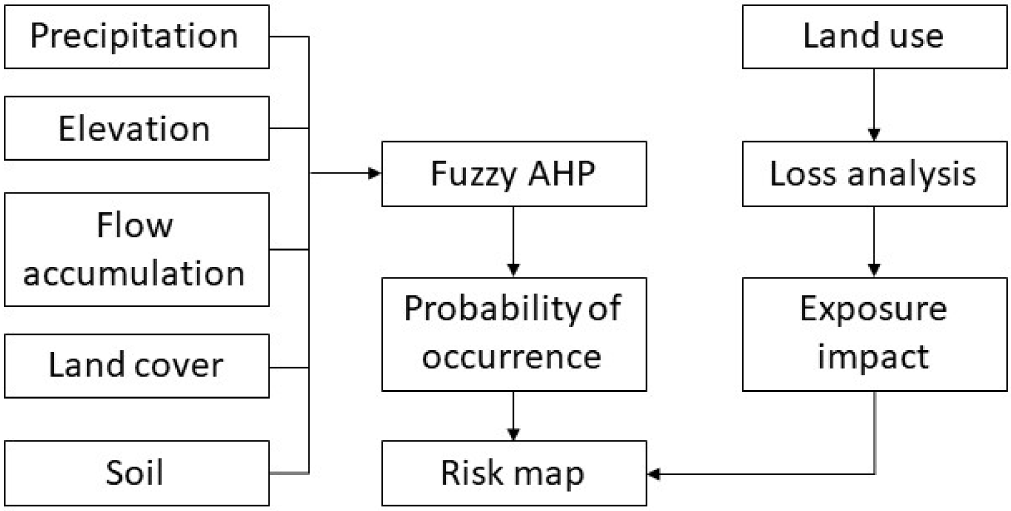

Figure 1. Stepwise methodology for fuzzy-AHP flood risk assessment.

Table 1. Classification of soil infiltration capacity.

Infiltration Capacity	Class
<0.13	0.1
0.13 to <0.20	0.2
0.20 to <0.28	0.3
0.28 to <0.36	0.4
0.36 to <0.46	0.5
0.46 to <0.56	0.6
0.56 to <0.66	0.7
0.66 to <0.74	0.8
0.74 to <0.85	0.9
≥0.85	1.0

The main challenge is to assign proper weights for those factors as they have different importance. For this reason, the F-AHP method was employed.

2.1. The Study Area

Qatar is one of the Gulf Cooperation Council (GCC) countries, located to the south-east of the Arabian Peninsula and covering an area of around 11,500 km^2 [38]. Qatar is bounded by the Arabian Gulf from the east, north, and west. In the west, Qatar has a land border only with Saudi Arabia (Figure 2). Qatar witnessed a huge development in infrastructure over the last decade as part of preparations for the FIFA World Cup [39].

As is the case with most arid countries in the region, the climate and rainfall patterns are very erratic, with rainfall occurring mainly between November and March [40]. Flash floods are very common in arid areas, as the soil is very dry with no vegetation coverage, which makes runoff significant and fast. The soil in Qatar remains dry and without vegetation for most of the year, as the average annual rainfall is less than 80 mm. However, several thunderstorms bringing heavy rain to Qatar have caused significant floods in the urban areas of the capital Doha and its surroundings. On 20 October 2018, Doha received rainfall of more than the annual average in less than two hours [41]. This storm resulted in massive floods that blocked the main roads and caused significant damage to properties and infrastructure. Groundwater recharge in Qatar has high variability which various studies have estimated to be between 5 and 166 million m^3 per year [40,42–50], and this reflects the high variability in rainfall. The population of Qatar was less than 40,000 prior to 1960 and has increased to more than 2.5 million at present [51].

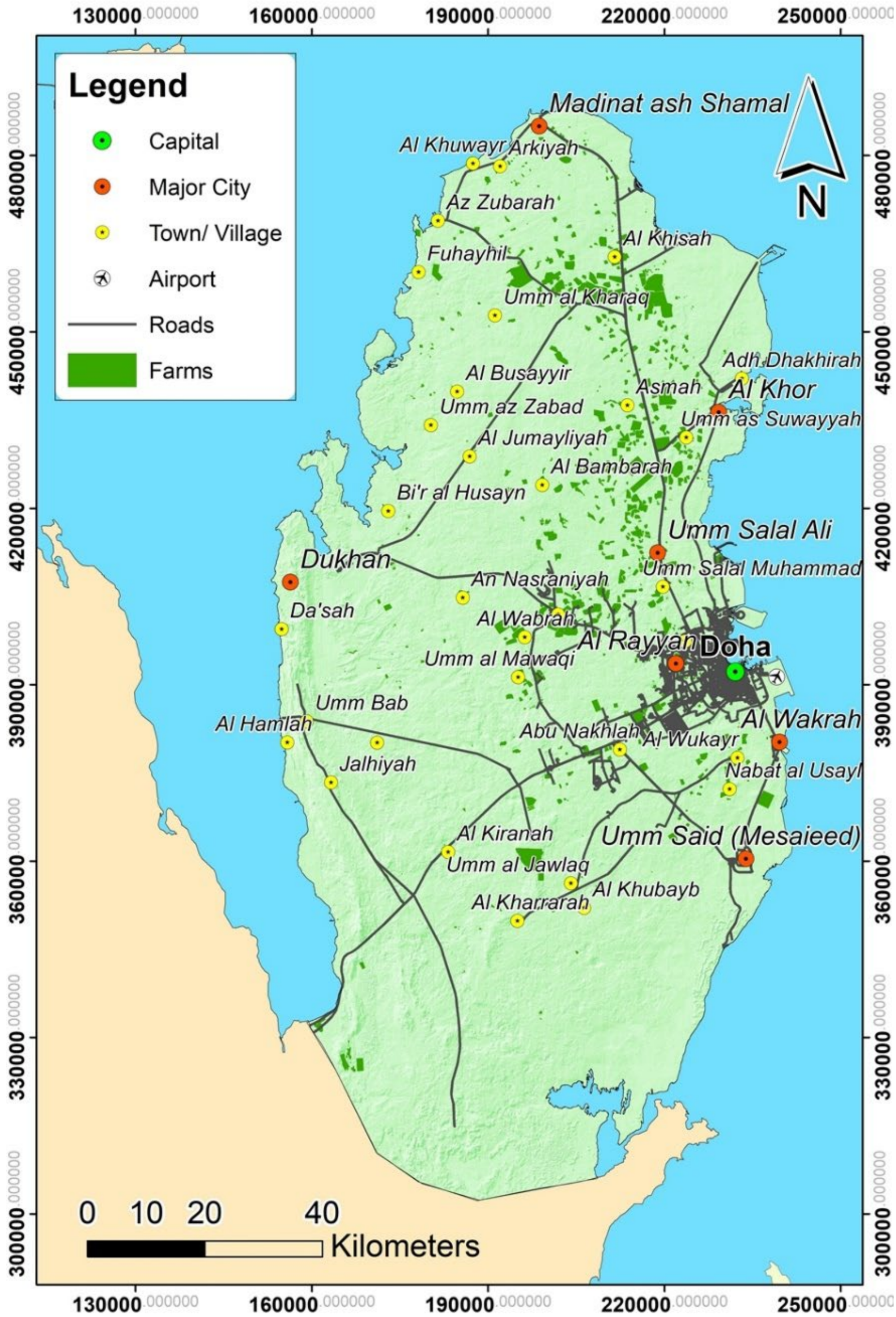

Figure 2. The study area.

Qatar's topography is flat in general except in some areas in the middle of the country. The terrain elevation is 40 m above mean sea level on average, and it reaches more than 100 m above mean sea level in some of the central parts (Figure 3). The terrain is characterized by numerous land depressions that vary in size from a few meters to more than one kilometer [40]. These land depressions are locally known as "roda", and they play an important role in the surface recharge. During the rainy season, rainfall would runoff and accumulate in these land depressions, bringing soil in, and making the depression suitable for agriculture. In the context of flood analysis, these depressions have a high likelihood of being flooded, but the risk is low due to the low exposure impact, as the next section explains.

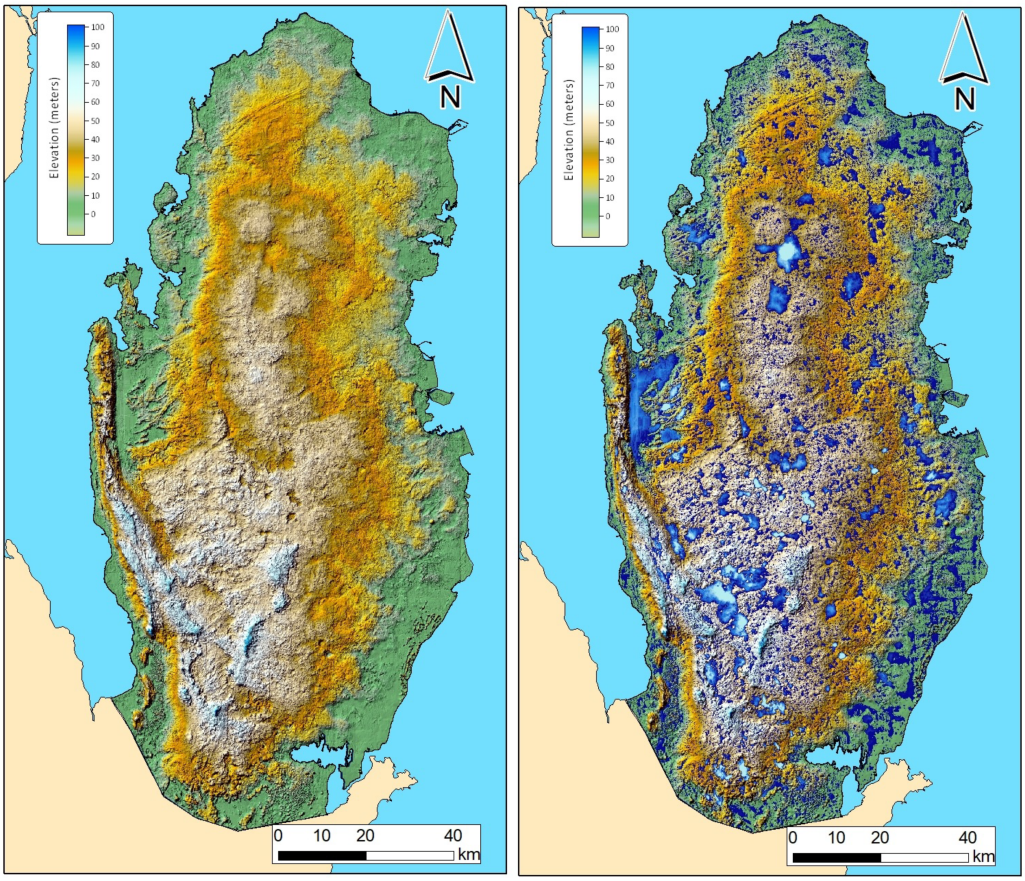

Figure 3. Topography map (**left**) and land depressions (**right**).

2.2. Flood Exposure Impact

As the flood effect has various effects on different land use, classification of the exposure impact was performed using land use and coverage. Figure 4 shows the varied land use and land coverage for the entire country of Qatar, using data from many sources [46,50,52–54].

Flood impacts can be monetary, non-monetary or both, as they may affect individuals, communities, and infrastructure. Consequences include the loss of life, destruction of important infrastructure such as communication and power lines, damage to property, loss of livestock, and damage to agricultural areas. Spreading of diseases is a possible indirect consequence of floods. Other indirect consequences include the disruption to transportation and communication lines, disruption to businesses, and disruptions to normal living [55–58]. Using the land cover map (Figure 4), various land uses were classified based on impact consequences and anticipated losses. Table 2 shows the impact classes, which vary between 0.1 for the lowest impact and 1.0 for the highest. Obviously, the residential areas (i.e., built-up areas) have the highest class (1.0), whereas the sabkhas (i.e., salt flats) and bare lands have the lowest. Figure 5 shows the resulting raster map of impact classification.

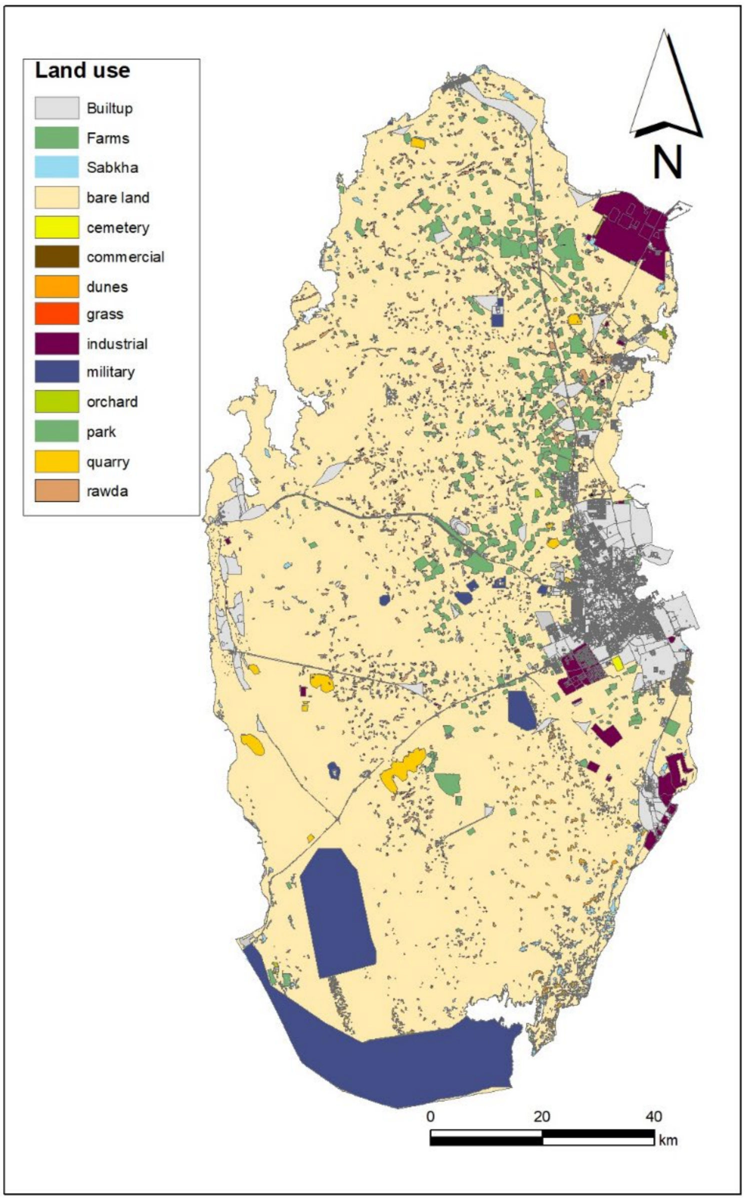

Figure 4. Land use map for Qatar based on data compiled from various sources [46,50,52–54].

Table 2. Land use/cover impact classification.

Land Use/Cover	Flood Impact
Sabkha (salt flat)	0.1
Bare land—dunes	0.2
Quarry	0.3
Roda—scrub	0.4
Forest—grass	0.5
Orchids	0.6
Farms–park–recreational	0.7
Military	0.8
Industrial—commercial	0.9
Built-up & residential areas	1.0

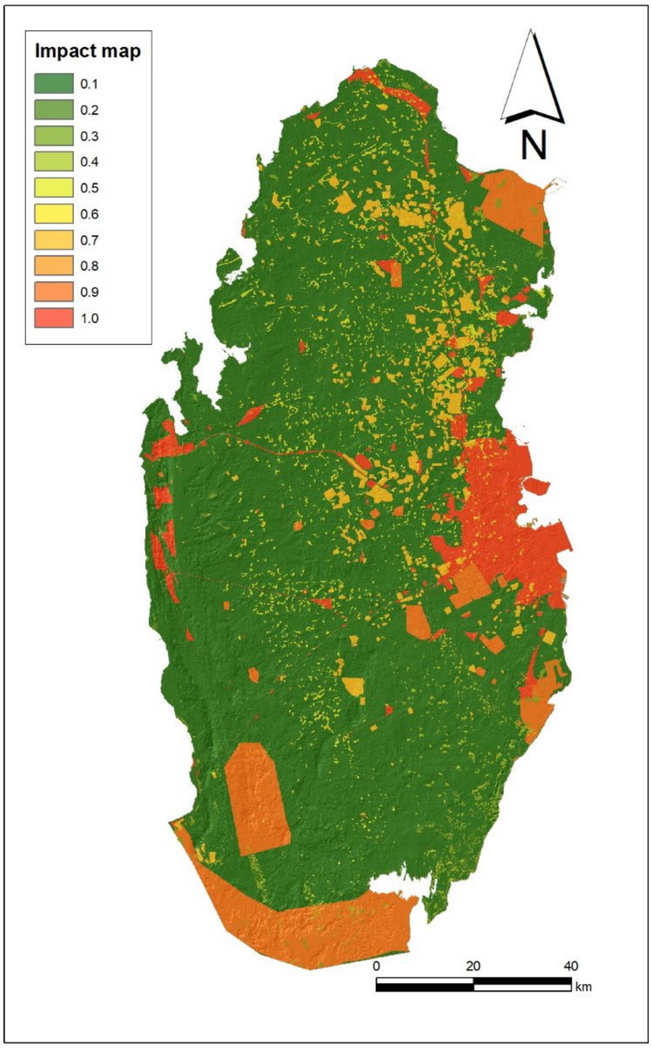

Figure 5. Flood exposure impact map based on land use/cover.

2.3. Probability of Occurrence

As per the stepwise methodology (Figure 1), the probability of occurrence was calculated using the F-AHP based on five parameters that play an important role in flood likelihood. The use of the F-AHP enables more flexibility in accounting for uncertainty. These parameters are the flow accumulation, elevation, precipitation, soil, and land use. The following sections discuss each of these parameters.

2.3.1. Soil

Soil is an important factor in flood analysis, as various types of soil have various infiltration capacities. Runoff normally occurs when the infiltration capacity is reached. As such, the higher the infiltration capacity is, the lower the runoff. Figure 6 shows the classified infiltration capacity map for Qatar based on data from Schlumberger Water Services [46].

2.3.2. Land Cover

Land cover plays an important role in flood occurrence, as various types of coverage enhance runoff more than others. Built-up areas and roads, for example, allow no recharge and most of the rainfall would go toward runoff. Forest and farmland, in contrast, would hinder the runoff through interception and infiltration into the soil. The land cover was classified using the curve number method based on the United States Department of

Agriculture [59] classification. The curve number is an empirical parameter used to predict whether precipitation would infiltrate the soil or run on the surface, based on the land cover [59]. The higher the curve number is, the higher the runoff. Table 3 shows the curve number for various hydrologic conditions and soil group, based on data from the United States Department of Agriculture [59].

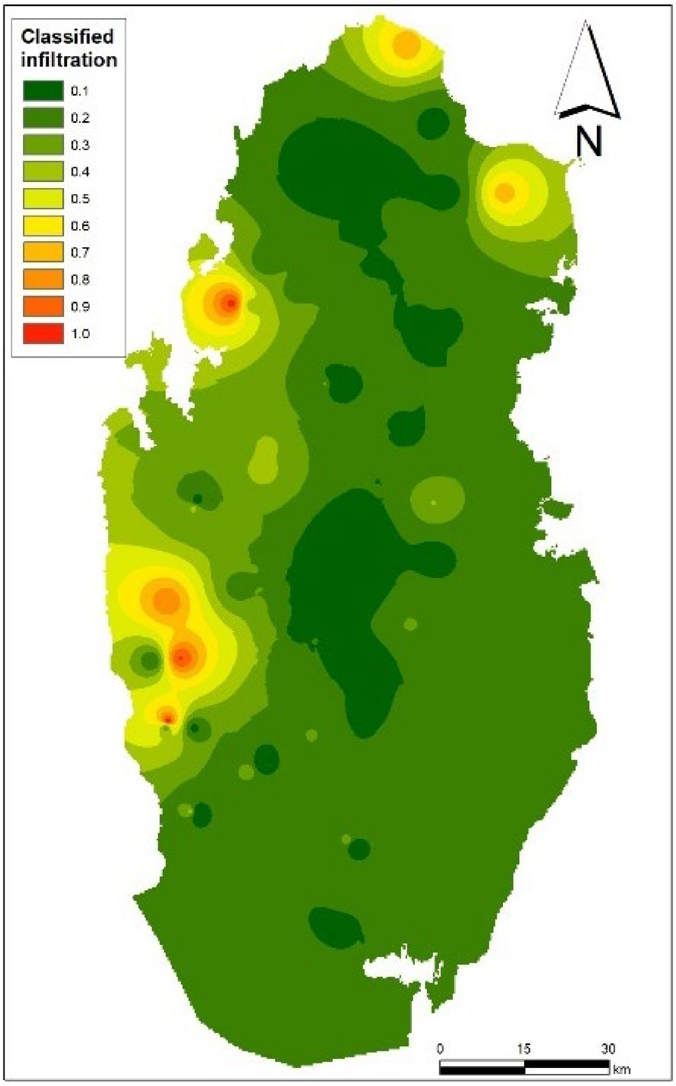

Figure 6. Classified infiltration capacity based on data from Schlumberger Water Services [46].

Table 3. Runoff Curve numbers (CN) for arid and semi-arid regions [59].

Cover Type	Hydrologic Condition	Curve Number			
		A	B	C	D
Herbaceous—mixture of grass, weeds, and low-growing brush, with brush the minor element	Poor		80	87	93
	Fair		74	81	89
	Good		62	74	85
Oak–aspen–mountain brush mixture of oak brush, aspen, mountain mahogany, bitter brush, maple, and other brush	Poor		66	74	79
	Fair		48	57	63
	Good		30	41	48

Table 3. *Cont.*

Cover Type	Hydrologic Condition	Curve Number			
		A	B	C	D
Pinyon–juniper—pinyon, juniper, or both; grass understory.	Poor		75	85	89
	Fair		58	73	80
	Good		41	61	71
Sagebrush with grass understory	Poor		67	80	85
	Fair		51	63	70
	Good		35	47	55
Desert shrub—major plants include saltbush, greasewood, creosote bush, black brush, bursage, palo verde, mesquite, and cactus.	Poor		63	77	85
	Fair		55	72	81
	Good		49	68	79

The curve number map was classified between 0.1 and 1.0, as shown in Table 4 and Figure 7. The classification was based on natural breaks, which maximizes the difference between breaks.

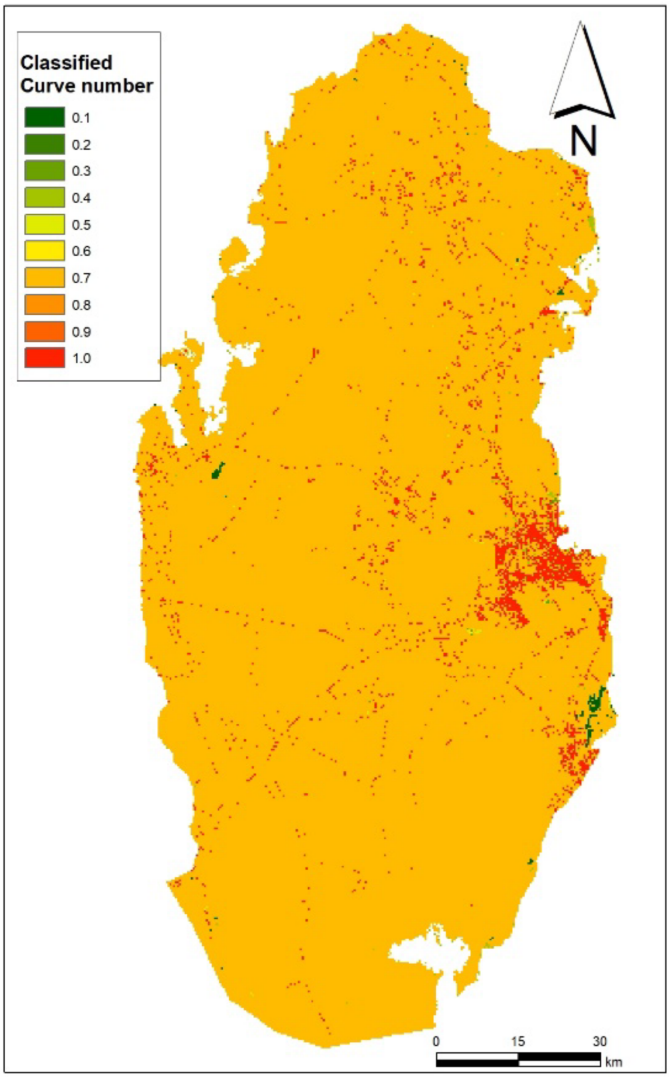

Figure 7. Curve number (CN) map for Qatar based on [59].

Table 4. Classification of curve-number map.

Curve Number	Class
<50	0.1
50 to <55	0.2
55 to <63	0.3
63 to <64	0.4
64 to <66	0.5
66 to <72	0.6
72 to <77	0.7
77 to <85	0.8
85 to <98	0.9
≥98	1.0

2.3.3. Precipitation

Precipitation in arid countries like Qatar is little in quantity but very erratic in nature [40]. It occurs only during the winter period between October and May and decreases from north to south. The amount of precipitation varies between 55 mm in the south, and 105 mm in the north. The average mean annual rainfall is around 80 mm [40,46,47], with a long-term average between 55.5–99 mm [60]. Thunderstorms are very common in Qatar, and heavy rainfall can cause flash floods [41]. During a thunderstorm in October 2018, the precipitation within two hours amounted to more than the annual average, resulting in a large flood in Doha [41]. Table 5 and Figure 8 show the precipitation classes for Qatar.

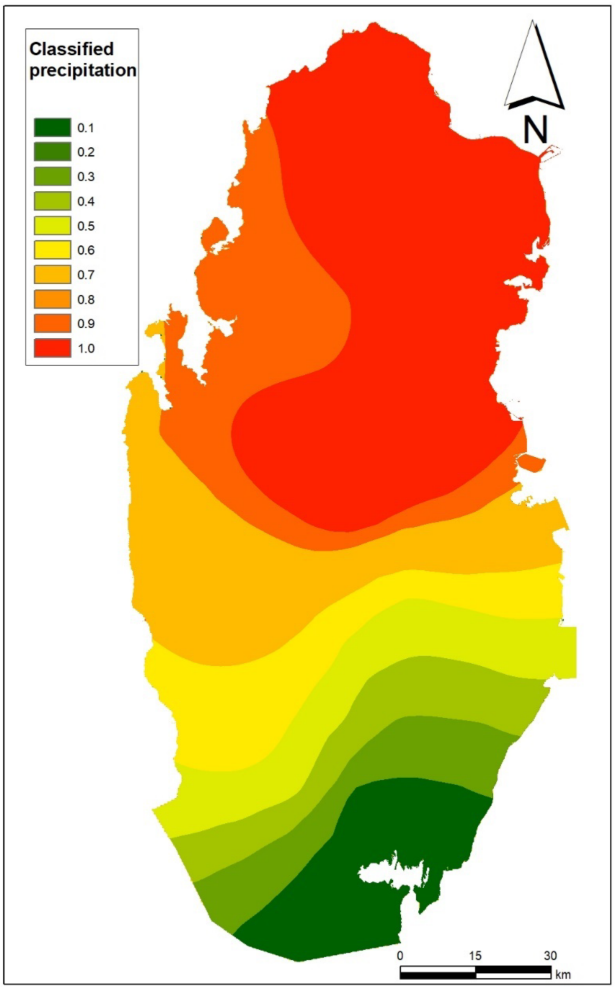

Figure 8. Precipitation classes based on long-term average.

Table 5. Classification of precipitation.

Precipitation Range (mm)	Class
55–60.0	0.1
60.1–65.0	0.2
65.1–71.0	0.3
71.1–76.0	0.4
76.1–81.0	0.5
81.1–86.0	0.6
86.1–92.0	0.7
92.11–97.0	0.8
97.1–101.0	0.9
101.1–105.0	1.0

2.3.4. Flow Accumulation

The flow accumulation procedure identifies the areas where the surface runoff would accumulate. This procedure is based on the digital elevation model to derive the slope, flow direction, and areas of flow accumulation. The latter can be determined using a tool in GIS, which calculates the value of the total water that may accumulate at any cell in a raster map representing the area of study. The flow accumulation tool also assigns a weight to each cell, and if not provided, it assigns an equal weight of one to each cell. Using the spatial analyst tool in GIS, a map of flow accumulation was created using the flow direction map. The latter was derived from the digital elevation model. Figure 9 depicts the classified map of flow accumulation. There are two flow accumulation classes, which show the areas of accumulation (class 1.0) and other areas with less accumulation (class < 1.0). The classification of flow accumulation is shown in Table 6.

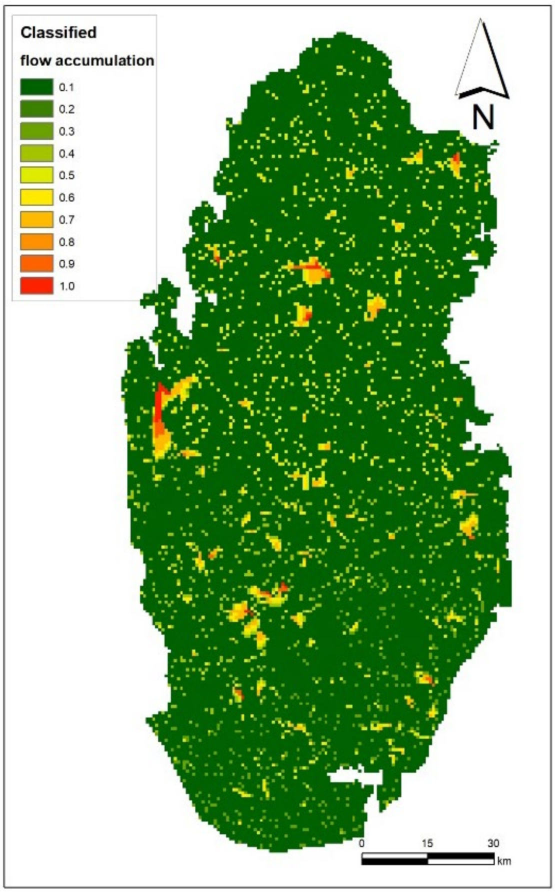

Figure 9. Flow accumulation classified map.

Table 6. Classification of flow accumulation.

Flow Accumulation	Class
0	0.1
0–2.0	0.2
2.1–2.8	0.3
2.9–4.7	0.4
4.8–8.4	0.5
8.5–14.1	0.6
14.2–22.8	0.7
22.9–35.9	0.8
36.0–58.0	0.9
58.1–102.5	1.0

2.3.5. Land Elevation

The terrain in Qatar is generally flat, as it varies from 0 m near the coastline to more than 100 m in some areas inland, with an average elevation of around 40 m (Table 7). Many land depressions occur in the country as a result of the collapse of karst limestone, creating lower elevation areas where surface runoff would accumulate. These land depressions are locally known as "roda" or "rawda", and they are considered good for agriculture. The size of the land depressions varies from a few meters to more than one kilometer in diameter [40]. Figure 10 shows the classified elevation map of Qatar.

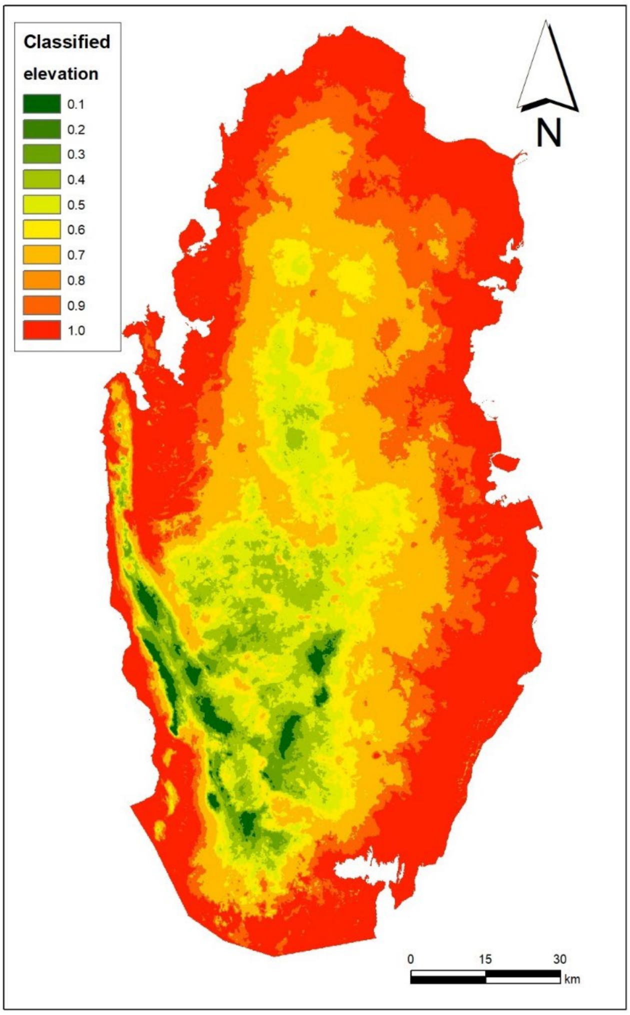

Figure 10. Classified elevation map.

Table 7. Classification of land elevation.

Elevation Range (m)	Class
−5.0–6.0	1
6.4–14.0	0.9
14.3–22.0	0.8
22.6–30.0	0.7
30.5–38.0	0.6
38.1–44.0	0.5
44.1–51.0	0.4
51.1–58.0	0.3
58.1–68.0	0.2
68.1–107.0	0.1

2.4. F-AHP and Triangular Fuzzy Number Design

The F-AHP process utilizes fuzzy theory with the classical AHP process that was proposed by Saaty [29]. The AHP process is based on constructing a pairwise matrix based on relative importance of criteria involved in decision making. The matrix then is normalized to get the relative importance of each criterion. The criteria weights are used for the decision-making process [61]. The original AHP approach can be combined with fuzzy theory to account for partial truth or vagueness in criteria weighting.

Zadeh [37] was the first to propose fuzzy logic, which allows the use of partial truth instead of deterministic values. While a deterministic decision can take a value of 0 or 1, fuzzy logic allows variation between them to represent the "partial truth". To represent the partial truth, a membership function is required to represent the fuzziness of a system [61]. The membership function was produced using the triangular fuzzy numbers (TFNs), which concern the replacement of crisp values in the original decision matrix. Each number in the AHP decision matrix is replaced by three numbers, l, m and u, representing low, middle, and upper values. Figure 11 shows an example of a TFN function denoted by $E = (l, m, u)$, which is defined as:

$$\mu(x) = \begin{cases} 0\ (x < l) \\ \frac{x-l}{m-l}\ (l \leq x < m) \\ 0\ (x \geq u) \end{cases} \tag{1}$$

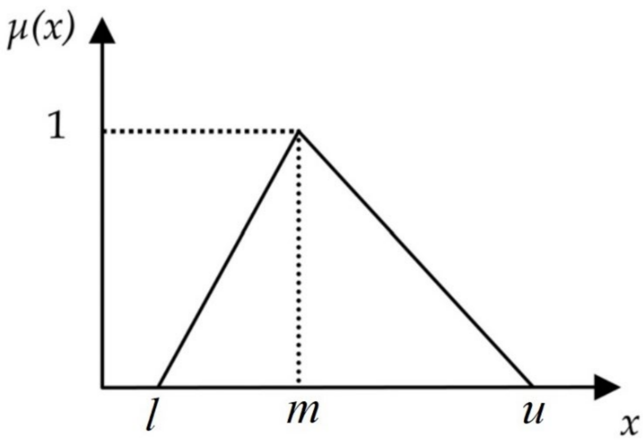

Figure 11. TFN function.

Saaty [31] identified the AHP scale of importance for each decision-making variable (Table 8). The conversion from crisp numbers to fuzzy TFNs is carried out as illustrated in Table 8 [31,62–64].

Table 8. Scale and description based on the AHP and F-AHP.

Definition	Intensity of Importance-AHP	F-AHP	Reciprocal Fuzzy Scale
Equal importance	1	(1, 1, 1)	(1, 1, 1)
Moderate importance of one over another	3	(2, 3, 4)	(1/4, 1/3, 1/2)
Essential or strong importance of one over another	5	(4, 5, 6)	(1/6, 1/5, 1/4)
Very strong importance	7	(6, 7, 8)	(1/8, 1/7, 1/6)
Extreme importance	9	(8, 9, 10)	(1/10, 1/9, 1/8)
Intermediate values between adjacent judgments	2	(1, 2, 3)	(1/3, 1/2, 1)
	4	(3, 4, 5)	(1/5, 1/4, 1/3)
	6	(5, 6, 7)	(1/7, 1/6, 1/5)
	8	(8, 9, 10)	(1/10, 1/9, 1/8)

2.5. The F-AHP Matrix and Consistency Check

Based on the scale classification in Table 8, the fuzzy decision matrix of 5 $\times$ 5 pairs was created using TFNs and the following criteria: flow accumulation, precipitation, land cover, soil, and elevation.

The AHP matrix was first created based on the relative importance of each criterion, as shown in Table 9. The results need to be normalized by dividing each value by the sum of each column to produce a normalized sum of 1. The normalized values are shown in brackets in Table 9, and the sum of each column must equal 1.0. The corresponding F-AHP matrix is shown in Table 10.

Table 9. AHP matrix and normalized pairs (in brackets).

Criteria	Flow Accumulation	Elevation	Precipitation	Land Cover	Soil
Flow accumulation	1 (0.500)	4 (0.522)	6 (0.563)	7 (0.355)	8 (0.375)
Elevation	1/4 (0.125)	1 (0.131)	1 (0.094)	3 (0.267)	3 (0.188)
Precipitation	1/6 (0.165)	1 (0.261)	1 (0.188))	2 (0.267)	1 (0.125)
Land cover	1/7 (0.125)	1/3 (0.043)	1/2 (0.062)	1 (0.0.089)	1/2 (0.250)
Soil	1/8 (0.085)	1/3 (0.043)	1 (0.094)	2 (0.022)	1 (0.063)
Sum (normalized values)	1.0	1.0	1.0	1.0	1.0

Table 10. F-AHP matrix and weights.

Criteria	Flow Accumulation	Elevation	Precipitation	Land Cover	Soil	F-AHP Weight
Flow accumulation	(1, 1, 1)	(3, 4, 5)	(4, 6, 7)	(6, 7, 8)	(7, 8, 9)	0.576
Elevation	(1/5, 1/4, 1/3)	(1, 1, 1)	(1, 1, 1)	(2, 3, 4)	(2, 3, 4)	0.163
Precipitation	(1/7, 1/6, 1/4)	(1, 1, 1)	(1, 1, 1)	(2, 3, 4)	(1, 1, 1)	0.122
Land cover	(1/8, 1/7, 1/6)	(1/4, 1/3, 1/2)	(1/4, 1/3, 1/2)	(1, 1, 1)	(3, 4, 5)	0.083
Soil	(1/9, 1/8, 1/7)	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/5, 1/4, 1/3)	(1, 1, 1)	0.056

It is important to check the consistency of the pairwise matrix in the AHP as given by Saaty [65], which should be less than 0.1. The consistency check is used to check and evaluate the eigenvalue matrix of the AHP (Table 9). It is given by:

$$CR = \frac{CI}{RI} \tag{2}$$

where CR is the consistency ratio, CI is the consistency index, and RI is the random index, which is given by Saaty (1980), depending on the size of the matrix. The CR is given by:

$$CR = \frac{\lambda_{max} - n}{n - 1} \tag{3}$$

where λ_{max} is the principal eigenvalue of the matrix and n is the matrix size. For this matrix, the random index is 1.12 (given by [65]), and the principal eigen value calculated for this matrix is 5.119; thus, the consistency ratio is 0.027, which is well below 0.1, as recommended by Saaty [65].

3. Results

The results of this study are presented in the following subsections, which include the results from the F-AHP, the F-AHP with equal weights, and fuzzy logic.

3.1. F-AHP Results

The risk map was obtained as a product of the probability of occurrence and the impact, as described in the methodology (Figure 1). The resulting risk map, based on the F-AHP, is shown in Figure 12. The map is classified into five categories based on the degree of risk.

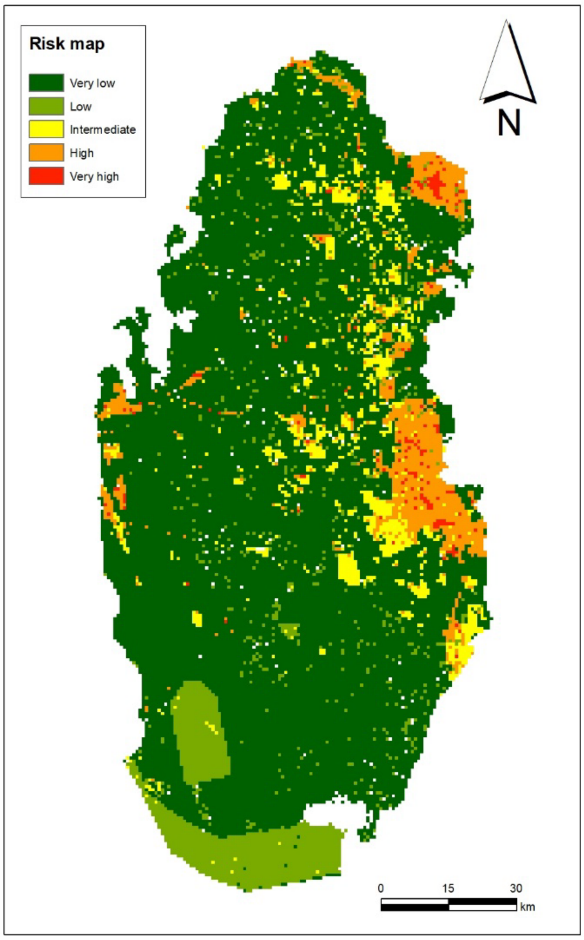

Figure 12. The resulting flood risk map using the F-AHP approach.

The results of the F-AHP reveal that most built-up areas are within the high flood-risk category, with some smaller parts, especially in Doha and in the northern townships located within the very high risk category. However, the majority of the country is within the very low risk category. It is also noted that the depression areas (refer to Figure 3) are of intermediate flood risk, despite the likelihood of flood being high. This is because the exposure impact is low at these depressions.

3.2. Equal Weights Results

In the preceding analysis, the F-AHP was performed using the relative importance of the various pairwise parameters that contribute to flood probability, as shown in Table 9. Their relative importance relies on the literature data and expert judgment. To examine the effect of the relative importance on the risk map, a new analysis was conducted using an equal weight for each of the five parameters listed in Table 9. In this case, each parameter has a weight of 0.2 because there are 5 parameters.

Figure 13 shows the resulting risk map using equal weights assigned to the five parameters listed in Table 9. While the low-risk areas are similar to those resulting from the F-AHP, the high-risk areas are different. In all cases, the high-risk zones are within the built-up areas, but the equal weights risk map contains larger areas of high risk than the F-AHP. This is probably because the equal weights make no differentiation within the likelihood parameters and, thus, is biased toward the exposure map (Figure 5). As such, the F-AHP is more accurate as it differentiates within one class of the exposure-impact map. Nevertheless, for low-risk areas, the equal weights analysis produces similar results to those from the F-AHP (and also to those from fuzzy logic, as discussed in the next section).

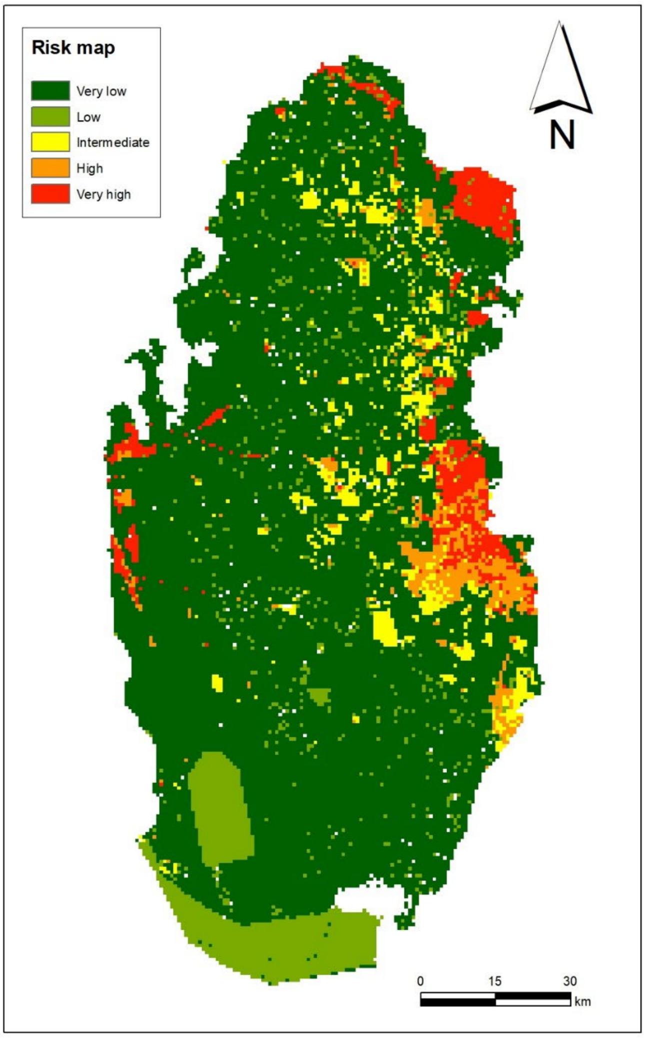

Figure 13. Risk map using equal weights.

3.3. Fuzzy Logic Results

The fuzzy logic approach was used to create a risk map and to compare the results with the fuzzy-AHP. Fuzzy logic is computing based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean logic on which the computer is based. Zadeh [37] developed the concept as an extension of classical (binary) logic, which only allows for binary truth values of either "true" or "false". Based on fuzzy logic, truth values are represented as degrees of membership on a continuous scale between 0 and 1, where 0 represents "false" and 1 represents "true". This allows for intermediate values that represent the degree of truth or uncertainty.

The membership function expresses the likelihood that a parameter is a member of a fuzzy set, which indicates the possibility and not the probability. It is a mathematical function that assigns a degree of membership or truth to an element in a fuzzy set. A fuzzy set is a set of values defined by a continuous membership function that maps each element to a degree of membership. The degree of membership represents the degree to which an element belongs to the set and how well it satisfies the set's characteristics.

In a fuzzy logic system, the membership function is used to describe the relationship between the input and output variables. The input variables are typically linguistic terms, such as "small", "medium", or "large", and the membership function is used to determine the degree to which an input satisfies the corresponding fuzzy set. The output of the system is then determined by aggregating the results of multiple fuzzy rules that relate the inputs to the outputs.

Within the GIS, fuzzy logic was used to create membership function and the fuzzy overlay function was used to sum up the fuzzy overlays [66]. Figure 14 shows the flood risk map using the fuzzy logic approach.

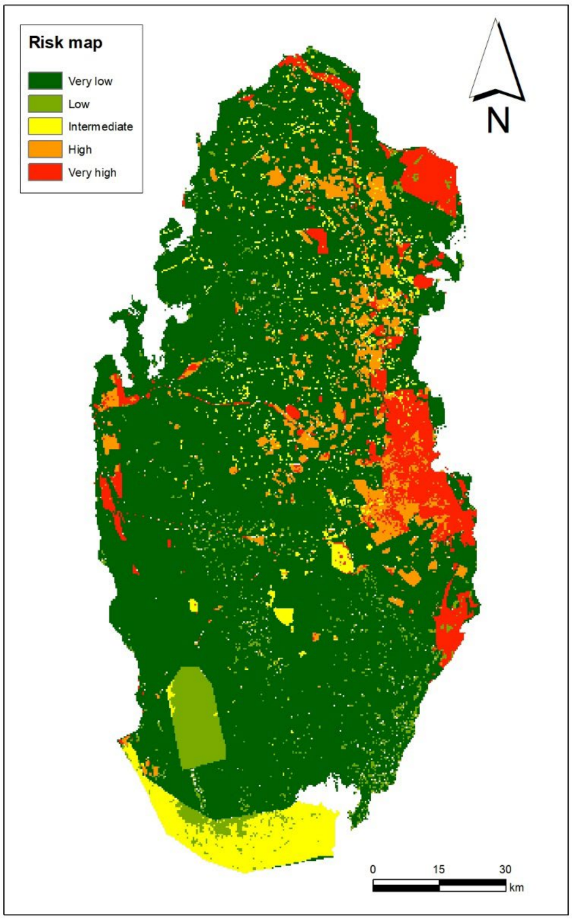

Figure 14. Flood risk map using the fuzzy logic approach.

4. Conclusions

Flood-risk mapping is a valuable tool for relevant authorities and decision makers, as it helps land management, planning and protection. The unique characteristics of arid regions, such as limited water resources, absence of vegetation, and very dry soil make them highly vulnerable to flood risks. This highlights the importance of flood risk assessment in these regions. The F-AHP provides a robust and flexible framework for evaluating the various criteria that contribute to flood risk, including precipitation, topography, land use, soil, and flow accumulation.

As the aforementioned parameters inherit a considerable margin of uncertainty, the F-AHP is more suitable for assessing the likelihood of flood occurrence than the classical AHP method. The exposure impact was produced through the classification of land use, where different land uses were ordered based on their flood impact. Risk mapping was calculated as the product of the probability of occurrence and exposure impact. Through the application of the F-AHP on Qatar as a case study, it is clear that the F-AHP can provide valuable insights into the importance of different factors that contribute to flood risk. By using the F-AHP to analyze these factors and their interrelationships, decision-makers can better understand the potential impacts of different flood risk management strategies and prioritize their efforts accordingly.

The comparison between the F-AHP, equal weights analysis, and fuzzy logic shows high similarities in the low-risk category and differences in the high-risk category. The three methods produce similar low-risk areas and the only variation is in the high-risk zones. Fuzzy logic results are more conservative than those of the F-AHP and the equal weights method. This is probably because the F-AHP accounts for uncertainty and considers a wider range of values compared to fuzzy logic. The F-AHP has the potential to play a critical role in improving flood risk management in arid countries. By providing a more comprehensive and accurate assessment of flood risks, decision makers can implement more effective strategies to reduce the negative impacts of floods on the environment, infrastructure, and communities. The use of the F-AHP can be further explored through the collection of more field data, application to various case studies, and validation through comparison with actual flood events.

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