Flood Susceptibility Mapping Using a Coupled Fuzzy-AHP MCDM Approach, a Case Study of the Gadarchay River Basin

By

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Abstract

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Floods are one of the most prominent threats to human life. Factors affecting a flood are rainfall, surface run-off, sea level, soil type, and regional topography. This study introduces the application of analytical hierarchy process coupled with fuzzy logic, altogether fuzzy analytical hierarchical process (FAHP), to address flood risk in Gadarchay River basin. The methodology is frequently used when access to exact numerical data, such as river bed boundaries, rainfall data, etc. is restricted or unavailable. To this end, five possible correlators of flood were used as input for the FAHP model. These input data are elevation, distance to river, population, slope and land use. They were fed into the FAHP model, and the model output was evaluated with the history of flood in two particular cities located in the basin. The results indicated that cities Naghdeh and Oshnavieh with 95% and 64% risk of flood are two of the cities with highest chance of flood with a population of 36315 and 15015, respectively.

"Scientists dream about doing great things,

Engineers do them."

–James A. Michener

To my mom and dad
and my brother for their endless love, support and encouragement…

Acknowledgments

First and for most I would like to dedicate this thesis to my family. I have to specially thank my mom and dad for their love and support throughout my life. Thank you both for believing in me and giving me the strength to reach this stage of my life. Furthermore I would like to thank my little brother Dave who deserves my wholehearted thanks as well.

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Table of Contents

List of Tables

List of Figures

List of Abbreviations

FAHP – Fuzzy analytical hierarchical process

AHP - analytical hierarchical process

MCDM – multi-criteria decision making process

ENSO - The El Niño Southern Oscillation

ERCC - Emergency Response Coordination Centre

FRA - Flood risk assessment

MAUT - multi-attribute utility theory

MAVT - multi-attribute value theory

ANP - analytical network process

MACBETH - measuring attractiveness by categorical base evaluation technique

ELECTRE - Elimination Et Choix Traduisant La Realité

PROMETHEE - Preference Ranking Organization Method For Enrichment Of Evaluations

ORESTE - Organization, Rangement Et Synthese De Donnes Relationnelles

TOPSIS - Technique for Order Preference by Similarity to an Ideal Solution

CP - Compromise programming

VIKOR - VlseKriterijumska Optimizacija I Kompromisno Resenje

SAW - Simple Additive Weighting

SMCA - spatial multi-criteria analysis

GIS - geographic information system

WSM - Weighted Sum Method

WLC - weighted linear combination

MFs - membership functions

1. Introduction

1.1. Flood and Climate Change

Floods are known to be a reason for overwhelming physical urban infrastructures and human tolerance are proved to be in a relationship with global warming (McMichael et al., 2006). Floods are one of the most ubiquitous natural disasters (43% of the total natural disasters) across the world, killing almost 100 000 people and impacting the life of 1.2 billion people (McMichael et al., 2006).

Factors affecting a flood are rainfall, surface run-off, evaporation, wind, sea level, soil type, and regional topography. Generally speaking, catchment size and topography have direct relationship with flood in a region (McMichael et al., 2006). Studies in flood impact assessment have proven that water management measures such as dams, dikes and canals, forestry, and land-use adaptation can alleviate flood risk in a particular flood-prone region (Bankoff, 2003, Bronstert, 2003, Tol et al., 2003, McMichael et al., 2006). These studies help to reduce the hazards of flood by assessing the impacts of hydraulic structures building. The economic status of a country also determines the tendency of people to resident near the coastline, which by increasing sea levels increase the possibility of flooding and deurbanization (McMichael et al., 2006). The El Niño Southern Oscillation (ENSO) indicates the variability of temperature and rainfall amount, hence storms, floods, and droughts in many regions (Philander, 1990, McMichael et al., 2006). Irrespective of diseases flood can cause as the aftermath, too much rainfall can increase the possibility of discharging wastewater and agricultural drainage into the drinking water, and make it unsanitary to consume.

As a natural disaster, floods are one of the most prominent threats to human life and economic devastation. According to the studies, climate change after industrial revolution impacted the flood frequencies and hurricanes around the world (Hirabayashi et al., 2013, Kay et al., 2009, Kay et al., 2006, Lane et al., 2007, Ranger et al., 2011). Hirabayashi et al. (2013) using 11 climate models predicted a large increase in flood risk in Southeast Asia, Peninsular India, Eastern Africa, and the northern half of Andes (see Figure 1).

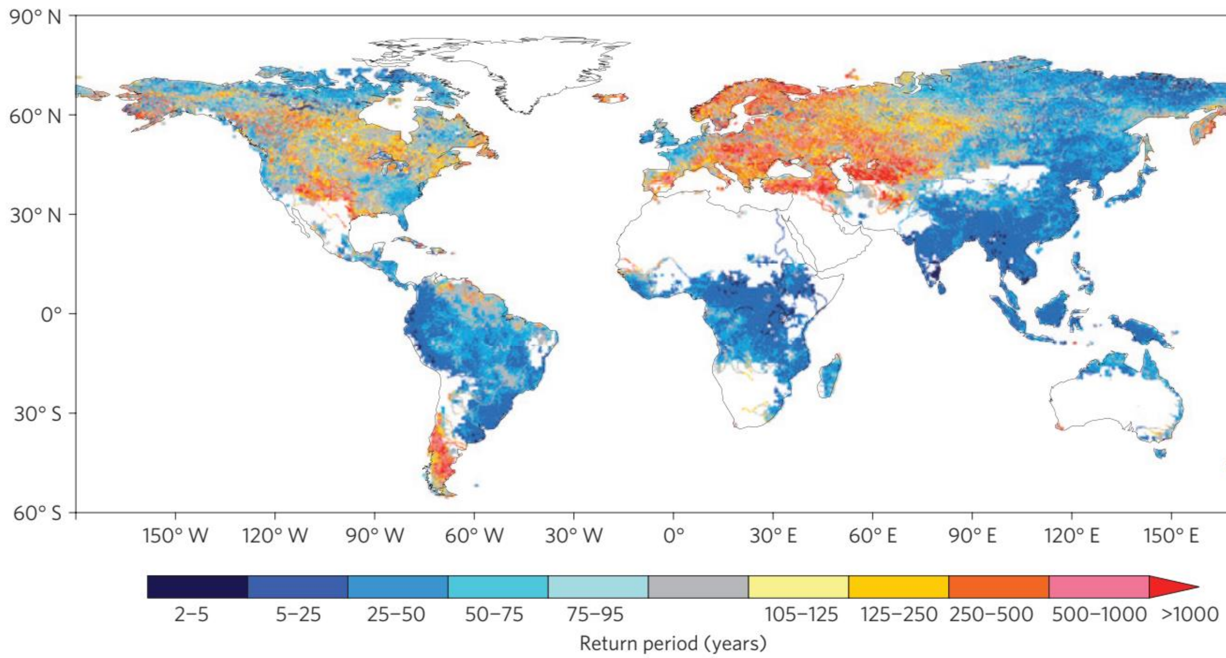

Figure 1: Multi-model median return period (years) from 2071 to 2100 for discharge corresponding to the 1971-2000 period of 100-year flood (Hirabayashi et al., 2013)

Referring to this figure, the flood return period (i.e., the average time between each flood to reoccur) of some specific regions in the world, such as South and East Asia, Western Iran, Central Africa, and South America are among the highest risks of flood.

Europe is another continent that is frequently battered by the side effects of climate change. Studies show that during the recent decade flood is becoming more and more frequent (see Figure 2) especially in several major European rivers, such as the Odra (Oder), Labe (Elbe), Po, Loire, and parts of the Danube (Dankers and Feyen, 2008, Kundzewicz et al., 2010, Hirabayashi et al., 2013).

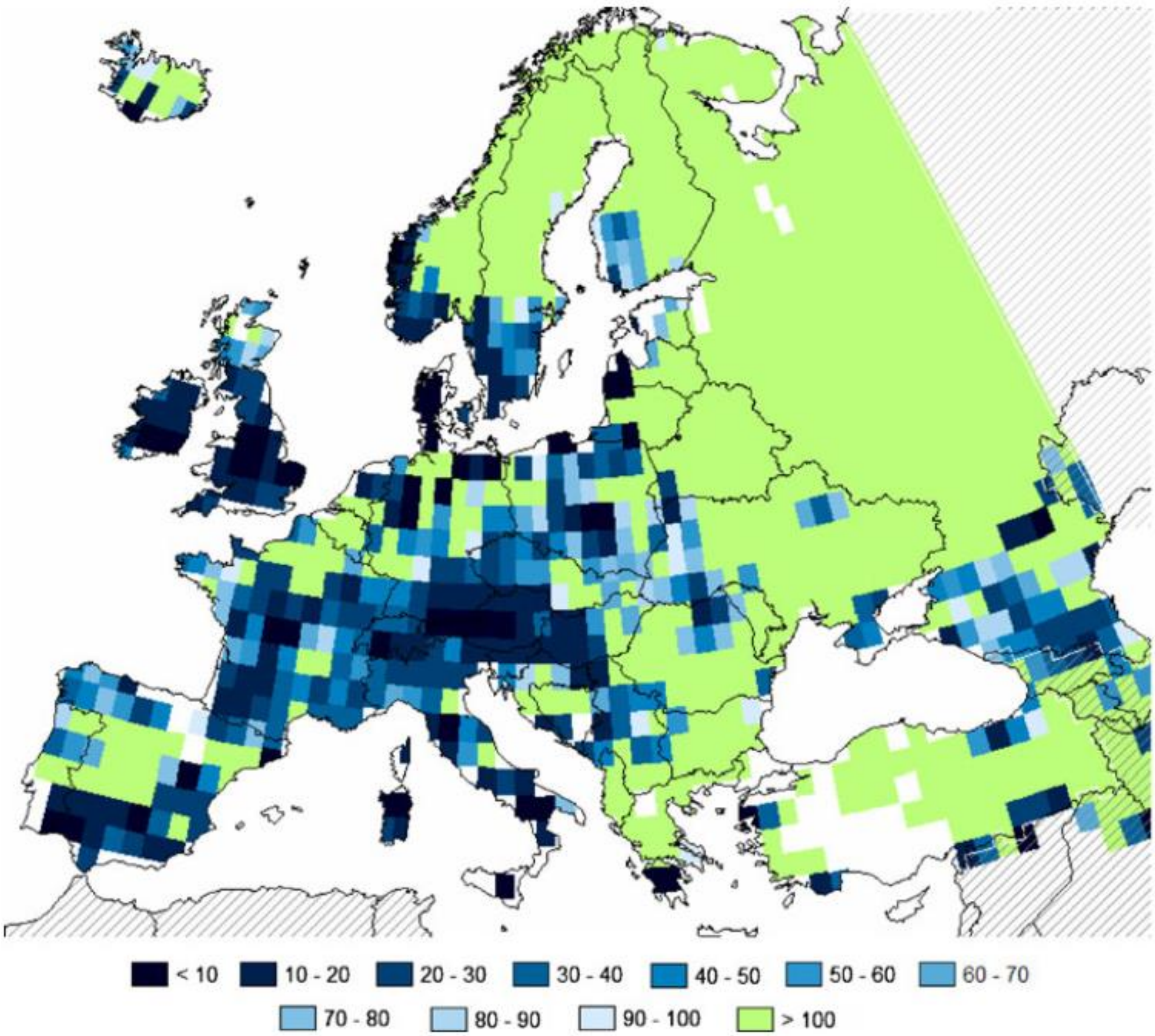

Figure 2: Recurrence interval (years) of today's 100-year flood (i.e. flood with a recurrence interval of 100 years during the period 1961–1990) (Kundzewicz et al., 2010)

1.2. Flood in Iran

As implied briefly in the earlier sub-section (the end of section 1.2), Iran is one of the most flood-vulnerable countries around the world. The Emergency Response Coordination Centre (ERCC), a worldwide institution which coordinates the support for disaster-stricken countries (both inside and outside the Europe), provides disaster-stricken countries with a piece of detailed information about the disaster. Iran, located in the middle-east, as a vulnerable country to natural mishaps, usually faces multiple natural disasters, including floods, earthquakes, storms, and drought during each year. According to the ERCC map of floods in Iran (see Figure 3), Orumiyeh centered in province Azerbayejan Gharbi, is one of the flooded areas indicated by NASA, the Terra (EOS AM) Satellite, MODIS payload imaging sensor. Interested readers can refer to Herring (1998) for more details about the procedure of flood mapping using remote sensing techniques. In this province, Gadarchay River (GR) is one of the most important rivers located in 36:45- 37:10'N and 44:45- 45:43E, enabling economic activities along the river, including fish breeding centers and agriculture, etc., and providing drinkable water for the nearest population centers.

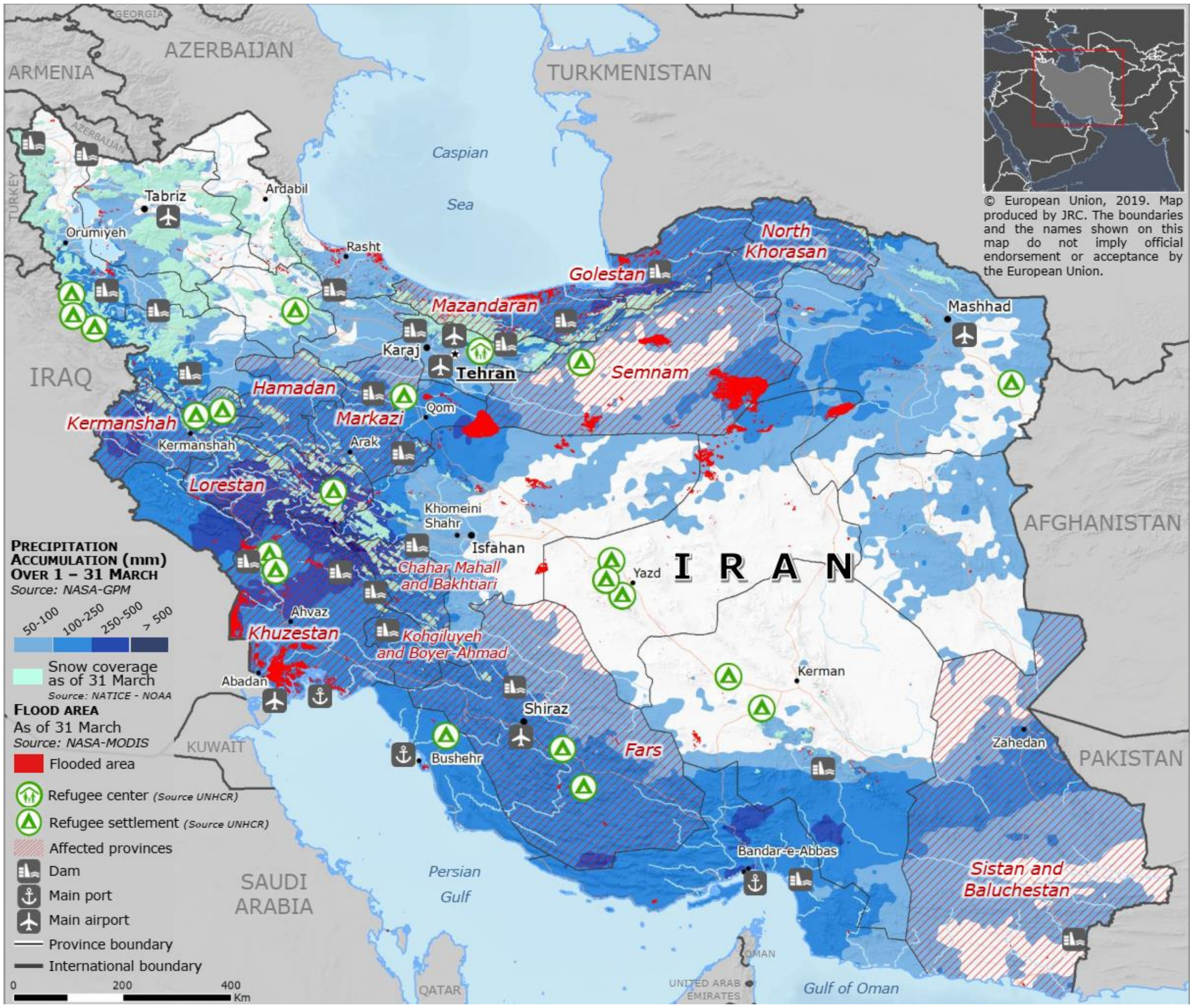

Figure 3: Flood risk across Iran (ERCC)

1.3. Problem Statement

Flood risk assessment (FRA) usually involves hydrological modeling of the region, which can be both a computationally intensive and a data demanding approach. This can be a problem for regions without sufficient amount of information available and instrument for accurate hydrological model calibration using samples taken along the GR. On the other hand, studies have shown hydrological models such as, HEC-RAS, HEC-HMS and HEC-GEORAS can suffer from uncertainty in model parameters, i.e., river bed roughness, turbulence and human error. Particularly, these process-based models require up- and downstream flow hydrographs, inundation records in urban areas and flow rate in multiple locations along river basin (Pappenberger et al., 2005, Dimitriadis et al., 2016, Merwade et al., 2008, Brandimarte and Di Baldassarre, 2012, Jamil et al., 2018). Since there is GIS data available for the GR river basin and no direct measurement of the river's hydrological parameters (to calibrate/validate the hydrological model), a fuzzy analytical hierarchical process (FAHP) approach can be potentially a suitable method to sufficiently address flood risk in this region.

1.4. Overview of Multi-criteria Decision-making Methods

Multi-criteria decision-making (MCDM) is a generic term used for a practice or a model that helps decision-makers considering multiple conflicting criteria (de Brito and Evers, 2016, Cinelli et al., 2014). It is reported that since the 1960s, many MCDM methods including, those mentioned in Table 7 were introduced (Mendoza and Martins, 2006, de Brito and Evers, 2016); however, these methods can be grouped into five categories that are:

1. Pairwise comparison methods:

According to Ishizaka and Nemery (2013), scoring should be performed by a group of experts to fill a pairwise comparison matrix of criteria on a predefined scale. The scale is in a way that the lower the score, the lower the suitability or, the higher the score, the higher suitability of criteria. Some of the most famous methods of this category are AHP, analytical network process (ANP) and measuring attractiveness by categorical base evaluation technique (MACBETH). It is noteworthy to state that AHP is the most commonly used method among those mentioned above, due to its simplicity and flexibility (de Brito and Evers, 2016).

2. Multi-attribute utility methods:

Based on Linkov et al. (2004), using utility functions and transforming criteria into a dimensionless scale, the purpose of this method is to define an expression for decision-makers' preference. Some well-known methods that fit into this category are multi-attribute utility theory (MAUT) and multi-attribute value theory (MAVT) (de Brito and Evers, 2016). The main feature of this group is the compensatory nature of it, which means poor performance of one criterion can be compensated by good performance of other criteria, e.g., expensiveness of a car can be compensated by high speed of the car (Linkov et al., 2004, Zhong et al., 2019).

3. Outranking methods:

Unlike multi-attribute and pairwise comparison methods, the goal of this group is to assume, rather than a single optimal solution may exist, one criterion may have a more significant impact over the rest of the criteria (Kangas et al., 2001). Some of the well-known methods of this category are Elimination Et Choix Traduisant La Realité (ELECTRE), Preference Ranking Organization Method For Enrichment Of Evaluations (PROMETHEE) and Organization, Rangement et Synthese de Donnes Relationnelles (ORESTE). According to Ishizaka and Nemery (2013), the primacy of this group of methods over AHP, ANP, MAVT, and MAUT is the nonexistence of compensatory effect and normalization of data. This feature brings some positive points for this group which make these methods suitable when criteria metrics are not easily aggregated, comparison scales vary over wide ranges, or the units of comparison are inconsistent or incomparable (de Brito and Evers, 2016, Ishizaka and Nemery, 2013, Kangas et al., 2001).

4. Distance to perfect methods:

The group of methods are based on assessing the distance of the alternatives to the ideal point. Accordingly, the alternative, which has the lowest hypothetical distance to the decision-makers' ideal point is the most suitable one (Malczewski, 1999, de Brito and Evers, 2016). Some the most famous methods of this category are Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), Compromise programming (CP), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (de Brito and Evers, 2016). The forte of this group is the ability to assess an endless number of alternatives and criteria (de Brito and Evers, 2016). Table 1 provides information about popularity of these mentioned methods.

Table 1: The ranking of MCDM methods (de Brito and Evers, 2016)

MCDM method	**Number of Occurrence in MCDM Studies**	**Percentage of Total (%)**
AHP, fuzzy AHP, trapezoidal fuzzy AHP and ANP	70	42.42
TOPSIS, fuzzy TOPSIS and modified TOPSIS	22	13.33
SAW	21	12.73

Others (MACBETH, NAIADE, goal programming, etc.)	20	12.12
CP, spatial CP and fuzzy CP	10	6.06
ELECTRE I, II, III and TRI	7	4.24
MAUT and MAVT	7	4.24
PROMETHEE I and II	5	3.03
VIKOR and fuzzy VIKOR	3	1.82
Total	165	100

Based on Table 2, AHP methodology has been widely used for risk assessment, hazard assessment, vulnerability assessment, flood mitigation, and susceptibility assessment (de Brito and Evers, 2016). In addition, among AHP, TOSIS, SAW, CP, ELECTRE, PROMETHEE, and VIKOR, AHP mostly used for risk assessment, TOPSIS mostly used for flood mitigation and risk assessment, CP, PROMETHEE and ELECTRE mostly used for flood mitigation, and MAUT and VIKOR mostly used for risk assessment (de Brito and Evers, 2016).

Table 2: Distribution of applications by MCDM method and area of application (de Brito and Evers, 2016)

Area of application/number of applications	**AHP**	**TOPSIS**	**SAW**	**Others**	**CP**	**ELECTRE**	**MAUT**	**PROMETHEE**	**VIKOR**
Ranking of alternatives for flood mitigation	14	10	9	8	9	5	2	3	1
Risk assessment	27	10	5	6	1	1	3	1	2
Vulnerability assessment	21	3	5	4	1	1	2	0	0
Hazard assessment	25	3	2	5	1	1	0	0	0
Susceptibility assessment	18	0	4	0	0	0	0	0	0
Coping capacity	8	4	2	0	0	0	1	0	0
Emergency management	5	0	1	0	0	0	0	1	0
Reservoir flood control	1	1	0	5	0	1	0	0	0

Total*	119	31	28	28	12	9	8	5	3

1.5. Background

As discussed before, a flood can damage a city both financially and civilian casualties. To mitigate this, researchers around the world are employing both hydrological modeling and MCDM. The decision-making process in an emergency situation tends to be somewhat uncertain and complex (de Brito and Evers, 2016, Akter and Simonovic, 2005, Kenyon, 2007). In this vein, a literature review is carried out to find conclusive remarks and specific details about each study. Among 167 studies of MCDM in FRA, about 42% of them applied fuzzy-AHP approach, 13% TOPSIS, 12.7 SAW and other methods (de Brito and Evers, 2016, Zhong et al., 2019). Table 7 provides the methods used for FRA in different studies (de Brito and Evers, 2016).

Wang et al. (2011) carried out FRA using a FAHP approach and a semi-quantitative method in the Dongting Lake region, Hunan, China. In this area, the flood is one of the most frequently-occurred natural disasters which is very prone to flood due to topography, soil and multiple other factors (see Table 3).

Table 3: Evaluation indicators with their corresponding standardization method (Wang et al., 2011)

Flood risk dimension	Criteria	Sub-criteria	Standardization
Hazard	Condition	Topography Vegetation cover	Maximum(II) Maximum(II)
		Drainage network	Direct, Maximum(I)
		Passing flood	Maximum(II)
		Flood control project	Maximum(II)
	Triggering factors	Rainfall	Maximum(I)
Vulnerability	Social	Population	Maximum(I)
	Economic	Production	Maximum(I)
		Cropland	Maximum(I)
	Physical	Transportation	Maximum(I)

The FAHP model was designed to conduct spatial multi-criteria analysis (SMCA) in the geographic information system (GIS). To this end, indicators for FR and flood hazard was first defined. Next, each indicator i.e., population information, GDP (see Table 4), soil type, topography and terrain feature, river properties, etc. was examined, normalized and weighted using AHP. Then, each of the mentioned indicators was combined to achieve the final flood risk map (refer to Table 5 to see state-by-state FRA score). The final index of FR was divided into five classes, i.e., very low, low, medium, high, and very high. The study suggested that the very high FRs were mainly located at central plains.

Table 4: The population and GDP information of Wang et al. (2011) study.

County	Population density (person/ sq. km)	GDP (million US $/km2
Lixian	345.67	0.27
Linxiang	284.35	0.22
Huarong	393.40	0.33
Anxiang	527.80	0.36
Lin Ii	361.23	0.31
Jinshi	2977.53	2.45
Yueyang(city)	832.27	0.67
Yueyang	258.03	0.19
Taoyuan	219.29	0.16
Changdc(city)	498. 18	1.03
Nanxian	585.24	0.26
Yua1tjiang	343.43	0.23
Hanshou	384.54	0.20
Miluo	429.76	0.33
Xiangying	440. 17	0.39
Yiyang	589.08	0.26
Yiyang(city)	1070.57	0.58
Taijiang	399.27	0.15
Changsha	349.03	0.72
Wangcheng	489.58	0.56
Ningxiang	443.25	0.34
Changsha(city)	5406.61	18.39

Table 5: The final output of the SMCA by Wang et al. (2011)

County	Very low risk (%)	Low risk (%)	Moderate risk (%)	High risk (%)	Very high risk (%)
Lixian	0.13	8.98	30.67	53.43	6.79
Linxiang	0. 12	8.40	34.86	32.24	24.38
Huarong	0	0	4.72	72.00	23.28

Anxiang	0	0	1.11	98.57	0.32
LinIi	0.06	7.59	71.2 1	21.14	0
Jinshi	0	0	0	0.21	99.79
Yueyang(city)	0	0	0.06	6.96	92.98
Yueyang	1.23	22.98	31.65	44.09	0.05
Taoyuan	25.63	54.82	16.01	3.54	0
Changde(city)	0.04	6.03	27.05	50.81	16.07
Nanxian	0	0	0	6.06	93.94
Yuanjiang	0	0	6.81	93.18	0.01
Hanshou	1.12	21.38	14.60	62.90	0
Miluo	2.39	16.31	32.94	46.82	1.54
Xiangying	0.55	8.28	53.32	37.85	0
Yiyang	22.82	24.2 1	37.24	15.73	0
Yiyang(c ity)	0	0.63	22.79	59.58	17.00
Taojiang	46.43	50.14	3.43	0	0
Changsha	8.12	75.63	16.07	0.18	0
Wangcheng	29.43	39.30	28.52	2.74	0.01
Ningxiang	88.91	8.27	2.62	0.20	0
Changsha(city)	0.02	0.09	0	0	99.89

Jun et al. (2013) conducted a fuzzy multi-criteria approach to assess flood vulnerability in South Korea, considering climate change factors. Twenty-one variables were selected and screened, and their respective weights were optimized by using the Delphi technique (see Table 6).

Table 6: Details of criteria used in Jun et al. (2013)

Criteria Number	Criteria	Weight	Source
1	Low-lying area of less than 10 m	0.31	GIS Analysis
2	Low-lying household of less than 10 m	0.23	GIS Analysis
3	Area ratio with the banks	0.19	GIS Analysis
4	Population density	0.16	National Statistics
5	The total population	0.11	National Statistics
6	Regional average slope	0.10	GIS Analysis

7	Percentage of road area	0.1	National Statistics
8	Cost of flood damage last three years	0.07	National Disaster Management Institute
9	Population of flood damage last three years	0.12	National Disaster Management Institute
10	Financial independence	0.10	National Statistics
11	Number of civil servants	0.11	National Statistics
12	GRDP	0.07	National Statistics
13	Number of civil servants	0.16	National Disaster Management Institute
14	Ratio of improved river section	0.15	National Statistics
15	Capacity of drainage Facilities	0.13	National Disaster Management Institute
16	Flood controllability of reservoirs	0.07	National Disaster Management Institute
17	Daily maximum precipitation	0.11	National Institute of Environmental Research
18	Days over 80 mm rainfall	0.13	National Institute of Environmental Research
19	5-day maximum rainfall	0.14	National Institute of Environmental Research
20	Surface runoff	0.21	National Institute of Environmental Research
21	Summer precipitation	0.21	National Institute of Environmental Research

To overcome uncertainty, the data from 16 provinces of South Korea were gathered and weighted, then, fuzzified. Furthermore, future meteorological data of climate change in 2020s, 2050s, and 2080s were predicted using the National Center for Atmosphere Research Community Climate System Model 3. Three multi-criteria techniques including Weighted Sum Method (WSM), Technique for Order Preference by Similarity to Ideal Situation (TOPSIS), and fuzzy TOPSIS were analyzed. The results suggested that the fuzzy TOPSIS method results are different from the rest of the abovementioned methods. Also it should be emphasized that uncertainty in the variable weights is suggested to be considered.

Table 7: Description of different MCDM methods cited in the reviewed papers (de Brito and Evers, 2016)

Abbreviation	Method	Description	Reference
AHP	Analytic hierarchy process	Structured technique for analyzing MCDM problems according to a pairwise comparison scale, where the criteria are compared to each other	(Vaidya and Kumar, 2006)
ANP	Analytic network process	Generalization of the AHP method which enables the existence of interdependence s among criteria	(Saaty, 2004)
CP	Compromise programming	Method based on the use of different distance measures to select the most suitable solution	(Ballestero and Garcia-Bernabeu, 2015)
ELECTRE	Elimination et choix traduisant la realite	Group of techniques addressed to outrank a set of alternatives by determining their concordance and discordance indexes	(Figueira et al., 2013)
MAUT	Multi-attribute utility theory	Method in which decisions are made by comparing the utility values of a series of attributes in terms of risk and uncertainty	(Wallenius et al., 2008)
MAVT	Multi-attribute value theory	Simplification of MAUT that does not seek to model the decision makers' attitude to risk	(Belton, 1999)
PROMETHEE	Preference ranking organization method for enrichment of evaluations	Family of outranking methods based on positive and negative preference flows for each alternative that is used to rank them according to defined weights	(Behzadian et al., 2010)

TOPSIS	Technique for order preference by similarity to an ideal solution	Technique based on the concept that the best alternative is the one which is closest to its ideal solution and farthest from the negative ideal solution	(Behzadian et al., 2012)
VIKOR	Vlsekriterijumska optimizacija i kompromisno resenJ e	Method that uses aggregating functions and focuses on determining compromising solutions for a prioritization problem with conflicting criteria	(Mateo, 2012)
SAW*	Simple Additive Weighting	Tool that aims to determine a weighted score for the alternatives by adding each attribute multiplied by their weights	(Abdullah and Adawiyah, 2014)
* Other such terms as weighted linear combination (WLC), weighted summation, weighted linear average, and weighted overlay are also used to describe SAW.			

Rahmati et al. (2016) carried out an MCDM approach for FRA in Yasooj region, Iran and compared the results with the results of a hydraulic model. In this vein, four parameters, including distance to river, land use, elevation, and land slope were selected. To define weights for each of those layers, an AHP approach was conducted by filling a questionnaire by experts. To this end, layer weights were normalized and zones were located by eigenvectors. In the hydrological modeling part, HEC-RAS model was used for 50- and 100-year intervals. The results (see Table 8) indicated that MCDM is a reliable method for the prediction of flood plain, and is suitable for the regions without enough data available.

Table 8: Assigned and normalized ranks for individual classes by Rahmati et al. (2016)

Parameters	**Class**	**Assigned rank (R)**	**Normalized rank (NR)**
Slope	0-10	5	5/15 = 0.33
	10-20	4	4115 = 0.27
	20-30	3	3/15 = 0.20
	30-50 >50	2	2/15 = 0.13 1/15 = 0.07
Total		15	
Distance	0-100	7	0.32

	100-200	6	0.27
	200-300	4	0.18
	300-400	3	0.14
	400-500	2	0.09
Land use/cover			
	River zone	6	0.32
	Residential areas and roads	5	0.26
	Bare lands	4	0.21
	Cropland	3	0.16
	Forest		0.05
Altitude	< 1700	6	0.38
	1700-1725	4	0.25
	1725-1750	3	0.19
	1750-1775	2	0.13
	> 1775		0.06

There are many counties involved in flood risk assessment studies (see Table 9); however, surprisingly, studies in countries that are most affected by flood, including Brazil and South American countries could not be found until 2016 in English journals (de Brito and Evers, 2016). Continental division of the studies indicates that Asia with 50% of the studies, followed by Europe (35.07%), North America (8.21%), Africa (3.73%) and Australia and South America both with 1.49% conducted the total 134 studies (de Brito and Evers, 2016).

Table 9: MCDM studies ranked by country (de Brito and Evers, 2016)

#	**Country**	**N**	**%**	**#**	**Country**	**N**	**%**
1	China	26	19.40	20	the Netherlands	2	1.49
2	Germany	13	9.70	21	Finland	2	1.49
3	South Korea	10	7.46	22	Italy	2	1.49
4	Iran	7	5.22	23	Kenya	1	0.75
5	Greece	6	4.48	24	Kuwait	1	0.75

6	India	6	4.48	25	Vietnam	1	0.75
7	Canada	6	4.48	26	Taiwan	1	0.75
8	Malaysia	5	3.73	27	Bhutan	1	0.75
9	Bangladesh	5	3.73	28	Switzerland	1	0.75
10	USA	5	3.73	29	South Africa	1	0.75
11	UK	5	3.73	30	Poland	1	0.75
12	France	4	2.99	31	Spain	1	0.75
13	Slovakia	3	2.24	32	Portugal	1	0.75
14	Egypt	2	1.49	33	Serbia	1	0.75
15	Turkey	2	1.49	34	Nigeria	1	0.75
16	Japan	2	1.49	35	Chile	1	0.75
17	Australia	2	1.49	36	Argentina	1	0.75
18	Croatia	2	1.49	37	Romania	1	0.75
19	Austria	2	1.49		Total	134	100.00

Yang et al. (2013) conducted a study to evaluate a hybrid model based on triangular fuzzy membership functions and analytical hierarchical process. The model comprised a flood risk evaluation and forecasting to achieve the rankings of risk factors and a comprehensive flood risk prediction. The study carried out in the Lower Yangtze River region. The results were suggesting that the model could be used in natural settings to predict flood inundated areas in this region. Moreover, a comparison with actual experimental models was made, and the results suggested the efficiency and the effectiveness of the proposed model.

Stefanidis and Stathis (2013) studied flood risk in Greece, which is one of the most occurring natural hazards in this region. The finding of this study could be used for the management of watersheds and flood risk evaluation plans in Greece and other places in the world. The study coupled analytical hierarchical process with geographic information system, considering both natural and anthropogenic factors. The study was performed on Kassandra Peninsula in Northern Greece. To this end, the morphometric and hydrographic characteristics of the watershed were assessed. Also, the natural flood genesis factors were examined and manmade embankments and other hydraulic structures within the stream beds were recorded.

Based on these mentioned factors, i.e., anthropogenic and natural effects on the proposed stream beds, flood hazard indexes were defined. On this basis, the river basin was divided into multiple flood hazard classes. The results indicated that the majority of the basin is in medium risk class due to either natural or anthropogenic causes. Furthermore, the results were validated by historical flood hazard data which suggested the accordance of the proposed model.

Nigusse and Adhanom (2019) studied urban flood risk in Adigrat city, Ethiopia. The main risk contributors to flood risk are poor urban drainage network and land use planning. The urban flood risk exacerbates even more due to the lack of a flood early warning system. A multi-criteria decision-making model and a geo-spatial mapping model were used to map the potential flood plains across the city.

The digital elevation model which was created using Landsat satellite imagery along with aerial photography, rainfall data and census population were used as input for the model. Using these sources, the following variables were extracted:

1. Slope from the digital elevation model
2. Elevation from the digital elevation model
3. Rainfall from the historical meteorological dataset
4. Flow direction was extracted using Flow direction toolbox in ArcGIS
5. Flow Accumulation was extracted using Flow accumulation toolbox in ArcGIS
6. Population density from census
7. Building and road density from the municipality of Adigrat

Since all contributing factors had a different impact on flood risk, each variable was weighed against the other factors until to get a rational consistency ratio. Subsequently, slope, elevation, population, and land use were found to be the most important factors. The results indicated that the downtown areas are more susceptible to flood due to high population, flat terrain, and low elevation.

Yeganeh and Sabri (2014) evaluated flood risk in Iskandar, Malaysia, South-east Asia, which is one the most flood-vulnerable areas in Asia. The city of Iskandar has been flooded several times during the last decade. The city's flood contributing factors are severe rainfalls, geographical situation, unplanned urban developments, and insufficient urban drainage network. The study employs fuzzy logic, weighted linear combination and geographic information system to address the crucial variables which contribute to the risk of flood in this city. The variables and extraction method are listed below:

1. Distance to the river was extracted using Distance toolbox in ArcGIS environment
2. Elevation was achieved using Landsat satellite imagery
3. Slope was extracted using Slope tool in ArcGIS environment
4. Land use was rasterized using Raster conversion tool in ArcGIS environment

The results showed that 658 sq. Km of 1614 sq. Km has a high level of flood risk within the region. Some highly populated regions in the study area are Pulai, SenaiKulai, Tebrau and Johor Bahru.

Papaioannou et al. (2015) provided a framework for GIS-based studies for flood-prone areas detection across Xerias River watershed, Thessaly region, Greece using fuzzy logic, and clustering techniques, and MCDM methods. To this end, factors were grouped into four categories, including geophysical, morphological, meteorological and hydrological. From these categories, ten important criteria were selected:

1. DEM
2. Slope
3. Aspect
4. Flow Accumulation
5. Horizontal Overland Flow Distance
6. Vertical Overland Flow Distance
7. Topographic Position Index
8. Wetness Index
9. Curve Number
10. Modified Fournier Index

Using these, flood-prone areas were divided into five categories two different scenarios were identified for FRA. First, all criteria were normalized before the MCDM process and then the output was clustered into five flood-vulnerable categories. Second, criteria were clustered both before and after MCDM process. The results indicated that for similar studies different combinations of these methods should be considered.

Table 10: Percentage of flood prone areas classes of AHP and FAHP "Expert Knowledge" for both approaches (Papaioannou et al., 2015)

1st approach	Methodology					
Flood prone areas classes	**Natural breaks**	**K-means euc.**	**K-means cit.**	**FCM***	**GMMC****	**CLARA*****
AHP expert knowledge						
Very low	17.31	17.29	20.53	17.10	8.22	20.26
Low	33.25	32.24	27.48	31.88	25. 18	27.43
Moderate	25.99	25.93	24.13	26.05	36.11	24.30
High	16.86	17.41	17.19	17.66	20.13	17.32
Very high	6.60	7. 13	10.66	7.30	10.35	10.69
FAHP expert knowledge						
Very low	20.76	20.45	22.44	19.80	19.31	22.2 1
Low	34.05	32. 19	27.47	32.07	15.89	27.19
Moderate	24.02	24.70	24.05	25. 18	37.72	24.44
High	15.63	16.67	16.47	16.94	20.92	16.58
Very high	5.54	5.99	9.56	6.01	6.16	9.57
2nd approach	**Natural breaks**	**K-means euc.**	**K-means cit.**	**FCM**	**GMMC**	**CLARA-CLARA**
AHP expert knowledge Very low	19.54	18.60	19.87	16.36	14.70	18.81
Low	28.28	27.45	24.94	25.69	15.31	23.00
Moderate	23.62	23.79	22.42	25.98	46.27	21.74
High	20.76	22. 18	21.34	22.07	0.00	21.16
Very high	7.80	7.99	11.44	9.90	23.73	15.29
FAHP expert knowledge						
Very low	2 1.09	23.08	21.77	2 1.10	14.53	29.46
Low	30.75	30.78	27. 18	27.70	25.06	28.14
Moderate	25.93	25.23	24.23	25.59	36.63	22.54
High	15. 18	14.27	18.19	16.15	9.79	12.33
Very high	7.05	6.64	8.64	9.46	13.99	7.53

Fuzzy C-Means *

Gaussian Mixture Model **
Clustering Large Applications method ***

Raaijmakers et al. (2008) combined three different methods of risk assessment techniques to analyze flood risk in the Ebro Delta in Spain. These methods include:

1. The quantifiable conventional approach to risk
2. The taxonomic analysis of perceived risk
3. The analytical framework of a spatial multi-criteria analysis

Based on the techniques mentioned above, by using risk perception-scores as weights in the MCDM process, a novel methodology for risk assessment of flood was defined. Also, the risk perception data had been collected through a survey in the region from the residents who were used in MCDM process in the Ebro Delta in Spain. The results of the study were presented for stakeholders and decision-makers for further investigation and operations.

2. Methodology

2.1. Study Area

The study area of the GR basin is surrounded by the Barandouzchay, Zaab, and Mahabad watersheds. The basin is majorly surrounded by mountains, e.g., of Dalamper Bozorg and Baadgoole. The Ghalazchay, Kaanirash, Sheykhanchay, Balaghchichay, and Mohamad Shah sub-streams flow into the Gadarchay River along the river's path to Lake Urmia, into which the Gadarchay River discharges (Rezaali et al., 2019).

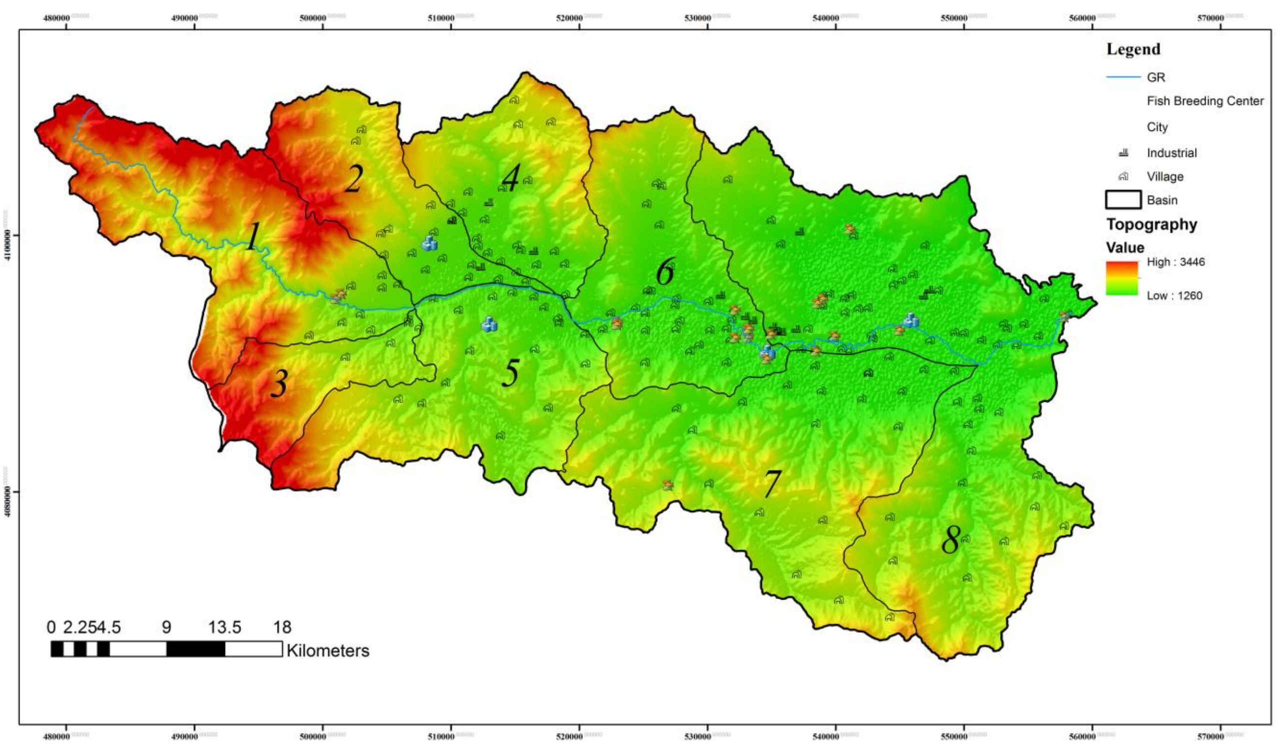

Figure 4: The topography and the population centers of study area

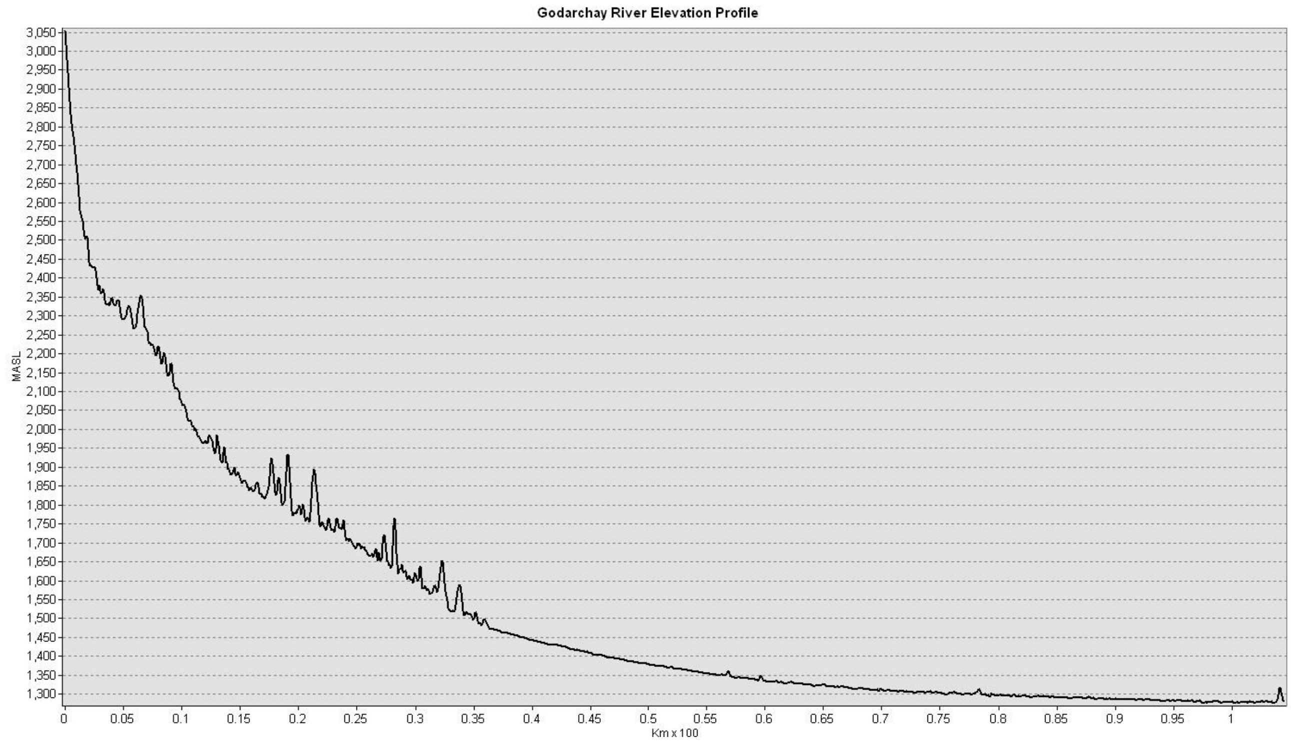

Figure 5: Gadarchay River elevation profile

The basin area of the GR is about 875 km^2, located in the province of West Azerbaijan, Iran. The annual cumulative precipitation in this province is 351.7 mm. The river is 110 km long, and the basin holds more than 14 rural districts and 168 villages with a total population of 119815 (see Table 11) (Rezaali et al., 2019). The high slope in this river compared to Nile River which is about 3000 Km and 600 m elevation difference is justified under the fact that the GR is located in a mountainous region (see Figure 4). The highest elevation in this river is almost the peak of mount Dalamper Bozorg and the lowest one is actually a plateau.

Table 11: Top 17 population centers in the study area

#	City/Village	Population
1	Naghdeh	36315
2	Oshnavieh	15015
3	Mohamadyar	3943
4	Chianeh	2283
5	Biegom Ghale	1670
6	Amir Abad	1478
7	Hasanlou	1398
8	Nalous	1236
9	Farahzad	1077

10	Mirabad	1041
11	Soufian	975
12	Ghalaz	935
13	Hegh	927
14	Sangan	925
15	Nalivan	878
16	Tajodin	873
17	Bimzarte	829
Total		71798

2.2. Input Data and Raster Processing

Input data is an integral part of the study. According to de Brito and Evers (2016), inputs should be chosen in a way that they both spatially and hypothetically correlate with flooding. Based on the literature, many inputs could be used in the study; however, data availability and the effect of unavailable data on flood risk should be analyzed carefully. To this end, all possible input data was extracted from the literature and were subjected to availability and their impact on flood risk. This is an important part of the study since redundant and uncorrelated input data could potentially bias the final results or add noise to it.

Table 12: Input data and the studies that used data

Input Data	Studies That Applied Each Input
DEM	(Akter and Simonovic, 2005, Dankers and Feyen, 2008, de Brito and Evers, 2016, Hirabayashi et al., 2013, Jun et al., 2013, Kangas et al., 2001, Papaioannou et al., 2015, Raaijmakers et al., 2008, Rahmati et al., 2016, Wallenius et al., 2008, Wang et al., 2011, Yahaya et al., 2010)
Slope	(Papaioannou et al., 2015, Rahmati et al., 2016, Wang et al., 2011)
Population	(Scheuer et al., 2013, Wang et al., 2011, Meyer et al., 2009, Jun et al., 2013)
Land use	(Wang et al., 2011, Rahmati et al., 2016, Papaioannou et al., 2015, Meyer et al., 2009)
Distance to river	(Rahmati et al., 2016, Yahaya et al., 2010)

2.3. Study Framework

The definition of risk may vary based on the application of risk assessment. As Maskrey (1989) suggested, FRA is the mathematical summation of hazard and vulnerability (see Equation 1):

Equation 1 $$Flood\ Risk = Hazard + Vulnerability$$

The present study would involve the factors and steps illustrated in Figure 6 (Wang et al., 2011). At the first stage the input data, i.e., DEM, slope, land use, distance to river and population were grouped into two main criteria that are hazard and vulnerability. Constraints are used to avoid the raster calculation in specific places, e.g., the river bed itself. Before any further processing, the proposed inputs were fuzzified using the membership functions which are discussed in the next sub-section. Then, an AHP weight was assigned to each of these inputs based on the review on the literature. It is worthwhile to note that to achieve weights, AHP calculation was done in the software environment which is discussed in section 2.5. Eventually, the output raster map of FR over the whole study area was created.

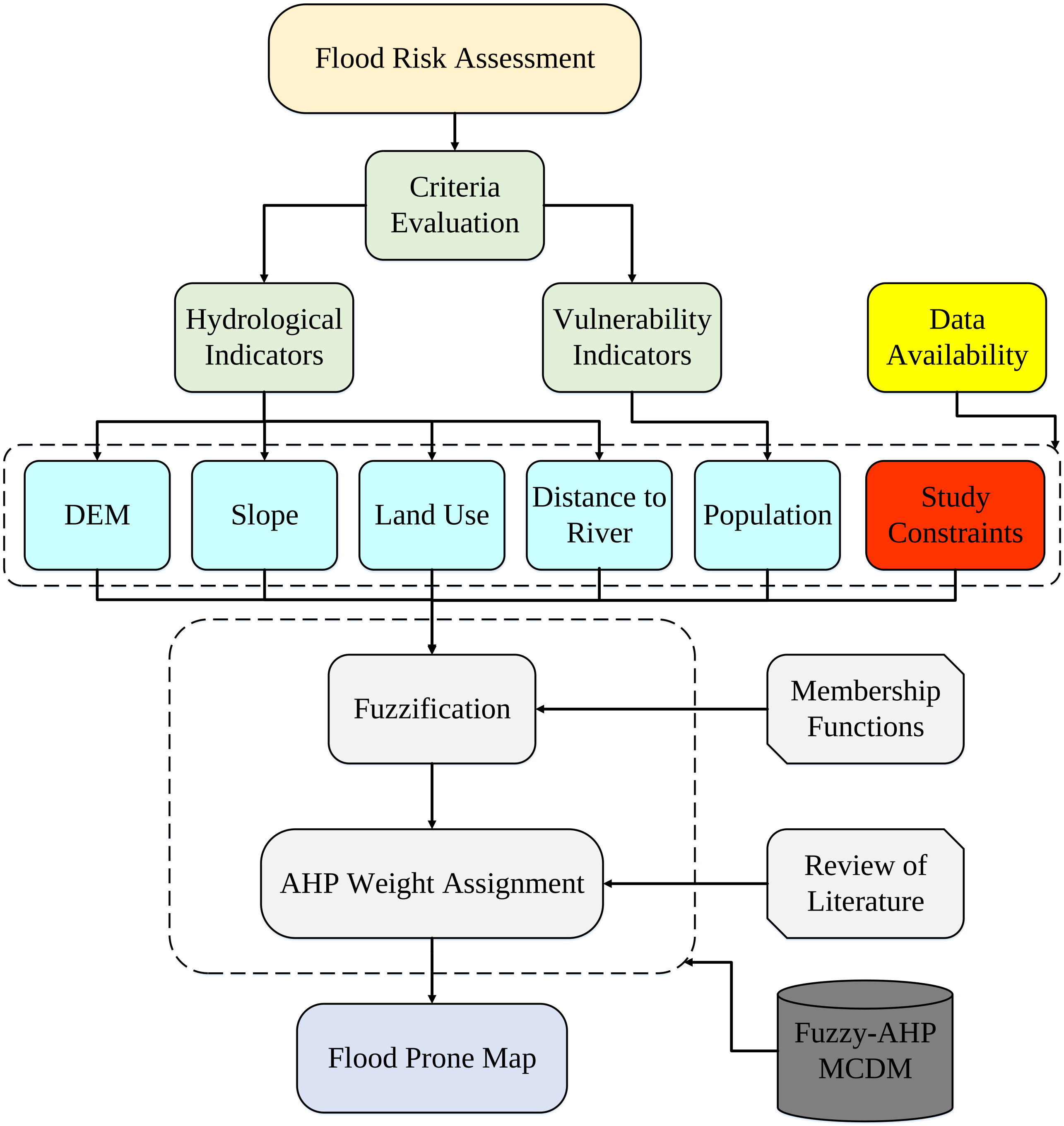

Figure 6: The flowchart of the study

Also, the following steps should be taken to conduct the study:

1. Confirming the aim of the study
2. Confirming the factors affecting flood risk
3. Using the previous research questionnaire to apply AHP weights on each layer
4. Defining fuzzy membership functions based on previous research

5. Fuzzfying each layer based on step 2
6. Applying AHP weights on each fuzzified raster layer
7. Conducting weighted linear combination (WLC)
8. Exporting the output layer

2.4. FAHP

The AHP methodology has been widely used in many studies including ecological assessment (Anselin et al., 1989, Bello-Dambatta et al., 2009, Kovacs et al., 2004), contractor selection (Fong and Choi, 2000, Cheung et al., 2001, Gilleard and Wong Yat-lung, 2004), supplier assessment (Handfield et al., 2002, Chan, 2003, Akarte et al., 2001), landslide susceptibility mapping (Yalcin, 2008, Komac, 2006, Pourghasemi et al., 2012), material selection (Dweiri and Al-Oqla, 2006, Mayyas et al., 2011, Hambali et al., 2010) and most relatively, FRA (Akter and Simonovic, 2005, Bankoff, 2003, Kundzewicz et al., 2010). The main flaw of the AHP method is the inability to address uncertainty and inaccuracy incorporated into decision-makers' using crisp values instead of linguistic scales (Su et al., 2010, Jessop, 2004, Dağdeviren and Yüksel, 2008, Aladejana et al., 2019). To overcome this issue, fuzzy-AHP (FAHP) methodology is used to address the uncertainties associated with uncertainty and translating linguistic variables into fuzzy membership functions (MFs) (Su et al., 2010, Levy, 2005, Tesfamariam and Sadiq, 2006). To do this, the necessary steps to couple fuzzy logic and AHP methodology are listed as follows:

1. Definition of fuzzy triangular MFs:

Triangular MFs were used as translators of linguistic variables into discrete values (see Figure 7).

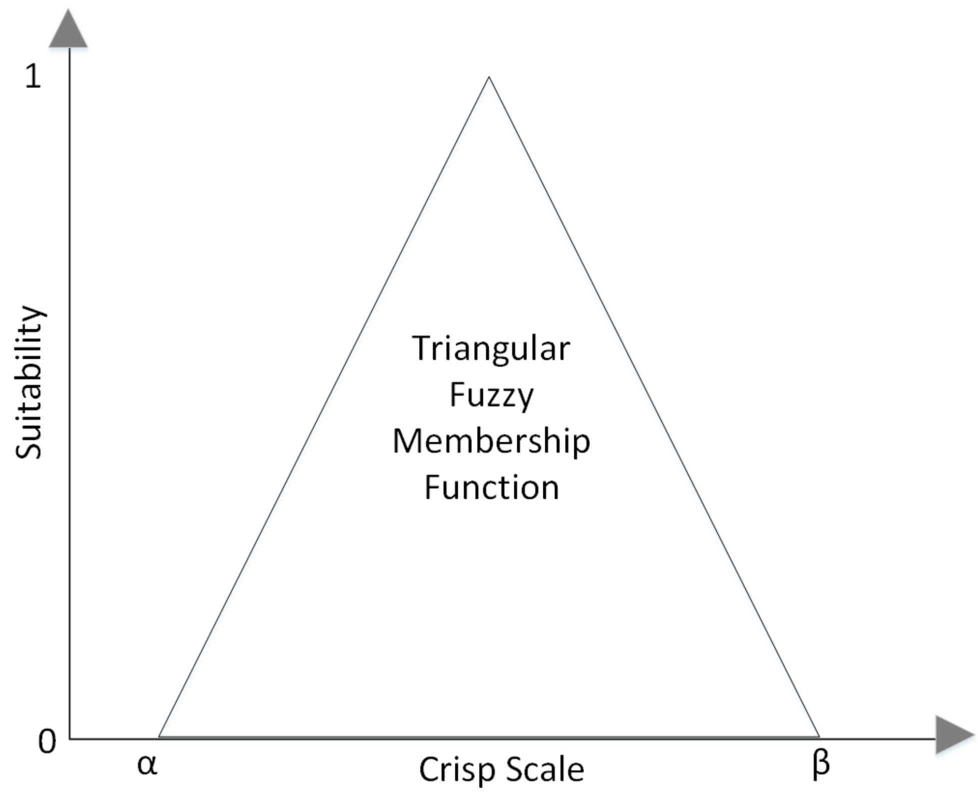

Figure 7: An example of a triangular fuzzy MF

Mathematically, a fuzzy number ($\tilde{\alpha}$) is a triangular MF only if it has the following conditions (see Equation 2):

Equation 2
$$\tilde{\alpha}_{(x)} = \begin{cases} 0 & x < b - \alpha \\ 1 & x = b \\ \dfrac{b + \beta - x}{\beta} & b < x \leq b + \beta \\ 0 & b + \beta < x \end{cases}$$

where parameters α and β are positive real integers called left and right width, respectively (Su et al., 2010).

2. Pairwise comparison matrix construction

After converting discrete numbers into fuzzy integers using MFs, a pairwise comparison matrix ($\tilde{A}$) should be defined to apply hierarchical rules on it (see Equation 3) (Su et al., 2010, Lyu et al., 2018).

Equation 3
$$\tilde{A} = \begin{bmatrix} 1 & \tilde{\alpha}_{12} & \dots & \tilde{\alpha}_{1n} \\ \vdots & \vdots & \dots & \vdots \\ \vdots & \vdots & \dots & \vdots \\ \tilde{\alpha}_{n1} & \tilde{\alpha}_{n2} & \dots & 1 \end{bmatrix}$$

$$\alpha_{ij} = \begin{Bmatrix} 1, & i = i \\ \tilde{1} - \tilde{9} \mid \tilde{1}^{-1} - \tilde{9}^{-1}, & i \neq j \end{Bmatrix}$$

where n is the dimension of the matrix. In this study, $\tilde{1} - \tilde{9}$ used as a triangular fuzzy number to take individual qualitative evaluation into account, which is according to Saaty (2004) nine-point scaling scheme (Su et al., 2010).

This scaling scheme is based on the hypothetical rule that $\tilde{1} - \tilde{9}$ represents from equally ($\tilde{1}$), moderately ($\tilde{3}$), strongly ($\tilde{5}$), very strongly ($\tilde{7}$) and extremely more important ($\tilde{9}$), while keeping $\tilde{2}, \tilde{4}, \tilde{6}$, and $\tilde{8}$ as intermediate values (Su et al., 2010). These values are defined by either distributing a questionnaire among experts in hydrology or by using AHP scores provided in research papers.

3. Upper and lower limits calculation

The process of the calculation of the upper and lower limits of a fuzzy number $\tilde{\alpha}_{ij}$ concerning a threshold number, η is based on Equation 4.

Equation 4
$$\tilde{\alpha}_{ijm}^{\eta} = \begin{Bmatrix} \tilde{\alpha}_{ij} & \tilde{\alpha}_{ij} = \tilde{1} \\ (\tilde{\alpha}_{ij} - \lambda) + \lambda\alpha & \tilde{\alpha}_{ij} = \tilde{2} - \tilde{9} \end{Bmatrix}$$
$$\tilde{\alpha}_{ijn}^{\eta} = \begin{Bmatrix} \tilde{\alpha}_{ij} & \tilde{\alpha}_{ij} = \tilde{1} \\ (\tilde{\alpha}_{ij} - \lambda) + \lambda\alpha & \tilde{\alpha}_{ij} = \tilde{1} - \tilde{8} \end{Bmatrix}$$

where λ is the maximum range of the input variable. Based on this equation, the upper and lower limits of the fuzzy numbers will be calculated. This equation will translate the input values from the previous step to a fuzzy number between 0 and 1.

4. Fuzzy number estimation

Optimism index (δ) is a parameter that represents the most likely value of the fuzzy number. Considering this parameter in Equation 4 yields Equation 5 (Su et al., 2010):

Equation 5
$$\tilde{\alpha}_{ij}^{\eta} = \lambda\tilde{\alpha}_{ijn}^{\eta} + (1 - \delta)\, \tilde{\alpha}_{ijm}^{\eta}, \qquad \forall\delta \in [0,1]$$

subsequently, based on Equation 5, a matrix can be derived that is as follows:

Equation 6
$$\tilde{A}^{\eta} = \begin{bmatrix} 1 & \widetilde{\alpha^{\eta}}_{12} & \dots & \widetilde{\alpha^{\eta}}_{1n} \\ \vdots & \vdots & \dots & \vdots \\ \vdots & \vdots & \dots & \vdots \\ \widetilde{\alpha^{\eta}}_{n1} & \widetilde{\alpha^{\eta}}_{n2} & \dots & 1 \end{bmatrix}$$

It is important to assess how consistent were the decision-makers or evaluators in the scoring process (Su et al., 2010). In this vein, CI is defined as consistency index to measure the decision-makers validity and fairness (see Equation 7).

Equation 7
$$CI = \frac{(\mu_{max} - n)}{(n-1)}$$

where μ_{max} is the biggest eigenvalue of the matrix $\tilde{A}^{\eta}$ and n is the dimension of the matrix (Su et al., 2010). To accurately denote the consistency of the decision-makers, consistency ratio (θ) is defined (see Equation 8).

Equation 8
$$\theta = \frac{CI}{RI}$$

where RI is a random index, it is noteworthy to state that θ should not exceed 10% otherwise the scoring process needs to be revised. The θ is an indicator of how consistent the AHP scoring process was. For example, the AHP scorer may not equally compare the AHP scores of hydrologic variables such as topology and distance to river.

Weight assignment to each hierarchy of the AHP process follows (see Equation 9):

Equation 9
$$W_i^k = \left(\prod_j^n M_{ij}^k\right)^{\frac{1}{3}} \otimes \left[\sum_{i=1}^n \left(\prod_j^n M_{ij}^k\right)^{\frac{1}{3}}\right]^{-1}$$

where $\prod_j^n M_{ij}^k$ is calculated by applying fuzzy multiplication to a particular matrix at a certain level by Equation 10 and Equation 11, which represents a summarized form of fuzzy multiplication (Su et al., 2010).

Equation 10
$$\prod_j^n M_{ij}^k = \left(\prod_j^n \tilde{\alpha}_{ijm}^{\eta} \qquad \prod_j^n \tilde{\alpha}_{ij}^{\eta} \qquad \prod_j^n \tilde{\alpha}_{ijn}^{\eta}\right)$$

Equation 11
$$\left(\tilde{A} \otimes \tilde{B}\right)_{(z)} = \underbrace{sup}_{x.y=z} T\left(\tilde{A}_{(X)}, \tilde{B}_{(Y)}\right)$$

Finally, fuzzy addition operation is calculated considering AHP weights using Equation 12 (Su et al., 2010):

Equation 12
$$W_i^k = \left[\left(\frac{\left(\prod_j^n \tilde{\alpha}_{ijm}^{\eta}\right)^{\frac{1}{3}}}{\sum_{i=1}^n \left(\prod_j^n \tilde{\alpha}_{ijm}^{\eta}\right)^{\frac{1}{3}}}\right) \qquad \left(\frac{\left(\prod_j^n \tilde{\alpha}_{ij}^{\eta}\right)^{\frac{1}{3}}}{\sum_{i=1}^n \left(\prod_j^n \tilde{\alpha}_{ij}^{\eta}\right)^{\frac{1}{3}}}\right) \qquad \left(\frac{\left(\prod_j^n \tilde{\alpha}_{ijn}^{\eta}\right)^{\frac{1}{3}}}{\sum_{i=1}^n \left(\prod_j^n \tilde{\alpha}_{ijn}^{\eta}\right)^{\frac{1}{3}}}\right)\right]$$

The output of this equation, i.e., W_i^k was calculated for each cell along the whole basin. Based on fuzzy addition operation and AHP weight assignment, the value of each cell cannot exceed 0 and 1 (see Equation 2).

2.5. Raster Processing

Each input vector layer, i.e., land use, river, etc., which was converted to the raster layer (for the raster calculation process discussed in section 2.2) needed to be classified into discrete numbers. To this end each of different land-use types such as urban, prairie, gardens, agriculture, dry farming, etc., was scored one to five based on evaluating previous literature (Rahmati et al., 2016, Su et al., 2010) and interpreting hydrologic features of each land-use type. Table 13 represent how each land use was converted to the raster map and how a score was assigned to each land use category.

Table 13: Scoring land use for raster processing

#	Land use	Quantitative score
1	Dry prairie	1
2	Garden	2
3	Mesic prairie	
4	Wetland	
5	Wet prairie	3
6	Urban	
7	Mix Wet prairie and bare land	4
8	Barren lands	5

The rest of the vector inputs, including population, constraint, and distance to the river, were rasterized without quantitative labeling. Raster layers such as slope and elevation were already of raster type.

After the fuzzification process mentioned in the previous sub-section, pixel computation or raster processing needs to be carried out to apply each layer weight on each fuzzified raster dataset. This process is called WLC which is mathematically described in Equation 13:

Equation 13
$$\mu_i = \sum_{j=1}^{r} V_i W_i$$

where W_i represents fuzzified inputs which range from zero to one, and V_i represents performance score (Wang et al., 2011).

Weight assignment was done by filling the pairwise comparison matrix based on previous research and with the goal to get the best consistency ratio (see Table 14). The procedure for filling an AHP pairwise comparison matrix comprises two main steps:

1. Scoring each alternative by itself which always is equal to one, e.g., population to population have the same score since it is compared to itself.

2. Scoring each alternative compared to another alternative. The more important the more score. For example, in this case, population to land use had higher importance, hence it was scored five. The opposite case of this can also be true, e.g., elevation is less important than distance to river, therefore it was scored 1/3.

Table 14: The pairwise comparison matrix of the study

	Land use	**Population**	**Distance to river**	**Elevation**	**Slope**
Land use	1				
Population	5	1			
Distance to river	3	1/2	1		
Elevation	2	1/3	1/2	1	
Slope	3	1/4	1/3	1/2	1

And the calculated eigenvector of weights for each layer is shown in Table 15 achieved by Equation 9. In addition the consistency ratio was calculated by Equation 7.

Table 15: The calculated eigenvector of the pairwise comparison matrix

Layer	**Eigenvector of weight**
Land use	0.067
Population	0.418
Distance to river	0.252
Elevation	0.150
Slope	0.112

Consistency Ratio (θ)	0.04

Since the consistency ratio is less than 10% or 0.1, the quantitative scoring is consistent enough for the next step, i.e., the fuzzification process.

2.6. Software Specification

ArcGIS™ and TerrSet™ are widely used in many studies for a wide range of applications such as remote sensing (Ganapuram et al., 2009, Kneissl et al., 2010, Kneissl et al., 2011), environmental applications (Zhan and Huang, 2004, Kneissl et al., 2011, Tuppad et al., 2009), air pollution (Mojarrad et al., 2019, Rezaali et al., 2019), and economics (Mellander et al., 2015, Paturska et al., 2015).

In this study, ArcGIS™ was used for introductory analysis and data preparation and TerrSet™ was used to create the FAHP model.

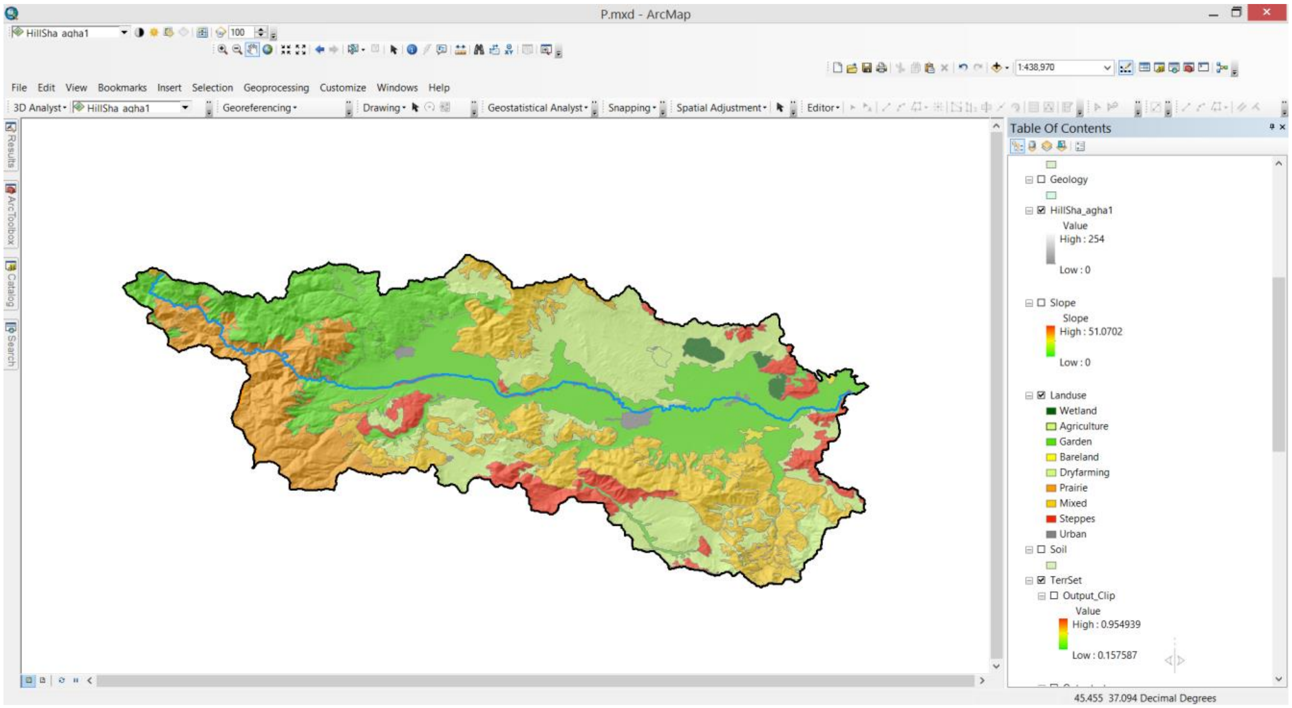

Figure 8: ArcGIS™ environment

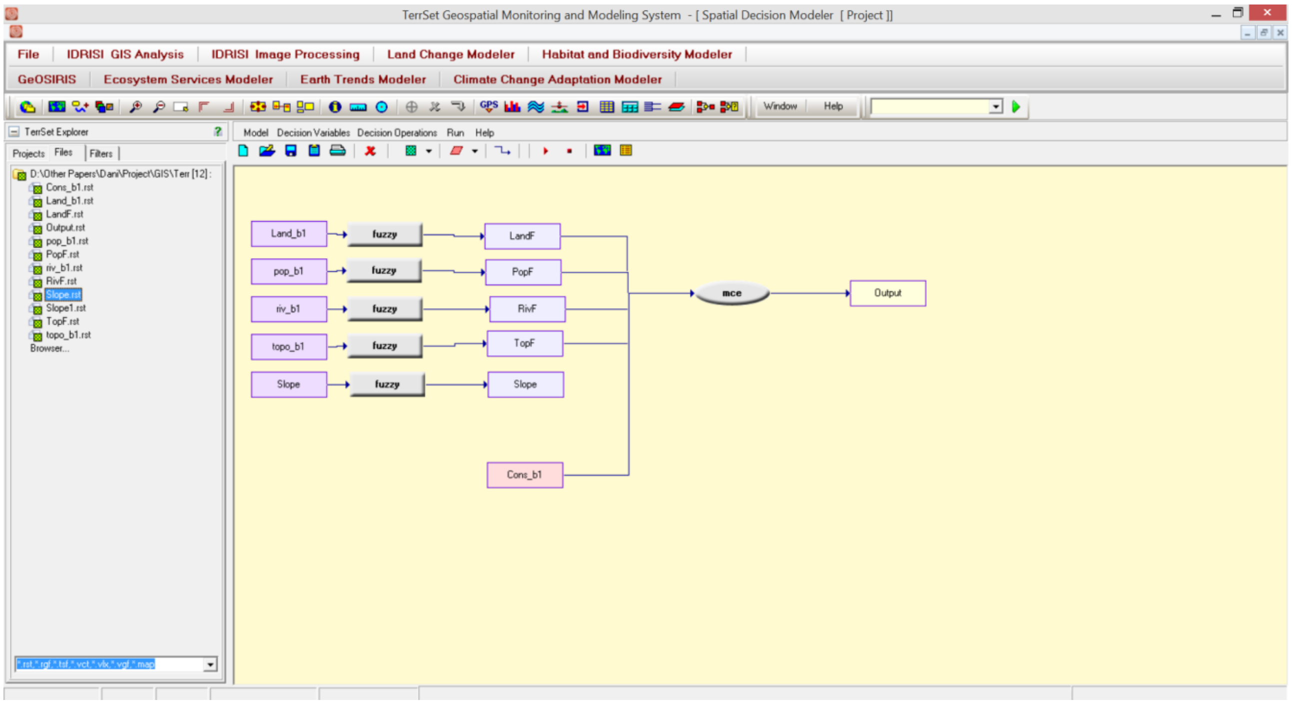

Figure 9: TerrSet™ environment and the FAHP model

3. Results and Discussion

3.1. Rasterized Input Data

Some input data such as distance to the river, land-use, and population were vector dataset in nature; hence, they had to be converted to raster dataset so that calculation can be performed on each pixel or cell. In this vein, input parameters including distance to river and land use as shown in Figure 10 and population density, slope, and elevation as shown in Figure 11 were used as input datasets for FAHP model.

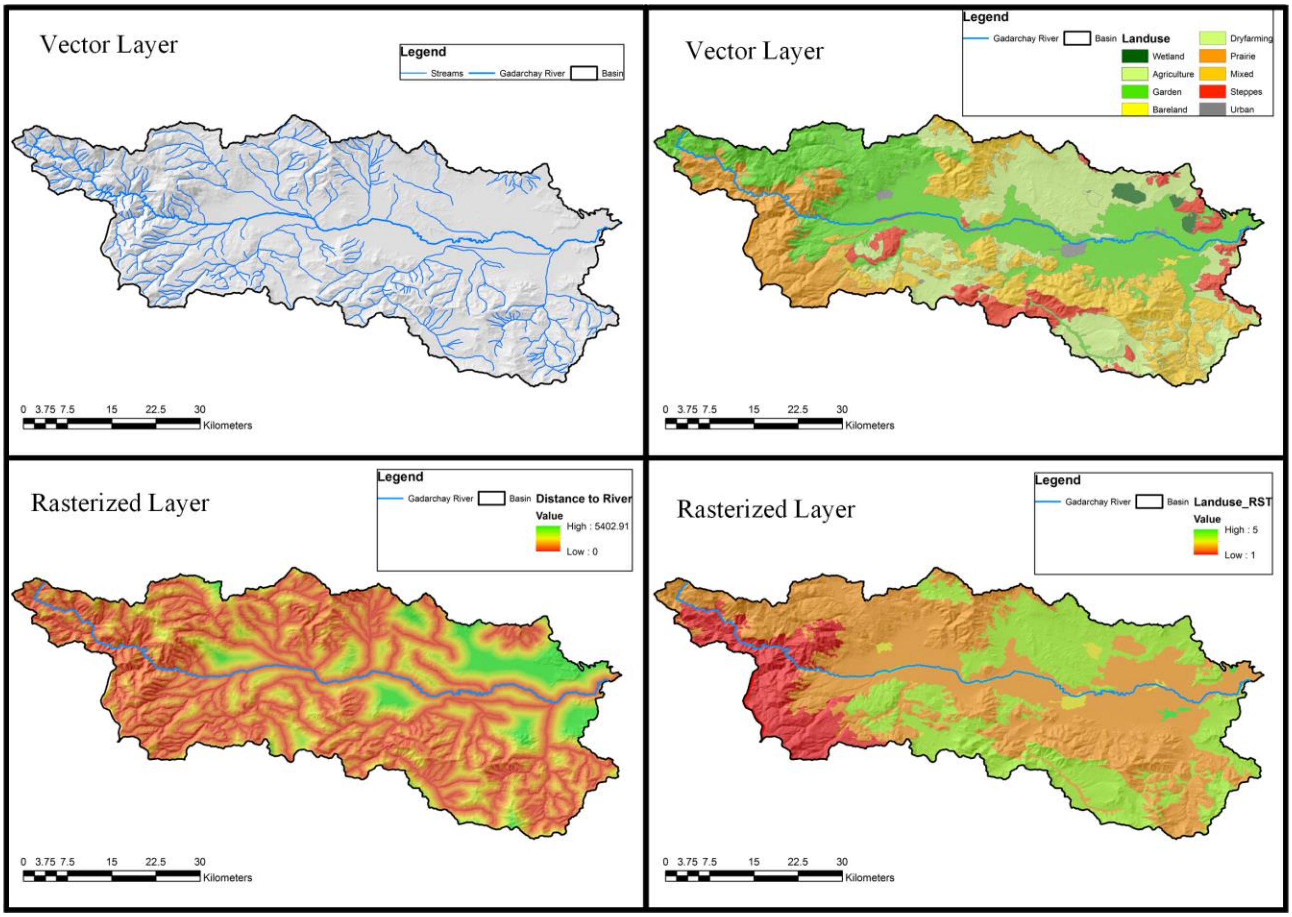

Figure 10: Distance to the river (left) and land use (right) in both rasterized and vector formats used as input data for the FAHP model

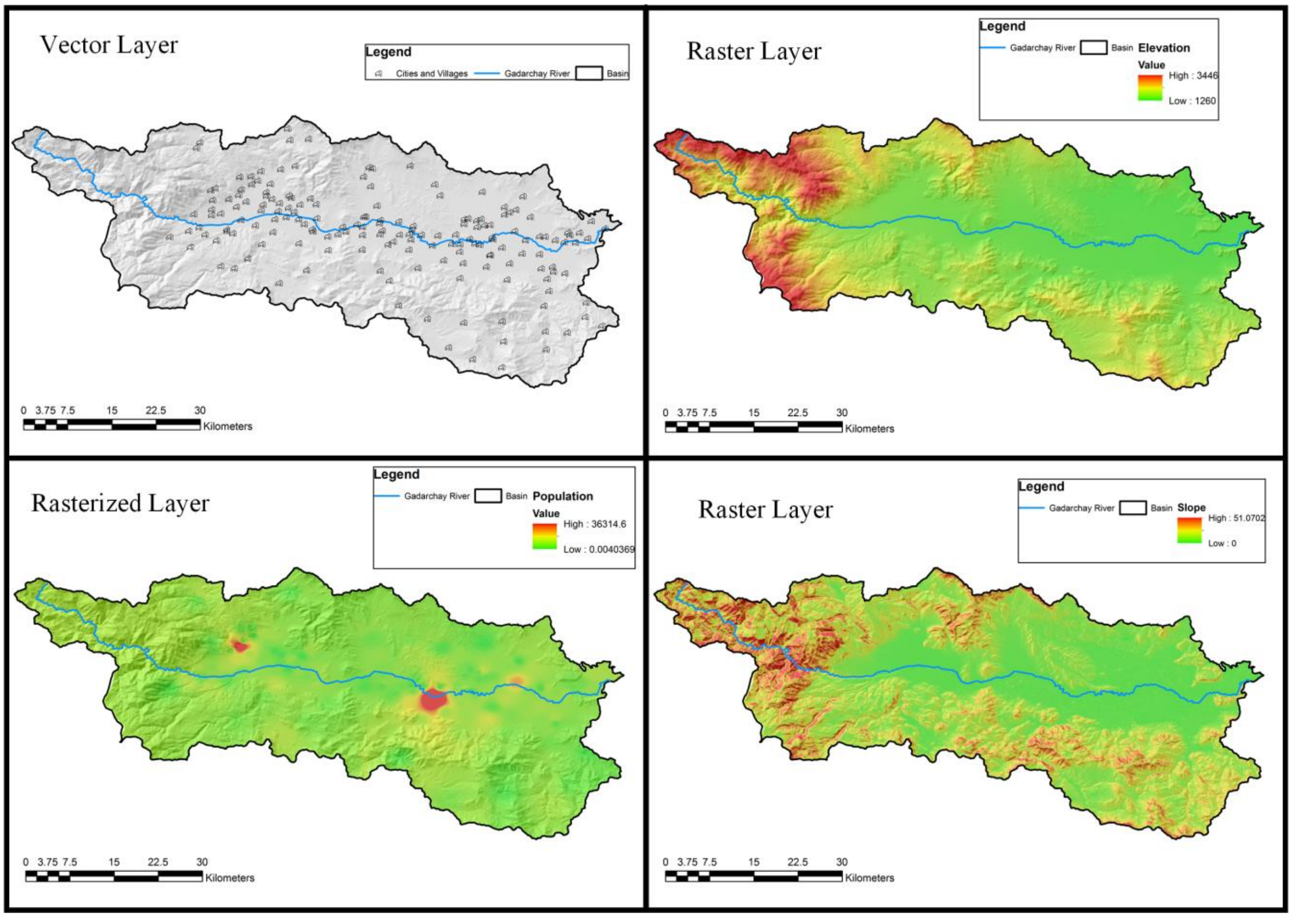

Figure 11: Population (left), slope (bottom right) and elevation (top right) used as input data for the FAHP model

Besides, some specific locations along the basin could not be evaluated in the FAHP model that is the river and its watershed itself. To avoid any possible miscalculation, a constraint raster layer was created (see Figure 12).

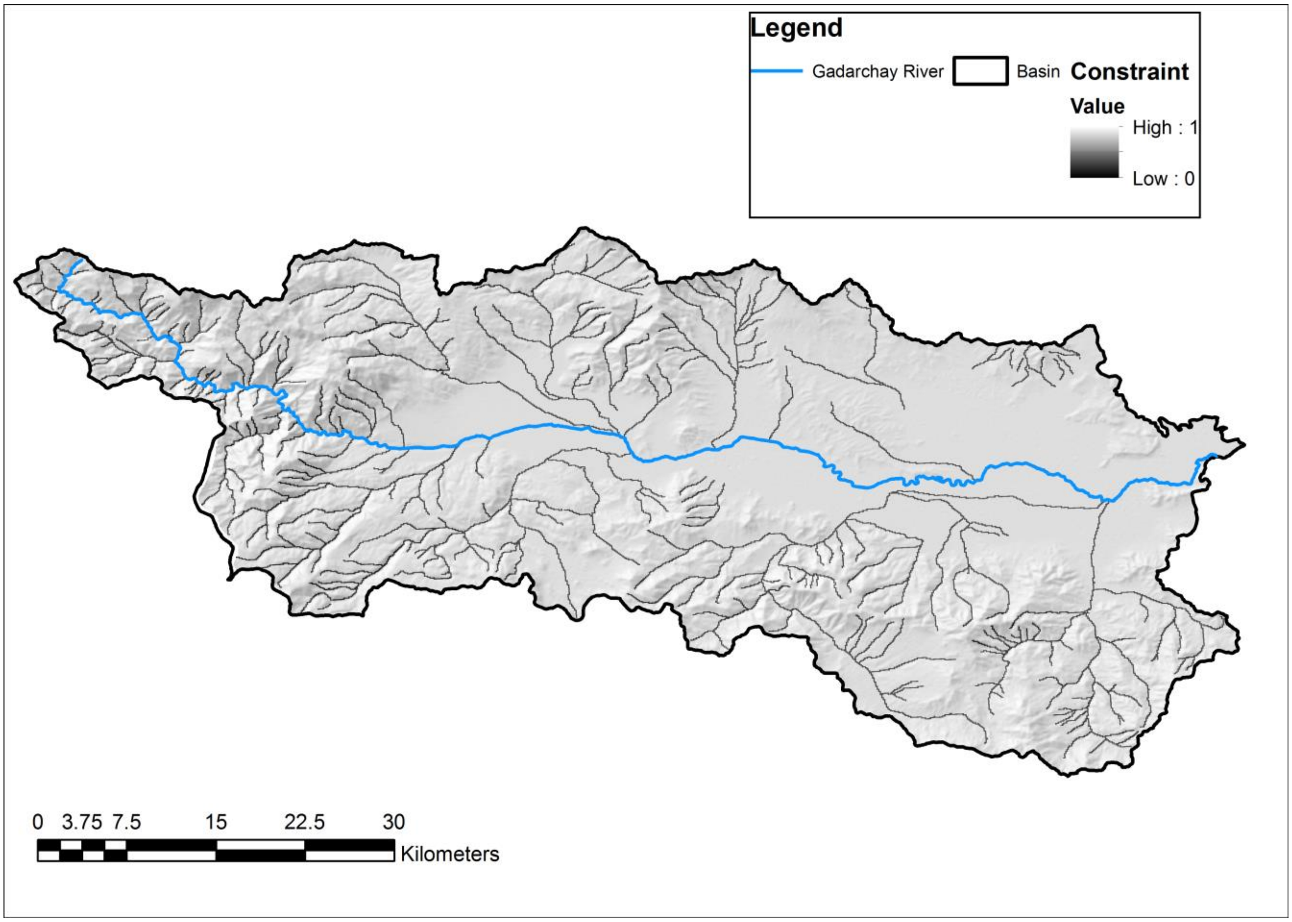

Figure 12: Constraints rasterized map

3.2. Flood Hazard Map

As shown in Figure 13, some specific areas are evaluated to be in serious danger. Referring to Table 11, these areas are mainly population centers that were repeatedly flooded during recent years. Other reasons for high flood hazards in these regions could be the nearness to the river, locating in the downstream of the river, and poor drainage network in these cities. For example, the city of Naghdeh, with a population of 36315 people has been flooded several times during the last year (iribnews, 2018). Also, other cities like Oshnavieh with a population of 15015 people have high flood risk, despite being located in the upstream of the river. The reason for high flood risk in this city could be due to being located in mountainous region, which can be flash flooded with no absorption; in summary, land use and slope and high population, which indicates high vulnerability.

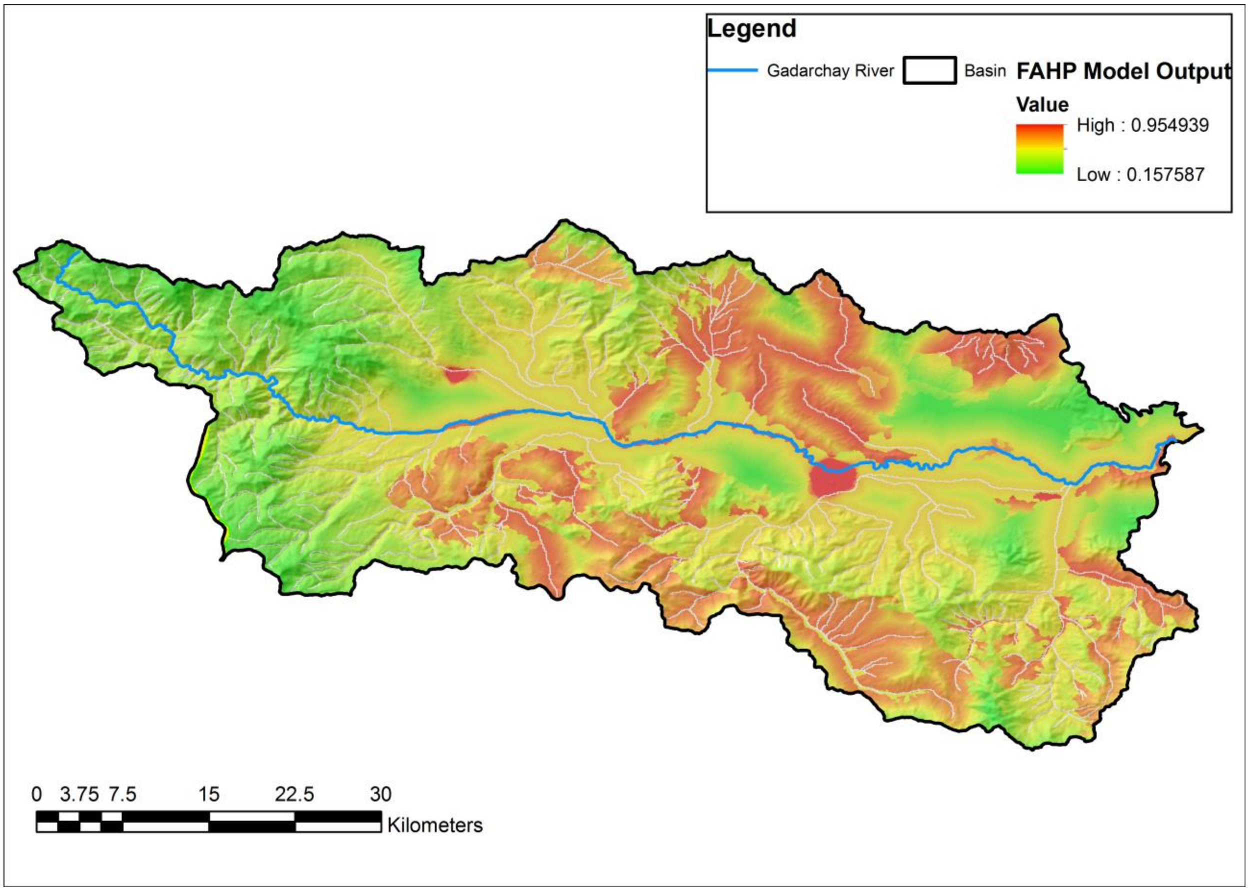

Figure 13: The final FAHP model output

It is suggested that precautionary measures should be carried out, such as building hydraulic structures, repairing drainage networks, making flood alarm systems and running flood awareness programs for residents. Table 16 represents top 20 cities/villages with highest flood risk. This table is obtained by intersecting each village/city to the final rasterized map Figure 13.

Table 16: Top 20 population centers with the highest flood risk

#	Village/City Name	Flood Risk Index
1	Salkeh	49.1%
2	Gouleh	50.0%
3	Adeh	50.1%
4	Erna	50.3%
5	Delme	50.1%
6	Bayzava	49.9%
7	Tazekendim	50.2%
8	Halabi	50.0%

9	Aliabad	42.8%
10	Kamous	50.2%
11	Kahriz	50.3%
12	Guik	49.7%
13	Lavashlou	49.6%
14	Yadegarlou	49.8%
15	Poushabad	50.1%
16	Chaparabad	49.7%
17	Dehgorji	50.1%
18	Kani Badagh	49.0%
19	Oshnavieh	64.3%
20	Naghdeh	95.5%
Average		52.5%
Std.		10.2%

4. Conclusion

The study introduced the application of FAHP for FRA in the GR basin for the first time. Five input parameters were considered into account as possible flood correlators, i.e., slope, population, distance to the river, elevation and land use. Unlike AHP methodology, the FAHP model could overcome the flaws, e.g., imprecision and the lack of qualitative scoring, associated with AHP. The results indicated that FAHP can be used as a valid tool for FRA. Also, FAHP was found to be an efficient tool when there is a lack of precise hydrological data, unlike numeric models.

According to the results, the city of Naghdeh and Oshnavieh with 36315 and 15015 population, respectively, were two of the most flood susceptible cities in this study area with the flood risk of 95% and 64%, respectively. Further analysis proved that these cities has been flooded several times during the last year. The study suggests improvement of the cities' infrastructures such as building hydraulic structures to control possible floods, increasing social awareness of flood and using precautionary measures.

It is important to state that for the basin that holds 119815 people with a long history of floods, the study can be a helpful source for decision-makers and stakeholders to screen the most flood-prone cities among 168 villages and 14 rural districts.

5. Research Limitations and Recommendation for Future Research

The current research was based on limited access to dataset which is usual for remote areas that construction and urban development is restricted due to topology, location, weather, etc. Hence, the main limitation for this study was the lack of perfect access to data.

For future research, it is suggested that the results being validated using a numerical model or a coupled version of a hydrological model with fuzzy logic and AHP methodology. Researchers may want to validate their results with onsite studies and the history of flood in this basin. It is recommend that, when access to further data is possible, researchers incorporate more input data in the model to see the efficiency and the final results of the model. An uncertainty analysis and a sensitivity analysis can potentially provide valuable information about the validity of the future model.

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