FLOOD SUSCEPTIBILITY MODELLING USING GEOSPATIAL-BASED MULTI-CRITERIA DECISION MAKING IN LARGE SCALE AREAS

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ABSTRACT:

Flood is one of the most hazardous natural disasters that cause damages and poses a major threat to human lives and infrastructures worldwide, and its prevention is almost unfeasible. Thus, the detection of flood susceptible areas can be a key to lessen the amount of destruction and mortality. This study aims to implement a framework to identify flood potential zones in an ungauged large-scale area with frequent flood events in recent years. We used two Multi-Criteria Decision Making (MCDM) approaches combined with geospatial analysis, and remote sensing observations for this susceptibility analysis. Nine geomorphological and environmental factors that have an impact on flood behaviour were selected and used for susceptibility modelling. At first, the criteria's weights were estimated using two MCDM approaches and based on experts' knowledge. The resultant weights revealed that Flow Accumulation, Topographic wetness index, and Distance to River were the most influential flood susceptibility criteria. After calculating these weights, the criteria's layers were aggregated through geospatial analysis, which resulted in generating flood susceptibility map. The area under the curve (AUC) and statistical measures such as the Kappa index were used to evaluate the proposed method's efficiency. The validation results illustrate that hybrid FAHP, with AUC= 96.68 and Kappa = 81.36 performed more efficiently than standard AHP, with AUC= 94.53 and Kappa=76.35. Overlaying these maps with the historical flood inventory dataset revealed that 86.43% of flooded areas were categorized as "high" and "very high". Therefore, the flood susceptibility maps generated through the proposed approach can help the decision-makers and managers allocate the mitigation equipment and facility in data-scarce and ungauged large-scale areas.

1. INTRODUCTION

Flood is one of the frequent natural hazards which threatens community stability and economic development human and wild lives worldwide and results in substantial economic, environmental, agricultural damages (Feizizadeh et al., 2021; Naseri & Hummel, 2022). Financial losses caused by floods are estimated to be 40% of the total economic damages related to natural hazards annually (Cabrera and Lee, 2020; Kanani-Sadat et al., 2019). Due to aggregative reasons such as climate change, population growth, deforestation, and human intervention like inappropriate land-use changes, the number of floods has risen in the past few decades (Arabameri et al., 2019). Climate change has been stated in many studies as the primary concern that has led to more frequent floods and more severe ones (Khosravi et al., 2016). Several developing countries, including Iran, are more harmfully affected by these geohazards than developed countries (Dodangeh et al., 2020). For example, during recent flood events in July 2022, 93 people were killed, many people were lost and communication routes were cut off in Iran (IRAN Front Page, 2022). Besides, floods subsequently can cause other disasters, such as landslides, erosion, ground cavity, etc. (Arabameri et al., 2019). Although floods are unfeasible to be prevented, flood-prone areas can be identified and predicted (Ali et al., 2020; Kanani-Sadat et al., 2019). As (Dodangeh et al., 2020) stated, a lack of proper knowledge of susceptible areas and a shortage of equipment to mitigate this phenomenon are the main reasons for the majority of harm. Therefore, one of the useful tools that can be used for spatial planning and developing the cities is flood susceptibility maps (FSMs), which aim to provide information about flood-prone areas to establish an early warning system, emergency plan, and execution of flood management strategies (El-Haddad et al., 2020). Therefore, investigating the ungauged areas to identify flood-potential areas is inevitable, and current research aims to fill this gap.

Many type of criteria affect the flood events procedure and severity, including geological, vegetation, topographical, morphometric, and hydro-meteorological factors, and they must be considered in analyzing flood susceptibility mapping. These criteria can be collected using RS technology and analyze in a GIS environment which can deal with a large amount of data (Kanani-Sadat et al., 2019). Since there are many criteria involve in the flood assessment analysis, we can use a Multi-Criteria Decision Making method to model flood susceptibility (Rahmati et al., 2016). Analytical Hierarchy Process (AHP) is one of the most widely applied MCDM methods, and it is the most preferred technique in natural hazards assessment and flood modeling studies (Mallick et al., 2018). da Silva et al. (2020) produced a map to detect flood susceptible areas with the joint application of geoprocessing techniques and multi-criteria analysis AHP. The authors of the study asserted that this mapping includes information about the area's critical points, making it possible to reduce uncertainties related to public interest policies such as housing plans. Despite the popularity of the AHP method, the major limitation of the AHP method is the possibility of bias or inconsistency in decision-makers' judgments, which can be a source of uncertainty due to using crisp numbers to express their

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opinions (Chen et al., 2011; Feizizadeh et al., 2014). Integration of AHP and fuzzy logic can be used to address this issue. Therefore, a solution to deal with the possible uncertainty is adoption of fuzzy membership functions instead of crisp numbers in experts' judgment (Feizizadeh et al., 2014). In fact, Fuzzy Analytical Hierarchy Process (FAHP) is able to reflect human opinion more naturally since it uses approximate information and qualitative linguistic language to generate decisions in complex problems which expressing thought in crisp number is not appropriate (Kahraman et al., 2004). Therefore, in this study, we aim to investigate an ungauged large-scale area to estimate its level of susceptibility to flood events by applying these two methods and compare the obtained result.

The following steps are describing the process of this research briefly: 1) a geospatial database of conditioning criteria is prepared using RS and GIS technologies. 2) the weight of each criterion is calculated using AHP and FAHP approaches. 3) The Weight Linear Combination (WLC) approach was then used to create final flood susceptibility maps (FSMs). Finally, historical flood points are used to evaluate the performance of the flood susceptibility maps' performance and validity using the area under the receiver operating characteristic curve (AUROC) and several statistical metrics.

2. STUDY AREA

This research aims to estimate flood susceptibility maps in a large-scale area using AHP and Fuzzy-AHP methods combined with GIS and RS technologies. Two basins were investigated in Iran's south-eastern part (Figure1). This region which lies between 25° and 31°40′ latitudes and 56° and 63°20′ longitudes, includes the Hamoon Jazmurian and Sistan Jonoobi basins with area of 69390 $km^2$and 48551 km^2, respectively. The average long-term precipitation in Hamoon Jazmurian and Sistan Jonoobi is 145mm and 113mm, respectively.

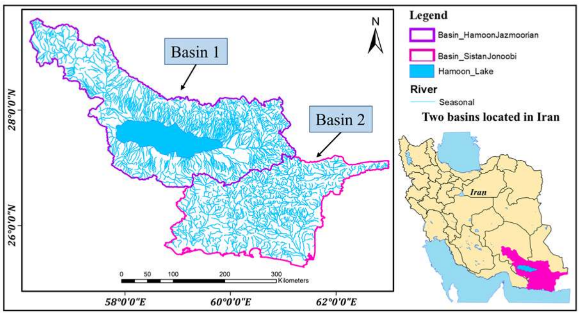

Figure 1. Study Area

3. SUSCEPTIBILITY ANALYSIS METHODOLOGY

In this paper, to establish flood-prone regions in a large-scale area, including two basins in the south-eastern part of Iran, two MCDM approaches combined with GIS technology are implemented and assessed. Represented in Figure 2 is the process of the proposed model. It can be summarized as following steps: I) preparation and normalization of selected data according to literature review and data accessibility, II) analysis of the experts' consultation and calculation of the weight of criteria using AHP and FAHP methods, III) integration of criteria based on obtained weights in the GIS environment, IV) Finally, assessment of the methods and analyse the results of the study using flood inventory points.

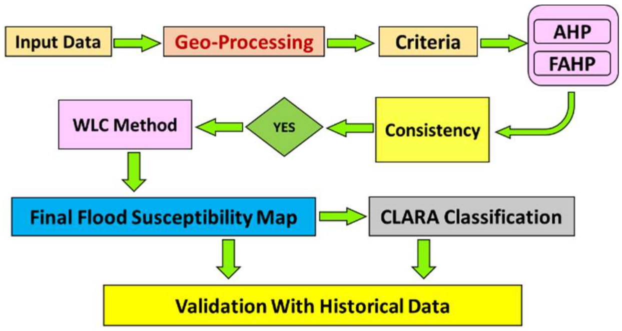

Figure 2. The proposed framework

3.1 Data Preparation

Based on literature review and available data, we ended up with nine flood conditioning factors, namely: Slope, Digital Elevation Model (DEM), Normalized Difference Vegetation Index (NDVI), Curve number (CN), Distance to River (DR), Topographic Wetness Index (TWI), Topographic Position Index (TPI), Flow Accumulation (FA) and Modified Fournier Index (MFI). Mentioned criteria were created and aggregated in a GIS environment to generate raster maps with a 30 × 30 m pixel size spatial resolution. In order to eliminate inhomogeneity, all layers normalized using Eq. (1) and Eq. (2). If the higher value of a criterion is associated with higher flood susceptibility, its layer would be normalized by Eq. (1); otherwise, Eq. (2) would be used (Kanani-Sadat et al., 2019).

$$Y = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

$$Y = \frac{X_{max} - X}{X_{max} - X_{min}} \quad (2)$$

Where X = un-normalized layers,
Y = normalized layers,
$Xmin$ = the lowest value of each layer
$Xmax$ = the highest value of each layer

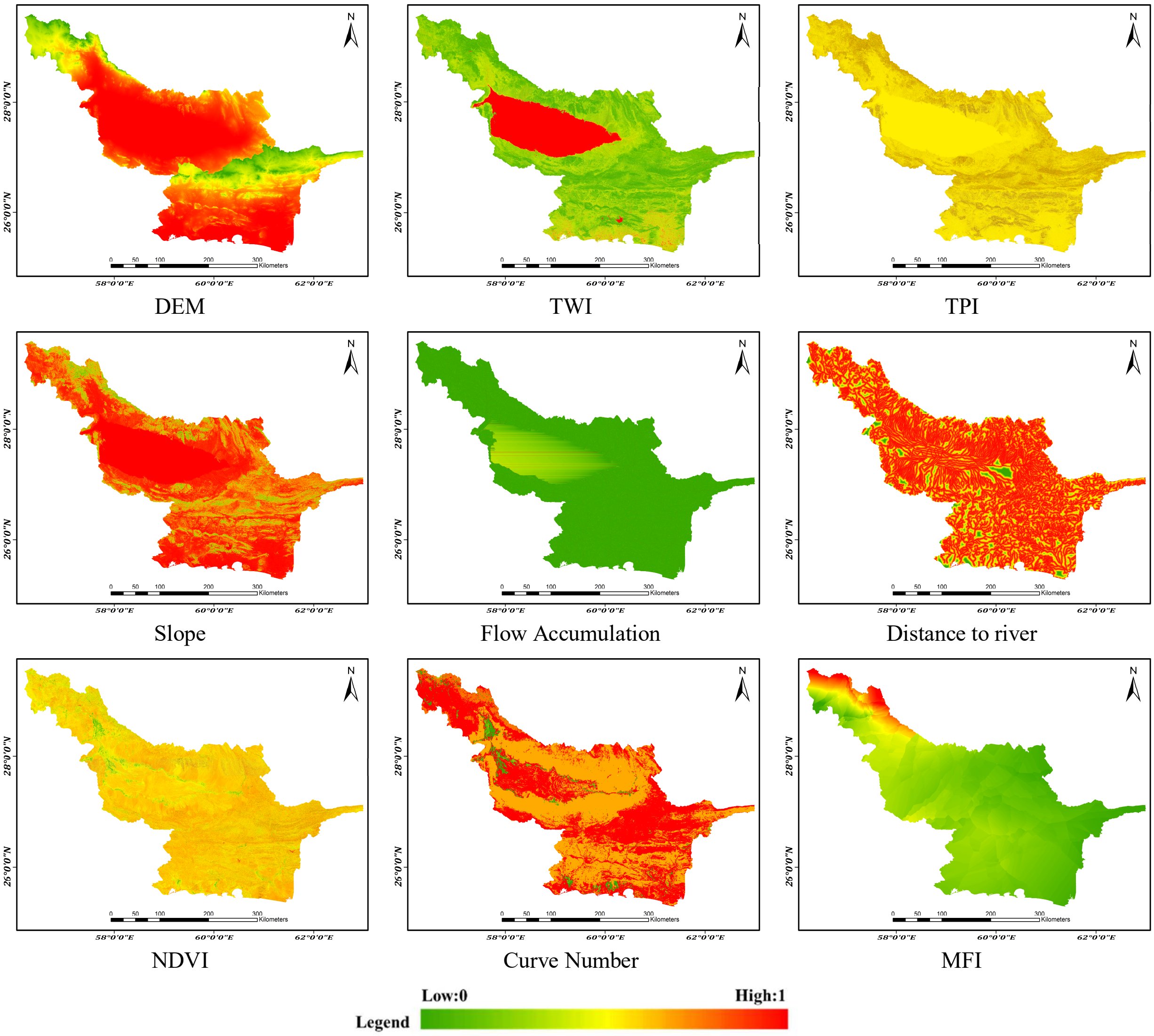

Figure 3. The normalized criteria's raster maps

3.2 Description of flood-influencing factors

Digital Elevation Model: Topographic features (Slope, DEM, TWI) are vastly used as the main influencing parameters in flood susceptibility modelling since floods are positively correlated with the topography and affect the hydrological process (Bui et al., 2020). The TWI indicates the quantity of water that can be aggregated in a pixel size of a watershed area or basin (Talukdar et al., 2020). TWI and flood have a direct relationship. TPI was calculated to identify upper, middle, and lower parts of the landscape. Slope affects water runoff and velocity. Areas with lower slopes are more prone to flood. NDVI determines the degree of dense vegetation coverage of the area (Bui et al., 2020). Areas with dense vegetation are not likely to be susceptible to flood. FA determines the total flow received from upstream areas to a specific point within the catchment. Curve Number which is used in hydrology determines the proportion of rainfall penetration into the soil or underground area. A high CN means more runoff water and less water penetration. Areas close to rivers have a higher chance of inundation. MFI is an index that determines the rainfall intensity. Flood severity can be affected by the level of rainfall (Kanani-Sadat et al., 2019).

3.3 Analytical Hierarchy Process

AHP method developed by Saaty (1996) was implemented in this study to define the weights. This hierarchy framework relies on the experts' knowledge and assigns the weights based on the relative importance of other reciprocal factors (Abdelkarim et al., 2020). Due to its simplicity in implementation and apprehension, it has been adopted widely and proven to be efficient in regional scales, and it is used to solve complex decision problems (Cabrera and Lee, 2020). The process of this method is described in the following steps: 1) Creation of pair-wise matrix, 2) Normalization of the pair-wise matrix, 3) Calculation of the weights, 4) Calculate consistency index.

3.4 Fuzzy Analytical Hierarchy Process

AHP method assumes the decision makers' opinions as it is precise and use crisp number leading to the inclusion of the ambiguity that came from linguistic variable and it is counted as a weakness. Because in the real world human options are prone to a degree of ambivalence, AHP is often criticized for its disqualification to incorporate the latent fuzziness and inaccuracy associated with mapping the decision-makers perceptions to exact numbers (Bouamrane et al., 2020;

Pourahmad et al., 2015; Vahidnia et al., 2009). The fuzzy logic can be applied to prioritizing criteria instead of utilizing crisp numbers to solve this problem. In fuzzy set theory, experts can assert their opinion using a range of values between 0 and 1 (Vahidnia et al., 2009). The value 0 determines the non-membership function, and 1 is an agent for the total membership function (Wang et al., 2020). The concept of fuzzy logic was developed by Zadeh (1996). Implementation of fuzzy sets reduces the level of uncertainty in experts' preferences in determining weights by considering the vagueness of personal judgements (Bouamrane et al., 2020). Chang's Fuzzy AHP method based on the triangular fuzzy number (TFN) is one of the several different FAHP methods proposed in the last decades (Chang, 1996). In FAHP, the pair-wise matrix is established based on the triangular fuzzy number (TFN) values in Table 1.

Linguistic scale for importance	AHP	Fuzzy AHP (TFN)	reciprocal (TFN)
Equally important	1	(1,1,1)	(1,1,1)
Moderately important	3	(2,3,4)	(1/2,1/3,1/4)
Important	5	(4,5,6)	(1/4,1/5,1/6)
Very important	7	(6,7,8)	(1/6,1/7,1/8)
Absolutely important	9	(9,9,9)	(1/9,1/9,1/9)
Intermediate	2,4,6,8	(1,2,3) (3,4,5) (5,6,7) (7,8,9)	(1,1/2,1/3) (1/3,1/4,1/5) (1/5,1/6,1/7) (1/7,1/8,1/9)

Table 1. Triangular fuzzy number of linguistic variables1

3.5 Weighted Linear Combination (WLC) and Classification

Once the weight of each factor is determined, according to Eq. (3), criteria aggregated based on their weights to generate the flood susceptibility map. WLC multiplies each normalized factor by its weight obtained by AHP and FAHP methods and sums the layers (Ogato et al., 2020):

$$FSM = \sum_{i=1}^{n} W_i * C_i \qquad (3)$$

Where FSM = the flood susceptibility map,
Wi = the weight and the normalized raster layer
Ci = the normalized raster layer of each criterion

In order to ease the apprehension of obtained susceptibility map and identify the flood-prone areas, FSM can be classified into five classes including "very high", "high", "medium", "low" and "very low".

4. RESULT AND DISCUSSION

In this study, nine criteria, such as, topographical, hydrological, meteorological, and geomorphological parameters, were incorporated into geospatial investigation in order to obtain flood susceptibility maps of two basins located in the south-eastern region of Iran. Unfortunately, this large scale area has experienced several severe flood incidents during last years. For this aim, two MCDM methods, namely AHP and FAHP, were applied, and the results of these methods were compared. Regarding the AHP method, at first, experts were asked to complete a questionnaire to compare criteria and specify relative importance to each pair of criteria. Doing this step results in pair-wise matrices. Then, we normalize the average pair-wise matrix. Finally, each row's average was computed to obtain the relative weight. After calculating weights, the consistency rate was computed to assure that weights are reliable. CR value was computed (CR=0.089 < 0.1), which is acceptable and it proves the trustworthiness of achieved weights. To reduce the uncertainty in experts' judgement and improve the efficiency of the results, weights were also calculated using FAHP. In this method, instead of using crisp numbers in AHP method, TFNs were used. To implement FAHP, the relative numerical importance of criteria is converted to fuzzy quantities using variables shown in Table 1. The rest of procedure is similar to AHP method.
The obtained relative weights are shown in Figure 4 and Table 2.

Weight of criteria	AHP	Fuzzy AHP
CN	0.097	0.088
DEM	0.043	0.045
FA	0.238	0.210
DR	0.182	0.184
NDVI	0.030	0.031
Slope	0.046	0.062
TPI	0.103	0.072
TWI	0.185	0.205
MFI	0.076	0.104

Table 2. The criteria's weights

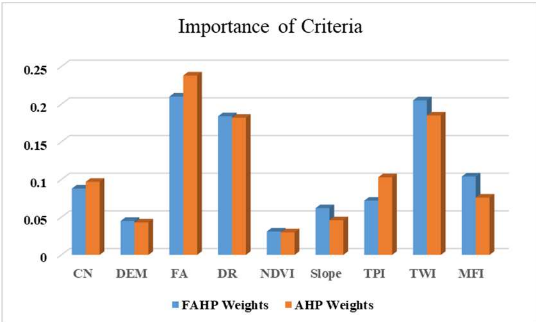

Figure 4. The criteria's weights

Based on Figure 4, in AHP method, FA, TWI, and DR had the highest weights, respectively. Therefore, the higher the level of these three parameters is, the more susceptible to flood events the area is. As it can be seen, combining fuzzy logic with AHP method changed the criteria rank slightly. For instance, in AHP method, TPI was ranked as the fourth criterion, while MFI was recognized as the sixth one. After combining AHP with fuzzy logic, MFI got more importance and its rank was higher (the fourth), while TPI was ranked as the sixth criterion. The final FSMs were produced by aggregating nine investigated criteria. According to Eq. (3), which is a linear combination, each criterion multiplies to its weight, and the sum of these values gives the final susceptibility maps (Figure 5).

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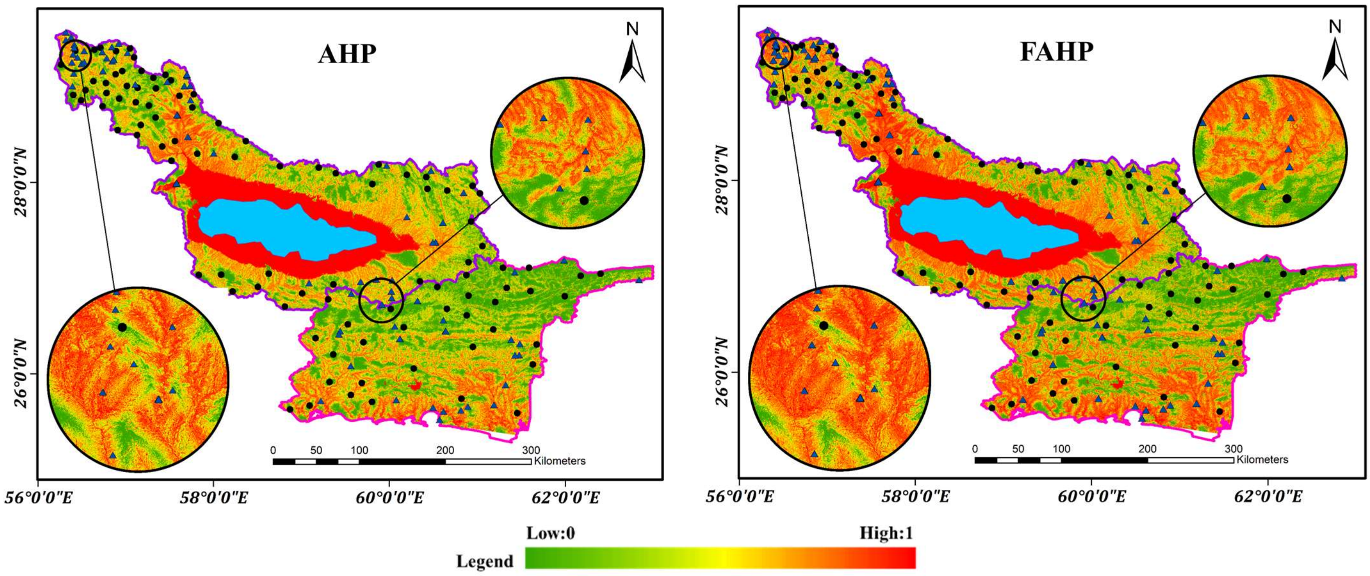

Figure 5. Final Flood Susceptibility Map

Validation measures	FAHP	AHP
Sensitivity (%)	90.07	85.82
Specificity (%)	91.30	90.58
Overall accuracy (%)	90.68	88.17
Kappa statistic	81.36	76.35

Table 3. Models performance based on validation measures

The accuracy and efficiency of applied approaches were examined through statistical measures. Based on validation results, it can be assume that FAHP method outperformed AHP method (Table 3). The justification is that fuzzy logic has decrease the level of vagueness in experts' opinion which result in more trustworthy outputs.

In order to simplify the interpretation of obtained flood susceptibility maps, the final FSMs have been classified into five categories, including "very high", "high", "medium", "low", "very low," using Kmeans classification approach. Classified resultant maps are illustrated in Figure 6.

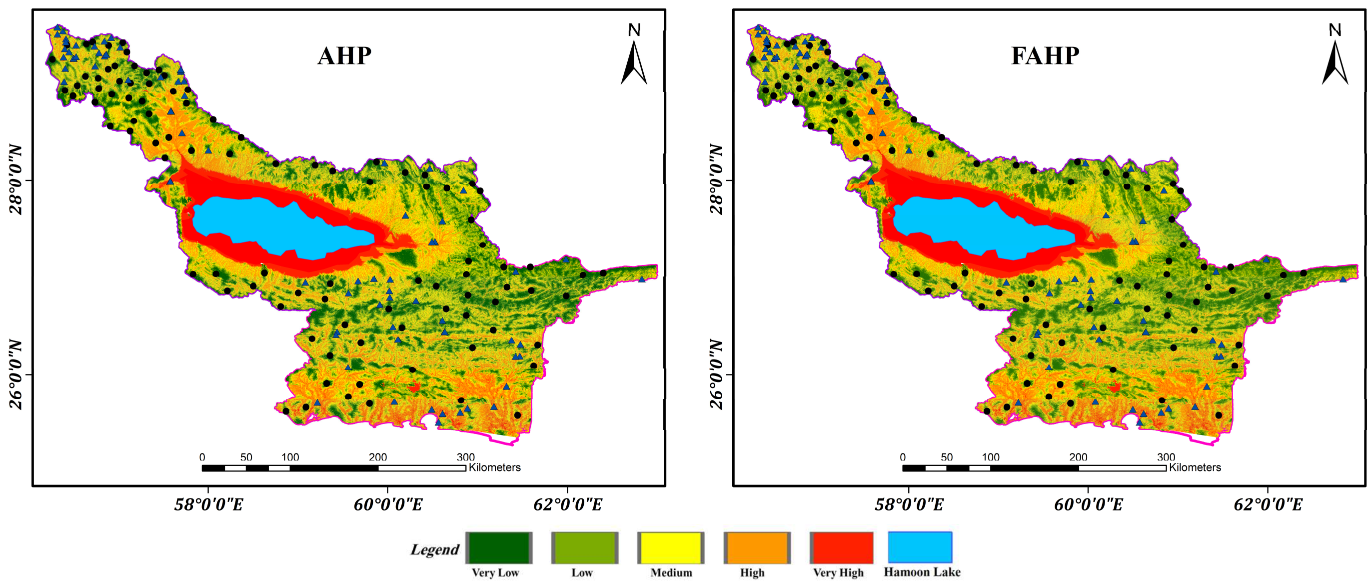

Figure 6. Classified flood susceptibility maps

Shown in Figure 6, the south part of the basin 2, the middle and north-western of basin 1 are categorized as "High" and "Very High" susceptive areas. Paying attention to the weight of criteria (Figure 4) and normalized map of criteria (Figure 3), it can be understand that the criteria with higher weights have more effect on FSMs. It means that, regions with a higher amount of FA, TWI, and near to river were recognized as "Very High" and "High" susceptible areas. For example, in southern parts of basin 2 and mentioned areas in basin 1, the level of TWI is high.

Furthermore, in the northern part of basin 2, the value of FA and TWI are low. As a result, these area are classified as low and very low classes. The obtained flood maps were overlaid on the flood inventory map to examine the trustworthiness of implemented methods. Table 4 illustrates the assessment results of the proposed methods. As it can be seen, a considerable share of historical flooded points are classified into "high" and "very high" classes.

Class	FAHP	AHP
Very Low	0	0.71
Low	0.71	1.43
Moderate	12.86	23.57
High	31.43	34.29
Very High	55	40

Table 4. Classes' participation percentage of on inventory points.

5. CONCLUSION

This study inspected the south-eastern part of Iran and developed a spatial flood susceptibility model in this large-scale area to identify flood-prone zones using MCDM methods combined with, GIS and RS technologies. The justifications of choosing mentioned area were occurring hazardous flood events in recent years and lack of knowledge regarding flood potential regions. Nine conditioning factors were investigated, namely DEM, TWI, TPI, Slope, NDVI, Flow Accumulation, Curve Number, Distance to the river, and MFI. All criteria's layers were generated in 30m spatial resolution in the GIS environment. The FAHP approach was applied to calculate the weight of criteria. By analysing the results, it can be concluded that Flow Accumulation, TWI, and Distance to the river have a significant effect on flood phenomenon. Moreover, NDVI has the minimum importance compare to other the criteria. Finally, the WLC method was applied to aggregate the factors by multiplying each criterion by its weight. The resultant map has been classified into five categories. Furthermore, the evaluation stage was carried out using historical flood events to ensure the model's result. Overlying the obtained classified map and flood inventory points proof the validation of the implemented approach. The current approach is also suitable for ungauged basins, which are dealing with a scarcity of data. Thus, the present approach for flood susceptibility analysis on a large-scale area can be useful in spatial planning procedure, and it aids decision-makers and managers to detect high susceptible areas. Consequently, by arranging mitigation equipment and inform people in those regions, the level of fertility and loss can be reduced.

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