

# FLOOD RISK ZONATION USING A MULTI-CRITERIA SPATIAL GROUP FUZZY-AHP DECISION MAKING AND FUZZY OVERLAY ANALYSIS

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## ABSTRACT:

In this study, a GIS based approach has been proposed for the flood risk zonation based on a multi-criteria spatial group fuzzy AHP decision making analysis and its integration with fuzzy overlay analysis. For this purpose, 10 layers affecting flood occurrence have been used including: the Digital Elevation Model (DEM), Slope, NDVI, Flow Accumulation (Flow Ac.), HOFD, VOFD, Topographic Position Index (TPI), Topographic Wetness Index (TWI), Curve Number (CN), Modified Fournier Index. Each layer was classified into 5 sub-classes and their preference at its layer was weighted by a group of experts using fuzzy analytical hierarchy processes (GFAHP) method. Finally, the risk map of the studied area with the weight of experts and fuzzy overlay method was product and divided into five categories.

## 1. INTRODUCTION

Flooding is one of the most devastating and costly natural events in all countries, causing lots of damages. The development of urbanization, especially in the riversides, as well as the human and financial losses due to the floods, indicate the need to provide maps of flood risk areas. According to statistics compiled by the United Nations in the midst of natural disasters, floods and storms inflicted the greatest casualties and damages to human communities. In a decade between 2000 and 2010, the amount of damage caused by flooding and the hurricane amounted to \$ 21 billion against \$ 18 billion in damage caused (AmirAhmadi et al. 2011). The flood risk zoning map can be used as an effective tool for planning the development of the city by the Minister of Construction (Buchele et al., 2006). Geospatial information systems (GIS), remote sensing, and Multi-criteria decision analysis propose techniques and methods for solving complicated problems that their criteria are often not comparable (Rashed and weeks, 2003; Gamper, et al. 2006; Delavar, 2004; Pahlavani et al., 2006; Pahlavani et al., 2017; Bahari et al., 2014; Bigdeli et al., 2013; Bigdeli et al., 2014). There have been several studies on flood risk zoning. Hyalmarson (1988) investigated the hazards of engineering operations to zoning flood risk in western and eastern Arizona using hydrological and geomorphological features. Liang and Mohanty (1997) introduced and optimized flood management based on zoning as a non-flood control method. Using the remote sensing data from the 1988 historical flood, Islam and Kimitero (2000) prepared a flood risk map for Bangladesh. They overlapped two digital flood risk maps using land cover, physiographic and geological classification data and prepared a flood risk map.

Correia et al. (1995) applied GIS, hydrological and hydraulic models in floodplains and urban development to evaluate the impact of land use control on flood risk. Fernandez and Lutz (2010) zoned the city of Yerba Buena, Argentina in terms of

flood risk using GIS and multi-criteria decision making system. They used the parameters of distance to drainage channels, area height, slope area, groundwater depth and land use. Multi-criteria decision making system was applied for determination of weights for each of five factors. They zoned their area into five zones with high risk, medium to high risk, medium risk, low risk and very low risk.

Ozturk and Batuk (2011) introduced GIS-MCDA with the help of Geographic Information System and Multi-Criteria Decision Making System, which is known as the Turkish Marmara area zoning program. This zoning has been done by selecting and providing effective layers including annual rainfall, sub-catchment area, elevation, slope, slope direction and drainage coefficient in creating flood zone. These layers were compared in the environment and the final GIS-MCDA coefficient was determined. The final AHP-based map for each layer divided the zones at high, high, medium, low and very low flood risk by the value of each pixel.

Moreli et al. (2012) investigated the potential of the Arno River flooding in Italy by navigating the river pattern in different areas using GPS and GIS, and concluded that areas with urban development were more at risk. Maantay and maroko (2009) zoned New York in terms of time span of different floods. Chen et al. (1997) developed a GIS-based urban flood model using cumulative surface runoff and rainfall runoff. Asgharpour and Ajdari (2011) studied seasonal floods in Iran's Qatari Watershed. AL-Ghamdi et al. (2011) Zoned Mecca using spatial analysis in GIS for flood risk based on two major floods of years 1990 and 2010 and obtained a map of the potential flooding in different areas of the city.

In this paper a GIS-based approach has been proposed for flood risk zonation using a spatial group fuzzy AHP multi-criteria decision making analysis and fuzzy overlay analysis.

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## 2. DATA AND METHOD

### 2.1 Study Area

Maneh and Samalghan are from the northern Khorasan province with an area of 4898 km<sup>2</sup> and a population of 103944 people. The city of Maneh and Samalghan is geographically divided into mountainous and plain areas, the mountainous part of which is in the West and Southwest and plain area in the North and Center of the province. Figure 1 shows the study area.

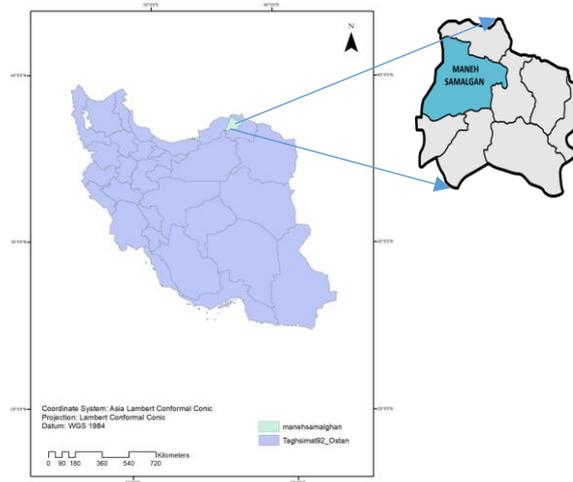


Figure 1. The study area

### 2.3 Proposed methodology

At first, the correlation matrix of generated spatial was calculated and the non-correlated layers were identified in the occurrence of flood and each layer was divided into 5 sub-layers. Then, using a group of experts for each sub-layer a weight was allocated using fuzzy AHP method. Each sub-layer was reclassified with the new achieved fuzzy AHP weighted. Accordingly, a Large fuzzy membership function prepared layers in order to apply them in fuzzy Gamma overlay. Finally, with fuzzy overlay, the flood risk map was produced and classified into 5 categories. The flowchart of the proposed method is shown in Figure 2.

#### 2.3.1 Producing effective spatial layers

In this study, 10 spatial layers affecting flood occurrence have been used including: The Digital Elevation Model (DEM), Slope, NDVI, Flow Accumulation, HOFD, VOFD, Topographic Position Index (TPI), Topographic Wetness Index (TWI), Curve Number (CN), Modified Fournier Index. A brief introduction of these layers are as follows:

- 1- DEM: The digital elevation model is a 3D representation of a terrain's surface
- 2- CN: The curve number is an empirical parameter for predicting direct runoff or infiltration from rainfall excess.

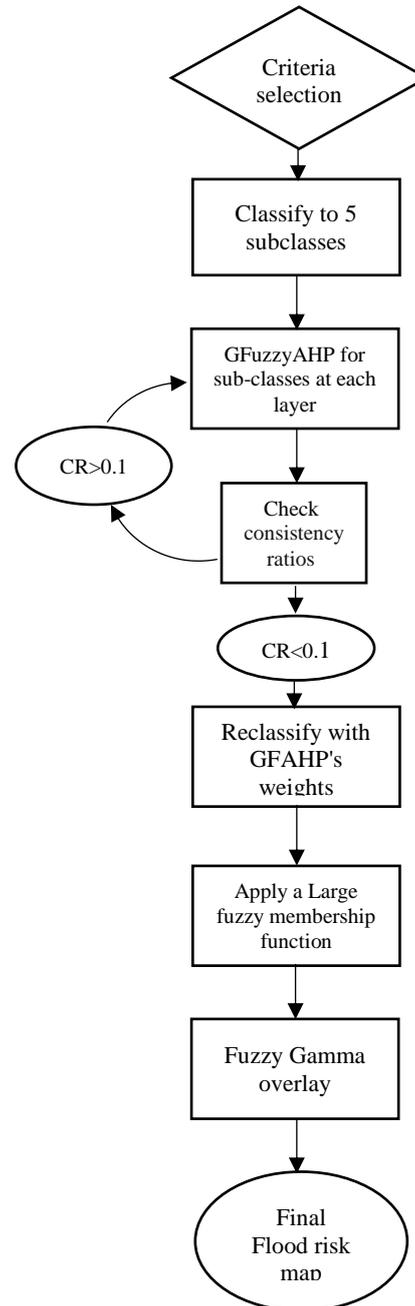


Figure 2. Flowchart of the proposed methodology

- 3- TPI: The topographic position index (TPI) shows the height difference of each cell with the mean heights of its neighboring cells.
- 4- TWI: Describes the humidity conditions of the basin.
- 5- VOFD: Vertical Overland Flow Distance.
- 6- HOFD: Horizontal Overland Flow Distance.
- 7- NDVI: It is known as a vegetation cover estimator.
- 8- MFI: Rainfall intensity maps are generated using the modified Fournier Index (MFI).
- 9- Flow accumulation: It shows the amount of current that goes from the upper cells to the desired cell.
- 10- Slope: The steepness value of a ground point.

Figure 3 shows some of these layers.

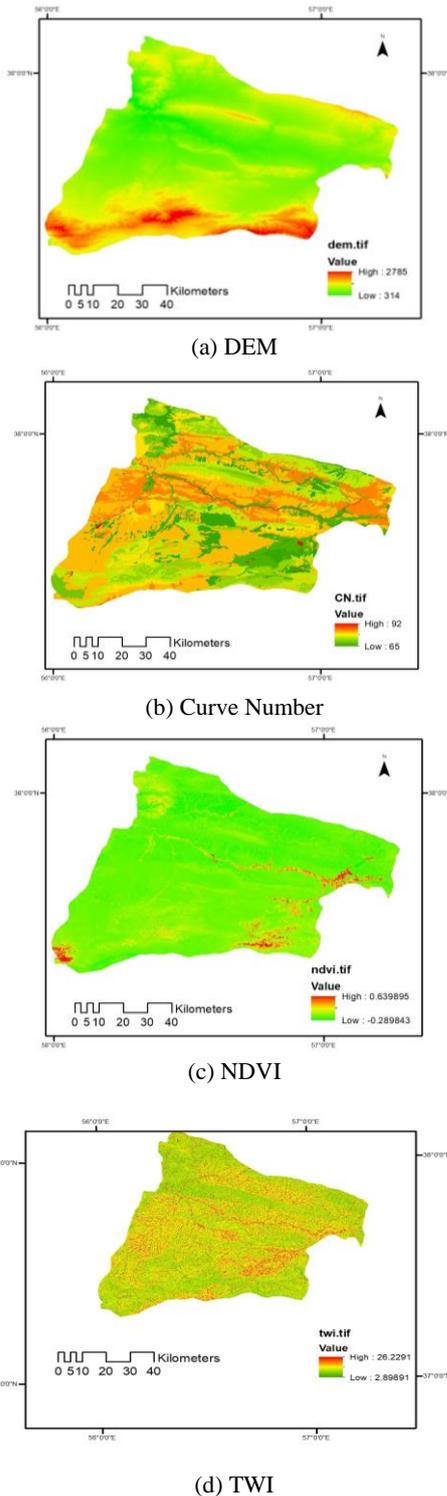


Figure 3. Some of spatial layers used

### 2.3.2 Fuzzy Analytical Hierarchy Process (FAHP)

Traditional AHP is often criticized for its inability to adequately address the uncertainty associated with mapping decision makers (Deng, 1999). Because fuzziness is a common feature in many decision making problems, a fuzzy AHP (FAHP) method would be able to tolerate ambiguity (Mikhailov and Tsvetnikov, 2004). In other words, decision makers are usually more confident about judging distance in the form of single numerical values, hence the FAHP is able to record human assessment ambiguity when complex decision-making problems are considered (Erensal et

al., 2006). This ability comes to exist when the crisp judgments transformed into fuzzy judgments. The main feature of fuzziness is individual grouping into classes without sharp boundaries (Hansen, 2005). A triangular fuzzy number is the special class of fuzzy number whose membership defined by three real numbers, expressed as  $(l, m, u)$ . The triangular fuzzy numbers are as follows:

$$\mu_A(x) = \begin{cases} \frac{(x-l)}{m-l} & l \leq x \leq m \\ \frac{(u-x)}{(u-m)} & m \leq x \leq u \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

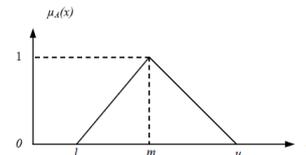


Figure 4. Fuzzy triangular number

The Triangular fuzzy numbers of linguistic variables used in this study are shown in Figure 5.

Linguistic variables	Triangular fuzzy numbers	Reciprocal triangular fuzzy numbers
Extremely strong	(9,9,9)	(1/9,1/9,1/9)
Very strong	(6,7,8)	(1/8,1/7,1/6)
Strong	(4,5,6)	(1/6,1/5,1/4)
Moderately strong	(2,3,4)	(1/4,1/3,1/2)
Equally strong	(1,1,1)	(1,1,1)
Intermediate	(7,8,9), (5,6,7), (3,4,5), (1,2,3)	(1/9,1/8,1/7), (1/7,1/6,1/5), (1/5,1/4,1/3), (1/3,1/2,1)

Figure 5. Triangular fuzzy numbers of linguistic variables used in this study.

To construct pairwise comparisons under each criterion, a triangular fuzzy comparison matrix is defined as follows:

$$\tilde{A} = (\tilde{a}_{ij})_{n \times n} = \begin{pmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, u_{21}) & (1,1,1) & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \vdots \\ (l_{n1}, m_{n2}, u_{n1}) & (l_{n2}, m_{n2}, u_{n2}) & (1,1,1) \end{pmatrix} \quad (2)$$

where  $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}) = \tilde{a}_{ij}^{-1} = (\frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}})$   
For  $i, j = 1:n$  and  $i \neq j$

In this paper, the weights of alternatives were obtained by 'Fuzzy Extent Analysis' method proposed by Chang (1996) as follows:

Step One: Calculate the normalized value of the row sums as follows:

$$\tilde{s}_i = \sum_{j=1}^n \tilde{a}_{ij} \otimes \left[ \sum_{k=1}^n \sum_{j=1}^n \tilde{a}_{kj} \right]^{-1} \quad (3)$$

where  $\otimes$  = the extended multiplication of two fuzzy numbers.

Step Two: Calculate the degree of probability of  $\tilde{s}_i > \tilde{s}_j$  by:

$$V(\tilde{s}_i > \tilde{s}_j) = \text{Sup}_{y \geq x} \left[ \min(\tilde{S}_i(x), \tilde{S}_j(y)) \right] \quad (4)$$

that can be equivalently expressed as:

$$\mu_A(x) = \begin{cases} 1 & m_i \geq m_j \\ \frac{(u_i - l_j)}{(u_i - m_i) + (m_j - l_j)} & l_i \leq u_j \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where  $\tilde{S}_i = (l_i, m_i, u_i)$  and  $\tilde{S}_j = (l_j, m_j, u_j)$ . Figure 5 shows the degree of possibility.

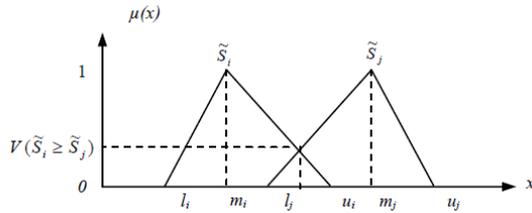


Figure 6. The degree of possibility

Third step: calculating the degree of possibility of  $\tilde{S}_i$  that is greater than all other fuzzy numbers  $\tilde{S}_j$  by:

$$V(\tilde{S}_i > \tilde{S}_j | j = 1, \dots, n; j \neq i) = \min V(\tilde{S}_i > \tilde{S}_j), i = 1, \dots, n \quad (6)$$

Fourth step: defining weights by:

$$w_i = \frac{V(\tilde{S}_i > \tilde{S}_j | j = 1, \dots, n; j \neq i)}{\sum_{k=1}^n V(\tilde{S}_k > \tilde{S}_j | j = 1, \dots, n; j \neq k)}, i = 1, \dots, n \quad (7)$$

### 2.3.3 Fuzzy Reclassification

The Fuzzy Membership method reclassifies the input data into the range [0,1] based on the possibility of being a member of a specified set. 0 is assigned to those locations that are definitely not a member of the specified set, and 1 is assigned to those that are definitely a member of the specified set. The entire range of possibilities between 0 and 1 are assigned to some level of possible membership (Hersh et al., 1979; Bonham-Carter 1994). This method can include different types of Fuzzy Gaussian, Fuzzy Large, fuzzy Linear, Fuzzy MS Large, Fuzzy MS Small and Fuzzy near. Due to the use of Fuzzy Large type in this study, we investigate this case. The Fuzzy Large transformation function is used when the larger input values are more likely to be a member of the set. The defined midpoint identifies the crossover point (assigned a membership of 0.5) with values greater than the midpoint having a higher possibility of being a member of the set and values below the midpoint having a decreasing membership. The spread parameter defines the shape and character of the transition zone. Figure 7 is shows variations of the Fuzzy Large membership function.

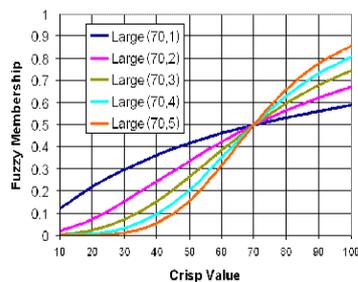


Figure 7. Variations of the Fuzzy Large membership function

### 2.3.4 Fuzzy Overlay method

The Fuzzy Overlay tool allows the analysis of the possibility of a phenomenon belonging to multiple sets in a multicriteria overlay analysis. Not only does Fuzzy Overlay determine what sets the phenomenon is possibly a member of, it also analyzes the relationships between the membership of the multiple sets (Baidya et al., 2014; Akgun et al. 2012). The Overlay type lists the methods available to combine the data based on set theory analysis. Each method allows the exploration of the membership of each cell belonging to various input criteria. The available methods are fuzzy And, fuzzy Or, fuzzy Product, fuzzy Sum and fuzzy Gamma. Due to the use of fuzzy Gamma Type in this study, we investigate this case. The fuzzy Gamma type is an algebraic product of fuzzy Product and fuzzy Sum, which are both raised to the power of gamma. The generalize function is as follows (Baidya et al., 2014):

$$\mu_{Gamma} = \left( \prod_{i=1}^n \mu_i \right)^{1-\gamma} \left( 1 - \prod_{i=1}^n (1 - \mu_i) \right)^\gamma \quad (8)$$

If the specified  $\gamma$  is 1, the output is the same as fuzzy Sum; if  $\gamma$  is 0, the output is the same as fuzzy Product. Values within the range (0,1) allow you to combine evidence between these two extremes and possibly different than fuzzy or fuzzy And. Fuzzy Gamma is a compromise of the increasing effect of fuzzy Sum and the decreasing effect of fuzzy Product.

## 3. EXPERIMENTAL RESULTS

Tables 2 to 11 show the results of GFAHP for all spatial layers.

DEM	314_808	808_1302	1302_1796	1796_2290	2290_2785	CR
Weights	0.374	0.266	0.145	0.136	0.079	0.023

Table 1. Weights of group FAHP for subclasses of DEM

SLOPE	0_13.7	13.8_27.5	27.6_41.3	41.4_55.1	55.1_68.9	CR
Weights	0.299	0.235	0.200	0.155	0.011	0.044

Table 3. Weights of group FAHP for subclasses of Slope

TPI	-52.8_-33.7	-33.7_-14.9	-14.9_4	4_22.9	22.9_41.9	CR
Weights	0.294	0.230	0.198	0.151	0.125	0.065

Table 4. Weights of group FAHP for subclasses of TPI

NDVI	-0.29_-0.1	-33.7_-14.9	-0.1_0.08	0.08_0.26	0.45_0.64	CR
Weights	0.320	0.268	0.195	0.120	0.095	0.078

Table 5. Weights of group FAHP for subclasses of NDVI

HOFD	0_3.1	3.1_6.1	6.1_9.2	9.2_12.3	12.3_15.4	CR
Weights	0.334	0.259	0.168	0.143	0.094	0.032

Table 6. Weights of group FAHP for subclasses of HOFD

VOFD	0_278	278_557	557_836	836_1114	1114_1393	CR
Weights	0.326	0.233	0.198	0.144	0.097	0.046

Table 7. Weights of group FAHP for subclasses of VOFD

FLOW-accumulation	0_34502 30	34502 30_69004 60	69004 60_10350 691	10350 691_13800 921	13800 921_1725 1152	CR
Weights	0.311	0.239	0.205	0.176	0.066	0.030

Table 8. Weights of group FAHP for subclasses of FLOW ACC

CN	65_70.4 70.4	70.4_75.8 75.8	75.8_81.2 81.2	81.2_86.6 86.6	86.6_92 92	CR
Weights	0.254	0.240	0.200	0.169	0.134	0.053

Table 9. Weights of group FAHP for subclasses of CN

TWI	2.9_7.56 7.56	7.56_12.2 12.2	12.2_16.9 16.9	16.9_21.5 21.5	21.5_26.2 26.2	CR
Weights	0.283	0.234	0.239	0.188	0.054	0.041

Table 10. Weights of group FAHP for subclasses of TWI

MFI	30.1_37.6 37.6	37.6_45.1 45.1	45.1_52.6 52.6	52.6_60.1 60.1	60.1_67.1 67.1	CR
Weights	0.273	0.244	0.239	0.199	0.156	0.058

Table 11. Weights of group FAHP for subclasses of MFI

Also, results of using fuzzy Large membership function for some layers are shown in Figures 8 and 9.

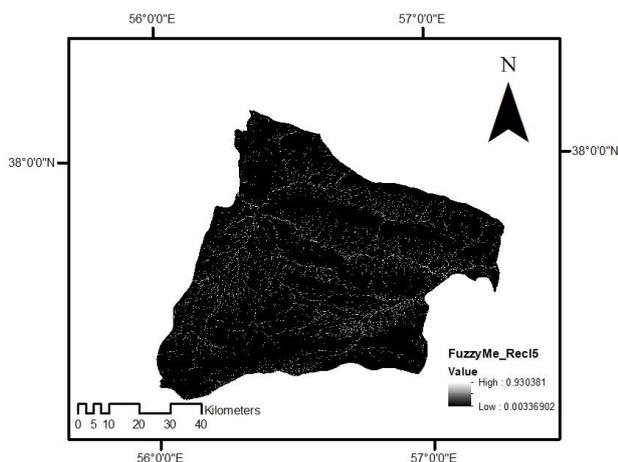


Figure 8. Using Large membership function for TWI layer

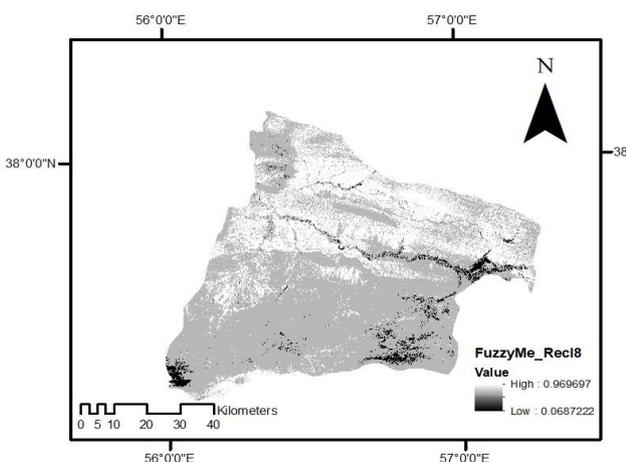


Figure 9. Using Large membership function for NDVI layer

Potential flood risk map was generated by Gamma fuzzy overlay with Gamma equal to 0.85 and classified into five categories:

very high risk, high risk, moderate, low risk, and very low risk (Figure 10).

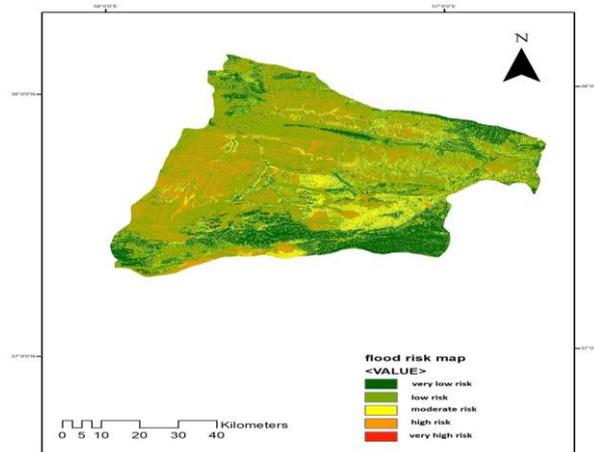


Figure 10. Final flood risk map

Figure 11 shows the flood risk map with 95% probability.

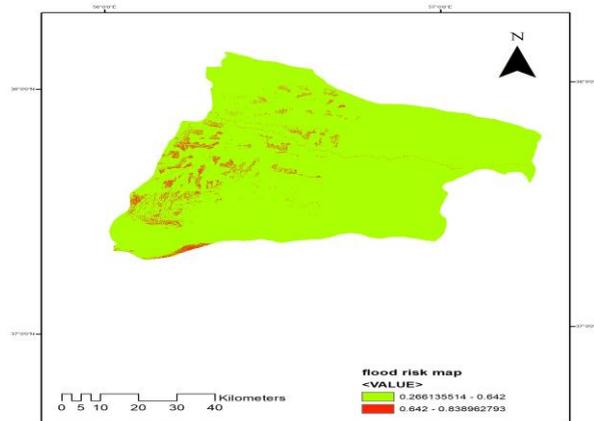


Figure 11. Flood risk map with 95% probability

#### 4. CONCLUSION

This study examines the role of GIS in a multi-criteria decision-making process for flood risk zoning. By integrating GIS and MCDA, the effective factors in the occurrence of flood are better evaluated and by weighing the sub-classes of each layer by the experts, each layer is used more effectively and accurately for flood risk zoning.

Finally, 5.8% of the area in the study area was in very high risk category, 14.1% high risk, 15.2% average risk, 44.3% low risk and 20.6% very low risk.

According to the floodiness of the area and the high flood events these maps can be used for crisis management and urban development studies.

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