Integrating GIS Based Fuzzy Set Theory in Multicriteria Evaluation Methods for Landslide Susceptibility Mapping

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Abstract
In this study we employ two GIS Multicriteria Decision Analysis (MCDA) methods for Landslide Susceptibility Mapping (LSM): Analytical Hierarchy Process (AHP) and Fuzzy Analytical Hierarchy Process (FAHP). First, a classic AHP method is used to carry out a LSM. AHP applies crisp pairwise comparisons and standardization techniques. In a second stage, fuzzy set theory is integrated in the AHP process, both for weighting the criteria and for the criteria standardization. The Triangular Fuzzy Numbers (TFNs) method is used to compare and reduce the error that is inherent in criteria ranking. This is achieved with Fuzzy Membership Functions and by assessing all criteria individually. For both approaches landslide susceptibility maps are produced and results are validated based on information on existing landslides. A particular measure used in the validation exercise is the 'Receiver Operating Characteristics' curve. Results of the validation exercise with known landslides indicate that the FAHP clearly performs best. The results of this study help to identify strategies of choosing an appropriate method for LSM studies and, respectively, to assess the reliability of the resulting maps.

1. Introduction

Landslide susceptibility mapping (LSM) is considered an effective solution to understanding and predicting future hazards in order to mitigate their consequences. LSM is defined as the proneness of the terrain to produce slope failures, and susceptibility is usually expressed in a cartographic way (Feizizadeh and Blaschke, 2011 and Feizizadeh et al., 2012 and Feizizadeh and Blaschke, 2013a). Multicriteria Decision Analysis (MCDA) is believed to be a powerful technique for the analysis and prediction of landslide hazards. It also provides a rich collection of techniques and procedures for structuring decision problems and designing, evaluating and prioritizing alternative decisions (Feizizadeh et al., 2012 and Feizizadeh and Blaschke, 2012a). GIS-MCDA methods provide a framework to handle different views and compositions of the elements of a complex problem decision, organize the elements into a hierarchical structure and study the relationships among the components of the problem (Malczewski, 2006). In the context of GIS-MCDA, the Analytic Hierarchy Process (AHP) method is considered as a widely used MCDA method that has successfully been applied to many practical decision-making problems (Lai, 1995 and Feizizadeh et al., 2013). In spite of its popularity, the method is often criticized for its inability to adequately handle the inherent uncertainty and imprecision associated with the mapping of a decision-maker's perception to crisp numbers (Chen et al., 2011). The AHP's pairwise matrix is based on expert opinion which is open to subjectivity in making the comparison judgements. As a result, any incorrect perception on the role of the different land-failure criteria can be easily conveyed from the expert's opinion into the weight assignment (Kritikos and Davies, 2011 and Feizizadeh and Blaschke, 2013b). In an effort to deal with this source of uncertainty, integration of GIS-MCDA and Fuzzy logic methods provide a framework for further analysis by means of using the advantage of Fuzzy Membership Functions (FMFs) for assessing criteria and improving the accuracy of results. In the context of MCDA, generally fuzzy sets have often been applied to standardize criterion maps by assigning the degree

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of membership or non-membership associated with criterion (Gorsevski and Jankowski, 2010). The fuzzy set theory employs the idea of a membership function that expresses the degree of membership with respect to some attribute of interest. On the other hand using the crisp methods, generally, the attribute of interest is measured over discrete intervals, and the membership function can be expressed as a table, relating map classes to membership values (Pradhan, 2011). Based on this idea, within this research the AHP and Fuzzy Analytical Hierarchy Process (FAHP) methods were employed to perform the landslide susceptibility map of Izeh basin in Iran.

2. Study Area and Data Process

The study area is located in the Izeh basin in south-western of Iran. The administrative unit is comparable to a county. It is part of the Khuzestan province and covers3929.8 km^2.In Izeh basin, the elevation increases from 342 m to 3579 m above sea level. The area experiences temperate climate and annual precipitation increases from 400 mm in low elevation part of the area to 800 mm in mountains. The Izeh basin is important in terms of its agricultural production and in particular hydropower plants. The Karun River, namely main and the longest river in all of Iran passes through this area. The suitable topography in Karun canyon provides the opportunities for construction hydropower plans and they are three main dams have been constructed so far on different branches of Karun River. However, the highly susceptibility for mass movement and in particular landslides is considered as potential natural hazard for the inhabitations of the area for economic activities such as hydropower plants in the Izeh basin. The geology of the area is very complex and landslides have been considered as one of the major natural hazards. The landslide inventory database of Izeh contains 106 locations landslide events. Tectonic activates in combination of susceptible geology formation for landslide (e.g. sedimentary formations, marl, shale, limestone, gypsum, and siltstone) turn this area into highly susceptible for landslide hazard. In this study the nine causal factors were analysed in the LSM process based on four main criteria including: topography, hydrology, climate and human factors. The nine causal criteria used for the mapping of landslide susceptibility are: slope, aspect, distance to stream, distance to road, drainage density, distance to fault, lithology, precipitation and land use/cover. A variety resource of dataset was used to prepare the selected criteria in GIS dataset form as input of evaluation model. In this respect, the lithology and fault maps were derived from geological maps in scale 1:100,000. The road and streams maps were extracted from topography maps of study area in a scale of 1:50,000. In addition, these maps were used to create a DEM. Subsequently, slope and aspect maps were derived from this DEM. The land use/cover map was derived from Landsat ETM+ satellite images with 30m spatial resolution through supervised image classification. Annual meteorological station data were used to create annual average precipitation using interpolation methods in GIS. We also used the landslide inventory database of the study area which was recorded by GPS in several field surveys. As the last part of the data preparation phase, all necessary data pre-processing and standardizing of nine selected LSM criteria were performed for the implementation of the fuzzy –AHP.

3. Methods

In this paper we follow the three step procedure of LSM according to Oh and Pradhan (2011) namely a) collection of data and construction of a spatial database from which the relevant landslide conditioning factors are extracted, followed by b) an assessment of the landslide susceptibility while using the relationship between landslide and landslide conditioning factors, and c) validation of the results. Further, each compared research methodologies consist of two stages. In the first stage, criteria weights are assessed using pairwise comparison matrix (i.e. crisp and fuzzy) and in the second stage, criteria were ranked according to levels of internal susceptibility which is between 1 and 10 for AHP and 0 and 1 for FAHP method.

3.1Fuzzy Sets Theory and FAHP

The fuzzy set theory was introduced by Zadeh (1965). The fuzzy set can be defined as follows: if (Z) denotes a space of objects, then the fuzzy set (A) in (Z) is the set of the ordered pairs (Gorsevski and Jankowski, 2010).

$$A\{z, MF_A^F(z)\}, z \in Z$$

Equation 1

Where the membership function $MF_A^F(z)$ is known as the "degree of membership of (z) in (A)". The higher the membership value of $MF_A^F(z)$, the most it belongs to the set (Gorsevski and Jankowski 2010). In fuzzy set theory, membership can take on any value between 0 and 1, reflecting the degree of certainty of membership (Zadeh, 1965). Figure 1 shows the Triangular Fuzzy Number (TFN), $\widetilde{M}$ as base of membership function. As it shown in this figure the TFN is denoted simply (m_1, m_2, m_3). The parameters m_1, m_2 and m_3 respectively denote the smallest possible value, the most promising value, and the largest possible value that describe a fuzzy event (Kahraman et al., 2003). Based on this approach each of TFS has linear representation on its left and right side which in case of memberships function can be defined:

$$\mu\,(x|\,\widetilde{M})\begin{cases}0 & ,x < m1\\ (x-m_1)/(m_2-m_1) & ,m_1 \le x \le m_2\\ (m_3-x)/\,(m_3-m_2) & ,m_2 \le x \le m_3\\ 0 & ,x < m3\end{cases}$$

Equation 2

A fuzzy number can always be given by its corresponding left and right representation of each degree of membership (Kahraman et al., 2003):

$$\widetilde{M} = \left(M^{l(y)}, M^{r(y)}\right) = (m_1 + (m_2 - m_1)y, m_3 + (m_2 - m_3)y).\, y \in [0,1]$$

Equation 3

Where $l(y)$ and $r(y)$ denotes the left side representation and the right side representation of a fuzzy number respectively. This particular process of codifying and describing the vagueness of criteria by fuzzy membership functions will vary among decision makers because their selection of the control points that govern the shape of the fuzzy function may also vary (Gorsevski and Jankowski, 2010). The AHP is a method widely used in MCDA to obtain the required weightings for different criteria (Saaty, 1977). It has been successfully employed in GIS-based MCDA since the early 1990s (Malczewski, 2006 and Feizizadeh and Blaschke, 2013b). The AHP method calculates the required weights associated with the respective criterion map layers with the help of a preference matrix, in which all relevant criteria identified are compared against each other on the basis of preference factors (Feizizadeh and Blaschke 2012b and Feizizadeh and Blaschke, 2013b). The weights can then be aggregated and the purpose of AHP is to capture the expert's knowledge. The conventional AHP still cannot reflect the human thinking style. Therefore, FAHP, a fuzzy extension of AHP, was developed to solve the hierarchical fuzzy problems. In the FAHP procedure, the pairwise comparisons in the judgment matrix are fuzzy numbers that are modified by the designer's emphasis (Kahraman et al., 2003).

3.2 Application of AHP and FAHP for LSM

The idea of using AHP and FAHP approach in LSM is to consider the pixels on any causal factor layer as susceptible to landslides. Pixel values can be numeric and range from 0 (i.e., not susceptible) to 10 (i.e., "susceptible") for AHP and 0 (i.e., not susceptible) to 1 (i.e., "susceptible") for FAHP techniques. Accordingly, pixel values must lie in the range of 0 to 10 and 0 to 1 respectively, but there is no practical constraint on the choice of values (Pourghasemi et al., 2012). During this research, in order to apply both AHP and FAHP approaches for LSM two stages were implemented as following:

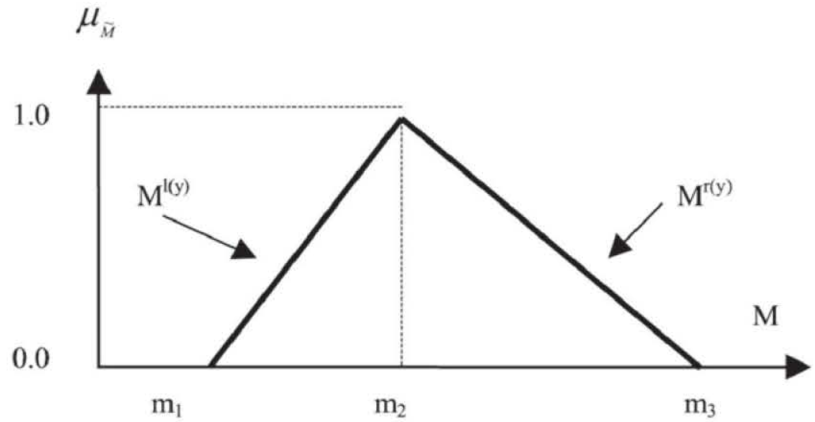

Figure 1: The triangular fuzzy number (Kahraman et al., 2003)

3.3 Step I: Assessing of Criteria Weights using FAHP

Criterion weights are the weights assigned to the objective and attribute maps (Meng et al., 2011; Feizizadeh and Blaschke 2013b). The first step was constructing a pairwise comparison matrix using the previous knowledge of goodness-of-fit in order to assign the relative importance of the predictor variables before deriving the LSMs. The standardized predictor variable values were aggregated with weights using the AHP and FAHP method in order to present the sensitivity of a landslide hazard map to different perceptions in the importance of predictor variables. Further, in order to obtain criteria weights, considering same groups of pairwise comparison matrices which are calculated for all the nine criteria in both compared methodologies, a unique pairwise comparison matrix was formed using simple weighted mean for AHP method and a FAHP based pairwise comparison matrix, composed of TFNs (minimum, mean, maximum values as m_1, m_2, m_3), has been calculated for FAHP method. According to the FAHP method, in order to obtain final criteria weights first the synthesis values should be calculated as FAHP pairwise matrix. Respectively the criteria weights can be calculated using the results of pairwise matrix as following:

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} = (74.18\ 105.98\ 164.15)^{-1} = (0.006\ 0.009\ 0.013)$$

Equation 4

S $_{slope}$ =(15.4 24.8 34.5)*(0.006 0.009 0.013)=(0.09 0.23 0.47), S $_{aspect}$ =(4.3 6.7 9.1)*(0.006 0.009 0.013)=(0.02 0.06 0.12), S $_{distance\ tostream}$ =(8.3 12.7 23) *(0.006 0.009 0.013)=(0.05 0.1211 0.31), S $_{drainage\ density}$ =(6.2 9.2 15.3)*(0.006 0.009 0.013)=(0.03 0.08 0.20),S $_{distance\ tofault}$ =(4.8 7.5 13)*(0.006 0.009 0.013)=(0.03 0.07 0.17), S $_{precipitation}$ =(3.7 5.1 8.1)*(0.006 0.009 0.013)=(0.02 0.05 0.11), S $_{distance\ to\ roads}$ =(5.75 13.5 19.1)*(0.006 0.009 0.013)=(0.03 0.12 0.26), S $_{lithology}$ =(13.1 19.429.2)*(0.006 0.009 0.013)=(0.08 0.18 0.4), S $_{land\ use/cover}$ =(5 6.7 11.7)*(0.006 0.009 0.013)=(0.03 0.06 0.16).

Equation 5

In doing so, these fuzzy values were compared as following:

$$W'(A_i) = min\{V(S_i \geq S_k)\}\ k = 1,2,\dots n;\ \ k \neq i$$ Equation 6

Then the weight vector can compute as following:

$$W'(A_i) = [W'(A_1), W'(A_2), .. W'(A_n)]^T$$

Equation 7

Where $A_i(i = 1,2,\dots n)$ are n elements. Via normalization, the normalized weight vectors are:

$$W(A_i) = [W(A_1), W'(A_2), \dots W(A_n)]^T$$

Equation 8

Where *W* is considered as a non fuzzy number. Calculation of the weight vector is respective step which in our research were calculated as following:

$$W'(x_i) = \left\{\begin{matrix} 1\ 0.33\ 0.613\ 0.478\ 0.434\ 0.294\ 0.612 \\ 0.708\ 0.39 \end{matrix}\right\}^T$$

Equation 9

$$W(x_i) = \left\{\begin{matrix} 0.177\ 0.07\ 0.13\ 0.101\ 0.092 \\ 0.062\ 0.131\ 0.15\ 0.083 \end{matrix}\right\}^T$$

Equation 10

It should be noted that after obtaining AHP weights, using a defuzzification process which converts TFNs to easily understandable definite values, we obtained the crisp weights (see table 1) to be used in data combination in the next step.

3.4 Step II: Application of FMFs

In the context of LSM using FAHP, the susceptibility values all lie between 0 and 1. Accordingly, 0 is assigned as NO susceptible areas and 1indicate the high susceptible areas. There is no optimal method for choosing the most appropriate FMFs and their respective parameters; these are generally selected according to the preferences of the decision makers. In this process, sigmoidal (s-shaped) fuzzy membership functions, i.e., monotonically increasing and monotonically decreasing, user-defined fuzzy membership functions along with crisp membership functions are The sigmoidal membership function is likely the most commonly used function in fuzzy set theory (Zadeh, 1965 and Liu et al., 2004), and provides a gradual variation from non-membership 0 to complete membership 1, whereas it is sometimes inevitable to use user-defined FMFs or crisp membership functions. In terms of AHP method, each related fuzzy membership functions are specified for each LSM criteria (see Figure 2). divided into 10 equal intervals. In other words, apart from starting and end points of each fuzzy membership functions, the area under the curve which is bigger than 0 and lesser than 1 is divided into eight equal-sized intervals. Nevertheless, all applied functions of LSM criteria outputs of each parameter are classified into groups in terms of landslide susceptibility (see Figure 3).

Table 1: The calculated weight vector from AHP and TFN

MCDA	Slope	Aspect	Stream	Drainage	Fault	Precipitation	Road	Lithology	Land use/cover
AHP	0.223	0.060	0.131	0.092	0.076	0.050	0.114	0.184	0.070
TFNs	0.175	0.068	0.128	0.110	0.095	0.046	0.139	0.154	0.086

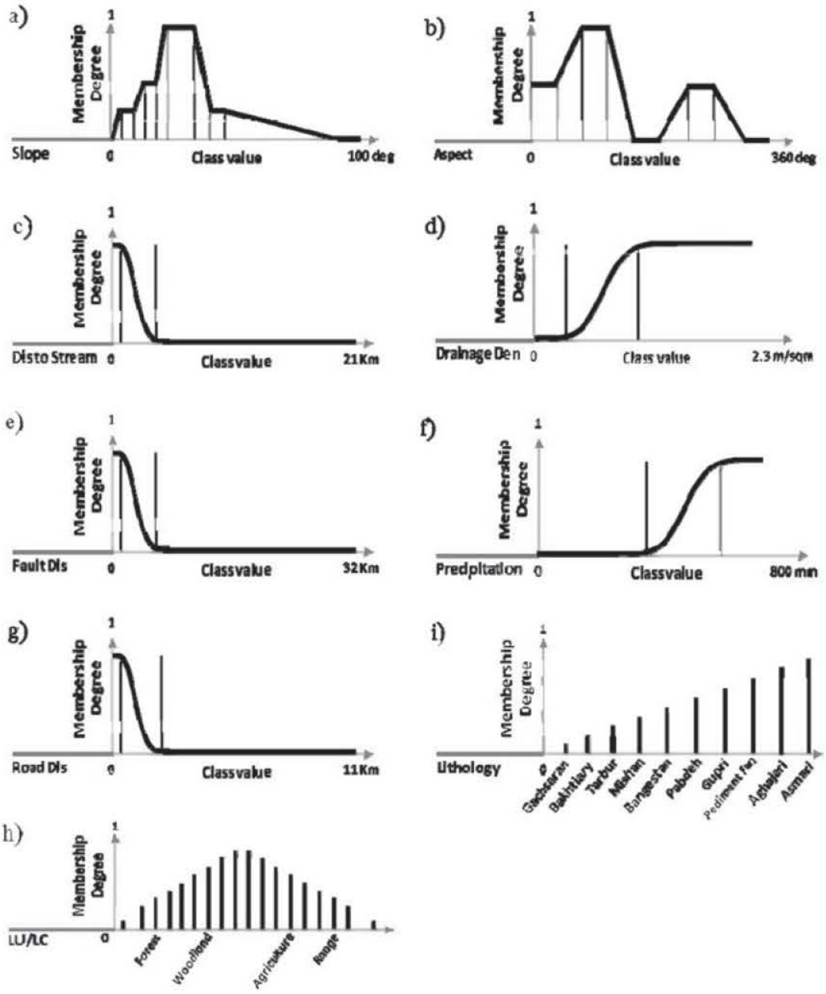

Figure 2: FAHP based membership functions including: (Type I) User defined FMF for a) slope and b) aspect). (Type II) Sigmoidal FMF for c) distance to stream, d) drainage density, e) distance to faults, f) precipitation, g) distance to road) and finally (Type III) Crisp MF for h) lithology and i) land use/cover

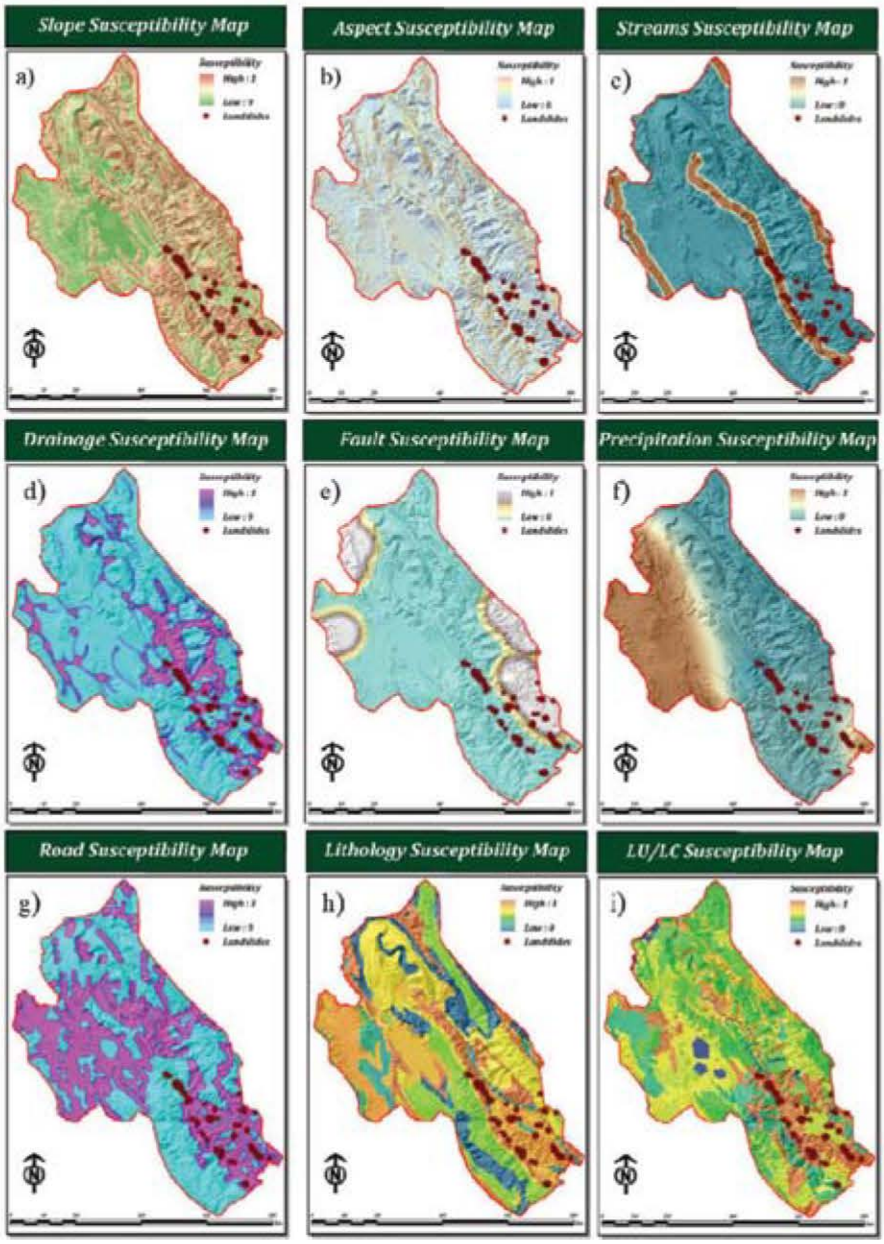

Figure 3: Results of landslide susceptibility assessment for each criteria based on fuzzy membership functions (i.e. fuzzy or crisp) on each parameter: (a) Slope, (b) Aspect, (c) Distance to streams, (d) Drainage density, (e) Distance to faults, (f) Precipitation, (g) Distance to roads, (h) Lithology and (i) Land us /cover

4. Results and Validation

The landslide susceptibility maps were produced using the results of the two stages (Step I and Step II) for both of the AHP and FAHP approaches as following:

LSM = ((slope * W) + (aspect * W) + (distance to stream *W) + (drainage density *W) + (distance to faults +W) + (precipitation *W) + (distance to roads *W) + (Lithology *W) + (Land use/cover *W)

Equation 11

Where W is the AHP weight of the first LSM criteria and FAHP weight for the second. Finally obtained landslide susceptibility maps are then classified into five categories (very low, low, moderate, high, and very high) based on quintiles classification technique to determine the class intervals (see Figure 4). The accuracy of the obtained LSMs was evaluated by calculating Relative Operating Characteristics (ROC) (Nandi and Shakoor, 2009) and numbers of known landslides were observed in various categories of the landslide susceptibility map. In the ROC method, the area under the ROC curve (AUC) values, ranging from 0.5 to 1.0, are used to evaluate the accuracy of the model. Based on this method, the ideal model shows an AUC value close to 1.0, whereas a value close to 0.5 indicates inaccuracy in the model (Nandi and Shakoor, 2009). In our research the AUC value of ROC curve for AHP methods was calculated to be 0.81 and for FAHP it is measured about 0.85.Respectively the standard errors for AHP measured about 0.031 and for FAHP it is calculated about 0.028 (see Figure 5). In addition the obtained LSMs were verified using the landslides inventory map. Accordingly, 109 known landslides were overlaid on the proposed LSM maps (see 5). The results indicated that approximately 89% and 91.7% of known landslides were observed in the 'very high susceptibility' and 'high susceptibility' zones of AHP and FAHP accordingly. Where, in each LSM these two categories make up of 40 % of the total area. Almost 10% and 7% of known landslides in AHP and FAHP fall into the 'moderate susceptibility' category respectively. However, only 0.9% of landslides lie within the 'low susceptibility category' in both LSMs. Furthermore, no landslide event was observed in the category of 'very low susceptibility' of AHP and FAHP LSMs. These results demonstrated the integration of fuzzy and AHP leads to produce landslide susceptibility map under higher reliability in comparison with conventional AHP method.

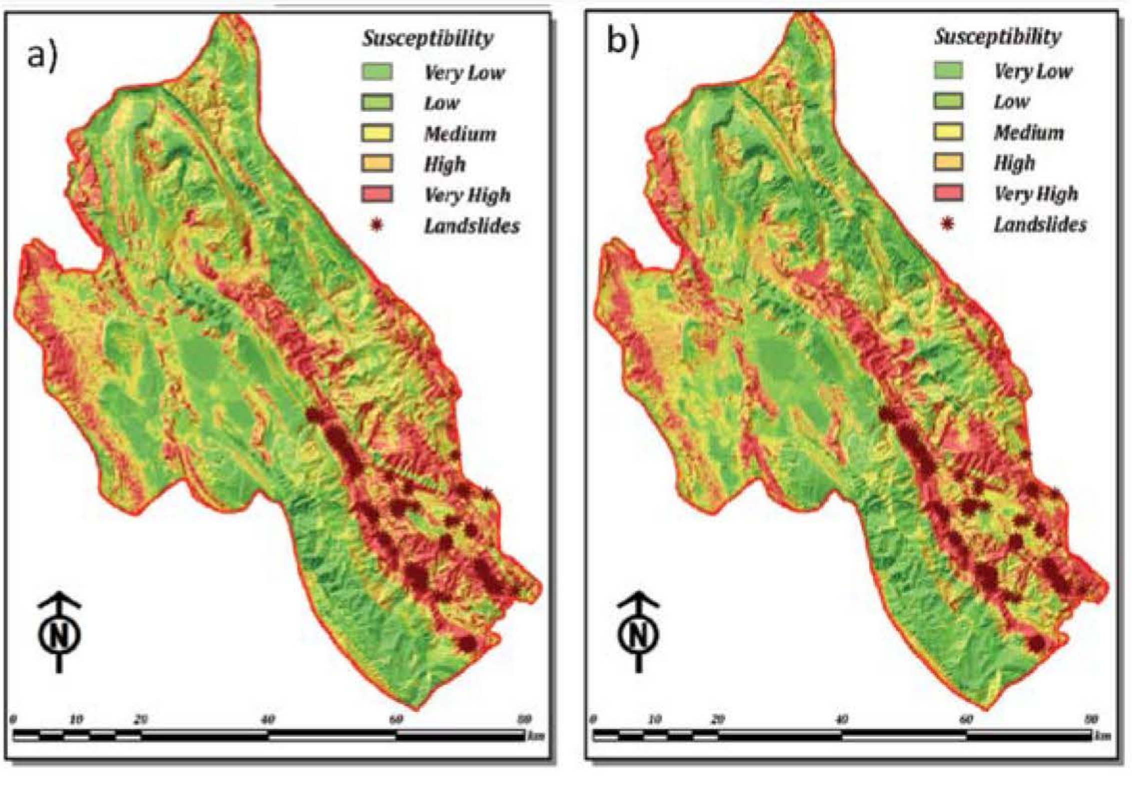

Figure 4: Results of LSM: a) The landslide susceptibility map obtained from AHP and b) The landslide susceptibility map obtained from FAHP

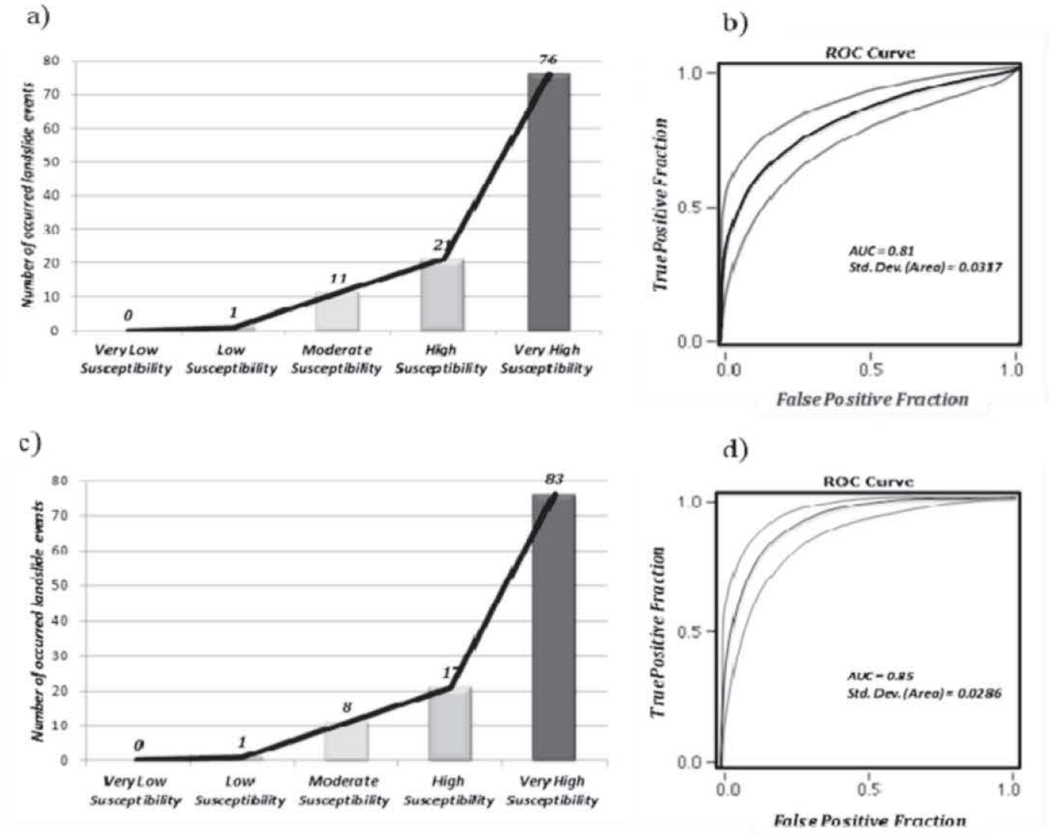

Figure 5: Validation results for the AHP and FAHP methods: a) comparison results of AHP with known existing landslides, b) ROC curve for the results of AHP, c) comparison results of FAHP with known existing landslides and d) ROC curve for the results of FAHP

5. Conclusion and Future Outlook

Our research started off by assuming that uncertainty is associated with AHP and integration of fuzzy logic with AHP (FAHP) leads to cover this issue and improve the accuracy of results. In order to achieve this objective, this study explores an approach of integrating fuzzy set theory and AHP-MCDA for LSM. The results clearly indicated that the integration of fuzzy set and AHP leads to more flexibility in judgment and decision making in comparison with conventional AHP. This holds true both criteria weighting and standardization takes uncertainties into account of LSM process not only by using FMFs in susceptibility modeling but also by means of using TFNs instead of crisp numbers for comparing the relative importance between LSM criteria. On the other hands fuzzy logic is attractive because it is straightforward to understand and implement. It can be used with data from any measurement scale, and the weighting of evidence is controlled entirely by the expert. The fuzzy logic method could be readily implemented with a GIS modelling language (Pourghasemi et al., 2012) and allows more flexible combinations of weighted maps. We conclude that the integration of fuzzy and AHP can in principal help to produce landslide susceptibility map with higher reliability. In this regard we may emphasize the importance of accuracy in landslide susceptibility maps where these maps can be used as a basis of decision making plans for reducing and mitigating further landslide hazards. It is believed that landslide susceptibility maps can help citizens, planners and engineers to reduce the financial and life losses caused by existing and future landslides by means of prevention, mitigation and avoidance. The results of LSM are therefore useful for explaining the driving factors of known existing landslides, for supporting emergency decisions and for supporting landslide hazards efforts on the mitigation of future risks (Feizizizadeh and Blaschke, 2013a). Based on this argument, we conclude that landslide susceptibility maps together with respective explanations are of great importance for authorities in Khuzestan province for responsibility of developing a landslide risk management strategy in Izeh

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