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Assessment of landslide susceptibility, semi-quantitative risk and management in the Ilam dam basin, Ilam, Iran

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Abstract

This research is focused on developing landslide susceptibility, risk and management zonation map in the Ilam dam basin, in the west of Iran. For this purpose, all existent landslide locations in the basin (50 landslides) were registered using GPS device and 70% of these points (35 landslides) were used for landslide susceptibility modeling and the rest (15 events) were used to evaluate the model. In order to prepare landslide susceptibility map, eight key factors were used for landslide occurrence such as distance to fault, distance to stream, distance to road, lithology, land use/cover, slope percent, aspect and precipitation derived from the spatial database in Arc GIS 9.3. A hybrid method of logistic regression and Analytic Hierarchy Process (AHP) were respectively used to determine the weight and rate of different factors and their classes. After applying rate to classes of parameters using the AHP method, landslide susceptibility map was prepared by means of logistic regression analysis tool in IDRISI software. The model accuracy was assessed by receiver operating characteristic (ROC) indicator and the pseudo-R^2 and used as a basis for risk mapping. The landslide risk map was prepared using Varnes equation through combining three maps of susceptibility, vulnerability and the elements at risk. In order to provide the landslide management map, multi-criteria evaluation (MCE) method was used incorporating susceptibility and risk variables. The results suggest the logistic regression and AHP model has high accuracy (ROC= 81.2%, pseudo-R^2= 0.32). We found that 39.84, 72.45, and 76.33 km^2 of Ilam dam basinare located in the high and very high classes of lands lide susceptibility, risk and management maps, respectively.

Keywords: Landslide Zonation, Analytical hierarchy process, Logistic regression, Varnes equation, Multi-criteria evaluation

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1. Introduction

There are many definitions for landslide presented by experts (e.g., Cruden 1991; Cornforth 2005). Heretofore the most common and simple definition is stated by Varnes (1976):"The term 'Landslide' comprises almost all varieties of mass movements on slopes, such as rock-falls, topples and debris flows, that involve little or no true sliding". There is a general consensus that a classification of GIS-based landslide susceptibility assessment methods may involve four different approaches: 1. Heuristic approach, 2. Multivariate statistical approach such as logistic regression model (Van Den Eeckhaut *et al.*, 2006; Rodríguez *et al.*, 2008; Chauhan *et al.*, 2010; Das *et al.*, 2010; Bai *et al.*, 2010) or Bivariateap proach such as Landslide nominal risk factor(LNRF) (Gupta and Joshi 1990; Mohammadi *et al.*, 2004; Fanyu lio 2007; Naderi *et al.*, 2010) and Information value models (Saha *et al.*, 2005; Ali Akbar and Ryong, 2011), 3. Landslide inventory-based probabilistic approach and 4. Deterministic approach (van Westen 2005).Never the less most of the spatial models lack the procedures and predictions reliability tests inestimation of future lands lide probabilities, thus precluding use of the maps for probabilistic risk analysis. Recently, some researchers have proposed systematic procedures and empirical estimations called "Blind test". Also, landslide risk zonation methods consist of three categories including qualitative (Anbalagan *et al.*, 1996; Espizua *et al.*, 2002), semi-quantitative (Zêzere *et al.*, 2008; Remondo *et al.*, 2008) and quantitative. Risk assessment has become an important tool in addressing uncertainty inherent in landslide hazards in recent years. Also recent advances in this case (Kunlong *et al.*, 2007) are beginning to provide systematic and rigorous processes to enhance slope management (Dai *et al.*, 2002) and validate the effect of the types of landslide inventories on hazard and risk assessment using satellite data through automatic and semi-automatic methods (Martha *et al.*, 2013). With the advent of numerical models, such as SHALSTAB model (Listo and Viera, 2012) for slow and shallow landslides and RAMMS model for rapid mass movements (Christen *et al.*, 2010; Graf *et al.*, 2011; Loup *et al.*, 2012), landslide simulation has improved. State of the art practices about landslides such as the ability to predict the approximate time of failure (Fujisawa *et al.*, 2010), constructing national and regional landslide databases with high potential for assessing landslide susceptibility, hazard and risk (Van Den Eeckhaut and Hervás 2012) and emersion of dynamic comprehensive methods for landslide control (Zuoan *et al.*, 2006), will be incomplete due to the lack of appropriate management plans at the end (Dai *et al.*, 2002; Einstein and Saldivar-sali 2007; Karimi Sangchini 2010; Andersson-Sköld *et al.*, 2013). In other words, the three factors of landslide susceptibility, risk and management are interdependent like rings of a chain. The main objective of this study was thus to provide the final management plan, which was achieved by using landslide susceptibility and risk maps as decision variables and combining them using MCE method.

2. Materials and methods
Study area description

The study area consists of 476.6 km^2 within 624594- 653234m UTM zone 38 latitudes and 3696126-3724011 m longitudes in the east of the Ilam city (Figurs 1 and 2).The mean annual precipitation is recorded as 595 mm in 30 years (1977-2006) provided by Ilam Natural Resources and Watershed Management (Hydrological Survey) Bureau. The elevation of the area varies from 936m to 2580 mabovesea level. The main land use/ coveris rangeland (76.1%).

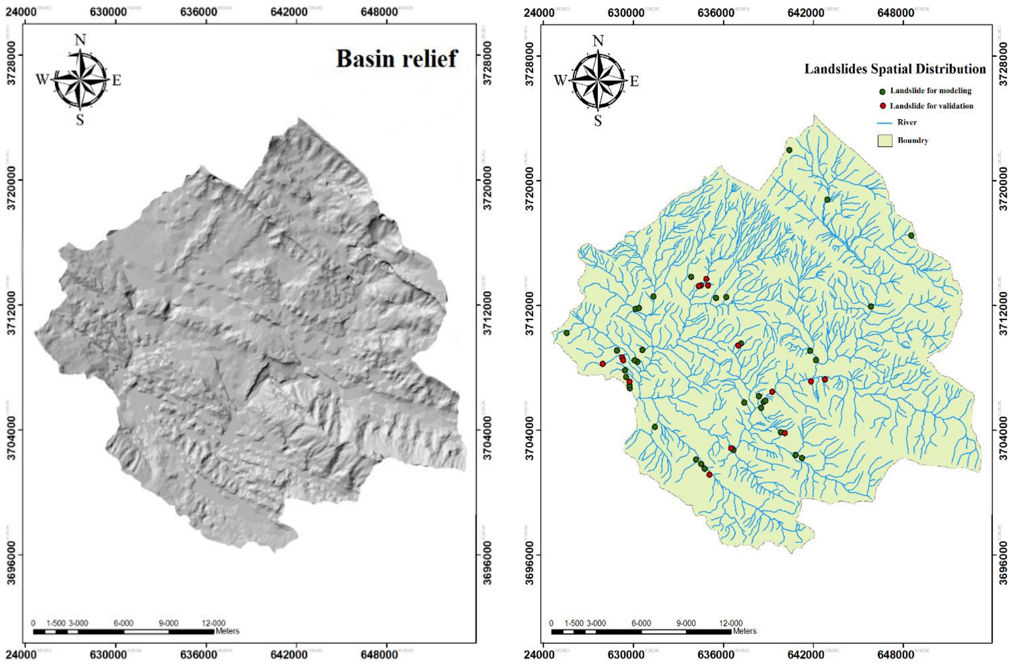

Figure 1. a: basin relief, b: Landslide spatial distribution in the Ilam dam basin

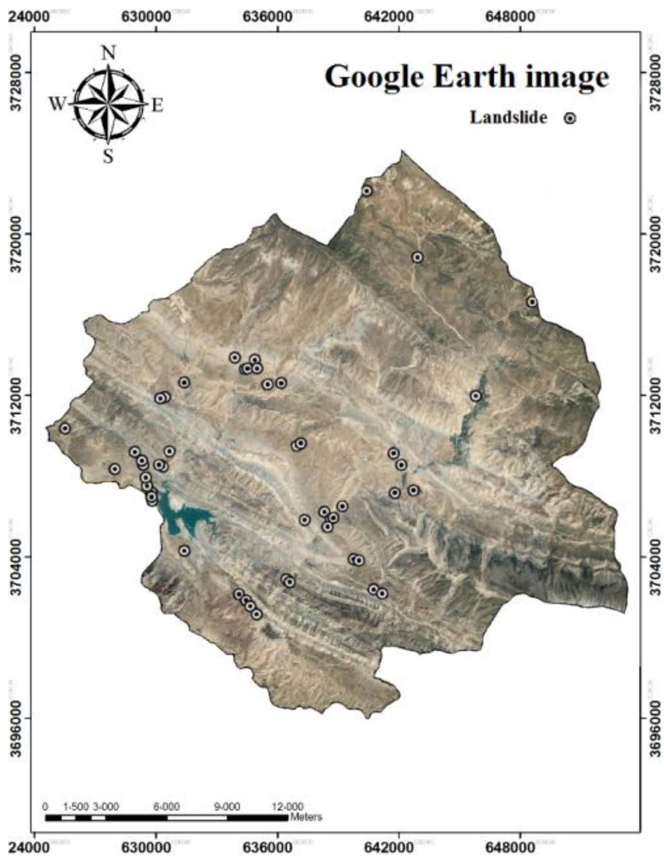

Figure 2. Ilam dam basin Google Earth image in June 6th, 2013

Landslide distribution mapping

One of the most important steps in landslide susceptibility assessment is to identify and map the landslide distribution over the basin area. For this purpose we used Google Earth imagery (June 6th, 2013) and software, field studies and inquiry, local guides and GPS device to prepare landslide map as point feature at 1:50,000 scale within the Ilam dam basin. Two pictures of big landslides in terms of extent in the basin are shown in Figure 3 (from a to b). All the events (50 landslides) were mapped, 35 landslides were used to model the area for susceptibility to landslide and the rest (15 landslides) were used for testing the model (Table 1).

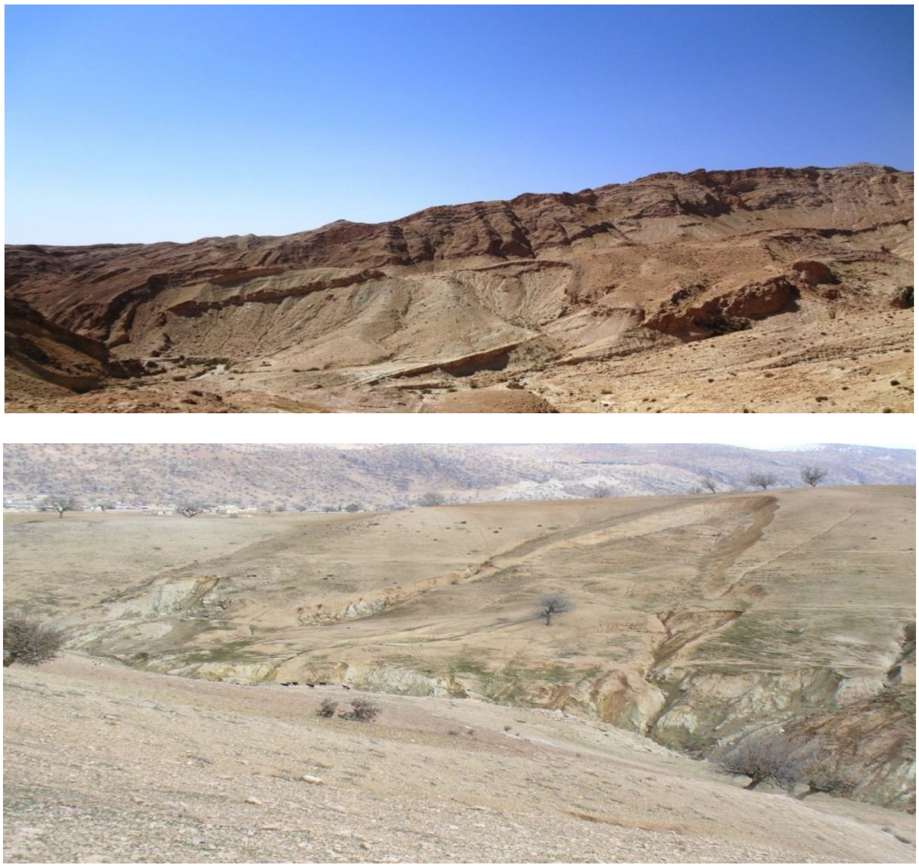

Figure 3. Pictures of big landslides in the Ilam dam basin

The general procedure of landslide susceptibility, risk and management mapping is drawn as a flowchart in Figure 4.

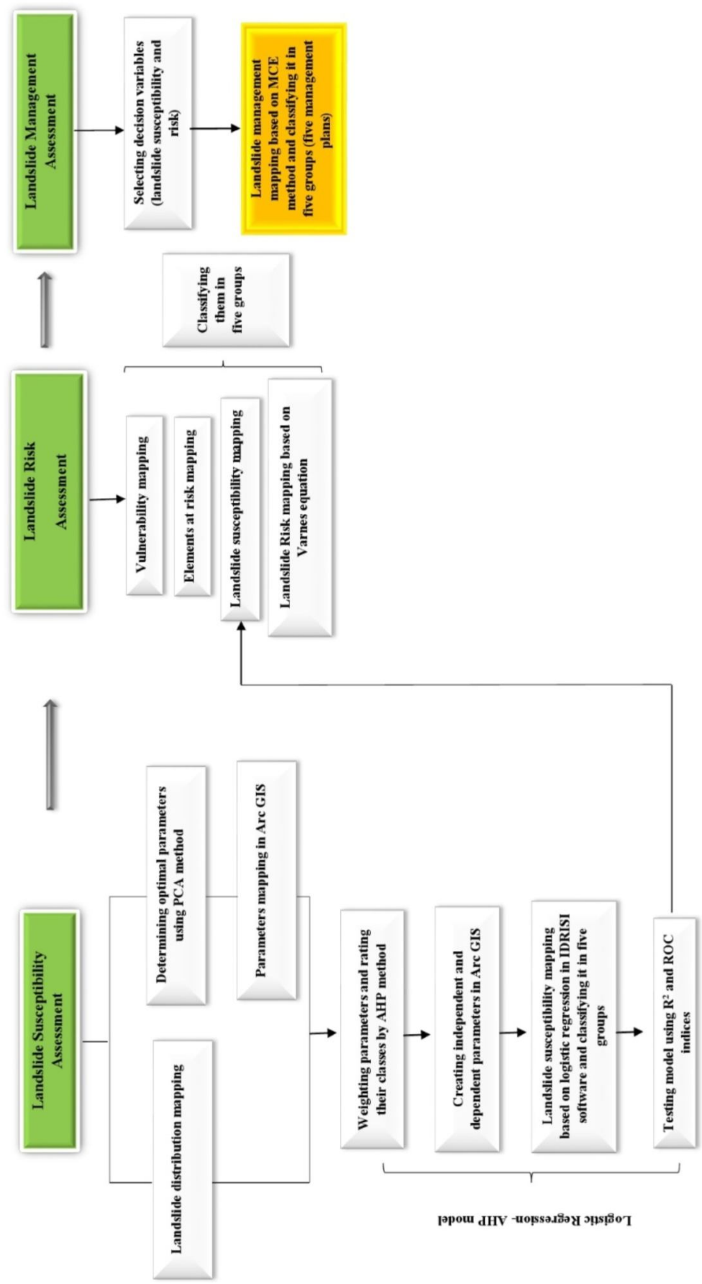

Figure 4. Flowchart of landslide susceptibility, risk and management mapping

Table 1. Landslide points in the Ilam dam basin

Landslide number	Coordinate X	Coordinate Y	Type	**Landslide number**	Coordinate X	Coordinate Y	Type
1	634978	3713286	Complex	**26**	638689	3705832	*Rock-fall*
2	634498	3713286	Creep	**27**	638817	3705896	*Rotational*
3	634370	3713254	Complex	**28**	638369	3706184	*Complex*
4	627941	3708264	Rock-fall	**29**	629764	3706696	*Rotational*
5	629252	3708679	Rock-fall	**30**	629732	3706888	*Transitional*
6	629316	3708488	Rock-fall	**31**	629508	3707432	*Transitional*
7	629732	3707112	Rotational	**32**	629444	3707848	*Rock-fall*
8	636993	3709447	Creep	**33**	630276	3708392	*Rock-fall*
9	642783	3707272	Rock-fall	**34**	630084	3708488	*Rock-fall*
10	641855	3707144	Rock-fall	**35**	642175	3708520	*Rock-fall*
11	639264	3706472	Rotational	**36**	641792	3709095	*Rotational*
12	640096	3703817	Rotational	**37**	628909	3709111	*Complex*
13	636513	3702858	Rotational	**38**	630596	3709159	*Rock-fall*
14	635074	3701162	Rock-fall	**39**	637185	3709575	*Complex*
15	634860	3713716	Transitional	**40**	625541	3710247	*Transitional*
16	634754	3701546	Complex	**41**	630148	3711782	*Rock-fall*
17	634530	3701834	Complex	**42**	630372	3711846	*Complex*
18	634178	3702122	Rock-fall	**43**	645854	3711942	*Rotational*
19	641248	3702218	Rock-fall	**44**	635522	3712486	*Complex*
20	640832	3702410	Rock-fall	**45**	636194	3712550	*Complex*
21	636673	3702730	Complex	**46**	631331	3712582	*Rotational*
22	639840	3703881	Complex	**47**	633852	3713838	*Rotational*
23	631427	3704233	Rock-fall	**48**	648543	3716492	*Complex*
24	638529	3705449	Complex	**49**	642943	3718788	*Rock-fall*
25	637392	3705787	Rock-fall	**50**	640416	3721987	*Rock-fall*

Description: Normal numbers and bold ones are the locations of testing and training landslides respectively.

Data production

The occurrence of landslides, in general, is mainly direct or indirect function of the interaction between natural phenomena and land parameters. Although, it is believed that the accuracy of susceptibility mapping increases when all events' controlling parameters are included in the analytical process, it is hard to find the detailed data and hence, it is hard to achieve that accuracy (Ayalew *et al.*, 2004). In this study, principal component analysis (PCA) in IDRISI software (Clark Labs 2003) and the subjective approach (expertise) were used to select optimal parameters as shown in Figure 5 (a to h).Principal component analysis (PCA) is a classical data analysis technique that finds linear transformations of data that retain the maximal amount of variance which is useful to discover or to reduce the dimensionality of the data set (Jolliffe, 1986). In this study, the parameters which have a high correlation (low variance) were removed based on the expert opinion, since presence of two maps with high correlation (two similar maps) causes a bias in final zoning result.

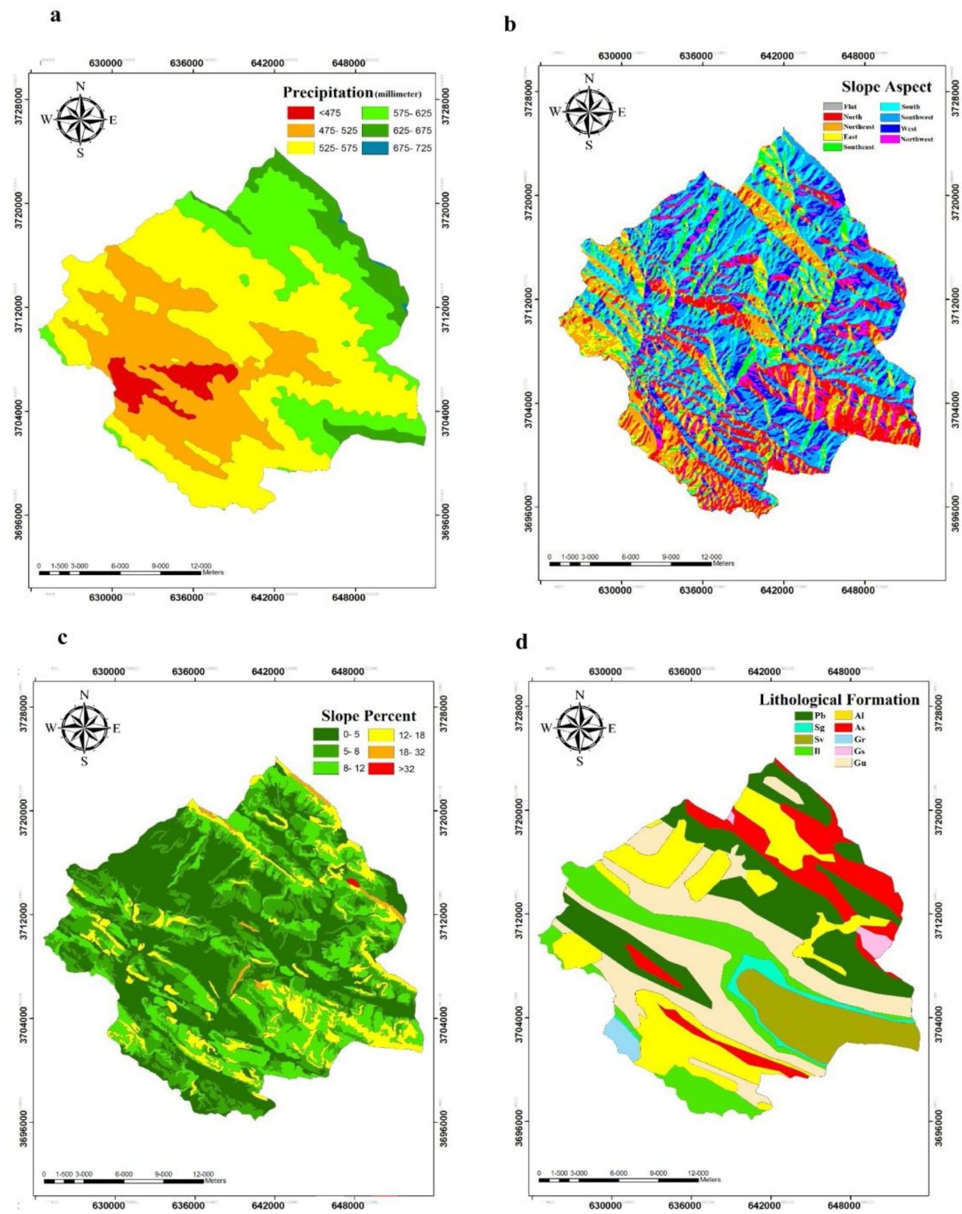

Figure 5. Key parameters affecting landslides in Ilam dam basin

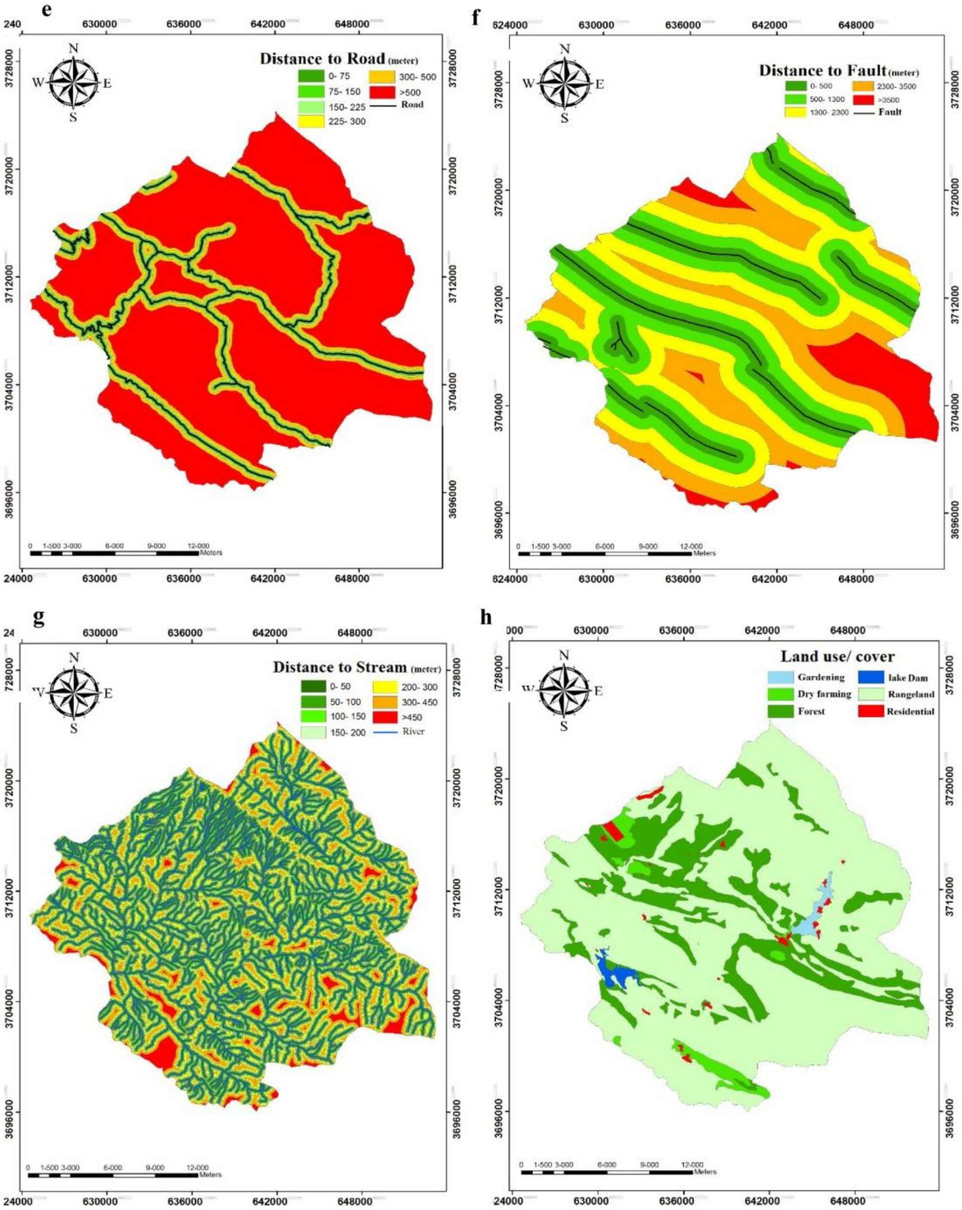

Figure 5. Continued

Hence eight parameters were chosen which are explained in the following sentences. Faults and lithology distribution obtained by digitizing the geological map (1:100,000) provided by the Ilam province Geological Survey Bureau. Geologically, Pabdeh formation has the most area among others which is 25% of the whole basin. Using the topographic and geological maps, the distance to roads, faults and streams (checked by Google Earth imagery) were calculated, respectively and classified based on Karimi Sangchini (2010).The digital elevation model (DEM) with 30×30 m grid size was created from contours extracted from the topographic maps (1:50,000) provided by the Ilam province Bureau of Surveying and Mapping and used as a input to create the slope percent and slope aspect maps. Precipitation map was created based on the precipitation gradient (Equation 1).

$$Y= 0.9158X-832.36 \qquad R^2=0.99 \qquad (1)$$

Where, Y is precipitation as dependent variable and X is digital elevation model (DEM) as independent variable.

Landslide susceptibility zonation using integrated logistic regression –AHP

Landslide susceptibility is the likelihood of landslide occurrence in an area affiliated to the local terrain conditions (Brabb, 1984). In order to get this degree, slope movements which can affect the terrains have to be studied, i.e., estimation of “where” landslides are likely to occur without considering the temporal probability of failure (like when or how frequently landslides occur), and without taking into account the magnitude of the expected landslide (i.e., how large or destructive the failure will be).In this research, a hybrid model is suggested to assess the landslide susceptibility. Since the dependent variable is dichotomous and the relationship between the dependent variable and independent variables is nonlinear, the logistic regression model was constructed based on the physical parameters defined above. Using logistic regression model needs to consider two issues which are the appropriate number of events to create dependent variables and conversion of nominal parameters such as land use/cover, slope aspect and lithology to numeric. In order to solve the last issue, the AHP method was used to weight and rate parameters and their classes respectively. According to this method, a question naire containing pairwise matrix parameter classes were presented to5 instructors and5 executive directors as well as 5 experts (Komac, 2006). Each of these judgments is assigned a number on a scale (0-9) adapted from Saaty (2000) (Table 2). Finally, nine reasonable questionnaires were selected and the geometric mean of responses (Kalantari, 2012) was used as the input to Expert choice software. Expert Choice is a decision-making software that is based on multi-criteria decision making created by Thomas Saaty and Ernest Forman in

1983 (French and Xu 2005).It undertakes the Analytic Hierarchy Process and is being used in different fields such as manufacturing, environmental management and Agriculture. In the method, checking for the consistency of judgments, a coefficient has to be calculated, called the inconsistency coefficient, which should be less than 0.1 (Deyv, 2000). For the first issue, inspired from common methods, usually 70% of samples can be picked for modeling and the rest for testing the model. Next is to determine the appropriate number of samples for modeling. In this context, there is no specific recommendation, but it is clear that this number is strongly dependent on the area of the region. According to the literature review, the ratio of landslides to area in this study in comparison with other researches has the acceptable value. Hence, after producing two sets of layers including: (1) key parameters as independent variables and (2) landslide (Code 1) and non-landslide units (code 0) of superimposed key parameters as dependent variable, the logistic regression was used to obtain an equation in the IDRISI software (Mosaffayi 2007).

Table 2. Saaty rating scale (2000)

Intensity of importance	Definition	Explanation
1	Equal importance	Two factors contribute equally to the objective
3	Somewhat more important	Experience and judgment slightly favor one over the other.
5	Much more important	Experience and judgment strongly favor one over the other.
7	Very much more important	Experience and judgment very strongly favor one over the other. Its importance is demonstrated in practice.
9	Absolutely more important	The evidence favoring one over the other is of the highest possible validity.
2,4,6,8	Intermediate values	When compromise is needed

The logistic regression equation given by Ayalew *et al.,* (2004) is as follows:

$$Y=\log(p)=\ln(p/(1-p))=\beta_0+\beta_1 X1+\cdots+\beta_n Xn \quad (1)$$

Where,

P represents independent variable probability (Y) and (p/(1-p) denotes likelihood ratio or disagreement, β0 is constant and β_1, β_2 and βn are coefficients indicating size and magnitude of independent variables (X_1 ،X_2 and X_n) contributions to the dependent variable. The best equation for controlling (key) factors and landslide and non-landslide was produced in IDRISI software, then classified based on natural break classification scheme into five classes of susceptibility (very low, low, moderate, high and very high).

Validation of landslide susceptibility zonation model

ROC (receiver operating characteristic) indicator can be obtained from ROC curve that is a fundamental tool for diagnostic evaluation test. In ROC curve the true positive rate is plotted as a function of the false positive rate for different cut-off points of a parameter. Therefore, the closer ROC curve to the upper left corner leads to the higher overall accuracy of the test (Zweig and Campbell 1993).The area under ROC curve (AUC) depicts the accuracy of a prediction system by describing the system's ability to expect the correct occurrence or non-occurrence of pre-defined “events” (Negnevitsky, 2002).This index was calculated in the IDRISI software from landslide susceptibility and landslide/non-landslide area maps.

Pseudo-R^2 is an index which evaluates the performance of the logistics regression model and it is calculated according to Equation 2.

$$\text{Pseudo } R^2=1-(\log(L))/(\log(L_0)) \quad (2)$$

Where,

L (Likelihood) is probability function value when model is fitted completely.

L_o is Probability function value when all coefficients are set as zero, except intercept.

Unlike R^2inordinaryregression, pseudo-R^2 does not indicate the proportion of variance explained by the model but it denotes the dependency between experimental data and output of regression model. So, its value is generally much lower than R^2. When pseudo-$R^2$is equal to1 it denotes the complete fitw here zeropseudo-R^2representsnosignificant relationship between the in dependent and dependent variables. In spatial studies, pseudo-R^2greater than 0.2 may be considered as a relatively good fit (Clark *et al.*, 1986). After evaluating the accuracy of the model, the next step is to assess landslide risk. We reiterate that the ultimate goal of this study is to provide a landslide risk management program which needs two variables including landslide susceptibility and risk for making a decision.

Landslide Risk Assessment

Landslide total risk as the expected number of lives lost, injured persons, damage to the property and disruption of economic activity for a given area can be estimated using the general risk equation (Equation 3):

$$R= \sum S\times E\times V \quad (3)$$

Where, "R" denotes risk, "S" susceptibility, "E" elements at risk as number or value of the particular elements at risk (e.g., number of buildings, cost of buildings, number of people, etc.) and "V" vulnerability as a physical vulnerability of particular type of element at risk (from 0 to 1) for a specific type of hazard and for a specific element at risk respectively. Risk formula might look deceptively simple, but when one tries to use it for a particular situation, like calculation of specific risk to buildings or persons in buildings, the formula quickly turns out to be very complicated and numerous factors should then be taken into account that are difficult to evaluate (van Westen, 2005). Vulnerability is determined by construction type (e.g., building materials, foundation types), which determines the capacity of the building to with stand impact. In addition, due to their usage, structure and size, the value or cost of these buildings will change. Therefore in calculation, each building will have a different value for risk that will make it more different (Kunlong, 2007). Furthermore, when we talk about the calculation of risk for persons, it has to be considered that temporal changes in vulnerability also play a significant role, both for persons in the buildings and for risky locations outside (e.g., in traffic). Buildings, on their own, might be affected by different types of landslides and in different ways. The vulnerability assessment of the elements at risk is a focal and a problematic point in risk assessment, and its level is qualitative or semi-quantitative. Due to the type of elements at risk, vulnerability assessment involves two types of elements: life and economy. Because of the difficulties in life and indirect economy losses calculation (telephone, electricity networks and dams) the research is limited to direct economy losses including damages to buildings, roads and land uses/covers. In vulnerability assessment of this research, AHP and Expert choice software were used as a semi-qualitative method which led to the semi-qualitative risk assessment. Beside the characteristics of elements at risk that should be considered and advised in questionnaires, vulnerability has also significant relation with susceptibility degree. Elements at risk in this study include roads (paved and unpaved) and natural resources (forest, rangeland, and reservoir).In the end, the total risk of the basin was created from product of classified maps of susceptibility, vulnerability and elements at risk and then it was classified for next step. The choice of classification method is a crucial step. Here, for reducing interference of expertise, natural break classification scheme was used to classify all maps. The final stage of the study was to propose management plans in a map format.

Landslide Management Assessment

This research attempts to deal with prevention measure sand management actions in term of scenarios, using field evidences to control landslides before their occurrence. Therefore, multi-criteria evaluation (MCE) method was used. The MCE is a general appraisal method for ranking decision variables (Mahini, 2010; Eastman, 1996).In the most common procedure for MCE, criteria are evaluated as fully continuous variables. Such criteria are typically called factors or variables, and express varying degrees of suitability for the considered decision. Landslide susceptibility and risk were selected as variables. The process which leads to converting data to this type of numeric scales is called standardization (Voogd, 1983). In this research landslide susceptibility and risk degrees (classes) is used (1 to 5). Each standardized variable is multiplied by its weight and then all of the variables are summed together (Equation 4). Weighting was done based on AHP in Expert choice software by experts.

$$MN=\sum_{(i=1)}^{n} Ri\ Wi \quad (4)$$

Where,

MN: management number, R_i: variable (factor) score (1 to 5) and W_i: variable weight
Management numbers are classified into five groups based on the natural break scheme.

3. Results and Discussion

In the study area, 50 landslides in total were recorded and their map was prepared in ArcGIS. Since the survey is not originated from satellite or aerial image interpretation (just Google Earth imagery), therefore some of landslides in far mountains might be missed which might lead to the deviation of training data, which is counted as the input noise (Lei and Jing-feng, 2006). Landslide controlling parameters were determined using PCA test (Table 3) and their map was prepared in ArcGIS. As it is shown in Table 3, the highest correlation was observed between elevation parameters and the precipitation as 85 % and the lowest correlation was between distance to fault and slope percent parameter as 31%.Thus, considering triggering role of the precipitation in landslide, elevation parameter was eliminated and other eight parameters including lithology, distance to stream, distance to road, distance to fault, slope percent, aspect, land use/ cover and the precipitation were considered. For AHP after entering the pairwise matrix of parameter classes (geometric mean of responses) (Tables 4 and 5) in Expert choice software, final weights of parameter classes were calculated using eigenvector method (Table 6).The inconsistency rate of judgments was 0.002 which is acceptable. In Tables 4 and 5, pairwise matrix of parameter classes, filled out by an expert, are shown. As it is indicated in Table 4 the expert considered lithology parameter more important than the other parameters. This is true also in Table 5 on "Gu" class (Lime-shale) of lithology parameter. In the logistic regression model, after entering independent variables (controlling parameters) and dependent variable (landslide and non-landslide units) in IDRISI software, the best equation was obtained (Equation 4).

Table 3. Correlation matrix between parameters (PCA)

PCA Matrix (%)	Slope Aspect	Distance to Road	lithology	Land use	Distance to river	Elevation	Precipitation	Distance to Fault	Slope
Slope Aspect	100	46	70	55	63	40	58	61	43
Distance to Road		100	71	67	55	55	38	50	51
lithology			100	51	47	69	73	53	47
Land use				100	35	44	50	79	55
Distance to river					100	67	65	44	67
Elevation						100	85	52	60
Precipitation							100	70	40
Distance to Fault								100	31
Slope									100

Table 4. Pairwise matrix of landslide controlling parameters

Parameters	lithology	slope	Slope aspect	Distance to road	Precipitation	Land use/ cover	Distance to fault	Distance to stream
lithology	1	4	8	5	2	7	3	6
slope		1	5	2	3	4	5	3
Slope aspect			1	4	7	2	6	3
Distance to road				1	4	3	3	2
Precipitation					1	6	2	5
Land use/ cover						1	5	2
Distance to fault							1	4
Distance to stream								1

Description: [black numbers: Rows priority over columns, Red numbers: Columns priority over rows]

Table 5. An example for pairwise matrix of parameter (Lithology) classes

Lithology				Gu	iL	Pd	As	Al	Gr	Sg	Sv	Gs
Code	Formation	Material description	Geological system (Period)									
Gu	Gurpi	Lime-shale	Neogene	1	9	8	8	7	6	5	4	3
iL	Ilam	Lime-Clay-Shale	Cretaceous		1	8	7	6	5	4	3	2
Pd	Pabdeh	Lime-shale	Cretaceous			1	7	6	5	4	3	2
As	Asmari	Limestone- Dolomite	Paleogene				1	6	5	4	3	2
Al	-	Alluvial	Quaternary					1	5	4	3	2
Gr	Garau	Shale	Cretaceous						1	4	3	2
Sg	Surgah	Shale	Cretaceous							1	3	2
Sv	Sarvak	Limestone, Karstic	Cretaceous								1	2
Gs	Gachsaran	Anhydride, Halite, Marl, lime	Neogene									1

Logit (dependent) = 14.2 (lithology) +33.3 (land use/cover) + 43.5 (precipitation) + 65.4 (road)+16.9(slope)+ 11.8 (aspect)-21.7 (stream)- 12.8 (fault)-3.8 (4)

Reviewing parameters’ impact coefficient in logistic regression method, it can be concluded that probability of landslide occurrence is directly related to precipitation and slope percent and reversely related to distance to fault and stream that is confirmed by experts opinions. Positive value for distance to road parameter seems to be unreasonable in the first sight. But it might be caused because of large area of the fifth class (>500 m from the road), so it covers more landslides. However, these parameters and landslide inventory method can cause input noises which will lead to unreasonable landslide distribution. On the other hand, software error in preparation of parameters should be considered. The other issue in this field is the location of landslides recorded by the GPS which can be at the toe, centroid, on the main scarp and so forth. Considering that the most accurate DEM of the area was 30 × 30 and dimension of most of the landslides were small, so the location of the recorded landslides would not have a large impact on the distribution of landslide in parameter classes (especially the distance to road parameter) and therefore will not change the rate of classes. Overall, according to the logistic regression-AHP model, distance to road and land use/cover were introduced as the most influential anthropologic parameters and precipitation as the natural controlling and triggering factor of landslide in the Ilam dam basin respectively. Considering the critical parameters are human induced, so it is essential to control and to manage the human activities in the basin. Of course, inherent potential of the basin to landslide occurrence should be taken into account.

Finally, the landslide susceptibility map derived from logistics regression-AHP model was presented based one equation 4 (Figure 6). To assess logistic regression model accuracy, thepseudoR^2andROCindiceswere used.ThepseudoR^2 of 0.32 indicates that them delis fairly well fitted. The qualitative relationship between AUC and prediction accuracy can be classified into the following categories: 0.9–1(excellent); 0.8–0.9 (very good); 0.7–0.8 (good); 0.6–0.7(average); and 0.5–0.6 (poor) (Yesilnacar, 2005). In figure 7, value 0.812 for AUC (prediction accuracy equals to 81.2%) indicates that the model has very good accuracy in landslide susceptibility zoning in Ilam dam basin.

Data required to identify elements at risk were extracted from different data sources such as Google Earth and Ilam Natural resources and Watershed management Bureau database. So, rangeland, forest and reservoir, residential areas as well as road length (paved and unpaved) were distinguished, counted in every single unit and then categorized into five classes (I to V as numbers of elements in each unit) (Figure 8). Classes IV and V of elements at risk accounted for 206.56 $km^2$of the area which means 44% of the basin has the most elements causing risk concentration than the other areas.

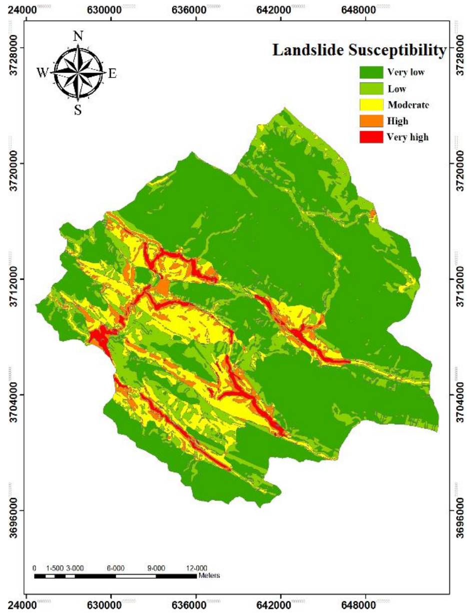

Figure 6. Landslide susceptibility in Ilam dam basin

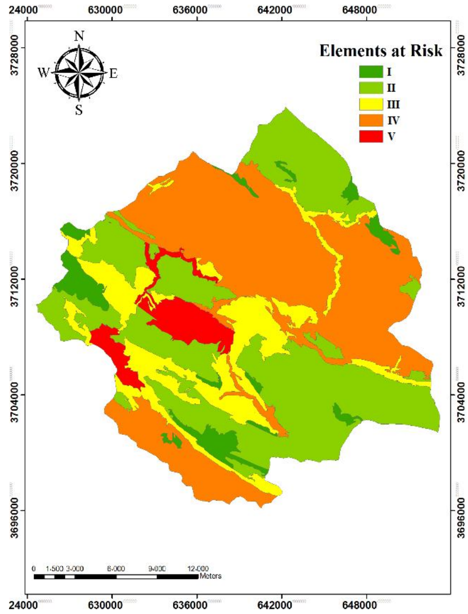

Figure 8. Elements at risk inIlam dam basin

Table 6. Final rates of parameter classes calculated in Expert choice software

Parameter	Class	Final rate	Parameter	Class	Final rate	Parameter	Class	Final rate
Land use/ cover	Gardening	1	Distance to Road	0-75	2.9	Slope (%)	0-5	4
	Rainfed farming	0.1		75-150	1.9		5-8	3.6
	Forest	0.8		150-225	0.9		8-12	1.6
	Reservoir	0.2		225- 300	0.4		12-18	1
	Rangeland	0.3		300- 500	0.5		18-32	0.4
	Residential	0.2		>500	0.2		>32	0.4
Distance to stream	0-50	1	Distance to fault	0-500	1.2	Lithology	Gu	10
	50-100	1.4		500-1300	5.2		iL	3.5
	100-150	0.6		1300-2300	2.7		Pd	3.9
	150-200	0.3		2300-3500	0.8		As	2.7
	200-300	0.4		>3500	0.5		Al	7.7
	300-450	0.2	Slope aspect	N	3.5		Gr	1.3
	>450	2.2		E	3.1		Sg	0.9
Precipitation	<475	2.2		SE	1.2		Sv	0.7
	475-525	4		S	0.2		Gs	0.5
	525- 575	1.5		NE	0.5			
	575-625	0.9		W	3			
	625- 675	3.7		NW	2			
	675-725	0.5		SW	1.2			
				F	0.3			

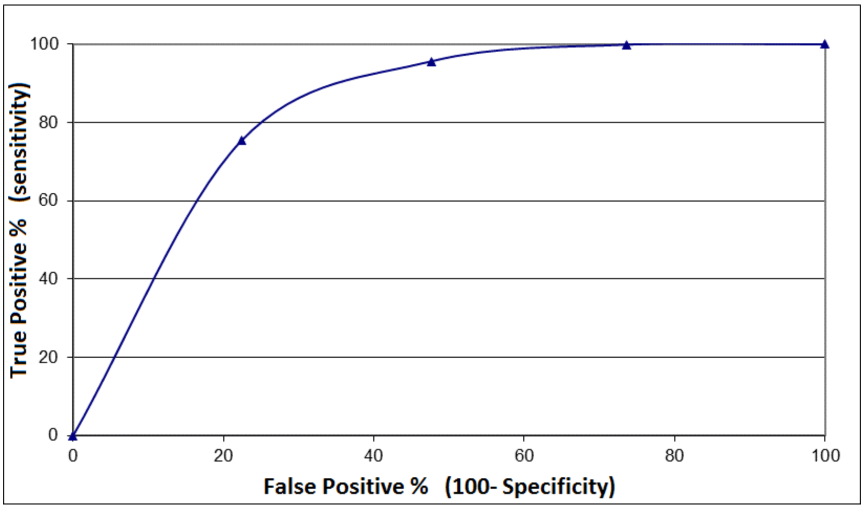

Figure 7. ROC curve to validate logistic regression-AHP model

Vulnerability classes were determined by expertise based on two main criteria including susceptibility classes and physical-biological characteristic of elements at risk. Vulnerability pairwise matrix of elements was filled out by experts and then Expert choice was used to determine the final values (0 to 1) with the inconsistency value of 0.04 which is acceptable (Figure 9). Eventually, vulnerability values were classified base on natural break scheme into five groups (Figure 10).

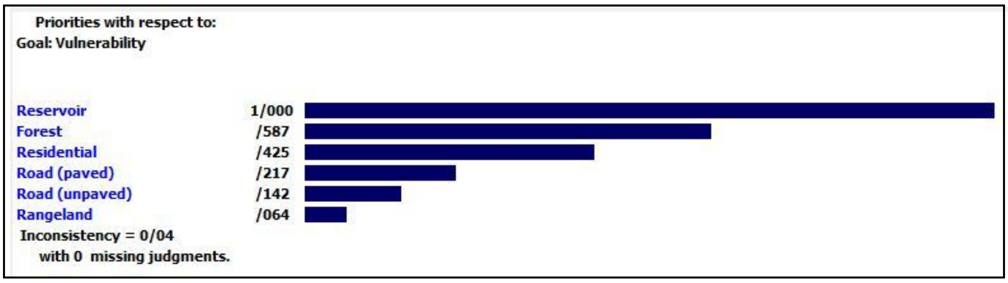

Figure 9. Column chart of vulnerability weights of elements at risk in Expert choice vs. 11software

Susceptibility, elements at risk and vulnerability maps were multiplied together by the means of total risk equation, and then risk values were calculated and classified into very low, low, moderate, high and very high groups based on the natural break scheme (Figure 11). Approximately, 39.84 and 72.45km^2 of the Ilam dam basin have high and very high landslide susceptibility and risk degrees respectively. Comparing landslide susceptibility and risk maps shows that 76.5% of high and very high classes of susceptibility map are located in high and very high classes of risk. In other words, in this basin, areas with high landslide susceptibility had the most elements at risk with high vulnerability which will lead to high risk and numerous casualties. Since the reservoir is located in the very high risk area, damages to weir and the body of dam, caused by probable landslides, are expected.

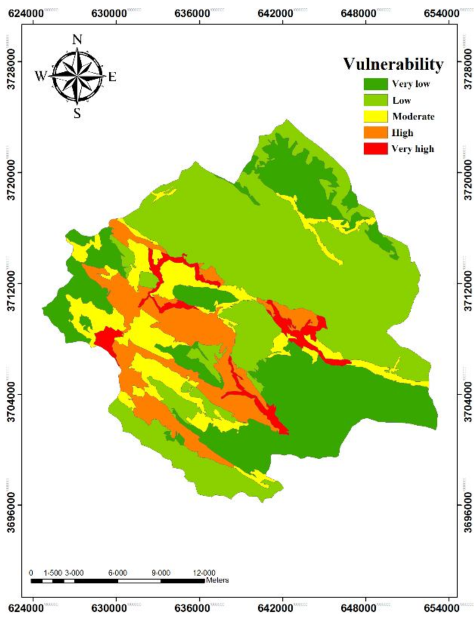

Figure 10. Vulnerability of elements at risk in Ilam dam basin

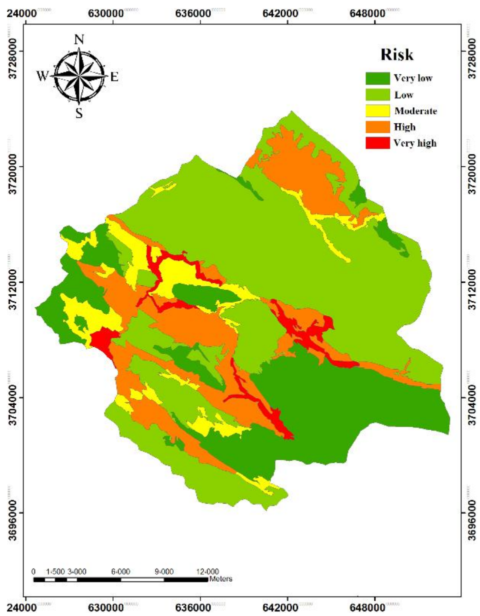

Figure 11. Risk map in Ilam dam basin

As it was mentioned before, the MCE method was used to prepare a map for management plans. Landslide susceptibility and risk were selected as decision variables and standardized by their class degrees, then Expert choice was used to calculate the final weights (0.5 and 1 for the susceptibility and risk respectively) (Figure12). The acquired weights for variables of landslide susceptibility and risk (giving more importance to risk variable by experts) can be known as more realistic definition of risk in contrast to susceptibility which comes from devoting more importance to risk in the life of experts. Each standardized variable was multiplied by its weight, then the variables were summed together and we arrived at the multi-criteria solution. Finally, management scores of pixels were classified by using natural break scheme into five groups and administrative plans and corresponding actions were proposed for each class (Table 7, Figure13). It should be noted that all plans and actions offered here are just for the Ilam dam basin and it's a result of field investigations, taking notes from comprehensive studies conducted in the basin and considering experts opinion with proper knowledge on the area. As it is indicated in Table7, the higher degrees of susceptibility and risk are, the more solid and more stringent management plans (relocating the villages in worst situation like V class). The IV and V classes of management plans containing intense actions such as avoiding from hazards and controlling actions, cover 15.5% of the basin including reservoir and adjacent areas.

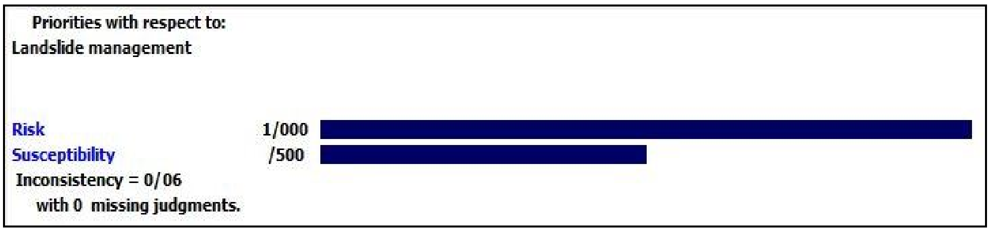

Figure 12. Chart of weights of decision variables in the Expert choice software

Table 7. Landslide management programs according to the priority

Management class	Management plan	Suitable action
I	No plan	No plan in short-term
II	Compromise- Tolerance against minor risk (natural tax)	Training the peasants- Constructing traditional drainage
III	Compromise- No tolerance against risk	Stop land-use changes and non-standard road building on unstable slopes
IV	Avoiding danger	Limiting construction activities to possible extent, converting rain-fed farming to gardening, suggesting mechanical operations on unstable slopes, road conservation, improving sanitation projects.
V	Controlling practices	Converting farming to gardening and forestry, suggesting mechanical and/or biological operations, draining water on unstable slopes, relocation of villages.

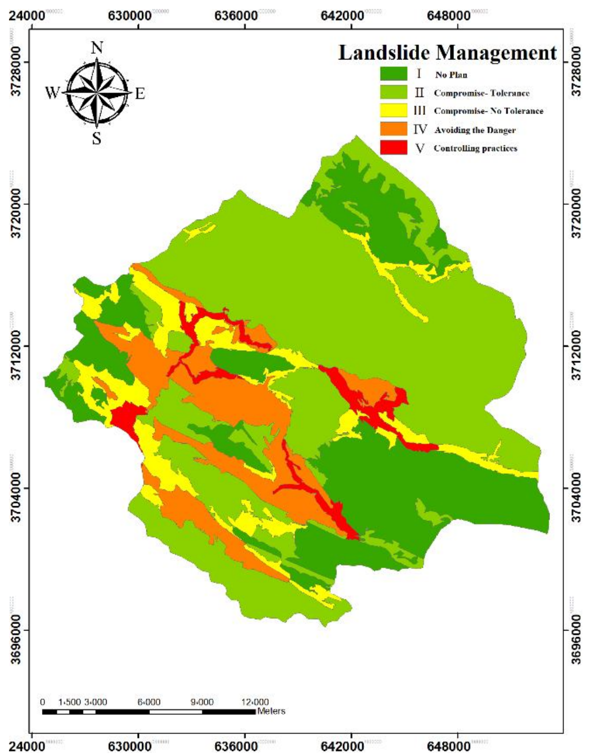

Figure 13. Landslide management plans in Ilam dam basin

4. Conclusion

Despite the extensive research in the field of landslide susceptibility and risk mapping, there is still uncertainty and inability of the parameters used in the estimation of landslide and this will be passed to the ultimate results. This problem makes us to resort to semi-qualitative (such as AHP) and qualitative methods. Even as such, because of the speed in assessment and providing an overview of the situation in the region and consequently a prelude to the future more accurate and detailed actions, we cannot dismiss these semi qualitative methods.

In this study, in the west of Iran, eight predisposing factors including lithology, distance to stream, distance to road, and distance to fault, slope percent, slope aspect, land use/cover and the precipitation were used in mapping landslide through a hybrid logistic regression –AHP model. The landslide susceptibility map was prepared in five classes of very low, low, moderate, high and very high. By using ROC curve and pseudo R^2 statistical test, the accuracy of the model was assessed. The pseudo R^2 value was 0.32 and AUC value (area under the ROC curve) was 81%, which shows the very good accuracy of landslide susceptibility zoning model. The MCE method was used to provide management map as the ultimate goal of this research. According to this method, both susceptibility and landslide risk were selected as the decision variables and after being weighted and standardized, they were combined together in the form of MCE equation and classified in five classes from I to V. Plans and management actions for each class were presented. With emphasis on the results of this study it can be concluded that the anthropogenic and environmental factors interact in the landslides occurrence of the basin (known as trade off). Also, as the reservoir of the dam is located in the landslide susceptibility, risk and management zone of very high, the damages caused by the occurrence of this phenomenon in this region (reservoir) including filling of reservoir by sediments transported by landslides, damages to the body and weir of dam and condition of the downstream watershed have to be studied and estimated in detail. Finally, we recommend to use other landslide susceptibility zoning models with other predisposing factors such as soil depth and type, elevation, plan-curvature and vegetation along with the present research parameters (through different classification). Applying other risk assessment algorithms (e.g. risk analysis matrix) and landslide management (e.g. multi criteria decision making method) as well as the present numerical models are also advised. Also, the results of this research can be used bycrisis management organizations, natural resources and agriculture organizations, students associated with this issue, experts and researchers interested in the critical subject of landslide.

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