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Landslide Hazard Zonation Using Multivariate Statistical Models in the Doab Samsami Watershed, Chaharmahal Va Bakhtiari Province, Iran

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Abstract

The Doab Samsami watershed is located in the Chaharmahal Va Bakhtiari province, and serves as one of the main tributaries of the Karoon River Basin. Using aerial photos interpretation and field studies, a landslide distribution map for the study area was prepared. Thirty-seven cases of landslide incidents were observed. Nine parameters including elevation, slope, aspect, lithology, distances from fault, stream and roads, land use, and annual precipitation were chosen as landslide determinant factors. Potential landslide hazard maps were prepared using the multivariate stepwise regression model and the logistic multivariate regression model; which were subsequently compared with field data. ROC Index was also considered for the models' accuracy assessment. According to the research results, the logistic multivariate regression model was considered as the superior model for Doab Samsami watershed with an ROC equal to 0.865. Furthermore, the results revealed that about 46% of the watershed area was located in high and very high hazard zones among others. The obtained landslide susceptibility maps may be promising in appropriate watershed management practices and for a sustainable development in the regions characterized by conditions similar to the study area.

Keywords: Landslide hazard, Multivariate statistical model, ROC Index, Doab Samsami.

1. Introduction

Landslides are one of the most important natural hazards, causing enormous financial and life losses on an annual basis worldwide (Kelarestaghi and Ahmadi, 2009). Landslides are amongst the most catastrophic natural hazards in mountainous terrains. The study of landslides has received attentions throughout the world mainly due to the increasing awareness regarding the socio-economic impact of landslides, as well as, the increasing pressure of urbanization on the mountainous landscape (Aleotti and Chowdhury, 1999). Each year, the phenomenon of landslides occurs around many parts of the world including Iran. By the end of September 2007, 4,900 landslides were recorded and the losses resulting from mass movements in Iran were estimated at about 317 million US dollar (Pourghasemi et al., 2013). The burying of Abikar village of the Charmahal Va Bakhtiari Province in the spring of 1997 is one of the most obvious catastrophic examples of landslide damages in the Iran. The volume of material transported by this landslide was 9 million cubic meters. Abikar village with all its 55 residents was buried under the materials of the landslide. Hence, landslide susceptibility mapping can be one of the preliminary steps to minimize such costs (Regmi et al., 2014). Also, landslide susceptibility assessment is found to be a crucial process for the prediction and management of natural disasters. Additionally, it can be considered as a necessary step for integrated watershed management, hazard mitigation, natural and urban planning in government policies worldwide (Dahal et al., 2008; Kayastha et al., 2012). The identification and classification of landslide-prone areas and the susceptibility zonation is a great step in the evaluation of environmental hazards and can make a great contribution to the watershed management (Sakar, 1995). Landslide susceptibility assessment is conducted using three approaches, namely the qualitative, semi-quantitative, and quantitative approaches (Lee and Jones, 2004). Quantitative methods are inspired by mathematical logic, the correlation between factors, and landslide occurrence which include

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bivariate regression analysis (Guzzetti 2002; Nandi and Shakoor, 2009; Yilmaz et al., 2012; Bijukchhen et al., 2013; Jaafari et al., 2014; Youssef et al., 2015b), logistic regression (Ayalew and Yamagishi, 2005; Park et al., 2013; Karimi Sangchini et al., 2014; Karimi Sangchini et al., 2015; Dou et al., 2015a; Dou et al., 2015b), Certainty Factor Model (Dou et al., 2014; Dou et al., 2015a), genetic algorithm (Dou et al., 2015c), fuzzy logic (Gupta et al., 2008; Tangestani 2009; Pourghasemi et al., 2012), and artificial neural network model (Caniani et al., 2008; Pradhan et al., 2010; Zare et al., 2013; Polykretis et al., 2015; Dou et al., 2015b). Qualitative methods are based on expert opinions (Rahman and Saha, 2008; Karimi Sangchini et al., 2011; Karimi Sangchini et al., 2016). Qualitative methods which utilize weighting and rating approaches are known as semi-quantitative methods (Yalcin, 2008). Some examples of such methods are the analytic hierarchy process (AHP) (Yalcin, 2008; Komac, 2006; Rahman and Saha, 2008; Ercanoglu et al., 2008; Akgun and Turk, 2010; Pourghasemi et al., 2012; Awawdeh et al., 2018) and weighted linear combination (Gorsevski et al., 2006; Kouli et al., 2010). Traditionally, the multivariate logistic regression approach has been applied by various researchers (Yesilnacar and Topal, 2005; Nandi and Shakoor, 2009; Felicisimo et al., 2013; Karimi Sangchini et al., 2016). In the previous research works, the abovementioned models had been used in a separate manner. The proposed methodologies use both expert opinions and ground truth simultaneously.

To generate statistics-based susceptibility maps, many modeling approaches for landslide hazard prediction can be applied. Logistic regression and discriminant analysis are the most frequently used models (Brenning, 2005). Logistic regression and statistical models have been developed using the geographic information system (GIS) for landslide hazard zonation (Lee et al., 2010). The multivariate approach was adopted by various practitioners worldwide (Yesilnacar and Topal, 2005; Nandi and Shakoor, 2009; Felicisimo et al., 2013). In the present research, landslide susceptibility mapping with a logistic regression and stepwise multivariate statistical models were used to determine the landslide-prone areas for the sake of landslide hazard management in Doab Samsami watershed.

2. Materials and Methods

2.1. Study Area

Doab Samsami Watershed is spanned over coordinates 421386 to 447042 E and 3550345 3568932 N, covering an area of 276.3 km2 in the Chaharmahal Va Bakhtiari Province, southwest of Iran (Figure 1). This watershed is one of the major sub basins of the Karoon River. The elevation in the study area varies from 1,775 to 3,825 m above sea level. According to the Iran meteorological organization report, the average annual precipitation in the study area is 970 mm. This watershed is nestled in the middle of Zagros Mountains. Subsequent erosion has removed erodible rocks, such as mudstone, and siltstone while leaving behind harder rocks exposed, such as limestone, and dolomite. This differential erosion has formed the linear ridges of the Zagros Mountains. Rangelands account for 66 % of this region and the rest of the area is covered by orchards, forests, agricultural and rocky lands.

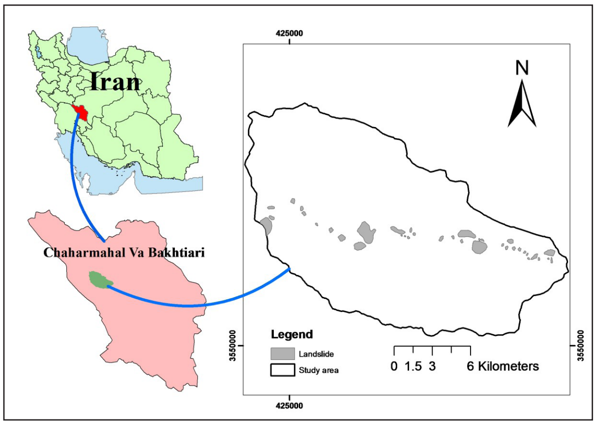

Figure 1. Location map of the study area.

2.2. Landslide Inventory Map

Landslide inventory maps are prepared by gathering the information and data on landslides, or by analyzing the data obtained from remote sensing and GIS techniques. In the current research, a landslide inventory map was prepared using field reconnaissance, local information, and aerial photograph interpretation.

2.3. Selection and Effective Factor Classification

According to the literature review and field conditions of Doab Samsami watershed, a total of nine factors including altitude, slope percentage, slope aspect, lithology, distance from faults, rivers, village and roads, land use, and precipitation amount were chosen as main determinant factors of land sliding. In the next stage, the area and landslide percentage, the density ratio, and landslide density percentage, in each class of these nine landslide factors, were calculated.

2.3.1. Landslide Determinant Factors

Those determinant factors in the occurrence of a landslide are described below (Table 1 and Figure 2). . Vector-type spatial database was extracted through transforming such factors using the ArcGIS 9.3 (ESRI 2008). The resolutions of the girds of the causative factors are 30×30 meters.

2.3.2. Topographical Factors

A digital elevation model (DEM) was created from 20m interval contours and survey base points which were extracted from the 1: 50,000-scale topographic maps (Cartographic Center of Iran, 2003). Based on this DEM, altitude, slope percentage, and slope aspect were prepared.

Altitude was classified into eleven classes with 200 m intervals (Karimi Sangchini et al., 2016). Slope percentage was grouped in six classes of 0-5°, 6-15°, 16-25°, 26-35°, 36-45°, and >45° (Kelarestaghi and Ahmadi, 2009). Slope aspect was classified into eight classes of N, NE, E, SE, S, SW, W, and NW. The slope conditions have received great attention, as slope configuration and steepness play an important role in landslide occurrence (Table 1 and Figure 2 (a-c)).

2.3.3. Lithology

The underlying geology is found to be one of the most substantial factors for landslide modeling. Different geological formations are characterized by various compositions and structures which in turn contribute to the strength of the material. In the current research, a 1: 100,000-scale geological map (Geological Survey and Mineral Explorations of Iran, 1996) was applied to lithology mapping which was then classified according to the lithological units (type) into eleven groups (Table 1 and Figure 2d). Geological formations in this watershed were fossiliferous marly limestones with intercalations of marls and sandy limestones (OM2), white nummulitic limestones, marly limstones and dolomitic limestones (EO), mainly orbitolina limstones, locally evaporites in the lower part (K), shale and marls interbedded with marly limstones containing Ammonites and Inceramuses (K8), marly fossiliferous limestones and thin sandy argillaceous limestones (K7), recent terraces and recent alluviumes (Qal), old terraces deposits (Qt and QR), carbonate-dominated sedimentary package with shale-marl intervals (Pd), and red conglomerates (mainly chert pebbles), sandstones (locally with volcanic intercalations), and silstone with evaporites intercalations (E).

2.3.4. Distance from Faults, Streams, and Roads

A topographical map was used to extract distance to streams, whereas, a distance to faults map was calculated drawing upon the geological map of the study area (Pourghasemi et al., 2012). On the other hand, the distance to roads map was prepared using a road map of the study area. The distance to faults factor was classified into five classes of 0-500, 500-1300, 1300-2300, 2300-3500, and >3500 m. In the case of distance from streams, there were seven classes with 50m intervals. As for the factor of distance from roads, there were six classes of 0-75, 75-150, 150-225, 225-300, 300-500, and >500 m (Table 1 and Figure 2e-g).

2.3.5. Land Use

The land use map was developed using Landsat images provided by Iranian forest, rangeland, and watershed management (http://www.frw.org.ir/pageid/34/language/en-US/Default.aspx). Five classes of rocky land, poor range, medium range, irrigated farming, and dry farming were detected in the study area (Karimi Sangchini et al., 2016) (Table 1 and Figure 2h).

2.3.6. Precipitation

There is no doubt that precipitation is the most important triggering factor in landslides (Naghibi et al., 2015). This factor was mapped using Inverse Distance Weighting (IDW) Interpolation method and classified into five classes of 850-1000, 1000-1200, 1200-1400, 1400-1600, and >1600 mm in the study area (Table 1 and Figure 2i) (Karimi Sangchini et al., 2014).

Table 1. Calculation of the final susceptibility value of each identified land unit

Data layers	Total area (ha)	% of total area (A)	area of Landslide	% of area landslide (B)	Area density value
Aspect					
N	1719.99	6.23	30.38	4.79	-5.32
NE	7715.25	27.93	262.21	41.30	11.01
E	2518.976	9.12	125.04	19.70	26.66
SE	2455.739	8.89	49.94	7.87	-2.64
S	4798.129	17.37	85.43	13.46	-5.17
SW	4676.126	16.93	59.57	9.38	-10.24
W	1370.671	4.96	0.00	0.00	-22.98
NW	2372.664	8.59	22.29	3.51	-13.58
Elevation (m)					
1775-1900	461.9037	1.67	57.97	9.13	102.53
1900-2100	2932.099	10.61	289.84	45.65	75.87
2100-2300	5057.21	18.30	172.11	27.11	11.05
2300-2500	4882.323	17.67	25.45	4.01	-17.77
2500-2700	4593.758	16.63	53.76	8.47	-11.28
2700-2900	3952.74	14.31	35.73	5.63	-13.94
2900-3100	2929.929	10.61	0.00	0.00	-22.98
3100-3300	860.752	3.12	0.00	0.00	-22.98
3300-3500	1532.477	5.55	0.00	0.00	-22.98

Data layers	Total area (ha)	% of total area (A)	area of Landslide	% of area landslide (B)	Area density value
3500-3700	382.009	1.38	0.00	0.00	-22.98
3700-3825	43.83642	0.16	0.00	0.00	-22.98
Slope (%)					
0-5	201.0076	0.73	21.17	3.33	82.34
6-15	2119.803	7.67	59.33	9.35	5.01
16-25	4522.01	16.37	244.67	38.54	31.13
26-35	2157.286	7.81	112.02	17.65	28.95
36-45	492.5005	1.78	7.39	1.16	-7.97
>45	18136.12	65.65	190.28	29.97	-12.49
Geology units					
OM2	449.9949	1.63	3.30	0.52	-15.63
E	190.4042	0.69	0.18	0.03	-22.04
EO	11334.27	41.03	27.59	4.35	-20.54
QR	1297.833	4.70	179.93	28.34	115.66
K	5018.204	18.16	10.84	1.71	-20.82
Qal	201.7005	0.73	46.45	7.32	207.33
Pd	898.8312	3.25	114.50	18.03	104.41
Qt1	542.9987	1.97	85.34	13.44	134.18
Qt2	399.7744	1.45	14.76	2.33	13.95
K8	2948.512	10.67	150.77	23.75	28.16
K7	3555.478	12.87	1.21	0.19	-22.64
distance from fault (m)					
0-500	2463.077	8.92	94.81	14.93	15.51
500-1300	3740.476	13.54	192.53	30.33	28.49
1300-2300	4152.376	15.03	141.37	22.27	11.07
2300-3500	6133.214	22.20	114.22	17.99	-4.35
>3500	11139.89	40.32	91.94	14.48	-14.72
distance from stream (m)					
0-50	2092.495	7.57	51.84	8.17	1.80
50-100	2011.261	7.28	52.52	8.27	3.14
100-150	1942.973	7.03	51.18	8.06	3.36
150-200	1882.406	6.81	47.21	7.44	2.10
200-300	3563.991	12.90	84.96	13.38	0.86
300-450	4803.816	17.39	106.37	16.76	-0.83
>450	11331.47	41.02	240.77	37.92	-1.73
distance from road (m)					
0-75	1583.822	5.73	140.51	22.13	65.74
75-150	1372.74	4.97	125.47	19.76	68.42
150-225	1234.877	4.47	109.28	17.21	65.52
225-300	1134.911	4.11	92.53	14.57	58.55
300-500	2622.979	9.49	121.87	19.20	23.49
>500	19679.09	71.23	45.20	7.12	-20.68
Land use					
Rocky land	5512.351	19.95	0.59	0.09	-22.87
Rainfed agriculture	1645.76	5.96	10.04	1.58	-16.88
Irrigated agriculture	2214.199	8.01	155.03	24.42	47.04
Poor range	12072.93	43.70	391.81	61.72	9.48
Medium range	6183.487	22.38	77.39	12.19	-10.46
Precipitation (mm)					
780-900	10589.69	38.33	539.27	84.94	27.95
900-1000	7996.283	28.94	69.14	10.89	-14.33
1000-1100	6078.483	22.00	26.45	4.17	-18.63
1100-1200	2292.567	8.30	0.00	0.00	-22.98
1200-1260	671.9949	2.43	0.00	0.00	-22.98

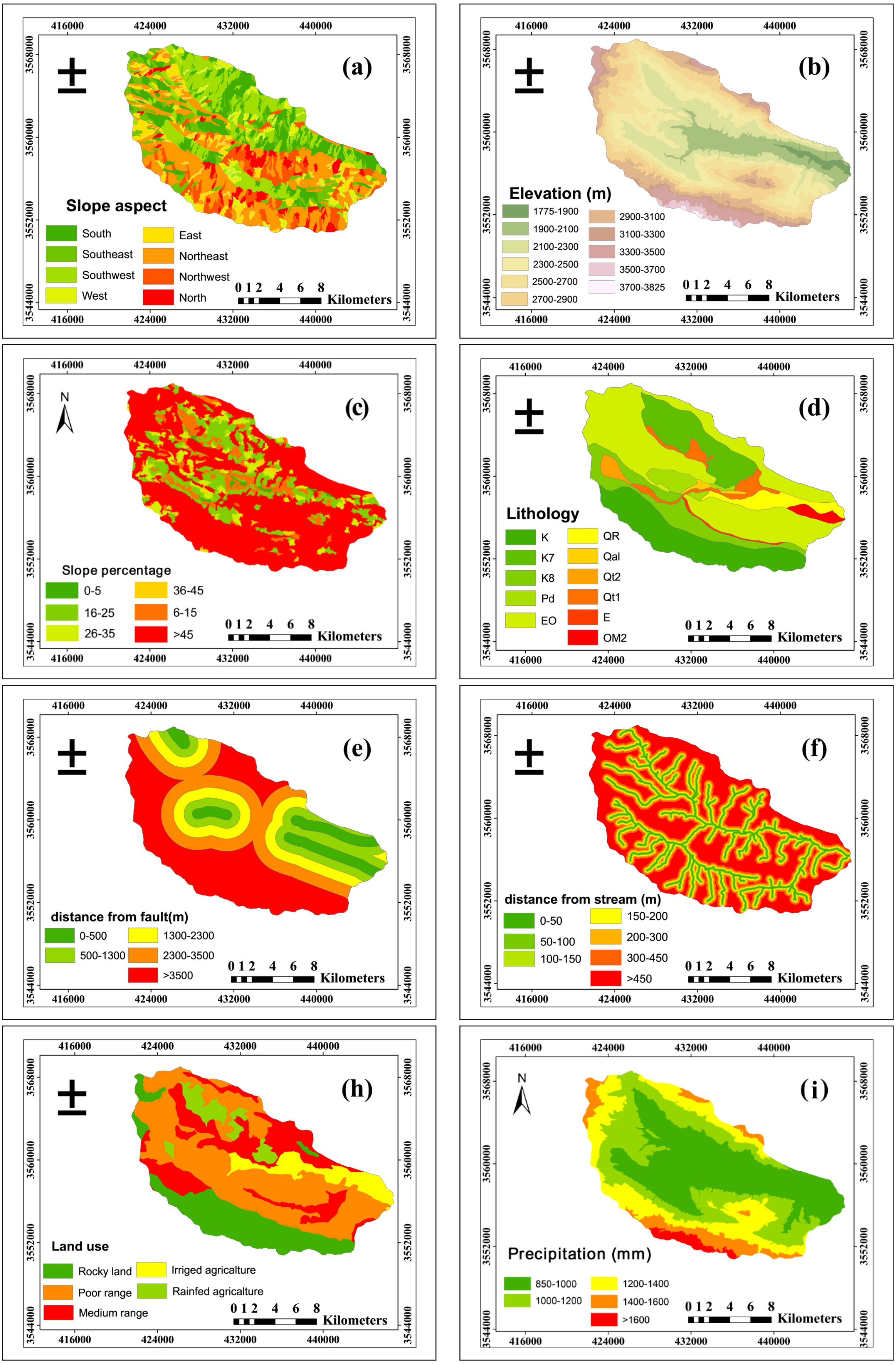

Figure 2. Landslide conditioning factors; **a** aspect, **b** elevation, **c** slope percentage, **d** lithology, **e**, **f** and **g** distance from fault, stream and road respectively, **h** land use, **i** precipitation.

2.4. Landslide Susceptibility Mapping Using Logistic Regression

Model In order to determine the zonation of landslide susceptibility using logistic statistical regression, the landslide density in each class of the nine causative parameters was calculated. To this end, through integrating maps of several factors, a homogeneous units' map was prepared. Homogeneous units were created by combining all the maps of effective factors, and had a unit value in terms of the characteristics of the effective factors. After overlying the homogeneous units' map on the landslide distribution map, the units of the landslide were specified, and all of the homogeneous landslide units were scored by the code (1), and all those with no landslide units were scored by the code (0). The absence or presence of landslide in the homogeneous units being a dependent variable, and the landslide density percentage in each class of the nine parameters in units being an independent variable were entered in the R statistical software. Logistic regression equation is as follows according to Ayalew and Yamagishi (2005):

$$Y = Logit(p) = \ln\left(\frac{p}{1-p}\right) = C_0 + C_1X_1 + C_2X_2 + \cdots + C_nX_n \quad ....(1)$$

where p is the probability of independent variable (Y), p/(1-p) denotes the so-called odds or the likelihood ratio, C_0 is the intercept, C_1, C_2,….C_n are coefficients (which measure the size and the contribution of independent factors (X_1, X_2, ... and X_n) in a dependent variable). Using the density of factors as independent variables, and the presence or absence of landslides as the dependent variable, is an attempt to determine the best equation as follows that is meaningful at 0.01 % error level. Using the resulting model, the landslide susceptibility map was produced and classified into very low, low, medium, high, very high classes.

*Y=(- 2.097 +(0.0074)*Aspect +(0.012) *Precipitation +(0.061)*Elevation +(0.0055) *Geology -(0.0288)*Fault -(0.1875)*Stream)* ....(2)

2.5. Landslide Susceptibility Mapping Using Stepwise Regression Model

To determine the numerical value of qualitative factors in different parameters (aspect, land use, and lithology), AHP was utilized, and the parameters were weighted according to slippage (landslide) rate in the factors' different classes, and the weight of each factor was assessed after making paired comparisons between classes (show the matrix of AHP). The nine layers were integrated together in a GIS environment, and the map of homogenous units was produced.

After that, the map of homogenous units was cropped with the landslide distribution map and nine factors and the logarithm of the sliding factor (it took place in order to standardize the logarithmic conversion) were, respectively, chosen as independent variables and dependent variable. The most effective factors were determined as elevation, slope, lithology, distance from the fault, distance from the road, land use and annual precipitation using the SPSS software and the stepwise method (Karimi Sangchini et al., 2011). The equation coefficient of determination equals to 67.96 % which is significant at a 95% confidence level.

*Y=(- 1.838 +(0.00059)*Aspect +(0.0692)*Slope +(0.00178)*Elevation +(0.00318)*Geology -(0.000077)*Fault +(0.00167)*Land Use -(0.000163)*Stream -(0.000415)*Road)* .(3)

The landslide hazard intensity mapping was conducted in an ArcGIS 9.3 environment using the abovementioned equation, and the pixels were classified into six classes based on the turning points of the cumulative frequency curve.

2.6. Evaluation of Landslide Hazard Model

Ultimately, the receiver operating characteristics (ROC) curve (Mohammady et al., 2012; Pourghasemi et al., 2012; Naghibi et al., 2015; Karimi Sangchini et al., 2016) was used to determine the accuracy of landslide susceptibility. The ROC curve is a diagram in which the pixel's ratio that correctly-predicted the occurrence or nonoccurrence of landslides (True Positive) is plotted against the corresponding amount that is the pixel's ratio that is wrongly predicted.

3. Results and Discussion

3.1. Performance of the Models

As can be inferred from the results, two models showed a high and a relatively close performance. However, the logistic multivariate regression (AUC= 0.865) was proven to be superior to the stepwise multivariate regression (AUC= 0.792) (Figure 3). AUC is the Area under the ROC Curve.

The main advantage of the logistic regression over the simple multiple regressions is that the former allows using binary dependent variable types in landslide susceptibility mapping. Although the logistic regression is a widely-used quantitative susceptibility mapping method, its major limitation is yielding average parameters for the study area (Erner et al., 2010), which may differ locally across different parts of the study area.

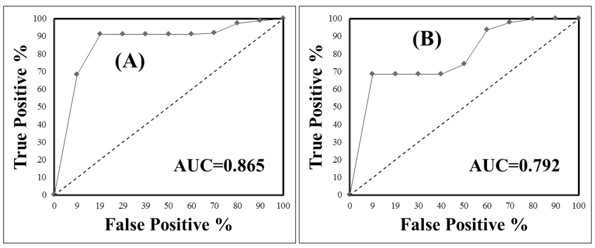

Figure 3. ROC curves **A:** Logistic regression model, **B:** stepwise regression model.

3.2. Landslide Hazard Maps

Landslide hazard maps which were generated by the logistic multivariate regression and stepwise multivariate regression models are illustrated in Figures 4 and 5. The mentioned hazard maps were classified into very low, low, moderate, high, and very high classes based on natural break scheme. The moderate land slide hazard map class derived from the logistic regression model accounts for 40.57 % of the total area; 4.97, 8.61, 8.88, and 37.04% of the total area are related to very low, low, high and very high HPM zones, respectively (Table 2). As for the stepwise multivariate regression model, very low, low, moderate, high, and very high land slide susceptibility map classes account for 19.34, 33.58, 15.29, 16.38, and 12.41% of the total area, respectively (Table 2). The different results are due to the fact that the two models use different algorithms. The step-by-step multivariate regression model uses a quantitative dependent variable, while the logistics model uses a qualitative dependent variable.

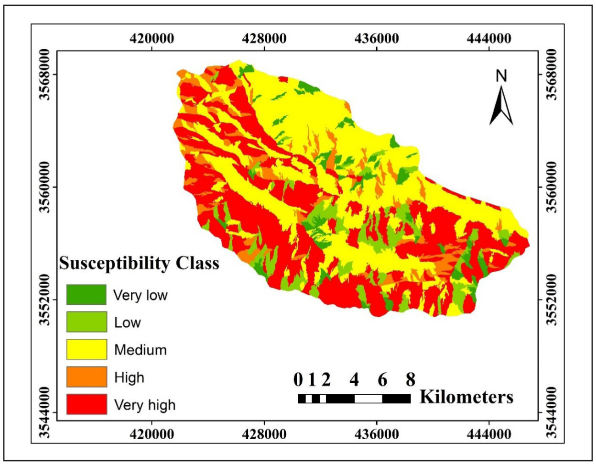

Figure 4. Landslide susceptibility maps based on: Logistic regression model.

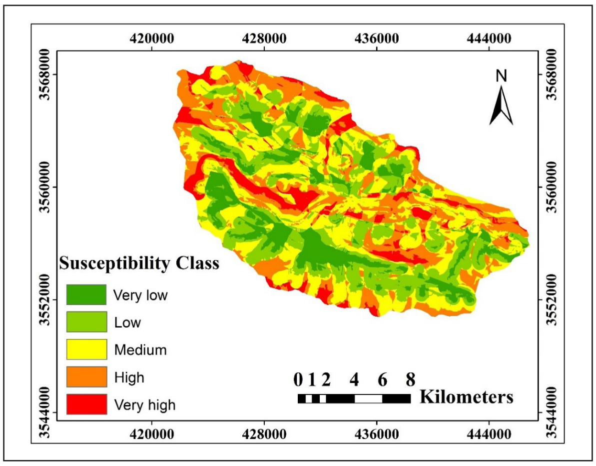

Figure 5. Landslide susceptibility maps based on: the stepwise regression model.

Table 2. The distribution of area in different landslide susceptibility classes.

Logistic regression model			Stepwise regression model		
Hazard class	Area (ha)	% Area	Hazard class	Area (ha)	% Area
Very low	1371.77	4.97	Very low	5340.13	19.34
Low	2377.39	8.61	Low	9271.99	33.58
Medium	11200.63	40.57	Medium	5049.92	15.29
High	2451.98	8.88	High	4521.22	16.38
Very high	10225.19	37.04	Very high	3426.38	12.41
Total	27627.19	100	Total	27627.19	100

3.3 Importance of Landslide Effective Factors

Given the results, the determinant factors such as slope aspect, precipitation, elevation, geology, and land use affect the multivariate logistic regression model function positively (Eq. 2). The highest positive β coefficient is attributed to the precipitation which is 0.00344. On the other hand, distance from faults, distance from stream and distance from roads negatively influence landslide occurrence with β coefficients of -0.000077, -0.000163, and -0.000415, respectively which are consistent with the results of Devkota et al. (2013). Also, distance from roads had the highest negative influence on logistic regression. 'Variance inflation factor' (VIF) and the 'Tolerance' (TOL) are two important indices for multi-collinearity diagnosis (O'Brien, 2007). The tolerance and variance inflation factors were computed for this study, and variables with VIF > 5 and TOL < 0.1 should be excluded from the LR analysis, but there was not any multi-collinearity problem in the landslide effective factors used in this study.

4. Conclusions

Conditions in the Doab Samsami watershed including geology, roughness, geomorphology and tectonic conditions as well as anthropogenic pressure factors such as land use and rural roads' changes have paved the way for landslide occurrence to the point that this phenomenon has occurred in thirty-seven cases with an approximate extent of 635 hectares in the watershed basin. Therefore, in the current study, the stepwise regression and logistic regression models have been used for the sake of mapping landslide hazards in the Doab Samsami Watershed, Chaharmahal Va Bakhtiari Province, Iran. A landslide inventory map and nine landslide effective factors were prepared for this investigation. After that, landslide susceptibility maps were generated using the two aforementioned modelsGiven the superiority of the logistic multivariate regression in landslide hazard mapping in the study area, taking very high susceptible class of landslide hazards produced by this model, which covered 46% of the study area, into account, is of great importance. Determining importance of different landslide effective factors is a necessary step in landslide susceptibility mapping. In several studies logistic regression model has been used in order to determine the importance of effective factors on landslide occurrence (Yesilnacar and Topal, 2005; Ayalew and Yamagishi, 2005; Nandi and Shakoor, 2009; Karimi Sangchini et al., 2016). According to the results, the effective factors such as slope aspect, precipitation, elevation, geology, and land use affect the multivariate logistic regression model function positively. The main advantage of logistic regression over simple multiple regressions is that LR allows the use of binary dependent variable types in landslide susceptibility mapping. Although logistic regression is a commonly applied quantitative susceptibility mapping method, it has a major limitation of yielding average parameters for the study area (Erner et al., 2010), which may differ locally in different parts of the study area. This implies a high susceptibility to landslide in the watershed basin which is to be considered in the susceptibility management, landslide losses, and land use planning. Finally, the methodology developed in the present study can be generalized in other areas with similar climatic, geological, and topographical conditions in order to facilitate land use planning and hazard management.

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