JOURNAL OF THE FACULTY OF FORESTRY ISTANBUL UNIVERSITY
İSTANBUL ÜNİVERSİTESİ ORMAN FAKÜLTESİ DERGİSİ
ISSN: 0535-8418 e-ISSN: 1309-6257
Available at http://dergipark.ulakbim.gov.tr/jffiu Research Article

Landslide susceptibility mapping using logistic statistical regression in Babaheydar Watershed, Chaharmahal Va Bakhtiari Province, Iran

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Received: 30 June 2014 - Accepted: 20 August 2014

Abstract: Landslides are amongst the most damaging natural hazards in mountainous regions. Every year, hundreds of people all over the world lose their lives in landslides; furthermore, there are large impacts on the local and global economy from these events. In this study, landslide hazard zonation in Babaheydar watershed using logistic regression was conducted to determine landslide hazard areas. At first, the landslide inventory map was prepared using aerial photograph interpretations and field surveys. The next step, ten landslide conditioning factors such as altitude, slope percentage, slope aspect, lithology, distance from faults, rivers, settlement and roads, land use, and precipitation were chosen as effective factors on landsliding in the study area. Subsequently, landslide susceptibility map was constructed using the logistic regression model in Geographic Information System (GIS). The ROC and Pseudo-R^2 indexes were used for model assessment. Results showed that the logistic regression model provided slightly high prediction accuracy of landslide susceptibility maps in the Babaheydar Watershed with ROC equal to 0.876. Furthermore, the results revealed that about 44% of the watershed areas were located in high and very high hazard classes. The resultant landslide susceptibility maps can be useful in appropriate watershed management practices and for sustainable development in the region.

Keywords: Landslide zonation, multivariate statistical model, Babaheydar watershed, Chaharmahal Va Bakhtiari province

İran’ın Çaharmahal ve Bahtiyari Bölgesi’nde yer alan Baba Haydar Havzası’nda lojistik regresyon kullanılarak heyelan hassasiyeti haritasının çıkartılması

Özet: Toprak kaymaları, dağlık bölgelerdeki en zarar verici doğal felaketler arasında yer almaktadır. Her yıl, dünyanın dört bir yanında yüzlerce insan toprak kayması neticesinde ölüyor. Ayrıca, bu olayların yerel ve global ekonomi üzerinde de büyük etkileri bulunmaktadır. Bu çalışmada, toprak kayması tehlikesine sahip bölgeleri tespit etmek üzere lojistik regresyon kullanılarak Baba Haydar Havzası’nda toprak kayması tehlikesi haritası çıkartılmıştır. İlk olarak, havadan çekilmiş fotoğraf yorumları ve saha incelemeleri kullanılarak toprak kayması envanter haritası hazırlanmıştır. Bir sonraki adımda rakım, eğim yüzdesi, eğim açısı, litoloji, fay hatlarına olan mesafe, nehirler, yerleşim yerleri ve yollar, arazi kullanımı ve yağış miktarı olmak üzere toprak kaymasına neden olabilecek on adet faktör, çalışma bölgesinde toprak kaymasında etkin faktörler olarak seçilmiştir. Ardından, Coğrafi Bilgi Sisteminde (GIS) lojistik regresyon modeli kullanılarak toprak kayması hassasiyeti haritası oluşturulmuştur. Model değerlendirmesi için ROC ve Pseudo-R2 endeksleri kullanılmıştır. Sonuçlar, lojistik regresyon modelinin, 0.876’lık ROC değeri ile birlikte Baba Haydar Havzası’nda toprak kayması hassasiyet haritasının yüksek bir tahmin doğruluğu sağladığını göstermiştir. Ayrıca sonuçlar, havza bölgelerinin yaklaşık %44’ünün yüksek ve son derece tehlikeli sınıflarda yer aldığını ortaya çıkartmıştır. Sonuç olarak elde edilen toprak kayması hassasiyeti haritaları, uygun havza yönetimi uygulamalarında ve bölgenin sürdürülebilir bir şekilde geliştirilmesinde faydalı olabilir.

Anahtar Kelimeler: Heyelan bölgelendirme, çok değişkenli istatistiksel model, Baba Haydar havzası, Çaharmahal ve Bahtiyari bölgesi

1. INTRODUCTION

Landslides are amongst the most damaging natural disasterin the mountainous terrain. Every year, hundreds of people all over the world lose their lives in landslides; furthermore, there are large impacts on the local, regional and global economy from these events. Over the past 25 years, many governments and international research institutions across the world have invested considerable resources in assessing

To cite this article: Sangchini, E.K., Nowjavan, M.R., Arami, A., 2015. Landslide susceptibility mapping using logistic statistical regression in Babaheydar Watershed, Chaharmahal Va Bakhtiari Province, Iran. Journal of the Faculty of Forestry Istanbul University 65(1): 30-40. DOI: 10.17099/jffiu.52751

landslide susceptibilities and in attempting to produce maps portraying their spatial distribution (Guzzetti et al., 1999, Yalcin et al., 2011).

Landslide susceptibility zonation is one of the ways that we can identify the critical regions and we can use the resulting zoning maps in sustainable development planning with its contribution. Dozens of numerical models were devised for the zoning of the relative risk of the slope instability with weight, rate, computational logic and different scale agents and modified in a variety of conditions based on land evidences (Sakar, 1995). Identification and classification of areas prone to landslide and its hazard zonation is a significant step in the evaluation of environmental hazards and plays an indispensable role in the management of watersheds (Sakar, 1995).

There are three main approaches in landslide susceptibility assessment such as qualitative (Hasekiogullari and Ercanoglu, 2012), semi-quantitative (Akgun and Turk, 2010, Pourghasemi et al., 2014) and quantitative (Lee and Jones, 2004). Quantitative methods are based on mathematical logic, the correlation between factors and landslide occurrence that include bivariate regression analysis (Guzzetti et al., 2002, Nandi and Shakoor, 2009; Pradhan and Lee, 2010a, 2010b, Yalcin et al., 2011; Yilmaz et al., 2012, Bijukchhen et al., 2013, Kayastha et al., 2013), multivariate (Suzen and Doyuran, 2004; Nandi and Shakoor, 2009; Pradhan and Youssef, 2010; Pradhan et al., 2011), and logistic regression (Ayalew and Yamagishi, 2005; Duman et al., 2006; Pradhan, 2010a; Akgun, 2012; Pourghasemi et al., 2013b; Eker and Aydın, 2014), fuzzy logic (Tangestani, 2009; Pradhan et al., 2009; Pradhan, 2010b, Pradhan and Lee, 2010a; Pradhan, 2011, 2011b, Pourghasemi et al., 2013, Pourghasemi et al., 2012b), artificial neural network model (Ermini et al., 2005; Pradhan and Lee, 2007; Melchiorre et al., 2008; Caniani et al., 2008; Pradhan and Lee, 2009; Pradhan et al., 2010a; Pouydal et al., 2010c; Pradhan and Buchroithner, 2010; Pradhan and Lee, 2010a; Pradhan and Lee, 2010b; Pradhan et al., 2011a; Pradhan et al., 2010; Pradhan, 2013). In multivariate statistical methods, the simultaneous analysis of several independent variables on space dependent variable is provided and since the phenomena such as landslides are due to simultaneous function and different effects of several variables, therefore the use of multivariate statistical models is suitable (Karimi Sangchini et al., 2011).

Many modeling approaches for landslide hazard prediction can be used to produce statistics-based susceptibility maps. 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 susceptibility mapping (Lee et al., 2010). The multivariate logistic regression approach was used by various researchers worldwide (Yesilnacar and Topal 2005; Lee and Pradhan, 2007; Nandi and Shakoor, 2009; Yilmaz, 2010; Oh and Lee, 2010; Felicisimo et al., 2013). In this paper, landslide susceptibility mapping in Babaheydar watershed with a logistic regression multivariate statistical model of quantitative models is to determine landslide susceptibility areas for its landslide hazard management.

2. MATERIALS AND METHODS

2.1 Study area

Babaheydar Watershed is located between 32° 13′ 21″ to 32° 24′ 1″ latitude and 50° 22′ 4″ to 50° 32′ 29″ longitude, occupying approximately 181.46 sq. km in the Chaharmahal Va Bakhtiari Province, southwest of Iran (Figure / Şekil 1). This watershed is one of the major sub basins of Karoon River. Altitude in the study area varies between 2,040 to 3,610 m. Based on the Iranian meteorological organization report; the average annual rainfall in the watershed is 672 mm. This watershed is located in the middle of the Zagros Mountains. Subsequent erosion removed softer rocks, such as mudstone (rock formed by consolidated mud) and siltstone (a slightly coarser-grained mudstone) while leaving behind harder rocks exposed, such as limestone (calcium-rich rock consisting of the remains of marine organisms) and dolomite (rocks similar to limestone containing calcium and magnesium). This differential erosion formed the linear ridges of the Zagros Mountains. 69% of this region is covered by rangelands and remaining lands are covered by Residential, agricultural and rocky lands (about 31% from region area).

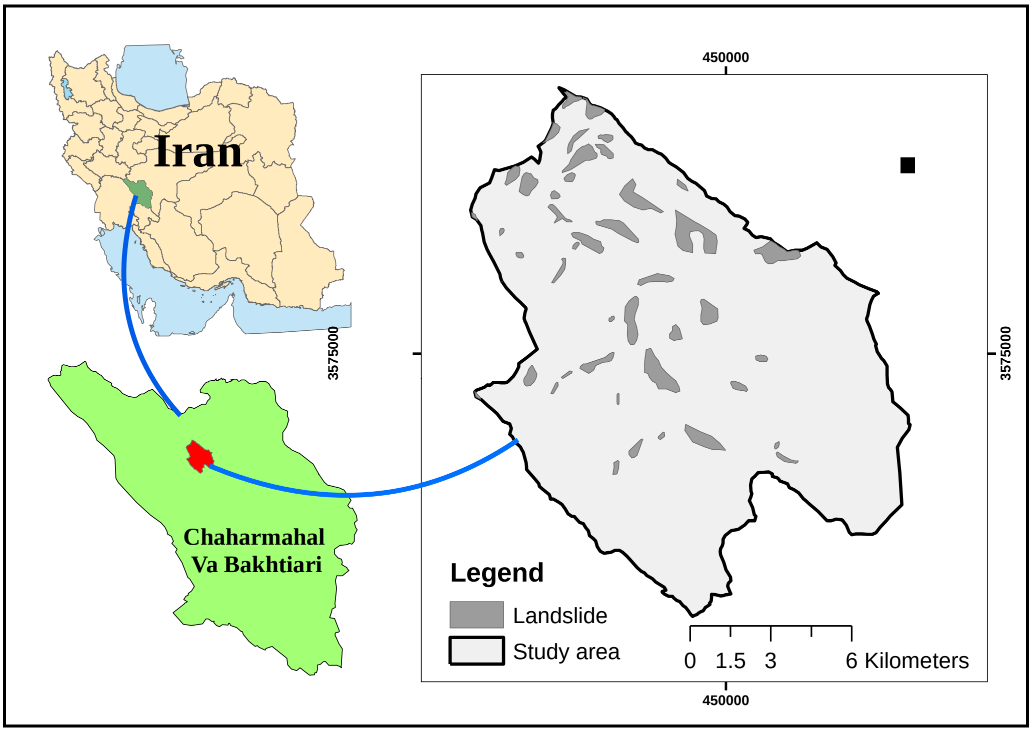

Figure 1. Location map of the study area
Şekil 1. Çalışma alanının konumu

2.2 Data preparation and landslide inventory

The landslide inventory map was prepared using gathering the information related to the landslides or by analyzing the data from remote sensing and GIS techniques. In the current study, a landslide inventory map was prepared using field investigations, information received from inhabitants and aerial photograph interpretation . From literature review and studying conditions of Babaheydar watershed, a total of ten factors such as altitude, slope percentage, slope aspect, lithology, distance from faults, rivers, settlement and roads, land use, and precipitation amount were chosen as effective factors on landsliding. In the next stage, the area and landslide percentage, the density ratio and landslide density percentage in each class of these ten landslide factors were calculated.

2.3 Landslide susceptibility mapping by using logistic regression models

For the landslide susceptibility zonation using logistic regression, the landslide density in each class of the ten parameters of landslides was calculated. For this purpose, homogeneous units' map was prepared by integrating maps of several factors. After matching the map of homogeneous units up with a landslide distribution map, the units of the landslide were determined and to all homogeneous landslide units, the code (1) and to all homogeneous with no landslide units, the code (0) was given. The absence or presence of landslide in homogeneous units as dependent variable and landslide density percent in each class of nine parameters in units as independent variable were entered in the R statistical software. The logistic regression equation is as follows (Ayalew and Yamagish 2005):

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

In this equation, p is the probability of independent variable(Y), p/(1-p) is 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) e) and e_i is error term. Using the density of factors as independent variables, and presence or absence of landslides as the dependent variable, attempted to determine the best equation as follows that is meaningful at 0.01 % error level.

$$susceptibility\ map = -10.8002 + 0.053\text{Village Value} + 0.068Aspect\ Value + \quad (2)$$
$$0.029Rainfall\ Value + 0.026Elevation\ Value + 0.05Geology\ Value + 0.055Fault\ Value + \quad (3)$$
$$0.019Land\ Use\ Value + 0.032Stream\ Value + 0.094Road\ Value + 0.072Slope\ Value \quad (4)$$

Using the resulting model, the landslide susceptibility map was produced and classified in very low, low, medium, high, very high classes.

2.4 Assessment of the landslide susceptibility model

2.4.1 Pseudo-R^2 index

The Pseudo-R^2 index is one of the indicators was used to evaluate the efficiency of logistic regression. This index based on the likelihood ratio principle, tests the goodness of fitting into the logistic regression and is calculated according to the following equation:

$$Pseudo\_R^2 = 1 - \left(\frac{\log(liklihood)}{\log(l_0)}\right) \quad (5)$$

Where:
Likelihood: the likelihood function amount in a case that the model is fully fitted.
L_0: the likelihood function amount in a case that all coefficients except for the intercept are zero.

Unlike R^2 in ordinary regression, Pseudo-R^2 does not indicate the proportion of variance explained by the model, but this indicates the dependency rate of the empirical and output data of the regression model, thus, its value is generally much lower than R^2. The Pseudo-R^2 equivalent to one indicates perfect fit and the Pseudo-R^2 equivalent to zero means that there is no significant relationship between independent and dependent variables. In spatial studies, Pseudo-R^2 more than 0.2 can be considered as a relatively good fit (Clark and Hosking, 1986).

2.4.2 ROC index

The efficiency of the susceptibility model can be evaluated by ROC index (relative operating characteristic). This index is computed from the ROC curve. The ROC curve is a diagram in which the pixel ratio that is correctly predicted the occurrence or nonoccurrence of landslides (True Positive) is plotted against the supplement amount that is the pixel ratio that is wrongly predicted. As already mentioned, the susceptibility model, computes the change in likelihood in each pixel in a continuous range of zero and one. By determining a threshold (e.g. 0.5) the model's output can be converted to a discrete scale of zero and one e.g. the pixels, in which that the change likelihood is more than their threshold, take 1 and pixels in which the change likelihood is less than their threshold takes 0 and the output is presented as a map. By comparing this with the landslide inventory, the pixel ratio can be plotted in ROC diagram.. The ROC index equals to the area under the curve (Pontius and Schneider, 2001).

3. RESULTS

The landslide inventory map showed that there are 46 distributed landslides in the whole area. Affected total area by landslide is 1103.97 ha (6.1% of the watershed area). The area and landslide percentage, the landslide density percentage in each class of ten landslide factors were calculated (Table / Tablo 1 and Figure / Şekil 2-3).

Table 1. Calculation of the final susceptibility value of each identified land unit
Tablo 1. Tanımlanan her alan için hassasiyet değerinin hesaplanması

Data layers		Total area (ha)	% of total area	Area of landslide	Landslide density percentage
Aspect	N	274.43	1.5	6.07	4.44
	NE	6804.61	37.5	230.67	4.96
	E	1786.22	9.84	64.54	2.92
	SE	1155.3	6.04	53.11	4.77
	S	2967.75	16.37	245.07	16.57
	SW	3658.39	20.16	258.70	13.44
	W	882.07	4.86	124.21	28.26
	NW	675.14	3.72	121.50	24.63
Rainfall (mm)	520-600	3110.39	17.14	76.52	8.36
	600-650	4069.86	22.43	290.95	24.30
	650-700	5085.55	28.02	433.04	28.95
	700-750	3044.14	16.78	220.90	24.67
	750-800	1975.51	10.89	79.70	13.72
	800-860	861.34	4.75	0.00	0.00
Elevation (m)	2040-2200	2324.89	12.81	32.49	4.34
	2200-2400	3476.85	19.16	248.68	22.20
	2400-2600	5473.35	30.16	444.82	25.23
	2600-2800	3300.00	18.19	247.23	23.26
	2800-3000	1872.17	10.32	104.75	17.37
	3000-3200	943.96	5.20	23.14	7.61
	3200-3400	481.76	2.66	0.00	0.00
	3400-3610	271.79	1.50	0.00	0.00
Distance from fault (m)	0-500	2131.41	11.75	238.98	31.02
	500-1300	3404.55	18.76	264.49	21.49
	1300-2300	3322.64	18.31	227.56	18.95
	2300-3500	3129.73	17.25	274.00	24.22
	>3500	6157.68	33.93	96.08	4.32
Land use	Rocky land	497.88	2.74	0.00	0.00
	Rainfed agriculture	3141.95	17.31	287.17	27.50
	Irrigated agriculture	1681.33	9.27	73.87	13.22
	Good range	4248.07	23.41	209.53	14.84
	Medium range	5929.01	32.67	302.13	15.33
	Poor range	2360.84	13.01	228.42	29.11
	Residential	286.95	1.58	0.00	0.00
Distance from stream (m)	0-50	4866.35	26.82	249.53	13.36
	50-100	6098.56	33.61	348.35	14.89
	100-150	1744.57	9.61	106.48	15.91
	150-200	2256.92	12.44	161.00	18.59
	200-300	1842.41	10.15	162.64	23.00
	300-450	1337.21	7.37	73.12	14.25
	>450	4866.35	26.82	249.53	13.36
Distance from road (m)	0-75	1501.19	8.27	141.30	21.13
	75-150	1391.97	7.67	123.95	19.99
	150-225	1249.77	6.89	99.97	17.96
	225-300	1115.01	6.14	83.59	16.83
	300-500	2421.83	13.35	141.46	13.12
	>500	10466.26	57.68	510.85	10.96
Slope (%)	0-5	806.21	4.44	8.22	3.24
	6-15	3188.02	17.57	70.12	7.00
	16-25	4205.63	23.18	353.74	26.75
	26-35	2514.79	13.86	182.72	23.11
	36-45	503.99	2.78	30.02	18.95
	>45	6927.41	38.18	456.29	20.95
Distance from settlement (m)	0-50	15.67	0.09	3.13	21.48
	50-100	47.08	0.26	9.73	22.20
	100-200	188.41	1.04	37.12	21.16
	200-300	300.65	1.66	47.72	17.05
	300-500	817.10	4.50	93.41	12.28
	>500	16777.11	92.46	910.00	5.83

Table / Tablo 1.Continued - Devam ediyor

Data layers		Total area (ha)	% of total area	Area of landslide	Landslide density percentage
Geology units	Qft_2 (Low level piedmont fan and valley terrace deposit)	6640.38	36.59	422.48	16.85
	Klsol (Grey , thick - bedded to massive orbitolina limestone)	1106.60	6.10	95.33	22.81
	E (Undivided Eocene rock)	6323.79	34.85	398.53	16.69
	Kbgp (Undivided Bangestan Group , mainly limestone and shale)	421.80	2.32	4.00	2.51
	KEpd-gu (Pabdeh and Gorpei formations)	1185.62	6.53	88.02	19.66
	Plc (Polymictic conglomerate and sandstone)	1093.43	6.03	73.21	17.73
	OMas (jointed limestone with intercalations of shale (Asmari FM))	1374.40	7.57	19.54	3.76

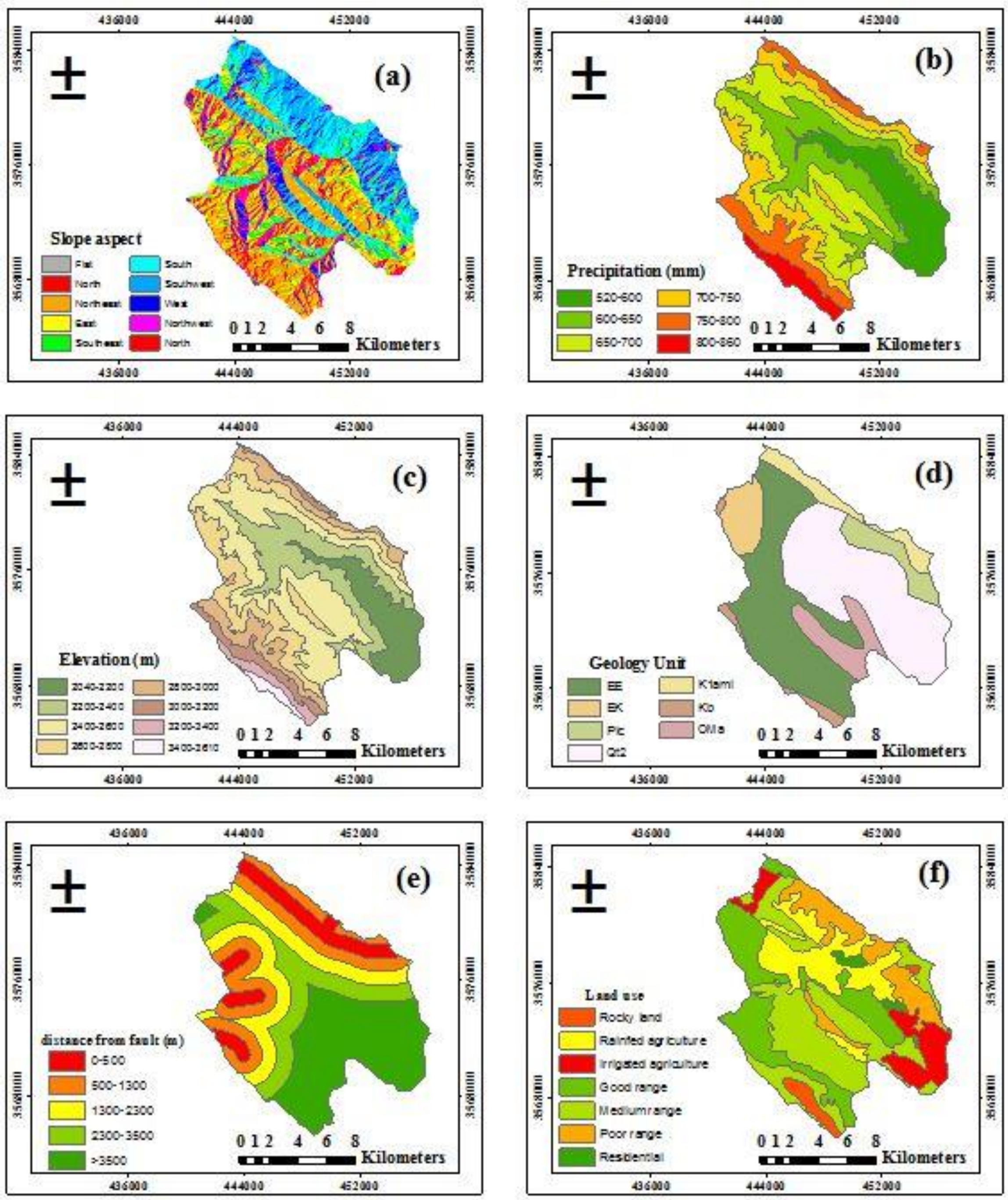

Figure 2. Landslide conditioning parameter; **a** aspect, **b** rainfall, **c** elevation, **d** lithology, **e** distance from fault, **f** land use

Şekil 2. Alan verileri; **a** bakı, **b** yağış, **c** yükseklik, **d** anakaya, **e** faydan uzaklık, **f** alan kullanımı

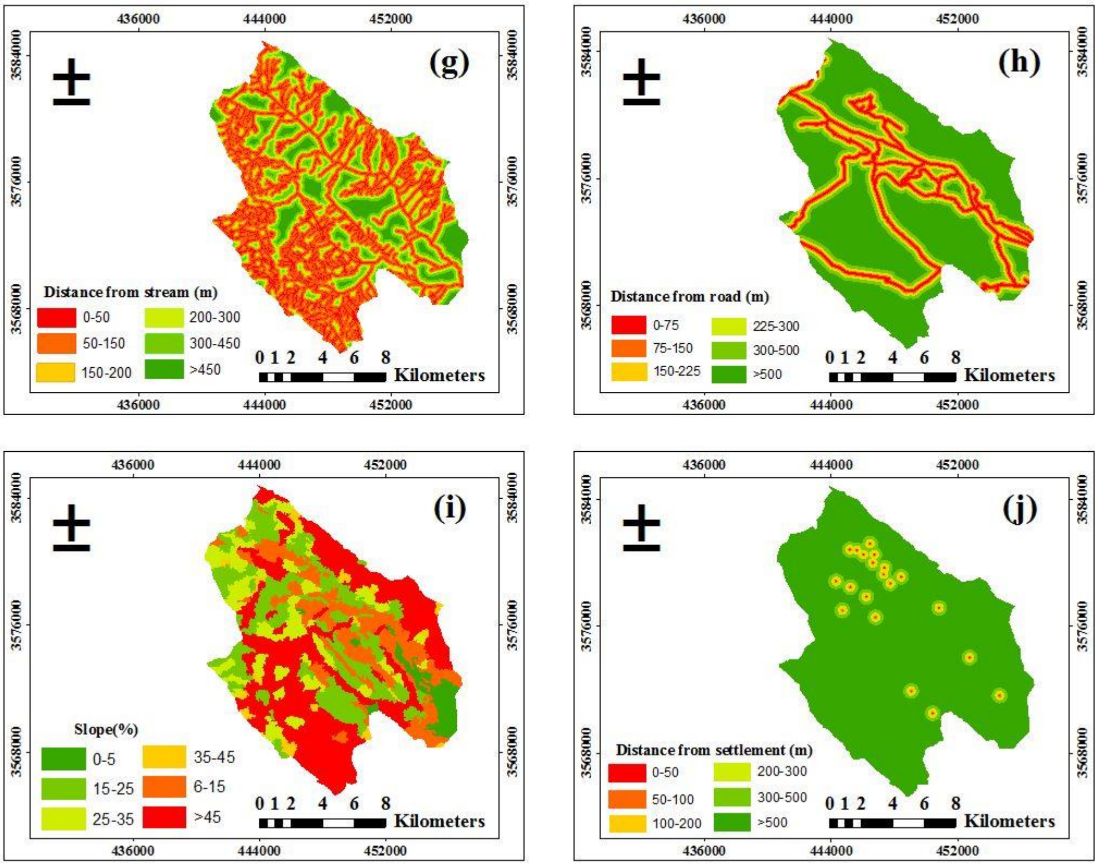

Figure 3. Landslide conditioning parameter; **g** distance from stream, **h** distance from road, **i** slope percentage, **j** distance from settlement
Şekil 3. Alan verileri; **g** sulu dereden uzaklık, **h** yoldan uzaklık, **i** eğim yüzdesi, **j** yerleşimden uzaklık

Using the resulting Logistic regression model, the landslide susceptibility map was produced and classified in very low, low, medium, high, very high classes (Table / Tablo 2 and Figure / Şekil 4).

In this study, we evaluated the accuracy of logistic regression using Pseudo-R^2 index. The Pseudo-R^2 amount was calculated to be equal to 0.48, thus we can consider this model's fitting is relatively good. The ROC index amount was 0.876 for logistic regression that its proximity indicates the model high potential of zoning and determining areas prone to landslide susceptibility in Babaheydar Watershed. Results showed that the logistic regression model is selected as suitable model Babaheydar Watershed (Figure / Şekil 5).

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

Susceptibility class	Area (ha)	% Area
Very low	1455.20	8.02
Low	3643.74	20.08
Medium	4977.72	27.43
High	4822.66	26.58
Very high	3246.76	17.89
Total	**18146.01**	**100**

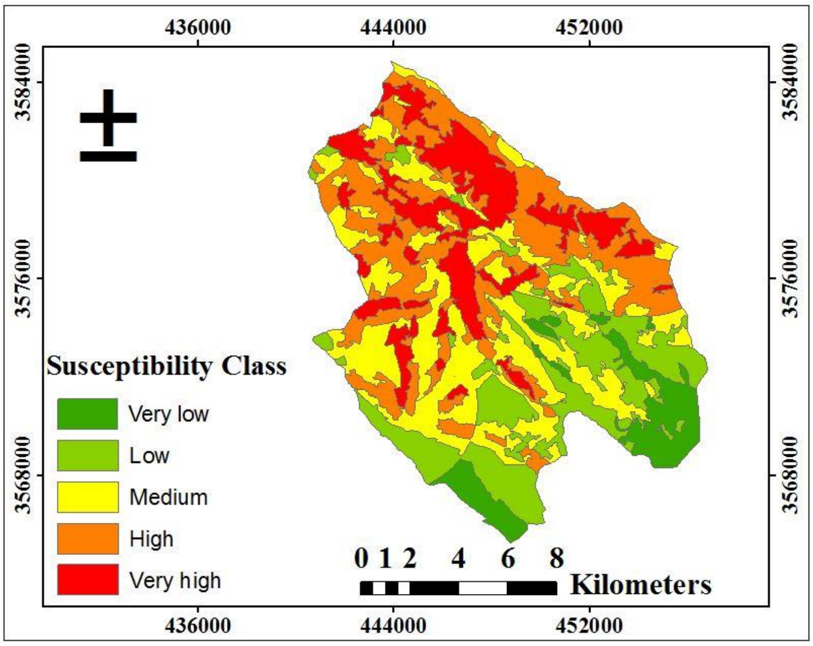

Figure 4 Landslide susceptibility map based on Logistic regression model in Babaheydar Watershed
Şekil 4. Lojistik regresyon modeli ile üretilen Babahaydar havzası heyelan hassasiyeti haritası

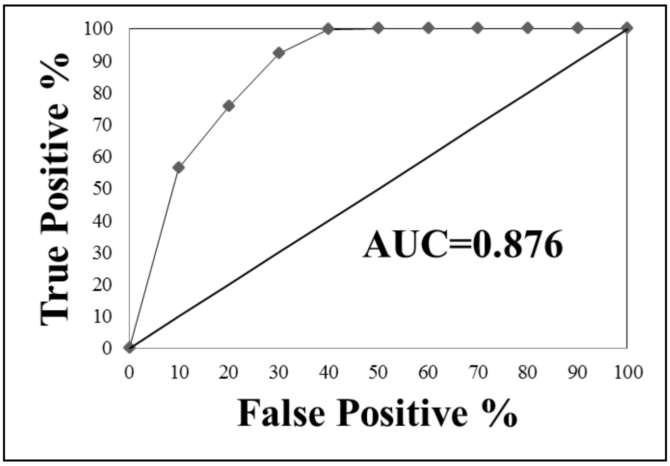

Figure 5. ROC curves for logistic regression model
Şekil 5. Lojistik regresyon modeli için ROC eğrisi

4. DISCUSSION AND CONCLUSION

This study tried to perform susceptibility zonation using logistic regression in Babaheydar Watershed. In the logistic regression as one of the multivariate statistical methods, the simultaneous analysis of several independent variables on the spatial dependent variable is provided and since the phenomena such as landslides, are caused by the simultaneous performance and different effects of several variable, so it's use is suitable. Yesilnacar and Topal (2005), Ayalew and Yamagishi (2005) Lee and Pradhan (2007), Nandi and Shakoor (2009), Akgun (2012); Pourghasemi et al. (2013b) used logistic regression in landslide susceptibility zonation. Their aim in watershed studies was to choose the best effective factors on landslide susceptibility.

The logistic regression model was chosen as the suitable model for Babaheydar watershed with ROC equal to 0.876. The Babaheydar watershed’s conditions such as geology, roughness, geomorphology and tectonic conditions as well as human pressure factors such as land use and rural roads' changes has created a proper background for the landslide that its occurrence is about 46 cases with an approximate extent of 1103.97 hectares in watershed basin. After the zonation using logistic regression model in Babaheydar watershed, about 44% of the watershed area are located in high and very high susceptibility classes which it is showing high susceptibility to landslide for watershed basin that should be considered in Susceptibility management, landslide losses and land use planning. Converting the rangeland to rain fed farming and road building is performed sharply in the Babaheydar watershed during recent years and led to presenting high role of human factors on landslide in comparing other factors.

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