Landslide Risk Assessment for Baba Heydar Watershed, Chaharmahal and Bakhtiari Province, Iran

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Abstract

Landslides are among the most damaging natural hazards in mountainous regions. In this study, landslide hazard zonation was conducted in the Baba Heydar Watershed using logistic statistical regression to determine landslide hazard areas. First, a landslide inventory map was prepared using aerial photograph interpretation and field surveys. Next, ten landslide conditioning factors including altitude, slope percentage, slope aspect, lithology, distance from faults, streams, villages and roads, land use, and precipitation were chosen as effective factors on landslide occurrence in the study area. Then, a landslide susceptibility map was constructed using a logistic regression statistical model in a geographic information system (GIS). Relative Operating Characteristics (ROC) and Pseudo R2 indices were used for model assessment. Finally, a risk map was created based on a risk equation using a combination of the susceptibility map, elements at risk and vulnerability. Results showed that the logistic regression statistical model provided slightly higher prediction accuracy of landslide susceptibility in the Baba Heydar Watershed with ROC equal to 0.876. The results revealed that about 44% of the watershed area was located in both the high and very high hazard classes. Additionally, 35% of the surveyed watershed was located in the high and very high-risk classes. This information is critical for the risk management, landslide risk and land planning of this mountainous area.

Keywords: *landslide hazard, risk, element at risk, vulnerability, Baba Heydar Watershed, Chaharmahal and Bakhtiari Province.*

1. Introduction

The purpose of this research was to evaluate and manage landslide risk for the Baba Heydar Watershed using hazard intensity, elements at risk and vulnerability degree. In this paper, landslide susceptibility mapping of the Baba Heydar Watershed with a logistic regression multivariate statistical model including quantitative models was used to determine landslide susceptibility for the purpose of landslide hazard management.

Landslides, debris flows and floods pose an ever-increasing risk to communities and infrastructure in many parts of the world. Landslides cause hundreds of deaths all over the world every year. They are among the most damaging natural hazards in mountainous terrain creating a large impact on local, regional and global economies. Identification and classification of areas prone to landslides and their hazard zonation is crucial in the evaluation of environmental hazards and plays an indispensable role in the management of watersheds [1]. Increased risk is fueled primarily by the expansion of development and infrastructure into more hazard prone areas Changing land use and drainage patterns can lead to increased levels of hazard while population expansion and investment in higher value land use can increase risk levels [2].

The availability of landslide hazard and risk maps is essential. They can help identify potential landslide areas, minimizing loss of life and property damage. Over the past 25 years, many government and international research institutions across the world have invested considerable resources in assessing landslide susceptibilities and attempting to produce maps portraying their spatial distribution [3,4]. Landslide zoning is one of the ways that we can identify critical regions in terms of slope stability. The resulting zoning maps can then be used in sustainable development planning. For this study, dozens of numerical models were devised for zoning of the relative risk of slope instability using weight, rate, computational logic and different scale agents and were modified in a variety of conditions based on land evidences. Many modeling approaches for landslide hazard prediction can produce statistics-based susceptibility maps. The multivariate logistic regression approach has been used by various researchers worldwide [5,6,7,8,9,10]. However, logistic regression and discriminant analysis, developed using a geographic information system

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(GIS) for landslide susceptibility mapping [11], are the most frequently used models [12].
There are three main approaches in landslide susceptibility assessment: qualitative [13], semi-quantitative [14,15] and quantitative [8]. However, the results of quantitative analysis can be more effectively communicated and provide more effective support management strategies [16,17]. Quantitative methods are based on mathematical logic, correlation between factors and landslide occurrences that include bivariate regression analysis [18,19,20,21,22,23], multivariate [24,25,26] and logistic regression [27,28,29,30], fuzzy logic [19,31,32,33,34,35,36,37] and artificial neural network modeling [19, 20, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47]. Multivariate statistical methods provide simultaneous analysis of several independent variables on space dependent variables. Because phenomena such as landslides are due to simultaneous functions as well as the different effects of several variables, the use of multivariate statistical models was chosen [48].
The first step is the preparation of a landslide susceptibility map is indicating the relative susceptibility of the terrain for the occurrence of landslides. When combined with temporal information, this is then converted into a landslide hazard map. Used in combination with elements at risk information, the estimation of potential losses due to landslides as well as long-term landslide risk management in mountainous areas can be done [49]. The general risk equation below shows the risk level as a result of natural hazards, elements at risk and landslide vulnerability. Risk (R) is a function of the probability of a hazardous event (H) and its consequences (C) for all the exposed elements. Landslide risk was calculated as the single product of three contributing factors: (1) the probability of landslide occurrence within a certain magnitude (2) risk valued elements and (3) vulnerability [50,51,52,53,54].

Risk = Natural hazard × Vulnerability × Elements at Risk
($R = H \times V \times E$)

2- Materials and Methods

2.1- Study Area

The Baba Heydar Watershed, located in the central portion of the Zagros Mountains, is one of the major sub basins of the Karoon River. It is between 32° 13′ 21″ to 32° 24′ 1″ latitude and 50° 22′ 4″ to 50° 32′ 29″ longitude and occupies approximately 181.46 sq. km in the Chaharmahal and Bakhtiari Province of southwestern Iran (Fig. 1). Rangelands make up 69% of this region. The remaining 31% contains residential, agricultural and rocky lands. The altitude in the study area varies between 2,040 to 3,610 m with an average annual rainfall in the watershed of 672 mm according to the Iranian Meteorological Organization report. Subsequent erosion has removed softer rocks, such as mudstone (rock formed by consolidated mud) and siltstone (a slightly coarser-grained mudstone) while exposing harder rocks 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.

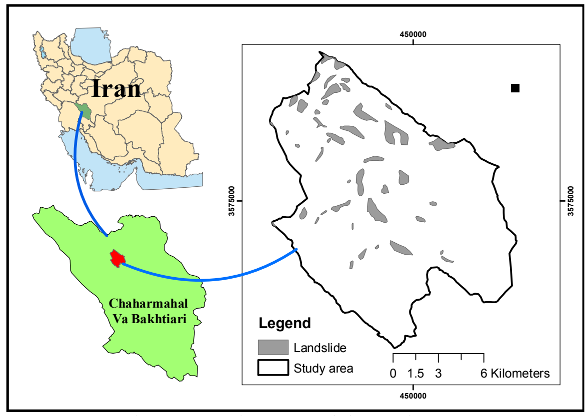

Fig. 1: Location map of the study area

2.2-Landslide Inventory Map

Different formats can be used to prepare a landslide inventory map including the use of gathered information related to landslides or analysis of the data using remote sensing and GIS techniques. For this study, a landslide inventory map was prepared using field investigations, local information and aerial photograph interpretation.

2.3-Selection and Effective Factor Classification

Using both literature review and a study of the conditions of the Baba Heydar Watershed, a total of ten factors including altitude, slope percentage, slope aspect, lithology, distance from faults, rivers, villages and roads, land use and precipitation were chosen as effective factors on landsliding. Next, the area and landslide percentage, density ratio and landslide density percentage for each of the ten landslide factors was calculated.

2.4-Landslide Susceptibility Mapping Using a Logistic Regression Model

Using logistic statistical regression for landslide susceptibility zonation, the landslide density in each class of the ten landslide parameters was calculated. A homogeneous unit map was prepared by integrating several factor maps. After pairing the homogeneous unit map with the landslide distribution map, the landslide units were determined. All homogeneous landslide units were given the code (1) and all homogeneous units not containing landslides were given the code (0). The absence or presence of landslides was entered in homogeneous units as a dependent variable in the R statistical software while the landslide density percentage in each class of the ten parameters was entered as an independent variable. The logistic regression equation is as follows [27]:

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

In this equation, p is the probability of independent variable(Y), p/(1-p) is the odds or likelihood ratio , C_0 is the intercept , C_1, C_2,…. and C_n are coefficients which measure the size and contribution of independent factors X_1, X_2, ... and X_n in a dependent variable. Using the density of factors as independent variables and presence or absence of landslides as the dependent variable, the following equation with an error level of 0.01 % was developed.

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

The resulting model was used to create a landslide susceptibility map containing the classes very low, low, medium, high and very high.

2.5. Evaluation of Landslide Susceptibility Model

2.5.1- Pseudo-R^2 Index

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

$$Pseudo_R^2 = 1 - \left(\frac{\log(likelihood)}{\log(l_0)}\right) \qquad (5)$$

likelihood: the likelihood function amount in a case where the model is fully fitted.

l_0: the likelihood function amount in a case where all coefficients except for the intercept are zero.

Unlike R2 in ordinary regression, Pseudo-R2 does not indicate the proportion of variance explained by the model. Instead, it indicates the dependency rate of both the empirical and output data of the regression model. Therefore, its value is generally much lower than R2. A Pseudo-R2 equivalent to 1 indicates a perfect fit while a Pseudo-R2 equivalent to 0 means that there is no significant relationship between independent and dependent variables. In spatial studies, a Pseudo-R2 more than 0.2 is considered a relatively good fit [56].

2.5.2- ROC Index

The efficiency of the susceptibility model can be evaluated using a ROC index (Relative Operating Characteristic). This index is computed using a ROC curve. The ROC curve is a diagram in which the pixel ratio that correctly predicted the occurrence or nonoccurrence of a landslide (True Positive) is plotted against the pixel ratio that gave a wrong prediction. As already mentioned, the susceptibility model computes the probable change in each pixel in a continuous range of zeroes and ones. By determining a threshold (e.g. 0.5) the model's output can be converted to a discrete scale of zeroes and ones. Pixels with a probability of change more than their threshold are assigned a 1, while pixels with a probability of change less than their threshold are assigned a 0. The output is then presented as a map. By comparing this with the landslide inventory, the pixel ratio can be plotted in a ROC diagram where the ROC index is equal to the area under the curve [55].

2.6-Landslide Risk Assessment

Overall landslide risk is estimated using the R=H. E. V risk equation in which R, H, E and V stand for risk, hazard intensity, elements at risk and vulnerability rate, respectively. In order to evaluate the risk to bridges smaller than 25 hectares (1×1 cm in a 1:50,000 scale), the logistic regression model hazard map was combined with larger adjacent bridges. As a result, 137 units of different classes were deduced .The resulting map is considered the basis of landslide risk evaluation in the studied area.

2.6.1- Elements at Risk Map

The elements were identified and a map of elements at risk was prepared incorporating land use and topographic maps along with a list of elements at risk for each unit of the risk class map (Table 4 and Fig. 5).

2.6.2- Vulnerability Map

Economic and ecological risk factors are important in the calculation of an element vulnerability score. Elements considered at higher risk are of more importance because of their higher vulnerability. There are no major industrial facilities, highways, tourist complexes or town houses in the studied area. However, communication pathways, land use and residential buildings are of great importance. The road in this area is essential for both vehicular traffic and the facilitation of communication between the village and the surrounding cities of Farsan and Shahrekord (Table 1, 5 and Fig. 5).

Table 1: Core vulnerability of elements at risk

Elements at Risk	Potential of elements at risk	Vulnerability Number
Roads	Increase due to paving, (including foundations) and increase in 3 coefficients and hazard class	1-15
Buildings	Increase in 3 coefficients and hazard class	1-15
Stream Network	Increase in importance, 2 coefficients and hazard class	1-10
Electrical Network	Increase in 3 coefficients and hazard class	1-15
Agriculture	Increase due to irrigation and increase in 3 coefficients and hazard class	1-15

2.6.3-Landslide Risk Map

The risk number was calculated using the R=H.E.V equation in which the numerical values of elements at risk, vulnerability and hazard intensity were multiplied. The final map was created using the 5 classes of very low, low, medium, high and very high based on the turning points of the pixel cumulative frequency curve (Table 6 and Fig. 6).

3- Results

3.1- Landslide Inventory Map

The landslide inventory map showed 46 distributed landslides in the area. The total area affected by landslides is 1,103.97 ha (6.1% of the watershed area).

3.2- Explanation of Effective Factors

The total area and landslide percentages, along with the landslide density percentage in each class of the ten landslide factors were calculated (Table 2 and Fig. 2).

Table 2: Calculation of the final susceptibility value for each identified land unit

Data layers	Total Area (ha)	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

Table 2. continued

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
Geologic Units				
Qft_2 (low level piedmont fan and valley terraces 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
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

Table 2. continued

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 Village (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

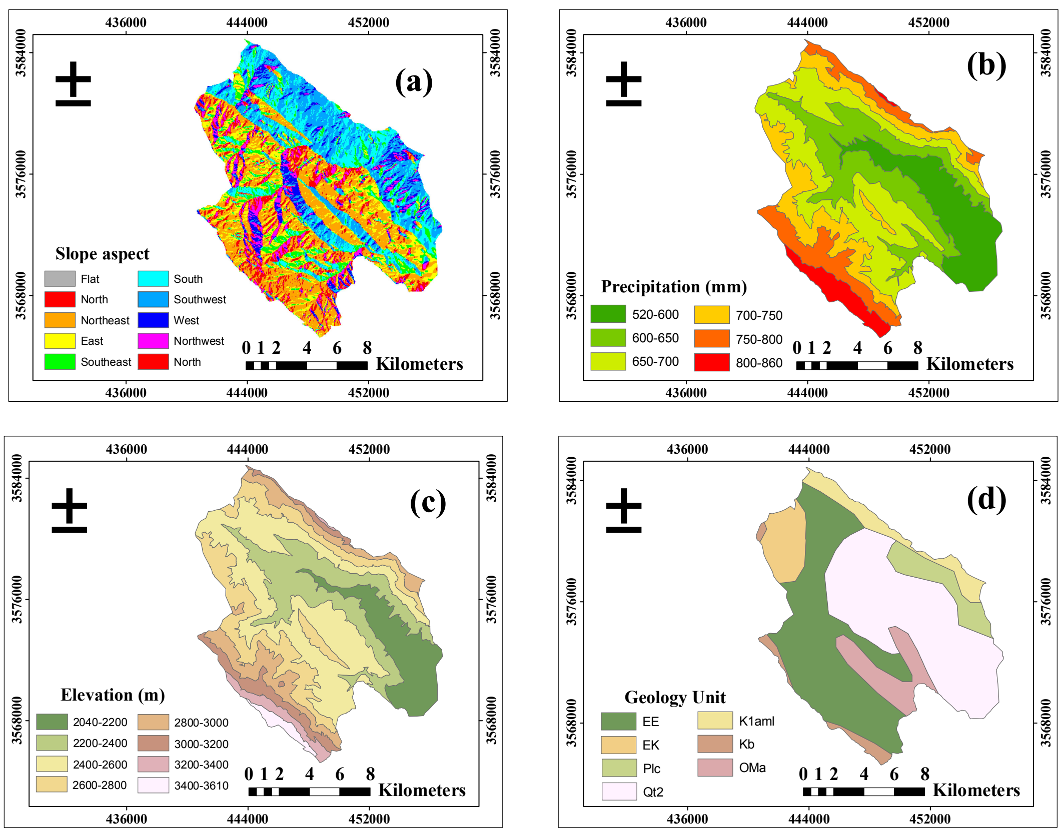

Fig 2: Landslide conditioning factors; (a) aspect, (b) rainfall, (c) elevation, (d) lithology,

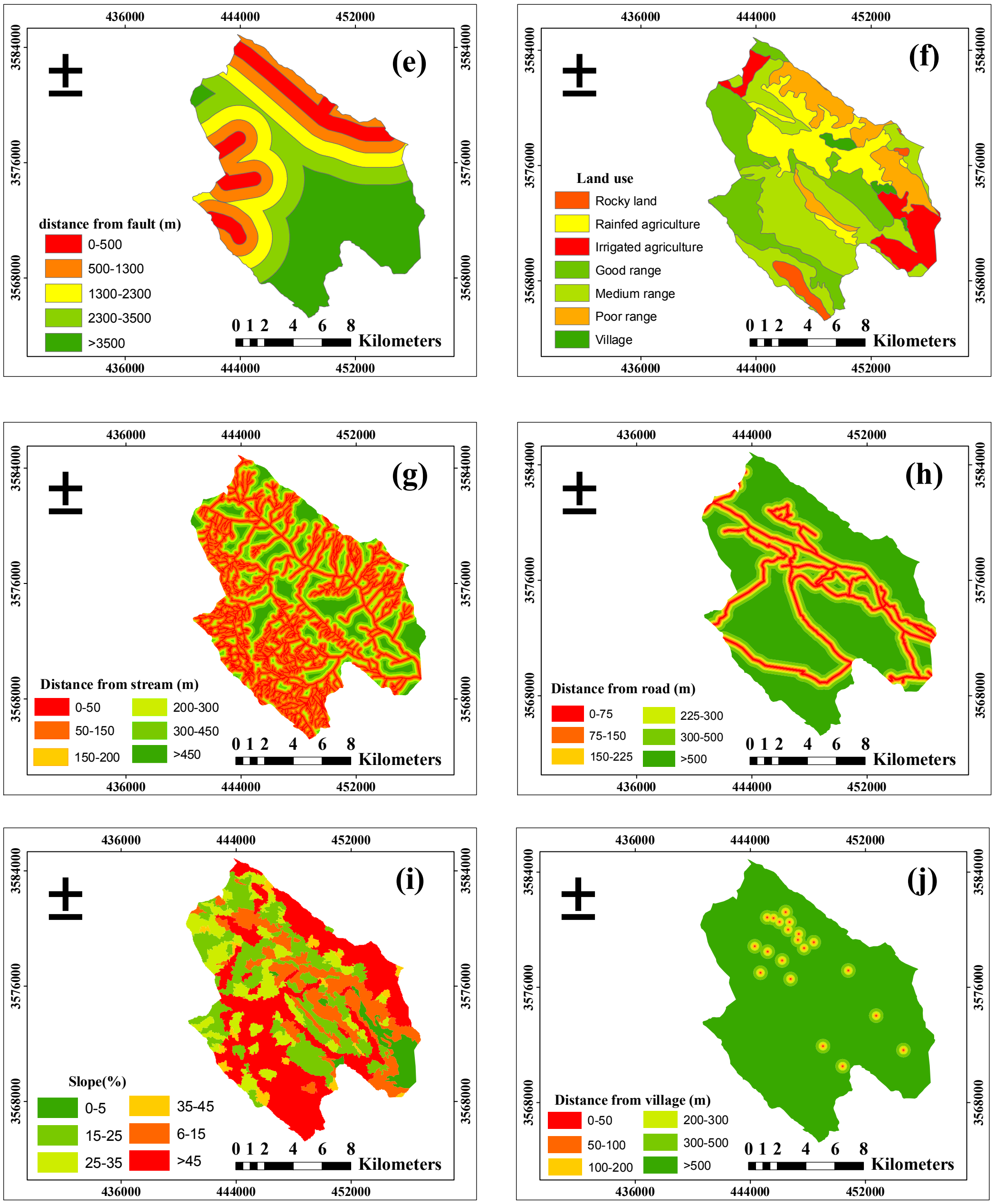

Fig 2 continued: Landslide conditioning factors; (e) distance from fault, (f) land use , (g) distance from stream, (h) distance from road, (i) slope percentage, (j) distance from village

3.3- Landslide Susceptibility Zonation

Using the resulting logistic regression model, a landslide susceptibility map was produced using the classifications of very low, low, medium, high, very high classes (Table 3 and Fig. 3).

Table 3: Distribution of area in different landslide susceptibility classes

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	18146.08	100

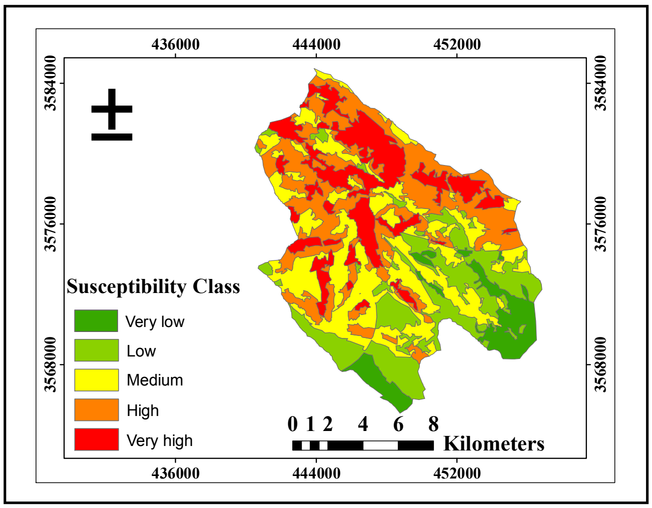

Fig. 3: Landslide susceptibility map based on logistic regression model in Baba Heydar Watershed

In this study the accuracy of logistic regression using Pseudo-R^2 index was evaluated. Because the Pseudo-R^2 amount was calculated to be equal to 0.48, this model's fit is considered relatively good. The ROC index amount of 0.876 for logistic regression indicates high potential for zoning and determining areas prone to landslide susceptibility in the Baba Heydar Watershed. The results suggest that the logistic regression model is a suitable model for the Baba Heydar Watershed (Fig 4).

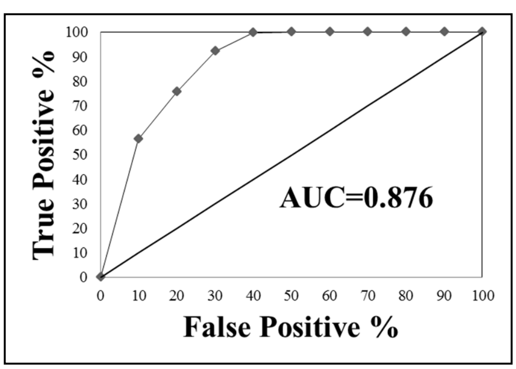

Fig. 4: ROC curves for logistic regression

3.4- Risk

The risk mapping was classified into the 5 classes of very low, low, medium, high and very high based on the turning points of the pixel cumulative frequency curve (Table 6 and Fig. 6).

4- Discussion and Conclusion

For this research risk evaluation was calculated using the R=H.E.V equation. Roads, residential properties, springs, stream networks and farmlands were selected as elements at risk. This model was also used for qualitative landslide assessment [53] in the Bajo Deba area of northern Spain and [52] northern Lisbon in Portugal. [53] selected roads and buildings as elements at risk while [48] selected houses, schools, cemeteries and roads as elements at risk.

This study focused on performing susceptibility zonation using logistic statistical regression for the Baba Heydar Watershed. Logistic regression multivariate statistical methods combine the simultaneous analysis of several independent variables with spatially dependent variables. Because phenomena such as landslides are caused by the simultaneous occurrence and effects of several variables, this method was considered appropriate. [5],

[6], [7], [15], [27] and [30] all used logistic regression in landslide susceptibility zonation.

The conditions taken into consideration for the Baba Heydar Watershed include its geology, roughness, geomorphology and tectonic conditions as well as human pressure factors such as land use and rural road changes. Forty-six cases covering 1,103.97 hectares in the watershed basin were examined. It was concluded that approximately 44% of the watershed area is located in both the high and very high hazard susceptibility classes. This is vital information to consider in the susceptibility management, landslide loss and land use planning of this area. After multiplying the hazard maps, elements at risk and vulnerability, a landslide risk map was produced showing approximately 35% of the watershed area located in both the high and very high risk classes. This information is vital to consider in the risk management, landslide risk and land logistics of this mountainous area. The conversion of rangeland to rain fed farmland along with the building of roads during recent years is considered a large contributing factor.

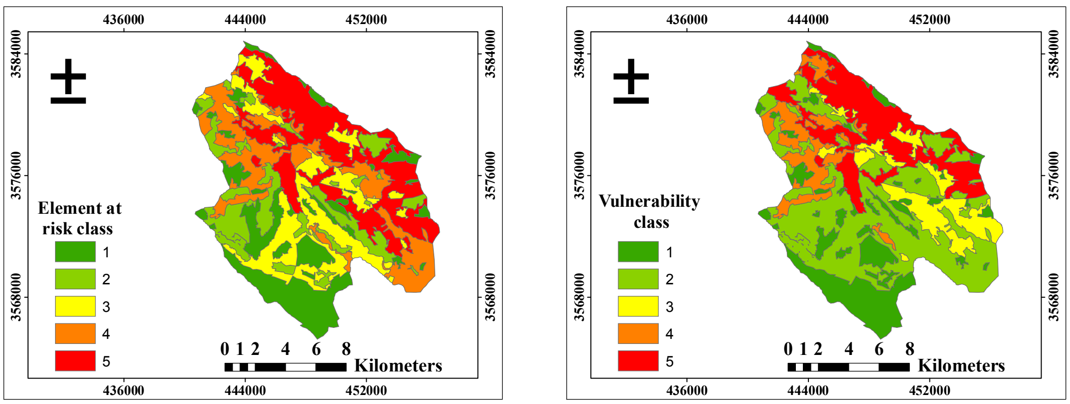

Fig. 5: Elements at risk and vulnerability map for Baba Heydar Watershed

Table 4: Elements at risk classes for Baba Heydar Watershed

Elements At Risk Classes	Number of Elements	Area (ha)	Area %
Very Low	0, 1	3592.96	19.86
Low	2	2814.30	15.56
Medium	3	3362.11	18.59
High	4	3437.71	19.00
Very High	5	4882.07	26.99
Total		18089.15	100

Table 5: Vulnerability classes for Baba Heydar Watershed

Vulnerability Classes	Vulnerability Number	Area (ha)	Area %
Very Low	0.0-10	3309.39	18.30
Low	11-25	7087.99	39.18
Medium	26-40	2057.04	11.37
High	41-55	1749.69	9.67
Very High	55-75	3884.45	21.47
Total		18088.56	100

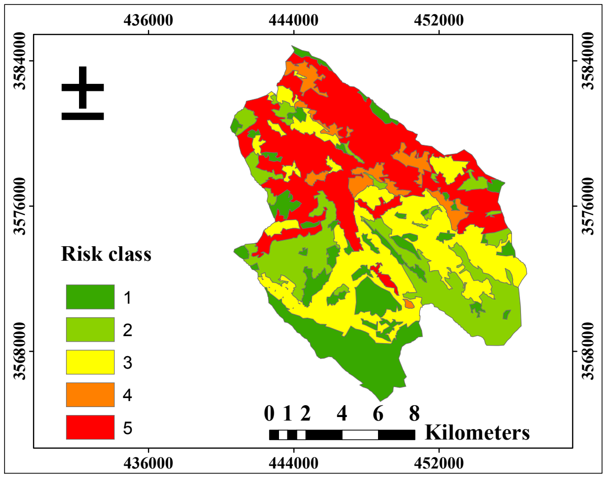

Fig. 6: Risk map for Baba Heydar Watershed

Table 6: Area distribution for landslide risk classes

Risk class	Pixel value	Area (ha)	Area %
Very Low	0-6	3309.39	18.30
Low	7-12	3586.07	19.82
Medium	13-30	4786.78	26.46
High	31-60	957.44	5.29
Very High	61-125	5449.18	30.12
Total		18088.86	100

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