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Landslide susceptibility mapping using logistic regression analysis in Latyan catchment

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Abstract

Every year, hundreds of people all over the world lose their lives due to landslides. Landslide susceptibility map describes the likelihood or possibility of new landslides occurring in an area, and therefore helping to reduce future potential damages. The main purpose of this study is to provide landslide susceptibility map using logistic regression model at Latyan watershed, north Iran. In the first stage, 208 Landslide locations were identified and mapped using extensive field surveys. 75 % of these landslides were used for training and 25 % of them for validation of the model. The mapped landslides were then georeferenced using ArcGIS 10 to provide the landslide inventory map. In the second stage, maps of factors affecting the occurrence of landslides were prepared in ArcGIS 10. Finally in the last stage, the relationships between these affecting factors and the landslide inventory map were calculated using Logistic regression algorithm. The amount of pseudo R^2 (0.32) and AUC (0.85) shown the high efficiency of Logistic regression model. According to the coefficients obtained by the model, lithology is the most important factor affecting landslide occurrence (coefficient= +12.032). Most landslides (69%) are located within Ek Formation. The results indicated that 7.56% of the basin is located in high susceptibility class and 2.88% in very high susceptibility class.

Keywords: Landslide; Logistic regression; Latyan watershed; PGA

1. Introduction

Landslides are amongst the most damaging natural hazards. Every year, hundreds of people all over the world lose their lives due to landslides. This phenomenon also causes extensive damages to constructions and infrastructures as well as a thousand casualties annually. In Iran, about 187 people have been killed by landslides and some infrastructure such as forest roads (3 km), railroads (6 km), main roads (252.67 km), and rural roads (46 km) have been damaged in a period of 25 years (between 1982 and 2007) (Iranian Landslide Working Party 2007). The monetary losses due to mass movements have been estimated to be 126,893 billion Iranian Rials until the end of September 2007 (Pourghasemi *et al*., 2012a, b). Preventing natural hazards such as landslide is one of the best practices in watershed management activities. Susceptibility map provides a document that describes the likelihood or possibility of new landslides occurring in an area, and therefore, helping to reduce future potential damages. Landslide susceptibility modeling (LSM) and analysis are performed through varieties of methods and techniques including artificial neural network models (Zare *et al*., 2013), support vector machine models (Dou *et al*., 2015), bivariate models (Youssef *et al*., 2015), weights-of-evidence models (Regmi *et al*., 2014), fuzzy logic models (Pourghasemi *et al*., 2012c), Dempster–Shafer model (Pourghasemi *et al*., 2013b), frequency ratio model (Jafari *et al*., 2014), simplified physically based models (Formetta *et al*., 2016), coupled hydrological and geotechnical models (Zhang *et al*., 2016) and multi-method integrated geophysical, geotechnical, mineralogical and precipitation

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time series (Soto *et al*., 2017). However, sufficient and accurate information about the landslide and contributing parameters are needed to construct landslide prediction model (Zhu and Huang, 2009). Logistic regression model was successfully used to map landslide susceptibility in the past (Ayalew and Yamagishi, 2005; Duman *et al*., 2006; Nefeslioglu *et al*., 2008; Pradhan, 2010; Ercanoglu and Temiz, 2011; Devkota *et al*., 2013). In Logistic Regression, spatial distribution of landslide is assessed on the basis of interaction of only statistically significant instability data and insignificant data are excluded from consideration. Additionally Logistic Regression analysis is free of data distribution issues and can handle a variety of datasets, such as continuous, categorical and binary data. (Dai *et al*., 2001; Lee and Min, 2001; Lee and Sambath, 2006). Depending on the case study, several factors can be used as the landslide controlling factors. According to the previous researches, earthquake (Yang *et al*., 2014), human activities (Ayalew and Yamagishi, 2005), land morphology (Gorsevski *et al*., 2006), soil characteristics (Regmi *et al*., 2010), slope (Lee, 2005; Yalcin, 2005), aspect (Lee *et al*., 2004; Yalcin, 2008), hydrological conditions (Komac, 2006) and the proximity to some watershed features such as rivers and faults (Ayalew and Yamagishi, 2005; Yalcin, 2005) are among the most important parameters in landslide occurrence. Lee and Min (2001) say that the major parameter of slope stability analysis is the slope angle. Slope angle is very regularly used in land slide susceptibility studies since landsliding is directly related to slope angle (Dai *et al*., 2001; Nefeslioglu *et al*., 2008). Aspect is also considered as an important factor in landslide susceptibility mapping (Lee, 2005; Yalcin and Bulut, 2007). Aspect associated parameters such as exposure to sunlight, drying winds, rainfall and discontinuities may affect the occurrence of landslide (Komac, 2006). Altitude is useful to classify the local relief and locate points of maximum and minimum heights within the trains (Yalcin *et al*., 2010). Altitude is a significant landslide affecting factor because it is controlled by several geologic and geomorphological processes (Gritzner *et al*., 2001; Dai and Lee, 2002; Ayalew *et al*., 2005). Lithology is one of the most important parameters in landslide studies because different lithological units have different erodibility degrees (Dai *et al*., 2001; Yesilnacar and Topal, 2005; Yalcin and Bulute, 2007; Garcia-Rodriguez *et al*., 2008; Regmi *et al*., 2013). Some researchers (e.g. Yalcin, 2007) have emphasized the importance of land use on slope stability. The effecting factor of distance from river, road and fault currently has been used successfully (Pourghasemi *et al*., 2013a).The influence of plan curvature on the slope erosion processes is the convergence or divergence of water during downhill flow (Oh and Pradhan, 2011). The plan curvature map was produced using a system for automated geoscientific analyses (SAGA) GIS. Another topographic factor used in landslide susceptibility is the topographic wetness index (TWI) which measures the degree of accumulation of water at a site (Pourghasemi *et al*., 2013c). The main goal of this study is to produce landslide susceptibility map using GIS-based Logistic regression model in Latyan watershed, Iran, where it is important for landslide hazards.

2. Materials and Methods

2.1. The study area

The study area is located in north of Tehran, Iran, which is one of the most landslide-prone areas in Iran. The watershed lies between the longitudes of 530000 to 580000 N and latitudes of 3950000 to 4000000 E, is mountainous and lies in the geological Alborz folded zone (Fig. 1). It covers four adjacent 1:50,000 topographic sheets and has an extent of about 70793 hectares. Latyan dam is located in the study area. Climate is cool mountainous based on Ambrose Climate Classification. The mean annual rainfall is around 573 mm. In general, the precipitation falls between November and January based on the records from the Iranian Meteorological Department. Altitude in the study area varies between 1,500 to 4,325m. From the view of landuse, some parts of the study area are pasture and forest lands and some parts are utilized for orchard, agriculture and residence.

2.2. Methodology

2.2.1. Preparing landslide inventory map

The mapping of actual landslides in the study area is essential for investigating the relationship between the landslide distribution and the effecting factors. To produce a detailed and reliable landslide inventory map, extensive field surveys and observations were performed in the study area. A total of 208 landslides were identified and mapped by investigating aerial photos with the scale of 1:25,000 supported by

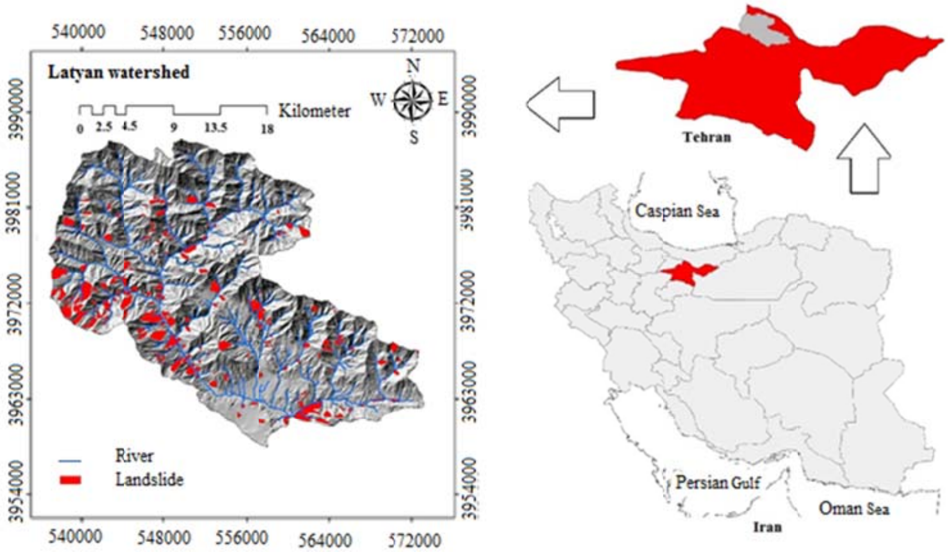

Fig. 1. Location of the Latyan watershed and landslide inventory map

field survey. Identified landslides were classified into rotational and translational ones according to the landslide classification system proposed by Varnes (1978).

2.2.2. Preparing maps of effecting factors for landslide occurrence

Various thematic data maps representing landslide effecting factors, such as slope degree, slope aspect, altitude, lithology, land use, rainfall, Peak ground acceleration (PGA), distance from faults, distance from rivers, distance from roads, plan curvature and topographic wetness index (TWI), were prepared. The layers of slope degree, slope aspect, altitude, TWI, rain fall, distance from river and plan curvature were produced using Digital elevation model (DEM) with 10 meters cell size created from digital topographic map of the study area with the scale of 1:25000. The geological map of the study area was prepared by the Geological Survey of Iran (GSI) at 1:100,000 scale, and was digitized in GIS. The land use layer was classified using a Landsat/ETM+ satellite image for the year 2010. The layers of PGA and distance from road and fault were derived from the geological map at 1:100,000 scale.

2.2.3. Landslide susceptibility mapping using Logistic regression (LR)

It is believed that among the wide range of statistical methods proposed in landslide susceptibility mapping, LR analysis has proven to be one of the most reliable approaches (Ayalew and Yamagishi, 2005). The logistic regression permits one to draw a multivariate regression relationship between a dependent variable and several independent variables. Logistic Regression, which is one of the multivariate analysis models, is helpful for forecasting the presence or absence of characteristic or outcome based on the values of a set of predictor variables. The advantage of Logistic Regression is that, through the addition of a suitable link function to the usual liner regression model, the variables may be either continues or discrete, or any combination of two types and they do not necessarily have normal distribution (Lee, 2005). In the landslide susceptibility studies, Logistic Regression Model is one the acceptable methods to characterize the association between the presence or absence of a landslide, the dependent variable, and a set of independent parameters such as slope, lithology and land cover (Ayalew and Yamagishi, 2005). Presence (1) and absence (0) coefficients can be utilized to calculate approximate ratios for each of the independent variables. Logistic Regression analysis is generaly used in earth science, and explained as a linear equation as given below (Lee, 2005).

$$Y = logit(p) = ln(p/1-p) \quad (1)$$

$$Y = C_0 + C_1 X_1 + C_2 X_2 + \ldots + C_n X_n \quad (2)$$

where p is the probability that the dependent variable (Y) is 1, p/(1-p) is the so-called odd or frequency ratio, C_0 is the intercept and $C_{1,}$ C_2… C_n are coefficients, witch measure the contribution of the independent factors ($X_{1,}$ $X_{2,}$ … X_n) to the variations in Y (Lee, 2005). The spatial association between landslide inventory and the landslide factor maps (slope, aspect, altitude, lithology, landuse, plan curvature, TWI, distance from river, distance from fault and distance from road) was assessed using the Logistic Regression method.

2.2.4. Model Validation

Two statistical tests were carried out using an IDRISI GIS environment, including: pseudo R^2 and ROC to validate model. The pseudo R^2 equal to 1 indicates a perfect fit, whereas 0 shows no relationship. When a pseudo R^2 is greater than 0.2, it shows a relatively good fit (Clark and Hosking, 1986). A disjunctive approach, which is much easier to interpret, is to look at how well the model actually predicts the dependent variable. In this case, IDRISI uses the relative operating characteristic (ROC) to compare a Boolean map of reality (the presence or absence of landslides) with the probability map. The ROC value ranges from 0.5 to 1, where 1 indicates a perfect fit and 0.5 represents a random fit (Ayalew and Yamagisi, 2005). ROC plots the different accuracy values obtained against the whole range of possible threshold values of the functions, and the AUC serves as a global accuracy statistic for the model, regardless of a specific discriminate threshold. This curve is obtained by plotting all combinations of sensitivities and proportions of false negatives (1-specificity), which may be obtained by varying the decision threshold.

3. Results and Discussion

A total of 208 landslides were identified in the study area based on the interpretation of aerial photographs and field surveys. Then the landslide inventory map was produced in GIS software (fig. 2). Of the 208 landslides identified, 120 landslides were classified transitional, while the remaining (88 landslides) cases were classified as rotational. Different landslide conditioning factor layers including slope, aspect, altitude, lithology, land use, rainfall, PGA, distance from faults, distance from rivers, distance from roads, plan curvature and TWI were prepared and shown in fig 2. The slope map of the study area was classified into nine categories namely: 0–5%, 5– 15%, 15–20%, 20–30%, 30–65%, 65–100%, 100–200%, 200–400% and 400–700%. ArcGIS analysis indicates most landslides (more than 50%) occur when the percent of slope is 30-65% (fig. 2a). The aspect map is also grouped into nine classes including flat and eight directions namely south, southwest, west, northwest, north, northeast, east and southeast. The distribution of landslide on different aspect classes shows about 45% of the landslides are located into three directions north, northwest and northeast (fig. 2b). The altitude map is grouped into 9 classes namely: 1577-1800m, 1800-2000m, 2000-2300m, 2300-2500m, 2500-2700m, 2700-3000m, 3000-3200m, 3200-3500m and 3500-4316m. However landslides in 2000-2300 m are domain (23%) (fig. 2c).The lithology maps of the study area were differentiated into 22 lithological units. As a result of the aerial distribution analysis performed according to the lithological units, most landslides (69%) are located within Ek formation (fig. 2l). The study area was divided to six land use classes. These classes are forest land, irrigation agriculture, lake, pasture land, rock land and residential land witch 76 % of the landslides happened in pasture lands (fig. 2i). In terms of rainfall six classes were divided that the rainfall class of 450-550 is domain (35%) (fig. 2e). PGA include five classes that the range of 0.34-0.41 have a higher percentage landslide (43%) (Fig. 2f). Plan curvature is described as the curvature of a contour line formed by intersecting a horizontal plane with the surface (Fig. 2j). TWI showed that most landslide occurred in the domain zon (Fig. 2k). In the case of distance from river the study area was divided into six different buffer ranges including 0-200, 200-400, 400-650, 650-1200, 1200-1800, 1800-3400. The distance class of 0-200 is more susceptible (30%) (Fig. 2g). The distance from the faults is calculated using the geological map. Results show that the interval 4000-6500 has more susceptible (31%) (Fig. 2k). Similar to the effect of the distance to river, landslides may occur on the road. Six different buffer zones are created on the path of the road to determine the effect of the road on the stability of slope. The results shown the importance of 0-500 interval (35%) in terms of susceptibility (Fig. 2d).

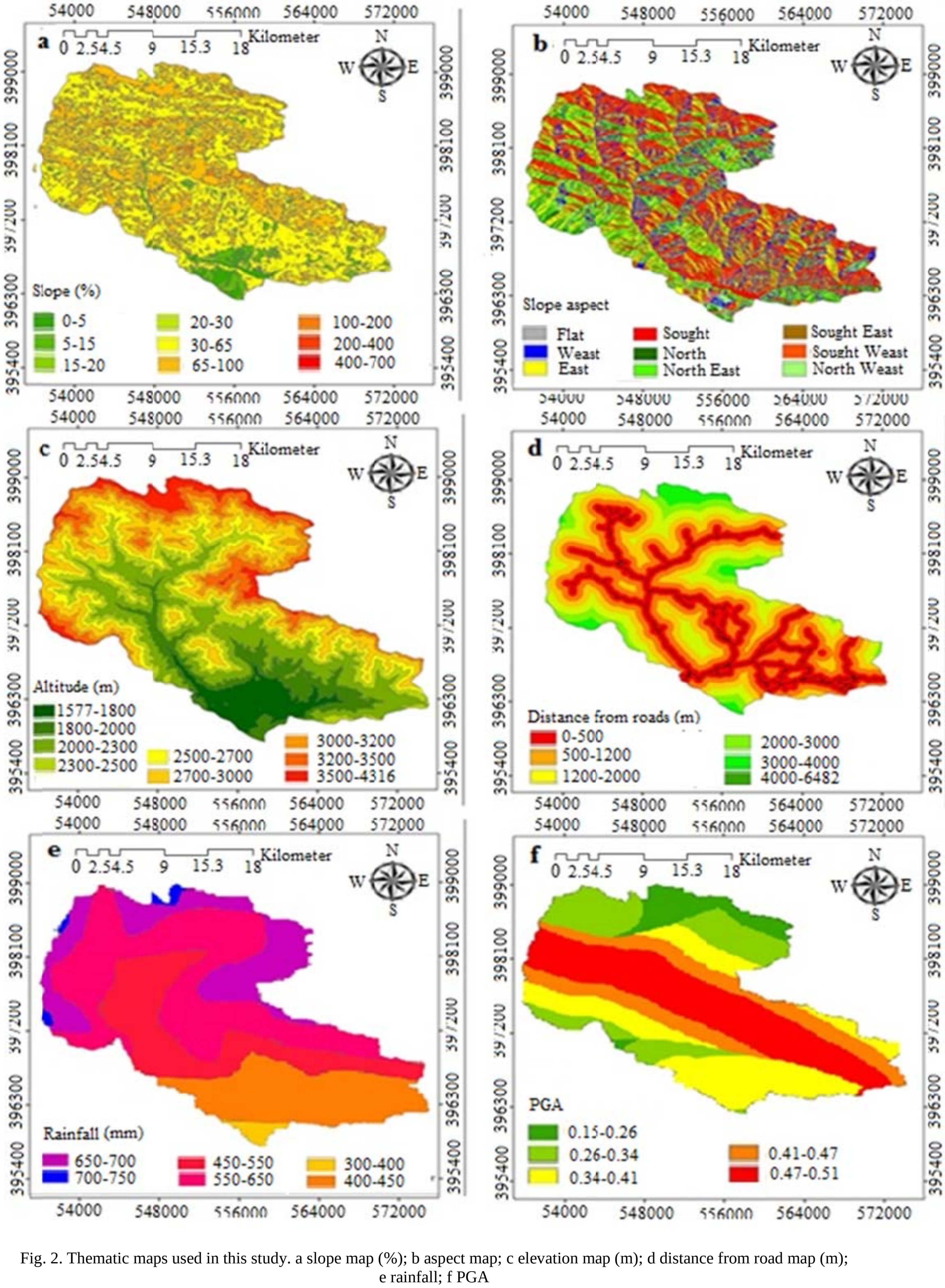

Fig. 2. Thematic maps used in this study. a slope map (%); b aspect map; c elevation map (m); d distance from road map (m); e rainfall; f PGA

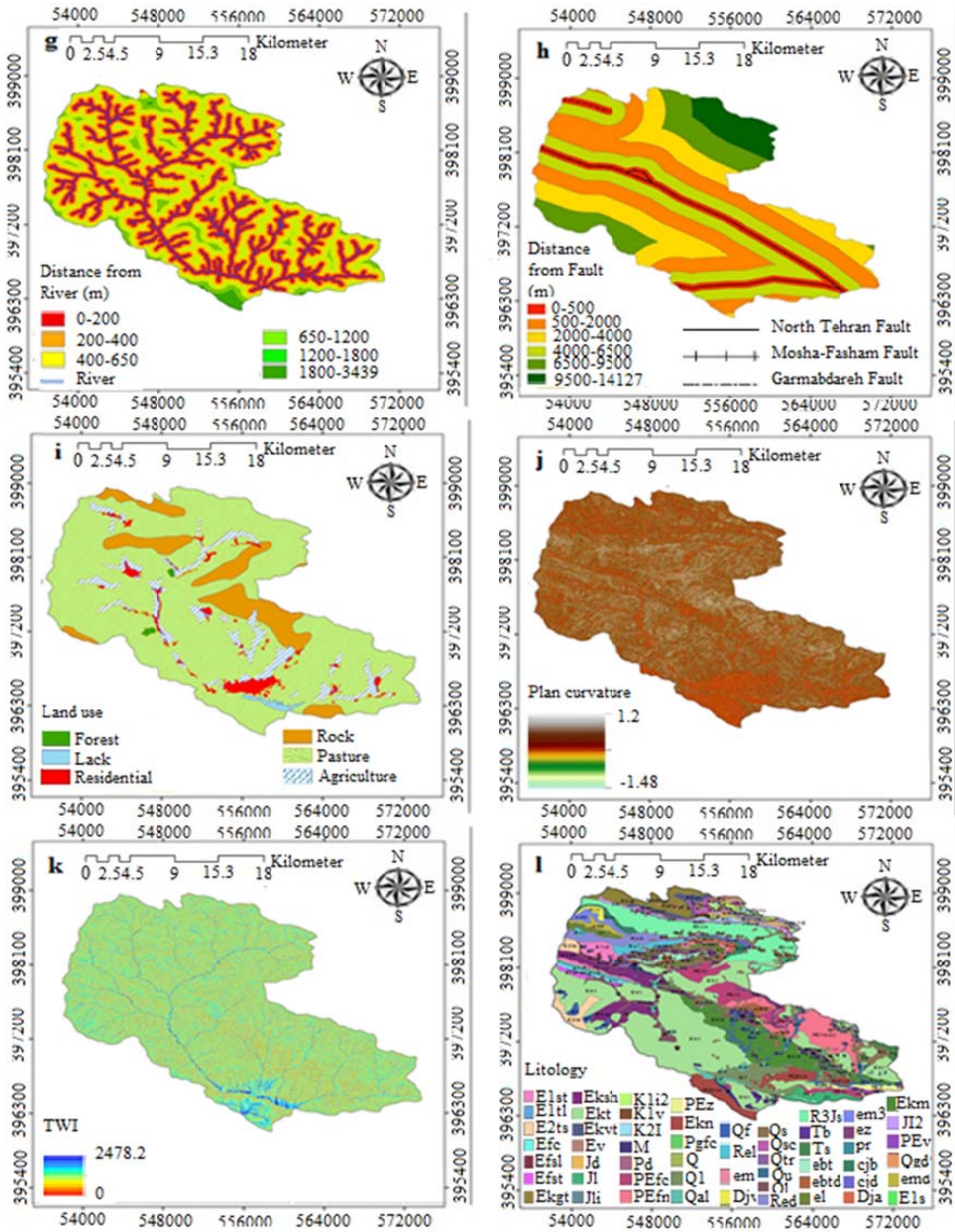

Fig. 2. Continued. g distance from river map (m); h distance from fault map (m); i land use map; j plan curvature map; k topographic wetness index map; l lithology map

After running Logistic Regression model using stepwise method, six important conditioning factors remained in the equation and removed other factors (Equation 3). The six remaining conditioning factors namely: lithology, distance from river, rainfall, distance from road, slope and PGA have the highest correlation with landslide. The results of spatial relationship between landslides and remaining conditioning factors using Logistic Regression model is shown in table 1. According to the model coefficients (Table 1), lithology is presented as the most important factor affecting landslide occurrence (+12.032). It is extensively accepted that lithology significantly influences the occurrence of landslide, because lithological variations often lead to a difference in the strength and permeability of rocks and soils (Yalcin *et al*., 2010). According to the lithology map (fig. 2), most of the landslides are seen in Ek Formation (69%). Parts of Ek Formation in the study area consist of shale and siltstone which increase erodibility. However lithology is one of the most important parameters in landslide studies because different lithological units have different erodibility degrees (Dai *et al*., 2001; Yesilnacar and Topal, 2005; Yalcin and Bulute, 2007; Garcia-Rodriguez *et al*., 2008). PGA, rainfall, slope degree, distance from road and distance from river are the next important effecting parameters. Lithology, rainfall, slope and PGA have shown direct relationship and distance from river and road indirect relationship with the landslide occurrence. By substituting coefficients, a Logistic regression equation was obtained as shown in equation 3.

Table 1. Selected conditioning factors based on Logistic Regression model

Landslide conditioning factors	Model coefficients
Lithology	+12.032
distance from river	- 0.003
Rainfall	+0.169
distance from road	-0.011
Slope	+0.146
PGA	+4.45
Constant coefficient	+7.710

$$Y= 7.710+12.032\ \text{Lithology}-0.003\text{River}+ 0.169\ \text{Rainfall}- 0.011\ \text{Road}+ 0.146\ \text{Slope}+4.45\ \text{PGA} \quad (3)$$

The landslide susceptibility map has a continuous scale of numerical values and there is a need to separate these values into susceptibility classes. There are several mathematical methods for classifying the susceptibility degrees. In this research, we used Natural break method (Pourghasemi *et al*., 212c). The landslide susceptibility map was classified into five following susceptibility classes: Very high, high, moderate, low and very low (fig. 3). The area and percentage of each susceptibly class is shown in Table 2. However, the statistic that can help to determine how well this method classified the areas of landslides is chi-square statistic (Yalcin *et al*., 2011). The results showed that the susceptibility classes are well separated by Logistic Regression and internal differences in susceptibility classes is significant at a confidence level of 95% ($p<0.05$). The results show that 34.71 % of the basin is located in very low susceptibility class, 34.68% in low susceptibility class, 20.19% in medium susceptibility class, 7.56% in high susceptibility class and 2.88% in very high susceptibility class.

Table 2. Landslide susceptibility classes in the Latyan Watershed based on Logistic regression model

Land slide class	Expressive traits	Area (ha)	Area (%)
I	Very low	24574.67	34.71
II	Low	24551.71	34.68
III	Medium	14294.51	20.19
IV	High	5353.14	7.56
V	Very high	2040.27	2.88
	Total	70793	100

In order to validate landslide susceptibility map, two statistics were used. The results are presented in table 3 and fig. 4. As it can be seen, the amount of pseudo R^2 (0.32) shows a good fit. In the ROC Method, it is necessary to apply, the landslide data sets that were not used in model building process. For doing this, the total landslides observed in the study area, were split into 2 parts, 156 (75 %) was randomly selected from the total 208 landslides as the training data and the remaining 52 (25 %) landslides are kept for validation propose. Spatial effectiveness of these susceptibility maps was checked by receiver operating characteristics (ROC). Since the area under the ROC curve (AUC) is high (0.85), the result of the test is excellent (table 1). The ROC method is already widely used as a measure of performance of a predictive rule (Yesilnacar and Topal, 2005; Van Den Eeckhaut *et al*., 2006; Pradhan *et al*., 2010 a, b).

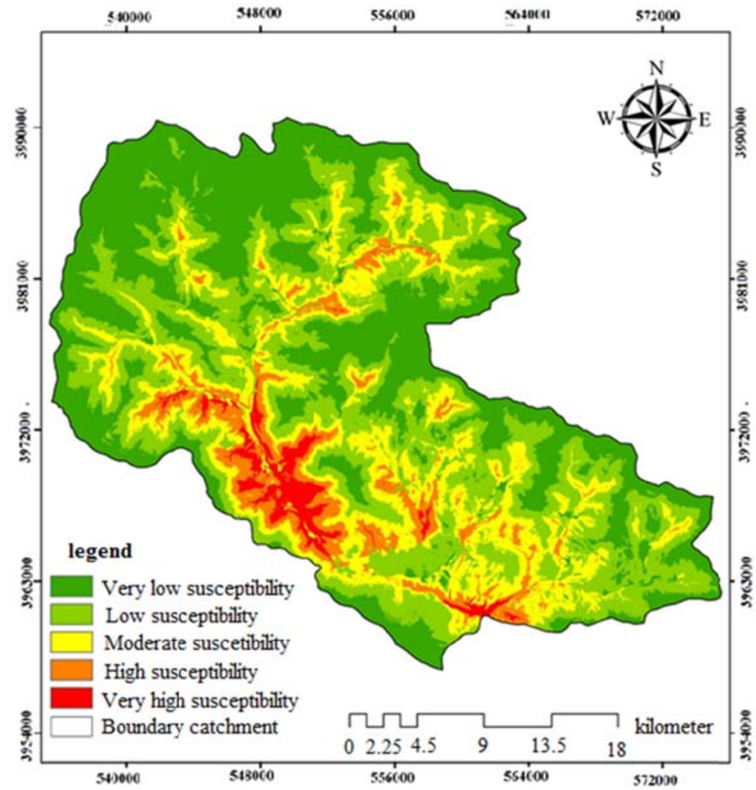

Fig. 3. Landslide susceptibility map based on LR model

Table 3. Summary statistics of the Logistic regression model

Statistics	Value
Pseudo R^2	0.32
ROC	0.85

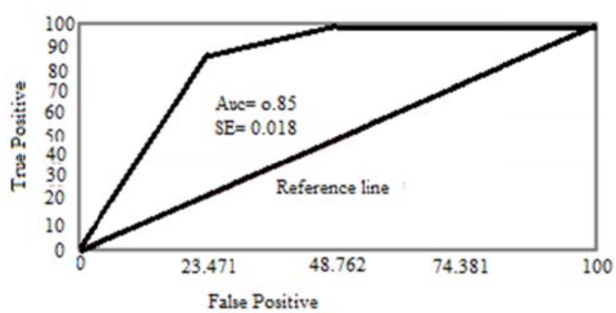

Fig. 4. Rock curve for the landslide susceptibility maps produced by Logistic Regression model

4. Conclusion

Since landslides are among the most dangerous natural disaster, for many years researchers worldwide have attempted to assess the landslide susceptibility analysis by using different methods. The preparation of landslide susceptibility maps is of great interest to planning agencies for preliminary hazard studies, especially when a regulatory planning policy is to be implemented (Pourghasemi *et al*., 2014). However, in this research, application of the Logistic Regression model for the spatial prediction of landslide susceptibility in Latyan watershed, Iran has been successfully demonstrated. The region is continually at risk of landslide since the topography and lithological materials make the area susceptible to landsliding. Logistic regression was used by many researchers successfully. For example, Brenning (2005) by comparing different methods, considered Logistic Regression model as an appropriate method to spatial prediction of landslide susceptibility. Lee (2004), also showed that the landslide susceptibility maps based on Bayesian probability model, a likelihood ratio model, and Logistic Regression was verified and compared with known landslide locations. The Logistic Regression model had higher prediction accuracy than the likelihood ratio model. However, proper efficiency of logistic regression has been shown in many other previous studies (Pourghasemi *et al.*, 2014, Ayalew and Yamagishi, 2005, Yalsin, *et al*., 2011). There are no universal guidelines to select casual factors in landslide susceptibility. In this study, we tried to use the maximum number of factors and 12 causing factors were finally selected to landslide susceptibility analysis. Of the 12 basic factors, six factors were selected and other factors were excluded by regression model. These six selected factors are: Lithology, distance from river, rainfall, distance from road, slope and PGA. According to the logistic regression output coefficients (table 1), Lithology is the most important causing factor in landslidnce occurrence (coefficient of +12.032). Most of the landslides are found in Ek Formation (69%). Model validation was performed using Pseudo R^2 and relative operating characteristics curve (ROC) by comparing the existing landslide locations with the landslide susceptibility map. Results indicated the high efficiency of the Logistic Regression model with pseudo R^2 (0.32) and AUC (0.85) (Table 3). The results show that 34.71 % of the basin is located in very low susceptibility class, 34.68% in low susceptibility class, 20.19% in medium susceptibility class, 7.56% in high susceptibility class and 2.88% in very high susceptibility class. As a final conclusion, results can provide useful information for planners, decision makers, and engineers to make better decisions in landslide areas.

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