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LANDSLIDE HAZARD ASSESSMENT IN HASHTCHIN AREA, NW-IRAN

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Abstract: Landslide hazard assessment is a key component of landslide studies. The most important and difficult task in landslide hazard analysis is estimating the probability of landslide occurrence in a study area. This task can be addressed with a spatial model that estimates the landslide probability in two stages. The proposed method has been used to perform a comprehensive landslide hazard assessment for Hashtchin area which is situated in the western Alborz Mountains, northwest of Iran. To this end, all the landslide data of the study area, which have occurred or have been reactivated at least once with moderate to high intensities in the last 50 years, were randomly divided into an estimation group containing 75% of landslide pixels and a validation group containing the remaining 25% of landslide pixels. In the first stage, the study area was divided into several prediction classes according to their relative likelihood of landslide occurrence, based on layers of effective factors. In the second step, the accuracy of the probability of landslide occurrence was examined using cross validation technique based on validation group, and by Receiver Operating Characteristic curve (ROC). The first stage of the research was repeated, but landslide occurrences were predicted based on all the landslide pixels. The sets of prediction classes were compared to the distribution of landslide occurrences in the validation group. Two approaches produced different prediction maps, and both of them generated acceptable results. The results, together with the hazard zonation maps, would allow planners to determine the actions for mitigating landslide effects, to avoid development in susceptible areas, and recommend adjustments to existing land use and restrictions for future land use. The map may also be used as a basis for the landslide risk assessment studies to be applied in the study area in the future. The introduced model can also be applied for mountainous areas with similar features including Alborz, Zagros and Caucuses Mountains.

Key words: Landslide, Prediction, Likelihood, Validation, Accuracy and Hazard

1. INTRODUCTION

Landslides, as one of the principal of hillslope erosion, are a dominant geomorphic process for mountain and hilly regions (Cruden & Varnes, 1996; Yalcin, 2007). They are a recurrent problem throughout most of northwest of Iran, where new landslides or reactivation of the old landslides result in significant damage to property, environmental losses, leaving the local residents and officials with serious concerns over likely occurrences of similar accidents elsewhere in the future. While there is no reliable report specifying the amount of damage caused by landslides in the study area, according to some unofficial reports, only the annual amount of direct damage has been estimated to be more than 50 million Dollars (Komakpanah & Hafezimoghadasi, 1994). In such landslide-susceptible area, any land-use planning or construction programs should be based on future landslide hazard analysis. Different multivariate statistical analyses, i.e. heuristic analysis, discriminant analysis, multiple regression and logistic regression approaches are available to assess landslide hazard in widespread and complex areas (Carrara et al., 1991; Lee, 2005; Chung, 2006; Guzzetti et al., 2006; Dragićević et al., 2012). In this research, a two-staged spatial analysis method is applied. In first stage, landslide hazard zonation map for estimating the probability of occurrence of future landslides is developed based on major landslide triggering factors in the region using 75% of landslide pixels. In second stage, the prepared landslide hazard prediction results are evaluated using cross validation technique based on 25% of pixels (not used in the predictive model). Temporal and spatial data regarding the occurrences of previous landslides in the region during the years 1997 to 2011 has been obtained using inventory maps. Since frequency-area relationships of the data set could be determined based on historical landslides inventory (Stark & Hovius, 2001; Guzzetti et al., 2002; Malamud et al., 2004; Guzzetti et al., 2006) and then the obtained information could be used in estimating the landslide intensity of a given area, hence based on the available data the intensity of the landslides occurred in the study area has been estimated and those landslides with moderate or high intensities activated in the region within the past 50 years have been selected (Talaei, 2012). Dividing the past landslides of the region into two groups based on a time or spatial division, the accuracy of the models could be evaluated (Cardinali et al., 2002; Chacón et al., 2006; Guzzetti et al., 2006; Chung, 2006; Chung & Fabbri, 2002, 2003 and 2008). A number of functions that could be used as favorability functions to construct the predictions have been proposed in the literature (Chung and Fabbri 1993, 1998, 1999, 2001, and 2004). In this study, for each variable, multivariate frequency distribution function have been calculated using likelihood ratio functions and then a prediction model has been generated to determine different zones for which the probability of occurrence of landslide exists in the future.

A number of researches have previously been conducted on landslides and their triggering factors in Hashtchin area (Ansari & Blurchi, 1996; Nikandish & Mir Sanei, 1996; Talaei et al., 2004). Hashemi Tabatabaei (1998), for instance, studied factors contributing to the occurrence of landslides in the region and produced a regional hazard map using qualitative model. Mahdavifar (1997), as well as Uromeihy & Mahdavifar (2000), studied factors causing landsides in Khoreshrostam area (part of Hashtchin region). In their studies, the Hazard Potential Index (HPI) was calculated by a computer program and using fuzzy sets. In fact, the prepared hazard zonation map was a susceptibility map the accuracy of which was not checked or assessed by the authors. To date, the present article is the only comprehensive research, based on author's information and the extensive literature review made, that has been carried out on landslide hazard zonation in Hashtchin area. Further, for the first time in this article, the accuracy of the obtained results has been evaluated using cross validation technique and based on the group of selected landslides not included in the model for the study area. The most important significance of the present research is that the modeled landslide hazard zonation map can be used as a reliable input to determine landslide type along with ways and countermeasures to mitigate its damages. The results can also be used as the basis for landslide risk assessment in the region.

2. THE STUDY AREA

Hashtchin area is situated in southwest of Ardebil province in northwestern Iran. The present study area lies between longitudes 48° 14' to 48° 44'E and latitudes 37° 06' to 37° 32'N (Fig. 1). It includes the parts of Talesh Mountains, the Agh Dagh massif, the Darram hills and Qezel Owzan valley and gorges in northwestern Alborz Range. The study area extends to 1645.84 km^2, and 9.52% of the area found to be affected by landslides. Currently, more than 9.52% of its territory is stricken by isolated and regional landslides (Mahdavifar, 1997; Talaie et al., 2004).

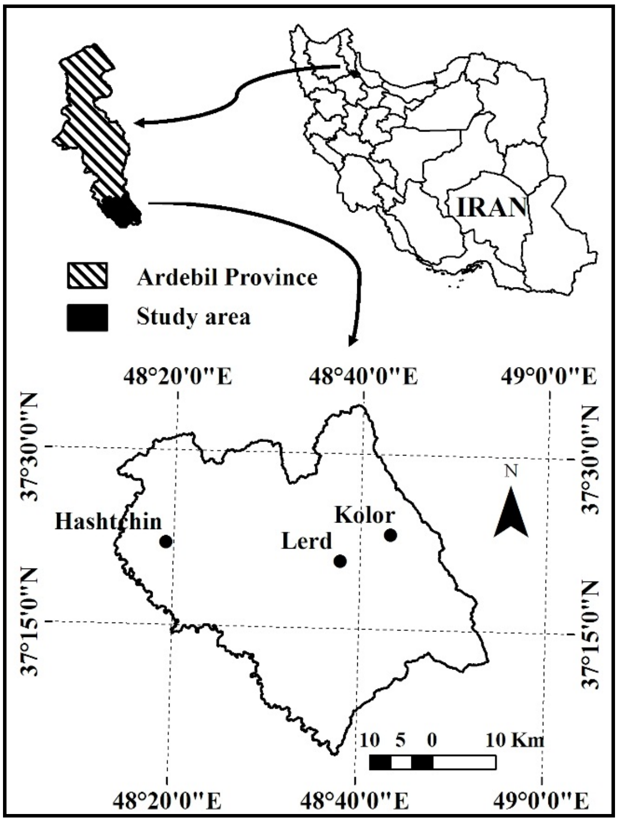

Figure 1. Location map of the studied area

A total 175 landslides (20.89 km^2 single landslides and 135.86 km^2 landslide zones) were mapped in the area covering about 156 km^2 (Fig. 2). The single landslides are classified as translational, rotational slides and combinations of these two types. The landslide zones are also classified as creep, unmappable and widespread types. It was found out that 103 cases (58.9%) of the landslides of the region are active at the present. In more than

60% of landslides which have been studied, signs of activities are shown within the past 50 years.

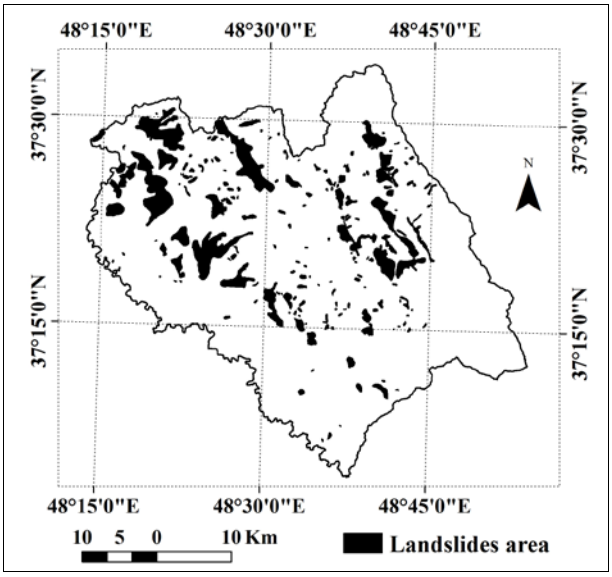

Figure 2. Landslide occurrence map of Hashtchin area

3. METHODOLOGY

3.1. MODELING DATABASE

To carry out the study, the following steps were taken: First, the landslide records were entered to standard forms and the inventory map was prepared using aerial photographs (scales: 1:50000 and 1:20000) and field works. As the next step, information regarding causes of landslides was collected using ArcGIS-10 package. Digital Elevation Model (DEM) was also prepared using topographic maps (scale=1:25000) with a resolution of 10×10 meters. Based on the Digital Elevation Model (DEM) obtained, information layers regarding geomorphologic parameters including slope gradient, slope aspect, profile curvatures and altitude were prepared in GIS system. Due to the importance of lithological and tectonic features of the region in causing landslides, strides were made to collect the required data with great care. The main mapping tools used included topographic maps at 1:50000 and 1:250000 scales and aerial photographs at 1:20000 scale and geological maps of Hashtchin (Faridi & Anvari, 1996), Masuleh (Davies et al., 1972), and Bandar Anzali (Davies et al., 1975) at 1:100000 and 1:250000 scales. The available information in the previous maps was used to prepare the geological map needed. During the field work, geological observations, important lithostratigraphic and geological structures were identified and transferred, after revisions, to the topographic maps. The data related to the type of plantation (land cover) and land use were extracted from topographic maps and satellite images of Landsat ETM+-2002. To study the impact of the earthquake on occurrence of landslides, the role played by active faults were studied, the Peak Ground Acceleration (PGA) map was also prepared. This map can be used as an important data layer in analyses related to landslide hazard and susceptibility (Turner & Schuster, 1996). Changes in slopes during road construction can reduce soil and layer stability and cause landslides (Knapen et al., 2006; Ayalew & Yamagishi, 2005). The layers related to distance to roads and settlements were produced using topographic maps in order to incorporate variables related to roads and buildings in the landslide hazard zonation analysis model. The impact of hydrology and climate on occurrence of landslides in the region was assessed in terms of mean annual precipitations and distance from rivers. Eq. 1 was used to determine the mean annual precipitations. Further, the isohyetal map was also designed with a scale of 1:25000 (Hemmati et al., 2007).

$$\text{Mean annual precipitations} = 471.162 - (X\times 4.81) + (Y\times 0.002) + (Z\times 0.063) \quad (1)$$

In this equation, X=longitude and Y=latitude in degree, and Z=altitude (elevation) in meters.

The data related to the independent and dependent variables were saved using nominal and scale group measures as a dBASEIV file in the form of 50×50 m cells, which were later imported to SPSS- version 21, for statistical analysis. A prediction model identifying areas likely to be affected by future landslides was generated based on the likelihood ratio function obtained from the multivariate frequency distributions calculated for each layer. To express this idea using equations according to Chung (2006), let us consider a point *c* with *m* pixel values $(c_1,...,c_i)$ in the study area. The study area can be divided into two subareas: the portion containing landslides *M* and the remaining area without landslides $\overline{M}$. Assuming that a pixel is from M and from $\overline{M}$, the corresponding multivariate frequency distribution functions can be denoted as $f\{c_1,...,c_m/M\}$ and $f\{(c_1,...,c_m/\overline{M}\}$ respectively. The likelihood function, which is the ratio of the two frequency distributions, can then be defined at point *c* as follows (Chung, 2006; Chung & Fabbri, 2005 and 2008):

$$\lambda(c_1,...,c_m) = \frac{f\{c_1,...,c_m/M\}}{f\{(c_1,...,c_m/\overline{M}\}} \quad (2)$$

By separating the categorical and continuous data layers at pixel c, it is assumed that the first k layers represent categorical data layers and the remaining h layers represent continuous data layers. The multivariate frequency distribution functions from M, and $\overline{M}$ will then be denoted as:

$$f\{(x_1,...,x_k,y_1,...,y_h)/M\}$$

and

$$f\{(x_1,...,x_k,y_1,...,y_h)/\overline{M}\}$$

respectively, where, the k values, $x_1,...,x_k$ correspond to categorical data layers and the h values, $y_1,...,y_h$ correspond to continuous data layers. The likelihood ratio function defined in Eq. 2 will then take the form:

$$\lambda(x_1,...,x_k,y_1,...,y_h) = \frac{f\{(x_1,...,x_k,y_1,...,y_h)/M\}}{f\{(x_1,...,x_k,y_1,...,y_h)/\overline{M}\}} \quad (3)$$

Each of univariate likelihood ratio functions can be estimated by considering an individual categorical data layer together with the distribution of occurrences of landslides:

$$\breve{\lambda}(x:x_i) = \frac{NL}{NNL} \quad (4)$$

NL: Number of landslide pixels in x_i category of the *i*th layer

NNL: Number of non-landslide pixels in x_i category of the *i*th layer

To estimate $\lambda(y_1,...,y_h)$, in this research, discriminant analysis is used, where the likelihood of occurrence of a landslide is estimated at every pixel using appropriate favorability functions. The simplest way, in order to achieve this, is by a linear combination of the independent variables as (Pohar et al., 2004; Guzzetti et al., 1999):

$$D = a + b_1x_1 + ... + b_px_p \quad (5)$$

Where: D: discriminate function (the presence or absence of a landslide); a: a constant; b_p: the discriminant coefficient or weight for that variable; p: number of independent variables (predictors) and x_p is the value of the predictor (causes of landslides). In the discriminate analysis method, in order to test functionality of the control in creating meaningful differences among the target groups, the Discriminant Analysis procedure provides the eigenvalues and Wilks' lambda tables for testing how well the discriminant model as a whole fits the data. Using the obtained functions, the value of $\lambda(x_1,...,x_k,y_1,...,y_h)$ was estimated at each pixel as:

$$\breve{\lambda}(x_1,...,x_k,y_1,...,y_h) = \breve{\lambda}(x_1,...,x_k) \times \breve{\lambda}(y_1,...,y_h) \quad (6)$$

Where $\breve{\lambda}(x_1,...,x_k)$ is an estimate of $\lambda(x_1,...,x_k)$ and $\breve{\lambda}(y_1,...,y_h)$ is an estimate of $\lambda(y_1,...,y_h)$.

The values of $\breve{\lambda}(x_1,...,x_k,y_1,...,y_h)$ range from 0 to ∞, with the largest estimated values considered to be the location most likely to be affected by the future landslides. The estimated values were standardized based on the "identical function" (Chung & Fabbri. 2008):

$$m(x_1,...,x_k,y_1,...,y_h) = \frac{h(\lambda(x_1,...,x_k,y_1,...,y_h))}{1 + h(\breve{\lambda}(x_1,...,x_k,y_1,...,y_h))} \quad (7)$$

The range of $m(x_1,...,x_k,y_1,...,y_h)$ is from 0 to 1 and is used as the favorability function in this study. The pixel with the largest estimated $m(x_1,...,x_k,y_1,...,y_h)$ near 1 is considered to be the location where landslides are most likely to occur in the future. Based on the computed values for every pixel, a predictive map showing the relative hazard level was generated for the study area.

3.2. TESTING MODEL

Validation of the landslide hazard zonation predictive model in the study area was performed using cross validation technique. Cross-validation is one of several statistical "resampling" techniques that is used to test the strength and performance of a predictive model (Geisser, 1974; Chung & Fabbri, 2008). Note that, "Validation" here is only used as a technical term to test the goodness-of-fit of the model in order to find out whether the obtained results are satisfactory and hence judging acceptance of the model (Sterman et al., 1994). There is another interesting method, namely receiver operating characteristic (ROC), to assess fitness of the model (Swets, 1988; Zweig & Campbell, 1993; Yesilnacar & Topal, 2005; Mathew et al., 2009). The ROC curves are equivalent to prediction and success-rate curves (Chung & Fabbri, 2003). In this method, a percentage of the observations (pixels) with landslides – that have correctly been predicted by the model – is called Sensitivity (probability of correctly identifying a positive or the true positives) based on Eq. 8.

$$\text{Sensitivity} = \frac{n_{tp}}{n_{tp} + n_{fn}} \quad (8)$$

n_{tp} : Number of true positive decisions; n_{fn} : Number of false negative decisions

The specificity of the model has been shown based on the percentage of the correct classified observations (pixels) with no landslides (probability of correctly identifying a negative or true negatives) (Eq. 9).

$$\text{Specificity} = \frac{n_{tn}}{n_{tn} + n_{fp}} \quad (9)$$

n_{tn} : Number of true negative decisions; n_{fp} : Number of false positive decisions

Commonly, sensitivity takes the y axis and (1 – specificity) takes the x axis. The Area under the ROC curve shows the increase in the probability of making a positive choice compared to a negative one.

4. RESULTS

8.2% of the total pixels of the Hashtchin area (57926 pixels) contain landslides that have occurred or reactivated with moderate to high intensity after the year 1960. In order to predict the probability of occurrence of a future landslide in the study area within the next 50 years, 43448 of the pixels with landslide (i.e. 75% of landslide pixels) were randomly selected (estimation group) and used to generate landslide hazard prediction model. The continuous variables used in statistical analysis included distance to main faults, peak ground acceleration, mean annual precipitations, distance to drainage, distance to settlement, distance to road and slope gradient while the lithology, slope aspect, altitude ,topographic curvature, land cover/land use were considered as categorical variables. Estimation of the landslide hazard for each class of the categorical variables was performed using the Eq. (4). The likelihood ratio function for categorical data layers, $\breve{\lambda}(x_1,...,x_k)$, was estimated at each pixel, where the minimum and maximum values were: 0 and 139.86, respectively. The $\breve{\lambda}(y_1,...,y_h)$ values for continuous data layers were estimated using discriminant analysis. By implementing this model and determining the best discriminant function, values of the likelihood ratio were estimated for each pixel of the study area. In this analysis, 43448 pixels (i.e.75% of the pixels with landslides that occurrence after 1960) and the same number of pixels without the landslide were randomly selected and put into the model to estimate the likelihood ratio. Based on the obtained significance level (Sig.<0.0001), it can be indicated that there are significant differences between all independent variables (distance to main faults, peak ground acceleration, mean annual precipitations, distance to drainage, distance to settlement, distance to road and slope gradient) and dependent variable. In this study, the dependent variable is defined as presence or absence of landslide deposits, while the independent variables are those thought to affect landslide hazard.

During the stepwise analysis, the independent variables (effective factors) were entered into the model in seven consecutive steps. The first input variable was the pixel distance from the main fault and the last one was the distance from roads. No input variable has been removed from the model during the analysis and the significance level represents the significant presence of all variables in the model.

In stepwise discriminant analysis, the most correlated independent factor is entered, first into the program, and then the second one until an additional dependent adds no significant amount to the canonical R squared. Among the variables, distance to main faults had the largest F (6837.417) and the smallest Wilks' lambda (0.927). It thus is the first variable entered into the model in the first step. Following factors in order of importance were slope gradient, peak ground acceleration, distance to settlement, distance to drainage, distance to roads and mean annual precipitations. Since no variable had smaller F values than 3.84, all variables were entered into the model in the final step.

The maximum number of discriminant functions produced is the number of groups minus 1. Only two groups were used here, one of them is 'landslide' and the other one is 'no landslide', so only one function is displayed. This function is highly significant (Sig. <0.0001) with a variance percentage of 100 and a Wilks' lambda of 0.796. The Standardized canonical coefficients for the discriminant function are shown in table 1.

Table 1. Standardized canonical discriminant function coefficients table

Independent variables	**Function**
	1
Distance to main faults (m)	0.516
Peak ground acceleration (g)	-0.461
Mean annual precipitations (mm/year)	-0.146
Distance to drainage (m)	0.372
Distance to road (m)	-0.085
Distance to settlement (m)	0.274
Slope gradient (°)	0.438

Finally the classification results are reported in table 2 according to which the overall prediction accuracy of the analysis has been 69.6%. Also as can be seen pixels with landslide were classified with a better accuracy of 76.8%. The classification results reveal that 69.6% of pixels were classified correctly into 'landslide' or 'no landslide' groups.

Table 2. The classification table

Observed	predicted		
	No landslide	Landslide	Percentage correct
No landslide	27090	16358	62.4
Landslide	10086	33362	76.8
Overall percentage	69.6		
Constant is included in the model and the cut value is 0.500			

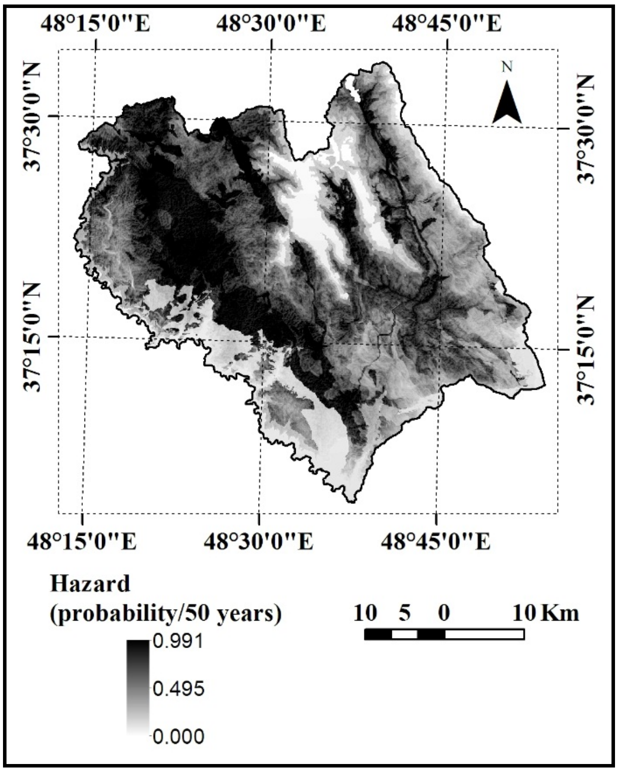

Figure 3. Landslide hazard prediction map for Hashtchin area obtained using post-1960 landslides

The main purpose of this analysis is to provide predictions for landslide occurrences at each pixel in the Hashtchin area. As a result of this analysis a discriminant function consisting of 7 independent variables was formed which suggest that almost 70% of predictions of landslide occurrences were correctly estimated for the study area. The obtained results were then used to estimate probability of landslide occurrences at each pixel based on conditional independence assumption and using $\breve{\lambda}(x_1,...,x_k,y_1,...,y_h)$. The estimated values were then standardized based on the Eq. 7. As it is shown by the results the standardized likelihood estimates, $m(x_1,...,x_k,y_1,...,y_h)$, ranges from 0 to 1, where the pixel with largest estimated $m(x_1,...,x_k,y_1,...,y_h)$, (i.e. 0.991) is considered to be the location most likely to witness landslide in the future. The computed values for this function are used to generate a prediction map showing the relative hazard level at each pixel of the study area (Fig. 3).

4.1. GENERATION AND VALIDATION OF THE LANDSLIDE HAZARD ZONATION MAP

As discussed earlier, the estimated relative hazard values ranges from 0 to 1, which could be replaced by their ranks (or orders) (Chung & Fabbri, 2008). Using Eq. (7) to obtain estimated values from M function yielded 708,456 scores which were first sorted in a decreasing order and then replaced by their ranks, from 1 to 708,456 at each pixel. Each of these scores was then standardized by dividing in the total number of pixels (i.e. 708,456). The resulting standardized ranks range from 1/708,456 to 1, where the pixel with the most hazardous predicted level obtained the value 1 and the pixel having the smallest predicted hazard level was assigned a value of 0.000001411. These standardized ranked values were used in this study. The values were subdivided into 100 equally sized hazard classes, with each class representing 1% of the study area or about 7084 pixels (17.71 km^2). The landslide hazard level is relative within each hazard class. The number of pixels in the landslide zones is shown as model fitting rate in the bar chart for hazard classes. The hazard classes are plotted on the horizontal axis (X) and the cumulative portion of areas on the vertical axis (Y) (Fig. 4).

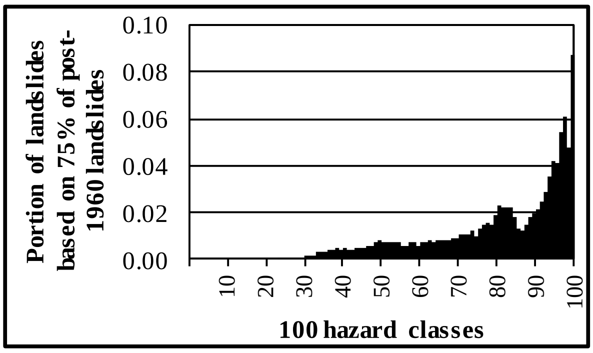

Figure 4. Histogram of model fitting rate for the 75% of post-1960 based on 100 hazard classes

According to the results, 24,242 pixels (about 68.105 km^2) of the region's landslides fall within 20% of the most hazardous classes which shows how well the model fits occurrences of the landslides in terms of the variables used in the prediction model. The landslide hazard prediction map based on these hazard classes is shown in figure 5.

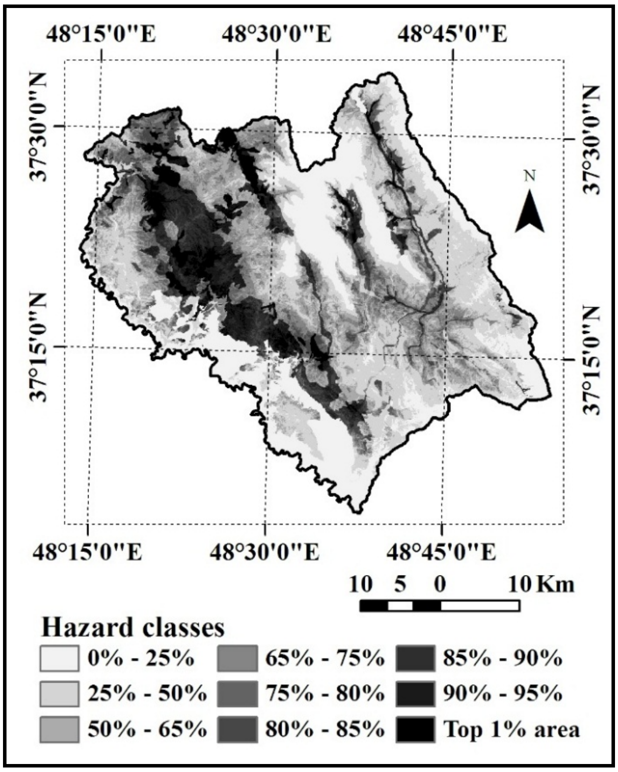

Figure 5. Landslide hazard prediction map of Hashtchin area obtained by subdividing ranked values in 100 equally sized classes

Since the information on the exact dates of occurrences of the past landslides in the region is limited, a time division of the landslide occurrences is not possible. Thus, in order to test the reliability of the prediction model, 25% randomly selected pixels containing landslides with medium to high intensities (those landslides occurred or reactivated after 1960) were used. The characteristics of these randomly selected pixels were not entered into the prediction model used for estimating landslide hazard of the next 50 years. The landslide pixels were overlaid on the prediction map based on the estimation group landslides (75% of post-1960 landslide pixels). The results show that most of the landslides namely 9052 pixels (22.63 km^2) fall within 20 most hazardous classes of the region (Fig. 6).

Also, 62.52% of the validation landslides and about 55.79% of the landslides in the estimation group fit into 20 most hazardous classes. The corresponding curves in figure 7 can be used to compare the results of prediction model which has been obtained by estimating and validating groups of pixels. For example point A= (0.40, 0.825) in the obtained curve based on estimation group (75% of post-1960 landslide pixels) and point B= (0.40, 0.841) in the curve corresponding to validation group (25% of post-1960 landslide pixels) indicate that 82% and 84% of the areas undergoing landslides in the past 50 years fall within 40% of areas classified as the most hazardous in the model. Based on this, it is expected that over 44% of the future landslides in Hashtchin area in the next 50 years occur in first 10 hazard classes marked as most hazardous classes.

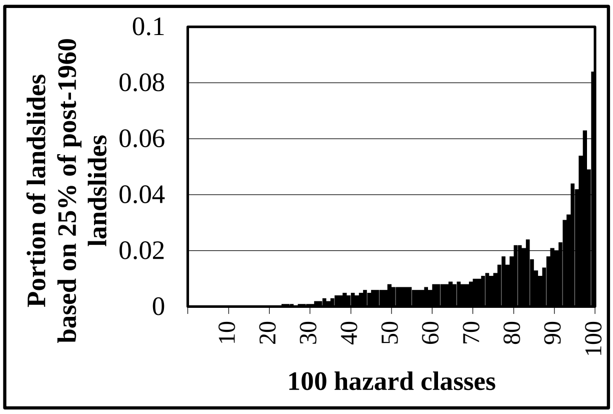

Figure 6. Histogram of model fitting rate for the 25% of post-1960 landslides based on 100 hazard classes

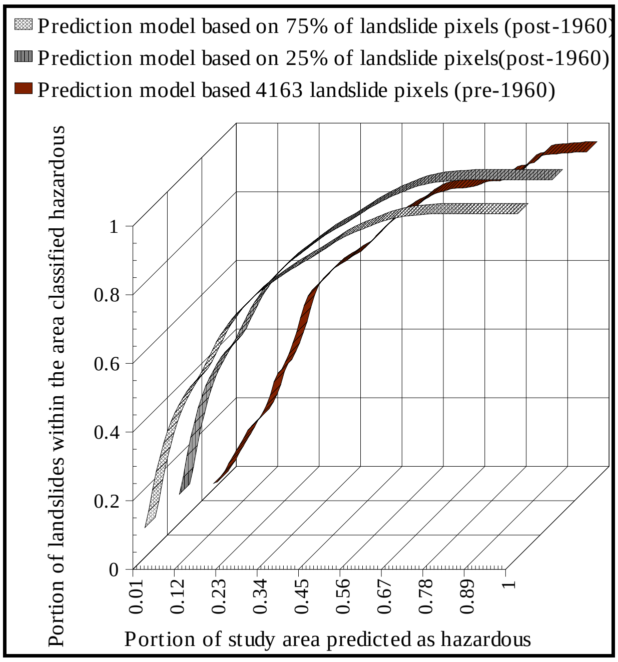

Figure 7. Cumulative prediction-rate curves for three landslide-hazard prediction models

Hence, in this section, by entering all the available information of the landslide occurred in the past 50 years into the model, the likelihood functions were computed and accordingly the landslide hazard levels were estimated at every pixel. To run the analysis, 57,926 randomly selected pixels with landslides as well as the same number of pixels without landslides were used. In this case, also, the probabilities of occurrences of landslides were separately estimated for categorical and continuous data layers using the conditionally independence assumption between the layers.

According to the results, 60.8% of the non-landslides pixels as well as 73.5% of landslides pixels have correctly been classified (predicted). By computing the likelihood function for each pixel with or without landslide based on categorical and continuous variables, the landslide hazard levels of the prediction results for the next 50 years was expressed for Hashtchin area. The generated landslide hazard prediction map is shown in figure 8.

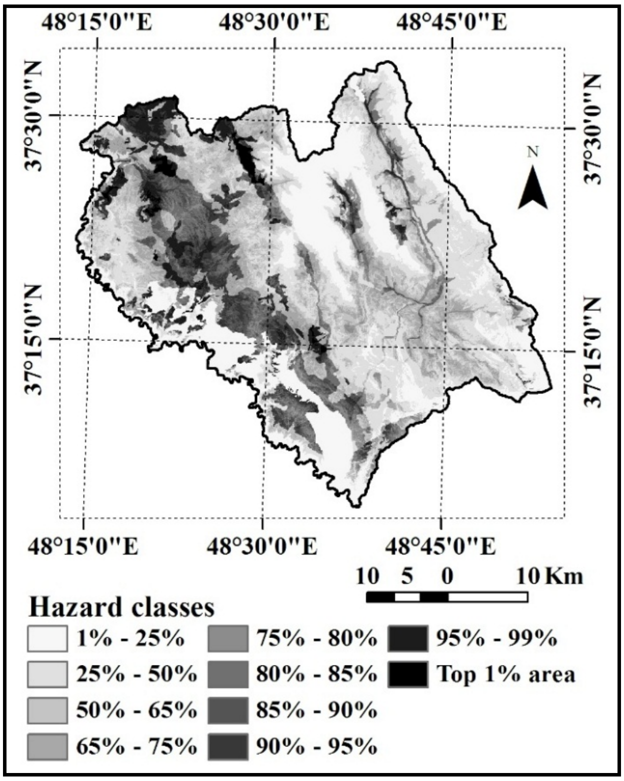

Figure 8. Landslide hazard prediction map for Hashtchin area, based on all post -1960 landslide pixels and layers: lithology, land cover/land use, elevation, slope gradient, slope aspect, topographic curvature, distances to major faults, distance to drainage, distance to road, distance to settlement, peak ground acceleration (PGA) and mean annual precipitations

4.2. EVALUATING THE ACCURACY OF THE FINAL MODEL

In this section, using the receiver operating characteristic (ROC) analysis method the overall accuracy of the presented prediction models has been evaluated. As it is shown in figure 9, in order to assess the accuracy of the prediction results, two curves: one for predicting the landslide hazard based on 75% of post-1960 landslide pixels and one for predicting the landslide hazard based on 100% of post-1960 landslide pixels were plotted and the total area under these curves were computed. Table 3 summarizes the results of ROC analysis. The results obtained for the areas under ROC curves shows the model using 100% of the landslide pixels has made less accurate predictions of landslide hazard compared with the other model, there is only a slight difference of 1.9% between two prediction models.

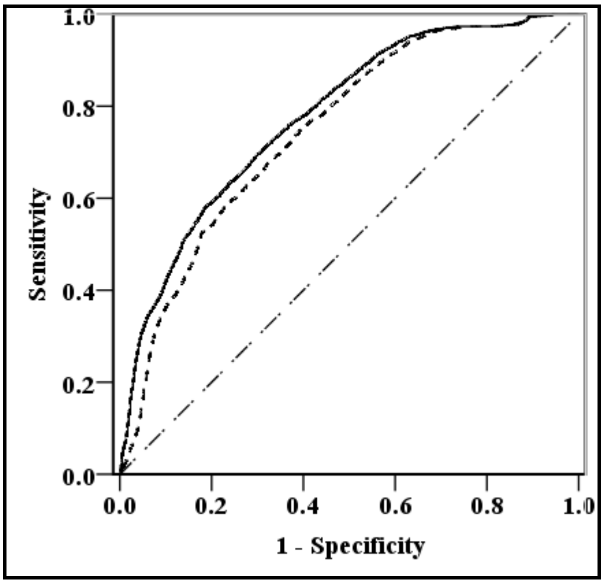

Figure 9. Receiver operating characteristic curve (ROC) for two models based on the estimation model with 75% of all landslide pixels (solid curve) and based on all post -1960 landslide pixels (dashed curve)

Table 3. The area under the curve

Models	Area
The prediction model of the landslide hazard based on 100% of post-1960 landslide pixels	0.776
The prediction model of the landslide hazard based on 75% of post-1960 landslide pixels	0.795

5. DISCUSSIONS

The proposed landslide hazard prediction model for Hashtchin area was developed based on the following assumptions (Guzzetti et al., 2005). 1) future landslides in Hashtchin area will occur under the same circumstances and due to the same factors that caused past landslides in the region; 2) landslides are considered independent events that occur randomly in time; 3) the average recurrence of landslides in the future will remain the same as it was in the past; 4) landslide size is a reasonable representation of landslide intensity; and 5) the probability of landslide size, the probability of landslide occurrence within specific time periods, and the spatial probability of slope failures, are all independent. The first assumption, i.e. occurrences of future landslides in an area under the same conditions and because of the same triggering factors of the previous landslides is considered as an accepted and sensible postulation in performing landslide susceptibility or hazard assessments (Carrara et al., 1991; Hutchinson, 1995; Aleotti & Chowdhury, 1999; Chung & Fabbri, 1999; Guzzetti et al., 1999). This assumption, however, may have some inherent limitations (Guzzetti et al., 2005). Environmental conditions and geomorphological features play an important role in occurrence and abundance of landslide and slope instability in an area. Normally it is under peak resistance conditions that first-time slope failures usually occur, while intermediate or residual conditions may result in reactivations of the old landslides. When a slope failure occurs in a terrain, it may change the morphology of the terrain, while landslide movements may lead to changes in the hydrological conditions of the slope. Also, type of movement of the landslides or their velocity may vary with time. In addition, environmental conditions may change with time because of different factors such as human involvements (e.g., changes in the land use, deforestation, etc.) or stream erosion and etc. All of these limitations and complications indicate that each landslide occur under a distinct local environmental condition. Despite these limitations, in this study, like many other researches, it has been assumed that in the study area future landslides will occur under the same conditions and as a result of the same factor that caused them in the past. It is assumed that the data of the previous landslides in this region had an acceptable and a complete accuracy. Based on the adopted assumption it is expected that the environmental conditions that caused landslides in Hashtchin area will remain the same in the future and will cause similar slope failures or reactivation of the region's past landslides. Hence, degree of reliability and accuracy of the proposed landslide hazard model will rely on the fact that main landslide triggering factors in the region will not change significantly in the future. Taking these matters into the consideration, it is safe to assume that the proposed hazard model can be considered valid for a short period of time in the future, for example 50 years, since significant changes in geological factors (such as lithology, structure, seismicity) would be very unlikely in such a short geological time. Extensive morphological changes are also not expected apart from some local modifications mainly because of erosion, landslides and human actions. The majority of the variables entered into the hazard model are thus not expected to change significantly in the considered period. However, there may be some possible changes in the land use in the area since natural resource management is planning to improve pasture and forest land conditions in the area. But these changes in the land use are not expected to be so significant that they can question the validity of the model. If no significant and unpredictable changes occur in the land use practices in the study area in the next 50 years, the input variables considered in developing the hazard model will be valid and effective in predicting the locations most likely to be affected by future landslides. Otherwise new variables describing land use changes should be considered to construct the landslide hazard prediction model. Based on the present data, mean annual precipitations and peak ground acceleration (PGA) were entered into the model as main triggering factors for landslide hazard assessment of the study area. Of all 106 post-1960 landslides occurred in the study area, 86 landslides have occurred in the terrains where previously have been affected by the landslides in the past (Talaei & Samadov, 2010). Information of inventory maps and tables for a period during the years 1997-2011 was prepared using field work and aerial photographs (Talaei et al., 2004). This information was then used to build a prediction model in order to perform a landslide hazard assessment for the study area within the next 50 years.

The exact measure of landslide intensity or magnitude is not available for the study site. In this work, following the proposed method by Hungr (1997) to use destructiveness as a measure of landslide magnitude, landslide area as well as expected landslide velocity was used as a proxy for landslide destructiveness and hence landslide intensity.

Magnitudes of the individual slope failures of the region were determined based on landslide area and their types of movements, where the required information was obtained from landslide inventory maps. According to available historical information on slope failures, 69.3% of the landslides in the region have an area which ranges from 250000 to 5000000 m^3. Intensities (magnitudes) of the landslide zones were estimated base on their expected velocity. The landslide hazard for those landslides with large areas, with the exception of the creeps, has been considered to be medium; Since the intensity of these type of landslides is normally high (Corominas et al., 2003). Flow landslides have shown to have maximum expected velocities while the minimum expected velocities were observed in rotational landslides. Some of the landslides in the region have occurred with very low (1.1% of the landslides) or with very high velocities (10.3% of the landslides). Based on the relationship between landslide area and expected landslide velocity, 63.24 % of the landslides are expected to have occurred with a medium intensity. Also, it can be said that 10.07%, 23.84% and 2.838% of the landslides are estimated to have occurred with very high, high and low intensities, respectively. In this study, landslides pixels with medium to high intensities have been entered into the hazard prediction model. The results indicate good correlation between hazard levels and slope failures, and show the usefulness of probability model for hazard assessment at a regional scale.

6. CONCLUSIONS

Landslide disasters have drastically increased over the last decades. This trend is expected to continue in the next decades due to increased urbanization and development, and continued deforestation and pasture destruction. This is particularly authentic in the Alborz Mountaines in Iran where landslides are one of the major natural hazards that account each year for significant property damage. To address the impact produced by landslides, residents and officials need to develop a better understanding of landslide potential and make rational decisions on resources allocation to manage the problem. Based on the findings it could be concluded that the spatial prediction model produces an appropriate model for prediction of landslide/no landslide in each pixel within the next 50 years. The landslide hazard maps produced in this study can increase awareness of landslide hazard and assist future planning decisions. These maps could be useful for explaining the known existing landslide and mitigation of future landslide hazards. The map may also be accepted as a basis for the landslide risk assessment studies in the study area. This study was carried out in Hashtchin area in the northwest of Iran, the proposed methodology can be used for mountainous areas with similar features including Alborz, Zagros and Caucuses Mountains.

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