Spatial prediction of slope failure in the Caspian forest using an adaptive neuro-fuzzy inference system and GIS

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Abstract

The main goal of this study was to produce a slope failure susceptibility map to support road designing and timber harvest planning. For this purpose, 15 data layers, including slope failure slope failure conditioning-factors, and a landslide inventory map were exploited to detect the most susceptible areas. Subsequently, slope failure susceptibility maps were produced using an adaptive neuro-fuzzy interface system (ANFIS) and GIS. The accuracy of the obtained maps was then evaluated by receiver operating characteristics (ROC). The ANFIS model with the input conditioning-factors of slope degree, slope aspect, altitude, and lithology performed the best among the various ANFIS models explored in the study. The predicted susceptibility levels were found to be in good agreement with the occurrences of pre-existing slope failures, and, hence, the produced maps are trustworthy for forestry activities and hazard mitigation planning.

Keywords: ANFIS; Landslide susceptibility; Road construction; Timber harvesting

1. Introduction

Construction and maintenance of road networks in mountainous forests are of challenging tasks because of geological and topographical complexities. The situation becomes more severe if a road network passes through a highly hazardous zone with respect to slope failure. Roadside slope failure is a common problem in the Caspian forest as naturally formed slopes are disturbed by road construction activities. The first attempts to road construction on steep terrains of the Caspian forest date back to the 1980s and early 1990s (Jaafari et al. 2014). History has shown that roads with improper terrain stability assessment in this area can cause significant slope failures and landslides. This trend is expected to continue in future; some estimates suggest that significant portions of the Caspian forest are prone to mass wasting and the forestry activities that regularly happening on this forest have the potential to accelerate landslide rates and magnitudes (IPBO, 2000). Therefore, landslide susceptibility maps are needed, particularly at the basin scale; they are a useful tool to make informed environmental decisions regarding the risks of proposed development (Guzzetti et al. 2006, Conforti et al. 2014).

According to Varnes (1978), the term “landslide” describes a wide variety of processes that result in the downward and outward movement of slope-forming materials including rock, soil, artificial fill, or a combination of them. On the other hand, landslide susceptibility can be defined as the probability of spatial occurrence of landslides on the basis of the relationships between distribution and a set of conditioning factors (Guzzetti et al. 2005). Landslide susceptibility assessment allows for the identification of slopes for which failure probability is high and to consequently make prevention and protection decisions accordingly (Guillard and Zezere 2012). Landslide susceptibility assessment can be used in several scientific studies; estimation of the cost of road development and maintenance (Saha et al. 2005), pavement maintenance priority map for highways (Pantha et al. 2010), and prediction of debris flow source areas (Blahut et al. 2010).

The effectiveness of slope stability studies around the world is apparent from the high prediction results of landslide susceptibility assessment reports from models such as logistic regression (e.g., Pourghasemi et al. 2013a), knowledge-based analytical hierarchy process (AHP) (e.g., Pourghasemi et al. 2013a, Pourghasemi et al. 2012a), fuzzy logic (e.g., Pourghasemi et al. 2012a), artificial neural networks (ANNs) (e.g., Zare et al. 2013, Conforti et al. 2014), support vector machine (SVM) (e.g., Pradhan 2013, Pourghasemi et al. 2013b) and adaptive neuro-fuzzy interface system (ANFIS) (e.g., Pradhan 2013, Bui et al. 2012, Vahidnia et al. 2010).

In the case of ANFIS, developed by Jang (1993), a little application to the landslide related studies has been reported (Bui et al. 2012). ANFIS is a multilayer feed-forward network in which each node performs a particular function on incoming signals and has a set of parameters pertaining to this node (Jang 1993). ANFIS combines fuzzy logic and ANNs by utilizing the mathematical properties of ANNs in tuning a rule-based fuzzy inference system that approximates how the human brain processes information (Akib et al. 2014).

The main objective of an ANFIS model is to determine the optimum values of the equivalent fuzzy inference system parameters by applying a learning algorithm using input–output datasets. The parameter optimization is done in such a way during the training session that the error between the target and the actual output is minimized. Further information on ANFIS can be found in Jang (1993).

Landslide susceptibility assessment involves handling, processing and interpreting a large amount of territorial data. Thus, Geographical Information Systems (GIS) have proved to be very useful in susceptibility assessment (Aleotti and Chowdhury 1999, Ayalew et al. 2005), as it allows frequent updating of the database related to spatial distribution of the landslide events and their predisposing factors, as well as the susceptibility assessment procedures (Aleotti and Chowdhury 1999). In recent years, the use of GIS-based approaches to study landslides are intensively reported; GIS-based frequency ratio and index of entropy models (Jaafari et al., 2014; Pourghasemi et al. 2012b), and GIS-based multicriteria decision analysis (Feizizadeh and Blaschke 2013). Bui et al., (2012) used a GIS-based ANFIS model for LSM in Vietnam. Their results showed that ANFIS can be considered as a robust method for landslide modeling. Pradhan (2013), in a comparative study, addressed the ability of the decision tree, support vector machine and ANFIS models for LSM within a GIS environment. According to the results, all the models faired reasonably well, however, the success rate showed that ANFIS has better prediction capability among all models.

In this study, we address the slope failure (landslide) susceptibility assessment in the Caspian forest using ANFIS within a GIS environment. The study is intended to tackle the main causal factors and to delimit the most susceptible zones for slope failure as a useful tool for the engineers involved in road construction and timber harvesting. The produced susceptibility maps are also compared with the known landslide locations according to the area under the curve (AUC) of receiver operator characteristic (ROC) curve in order to test the reliability and accuracy of the approach used. The susceptibility assessment presented in this study enable planners to avoid areas where forestry activities could cause slope failure and helps identify where field-based assessments are necessary.

2. Materials and methods

2.1. Study area characteristics

Our study area is situated in Mazandaran Province, northern Iran. The study area having an approximate area of 52 km^2 located between 36º29′10″ N and 36º32′50″ N latitude and 51º40′60″ E and 51º48′20″ E longitude (Fig. 1). The area is a part of the Educational and Experimental Forest of Tarbiat Modares University (EEFTMU) in the Caspian forest with slope variations between flat and >50°, and altitudes between 160 and 2190 m. Slope shape varies but frequently they represent convex and concave elements and are, mainly, incised by concave valleys. In this area, the stream network flows from the north-east to the south and south-west with a dendritic pattern. Given the proximity to the Caspian Sea, the study area enjoys a humid and mild climate with average annual precipitation between 414 to 879 mm. The average summer and winter temperature are recorded to be 22.5 and 10 ºC, respectively. The vegetation cover is quite continuous, formed by deciduous trees with dominant species of *Fagus orientalis* Lipsky, *Carpinus betulus* L., *Acer velutinum* Boiss, and *Quercus castaneifolia* C.A. Mey.

The major portion of the study area is underlain by dolomitic limestone. Alborz fault, as the most important fault in the area, is a reverse fault that follow the west-east orientation and dip toward south. This fault is active, and most of earthquakes and landslides which occurred in Mazandaran Province are the result of displacements and the activity of this fault (Darvishzadeh 2004). Therefore, our study area, as one of the most susceptible areas to natural hazards and slope instability, is characterized by the prevalence of slides of shallow translational, deep translational, rotational subtypes, small debris flows and rock falls.

2.2. Spatial database construction

2.2.1. Landslide inventory map

Since landslide occurrences in the past and present are keys to future spatial prediction (Guzzetti et al. 1999), a landslide inventory map is a pre-requisite for such a study (Bui et al. 2012). The landslide inventory map of our study area was compiled by inheriting the landslide locations from aerial photographs interpretation and field-based inspection. In the aerial photographs, historical landslides could be mapped by using evidences such as breaks in the forest canopy, denudes vegetation on the slope, bare soil, and other typical geomorphic characteristics (Pradhan 2013, Jaafari et al. 2014). Given the abundant over- and understory vegetation in the study area, we also conducted multiple field surveys and observations to produce a more detailed and reliable landslide inventory map.

2.2.2. Slope failure (landslide) conditioning factors

The recognition and mapping of an appropriate set of instability factors related to slope failures require a previous information of main causes of landslides (Guzzetti et al. 1999). In the present study, the conditioning factors were selected among the most commonly used in literature to assessment slope failures susceptibility (Table 1). The significance of these factors in landsliding has explicitly been presented in Jaafari et al. (2014). Incorporation into the GIS was via a 20-m Digital Elevation Model (DEM) of the study area, and the slope degree, slope aspect, altitude, plan curvature, TWI, SPI, STI layers were created from the DEM using ArcGIS and SAGA GIS. Distance to faults and distance to streams were computed using spatial analyst tool of ArcGIS. The geological map prepared by Geological Survey of Iran (GSI) on 1:100,000 scale was used for the present study. The rainfall map was prepared using the mean annual precipitate data from the meteorological station for the study area over last 20 years. Extensive investigations by the

Tarbiat Modares University on the study area have been the major source of data associated with NDVI, forest plant community, forest canopy, and timber volume used in the present study.

Since raster dataset has enriched capability for spatial analysis, all factor layers were converted into raster format. Given the extent of the study area and the landslide distribution, grid cells having a spatial resolution of 20 × 20 m (Ozdemir 2011, Bui et al. 2012, Kayastha et al. 2012, Ozdemir and Altural 2013, Jaafari et al. 2014) were selected as the mapping unit, which was small enough to capture the spatial characteristics of landslide susceptibility and large enough to reduce computing complexity.

In this study, we also carried out a series of tests by considering different input datasets from the landslide conditioning factors. The purpose of selecting various datasets was to explore the influence of parameter enrichments on the performance of the ANFIS model and, additionally importance of the added parameter on the landslide assessments (Pradhan 2013). From table 2 can be seen that dataset-1 includes maximum number of landslide conditioning factors, and it continues to narrow down to dataset-5 (Table 2).

2.3. Preparation of training and validation dataset

In landslide modeling, the landslide inventory map need to be split into two subsets for training and validation. Without the splitting, it would not be possible to validate the results (Jaafari et al. 2014). In this study, the inventory map was randomly divided into two datasets. Part 1 that contains 70% of the data (73 landslides) used in the training phase of the five ANFIS models. Part 2 is a validation dataset with remaining 30% of the data (31 landslides) for the validation of the models and to estimate their accuracy. All of the 73 landslide locations in the part 1 dataset denoting the presence of landslides were assigned the value of 1. The same number of points denoting the absence of landslide were randomly sampled from the landslide-free area and assigned a value of 0. Values for the 15 landslide conditioning factors were then extracted to build a training dataset (Bui et al. 2012, Pradhan 2013). This dataset contains a total of 146 points, with one target variable denoting the landslide presence/absence and the 15 landslide conditioning factors. This dataset was further randomly partitioned into three subsets including: training, testing and checking to develop the ANFIS models (Ghajar et al. 2012). Training set was used to adjust the connections weights, membership functions and model parameters. Testing set was used to evaluate the trained ANFIS performances and generalizations power. Checking set was used to check the performance of the model through the training process and stop the training to avoid over-fitting. This method of data division is recommended to control over-fitting of the models (Jang et al. 1997). In this study, approximately 70% (102 points) of the extracted database was randomly selected as the training dataset, 15% (22 points) as testing dataset, and the remaining 15% (22 points) as the checking dataset. In this study, we used a commercially available canned software, called Neuframe (Neusciences 2000), to select the datasets at random.

Due to the different scales of input variables, and in order to increase the speed and accuracy of data processing, input data need to be normalized in the range of 0 and1 before using them in the ANFIS model (Ghajar et al. 2012). For this purpose, the extracted values from landslide conditioning factors were normalized using the normalization formula as follows:

$$X_n = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \qquad (1)$$

A part of normalized data used as training, testing and checking the ANFIS model is shown in table 3.

2.4. Development the ANFIS models for the spatial prediction of slope failure

In the light of suggestion by Pradhan (2013), we employed type-3 ANFIS model (Takagi and Sugeno 1983) to produce susceptibility maps of our study area. In this type of ANFIS model, the output of each rule is a linear combination of input variables added by a constant term. The final output is the weighted average of each rule's output. In this study, we constructed a total of five ANFIS models to produce susceptibility maps of the study area. To implement ANFIS, MATLAB programming language version R2011a was used. GENFIS1 and GENFIS2 functions are two available methods that have been widely used for generating the initial fuzzy inference system (FIS). The GENFIS1 generates an initial Sugeno-type FIS for ANFIS training using a grid partition, and the GENFIS2 uses a subtractive clustering generates to generate the initial Sugeno-type FIS. As proposed by Chui (1997), due to the large number of input variables considered in our study, GENFIS2 function was used to generate the initial FIS for ANFIS training by first applying subtractive clustering on the data. GENFIS2 accomplished this by extracting a set of rules that models the data behavior.

After constructing the Sugeno-type FIS for our five ANFIS models, each model is trained by considering 200 epochs. Finally, the output data obtained from the models were converted to GIS grid data to create the slope failure susceptibility maps.

2.5. Validation and comparison of susceptibility maps

Prediction modeling does not have a scientific significance without computing the validity of the results. In this study, the susceptibility assessment results were tested using known landslide locations. Testing was performed by comparing the known landslide location data with the landslide susceptibility map. In order to validate the results of the susceptibility assessment, AUC of ROC curve (Bui et al. 2012, Pourghasemi et al. 2012a, Pradhan 2013, Pourghasemi et al. 2013a, Jaafari et al. 2014) was used. The ROC curve is a graphical representation of the trade-off between the false-negative and false-positive rates for every possible cutoff value.

The area under the ROC curve (AUC) characterizes the quality of a forecast system by describing the system's ability to anticipate the correct occurrence or non-occurrence of pre-defined ‘‘events’’. The best method has a curve with the largest AUC; the AUC varies between 0 and 1, where 1 indicates perfect prediction, while 0.5 indicates random prediction. The larger the ROC value is, the better the compatibility between dependent and independent variables. The quantitative-qualitative relationship between AUC and prediction accuracy can be classified as follows: 0.9–1, excellent; 0.8–0.9, very good; 0.7–0.8, good; 0.6–0.7, average; and 0.5–0.6, poor (Yesilnacar 2005).

2. Results and discussion

A total of 103 landslides that occurred during recent years were detected and mapped through the aerial photographs interpretation and field surveys within 52 km^2 to assemble a database to evaluate the spatial distribution of slope failures in the study area (Fig. 1). Shallow landslides were dominant, but large deep-seated landslides also observed in the study area.

The susceptibility maps produced by the five ANFIS models are shown in Fig. 2a–e. According to Van Westen et al. (2006) the susceptibility classes, categorized with such terms as ‘‘very high’’, ‘‘high’’, ‘‘moderate’’, ‘‘low’’ and ‘‘very low’’ risk, should be defined on the experience of the expert with support from sufficient models and depend on the likelihood that a slide will occur and the consequences that such an event would have for the elements at risk. In our study, each susceptibility map is assigned a set of symbol (I to V) to indicate the likelihood of slope failure (landslide) initiation. A detailed interpretation of susceptibility classification is presented in table 4. From this table, it is seen that the susceptibility classes I, II, III, IV and V range from very low to very high susceptible, providing a relative ranking of the likelihood of a landslide occurring after road construction or timber harvesting. It is worth noting that the assignment and interpretation of the susceptibility classes is subjective and specifically reflects forest management considerations that are applied by the managers who make decision about management purposes. Therefore, other interpretations can also be added to the susceptibility symbol, if necessary. These may include: soil erosion potential, risk of sediment delivery to streams, and the potential for landslide debris to enter streams.

Five ANFIS models developed herein offer the possibility to compare the landslide distribution map with each conditioning factor. When ROC curves of these five models were considered together, their overall performances are found to be close to each other. From figures 4 and 5 can be seen that the most successful ANFIS model is model 5, which has much less attributes than model 1–4. According to obtained AUC, model 5 has slightly higher prediction performance (75.75) than the other models (Fig. 4). Therefore, we can conclude here that altitude, slope angle, aspect, and lithology are most suitable conditioning factors for landslide susceptibility mapping in the study area. After ANFIS model 5, which produced the best results, ANFIS model 4 was determined as the second successful model from the viewpoint of AUC criteria (72.48) (Fig. 3 and 4). According to Remondo et al. (2003a, b), the best landslide susceptibility models can be produced only with the digital elevation models (DEM)-derived factors. They concluded that some of the landslide conditioning factors, such as the lithology and the land cover (vegetation), improve predictions only slightly. Other factors, such as regolith thickness, do not improve the predictions at all, probably because the variables are not represented accurately enough.

However, a different result was reported by Pradhan (2013), who found that the increment on the number of conditioning factors has a positive impact on the overall prediction performance of landslide susceptibility assessment using ANFIS. Given that there is no common guiding principle for selecting landslide conditioning factors (Ayalew et al. 2005), the results are quite different according to various researchers and study areas.

Our results suggest that the high and very high susceptibility classes cover more than 50 % of the study area. Due to the dynamic nature of precipitation, deforestation and anthropogenic activities (e.g. a road with steep cuts is constructed in a slope which was considered as low susceptible before), the presented landslide susceptibility maps are subjected to change. Hence, these map needs to be updated continuously depending on the dynamics of changes in the area.

There is always a trade-off between the quality of the data and the cost/resources involved and the reliability of the landslide susceptibility assessment. In order to achieve the best quality/cost relation, it is very important to invest in landslide inventory databases (Van Westen et al. 2008).

4. Conclusion

This study analyzed the potential of slope failure in Iranian mountain forest using ANFIS models within a GIS environment. The outcome of GIS-based ANFIS application was a set of susceptibility maps, which could be used to predict the stability of slopes from 15 basic factors including slope degree, slope aspect, altitude, lithology, rainfall, distance to faults, distance to streams, plan curvature, TWI, SPI, STI, NDVI, forest plant community, forest canopy, and timber volume. Our findings suggest that all of the five ANFIS models have performed reasonably well with more than AUC > 70 prediction performance. Therefore, they are trustworthy for forestry activities and hazard mitigation planning. However, the best model can be produced only through using altitude, slope angle, aspect, and lithology. When the purpose of the study was considered, forest engineers can select one of these models according to their circumstances in order to produce susceptibility maps.

The susceptibility assessment of slope failure represent an essential resource of knowledge of our study area for its capacity for supporting individual uses or combination of uses, such as road construction and timber harvesting. Managers and foresters can then make decisions and prepare prescriptions that will have highly predictable results for producing sustainable products, maintaining site quality, and substantially reducing risk of any adverse impacts. Unfortunately, such studies are far from common in the Caspian forest, implying great difficulty for comparative analyses. It is therefore worthwhile to apply the method used in this study to different environmental settings.

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