Spatial Prediction of Slope Failures in Support of Forestry Operations Safety

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Abstract

This study produces a slope failure susceptibility map for evaluation of the Caspian Forest for its capacity to support road construction and timber harvesting. Fifteen data layers were used as slope failure conditioning factors, and an inventory map of recent failures was used to detect the most susceptible areas. Five different datasets of conditioning factors were constructed to compare the efficiency of one over the other in susceptibility assessment. Slope failure susceptibility maps were produced using an adaptive neuro-fuzzy interface system (ANFIS) and geographical information system (GIS). The accuracy of the maps was then evaluated by the area under curve (AUC). The validation results suggest that the ANFIS model with input conditioning factors of slope degree, slope aspect, altitude, and lithology performed the best (AUC=83.74%) among the various ANFIS models explored here. The five ANFIS models have performed reasonably well, and the maps allow development of prudent hazard mitigation plans for the safety in forestry operations.

Keywords: ANFIS, GIS, Caspian Forest, landslide susceptibility, forest road, timber harvesting

1. Introduction

Landslides are one of the most devastating natural hazards in mountainous terrains. Although the action of gravity is the primary driving force (Gorsevski et al. 2006), landslides are also aggravated by human activities such as mining, agriculture, and forestry operations. With respect to forestry operations (timber harvesting and road construction activities), landslide often increases with long-term consequences and has been reported worldwide (e.g., Sessions et al. 1987, Duncan et al. 1987, Larsen and Parks 1997, Allison et al. 2004).

When damaging landslides occur on forestlands, it is not unusual to hear appeals for a broad ban on forestry operations. However, such a ban would be very costly to many forest landowners and it would impact their contributions to state and local economies. Therefore, apart from regular hazard reduction plans, landslide susceptibility (LS) assessments should also be developed and implemented for the safety in forestry operations. Landslide hazard reduction plans, which are generated as the site is handed over to a contractor, are important tools to ensure everybody understands how to deal with different levels of LS across the working site.

In the Caspian Forest in northern Iran, landslides and slope failures are a common problem because naturally formed slopes are disturbed by forestry operations. History has shown that roads with improper terrain stability assessment in this area can cause significant slope failures. This trend is expected to continue and may increase in the future; some estimates suggest that significant portions of the Caspian Forest are prone to mass wasting, and forestry operations in this forest can accelerate landslide rates and magnitudes (Jaafari et al. 2014). Therefore, understanding of LS is needed to evaluate forestry strategies including alternate choices of road location, choice of road standards, choice of transport mode, and understanding whether timber harvesting on and around steep slopes is reasonable.

The effectiveness of slope stability studies is apparent from the high prediction results of LS assessment reports from models such as logistic regression (e.g., Pourghasemi et al. 2013), knowledge-based analytical hierarchy process (e.g., Pourghasemi et al. 2012, Pourghasemi et al. 2013), fuzzy logic (e.g., Pourghasemi et al. 2012, Akgun et al. 2012), artificial neural networks (ANNs) (e.g., Conforti et al. 2014), support vector machine (e.g., Pradhan 2013) and adaptive neuro-fuzzy interface system (ANFIS) (e.g., Vahidnia et al. 2010, Sezer et al. 2011, Bui et al. 2012, Pradhan 2013). In the case of ANFIS, developed by Jang (1993), only minor applications of landslide-related studies have 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 using 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 ANFIS model is implemented as a first order Takagi and Sugeno's type fuzzy inference system (Takagi and Sugeno 1983) that consists of 2 fuzzy if-then rules:

Rule 1: If x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$ (1)

Rule 2: If x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$ (2)

Where:

x, y are inputs
A, B corresponding term set
f output
p, q, r constant

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 that during the training session, the error between the target and the actual output is minimized. Further information on ANFIS can be found in Jang (1993).

LS assessment involves handling, processing and interpreting a large amount of territorial data. Geographical Information Systems (GIS) are very useful in susceptibility assessment (Ayalew et al. 2005), because they allow frequent updating of the database related to spatial distribution of landslide events and their predisposing factors, as well as the susceptibility assessment procedures (Conforti et al. 2014). In recent years, the use of GIS-based approaches to study landslides has been frequently reported. These include GIS-based frequency ratio, index of entropy, and weights of evidence models (Jaafari et al. 2015a, Jaafari et al. 2014), and GIS-based multicriteria decision analysis (Feizizadeh and Blaschke 2013). Bui et al. (2012) used a GIS-based ANFIS model for LS mapping in Vietnam. Their results showed that ANFIS is a robust method for landslide modeling. Pradhan (2013) compared the ability of the decision tree, support vector machine and ANFIS models to do LS mapping within a GIS environment. The results showed that all the models faired reasonably well, however, the success rate showed that ANFIS had better prediction capability.

This paper addresses the slope failure (landslide) susceptibility assessment in the Caspian Forest using an ANFIS suitable to GIS-based analysis. The study tackles the main causal factors and delimits the most susceptible zones for slope failure as a useful tool for the engineers involved in road construction and timber harvesting. The susceptibility maps are also compared with the known landslide locations according to the area under the curve (AUC) of receiver operator characteristic (ROC) curve to test the reliability and accuracy of the modeling approach. The susceptibility assessment presented here enables forest practitioners to avoid areas where forestry operations could cause slope failure, help identify where monitoring programs are necessary, and adopt appropriate policies to guide more efficient forestry operations.

2. Materials and methods

2.1 Study area

The study area is situated in Mazandaran Province, which shares a border with Golestan and Guilan Provinces in the north of Iran. The study area has an approximate area of 52 km^2 and is 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 in the Caspian Forest with slope variations between flat and >80°, and altitudes between 160 and 2190 m. Slope shapes vary but frequently represent convex elements. They mainly feature concave valleys. In this area, the stream network flows from the north-east to the west with a dendritic pattern. Due to proximity of 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 was 22.5 and 10ºC, respectively (Jaafari et al. 2015b). The vegetation cover is quite continuous and is formed by deciduous trees.

According to the geologic map of the area, prepared by Geological Survey of Iran (GSI), the major portion of the study area is underlain by dolomitic limestone. The Alborz fault is the most important fault in the area and is a reverse fault that follows the west-east orientation and dip toward the south. This fault is active, and most earthquakes and landslides in Mazandaran Province are the result of displacements and activity of this fault (Darvishzadeh 2004).

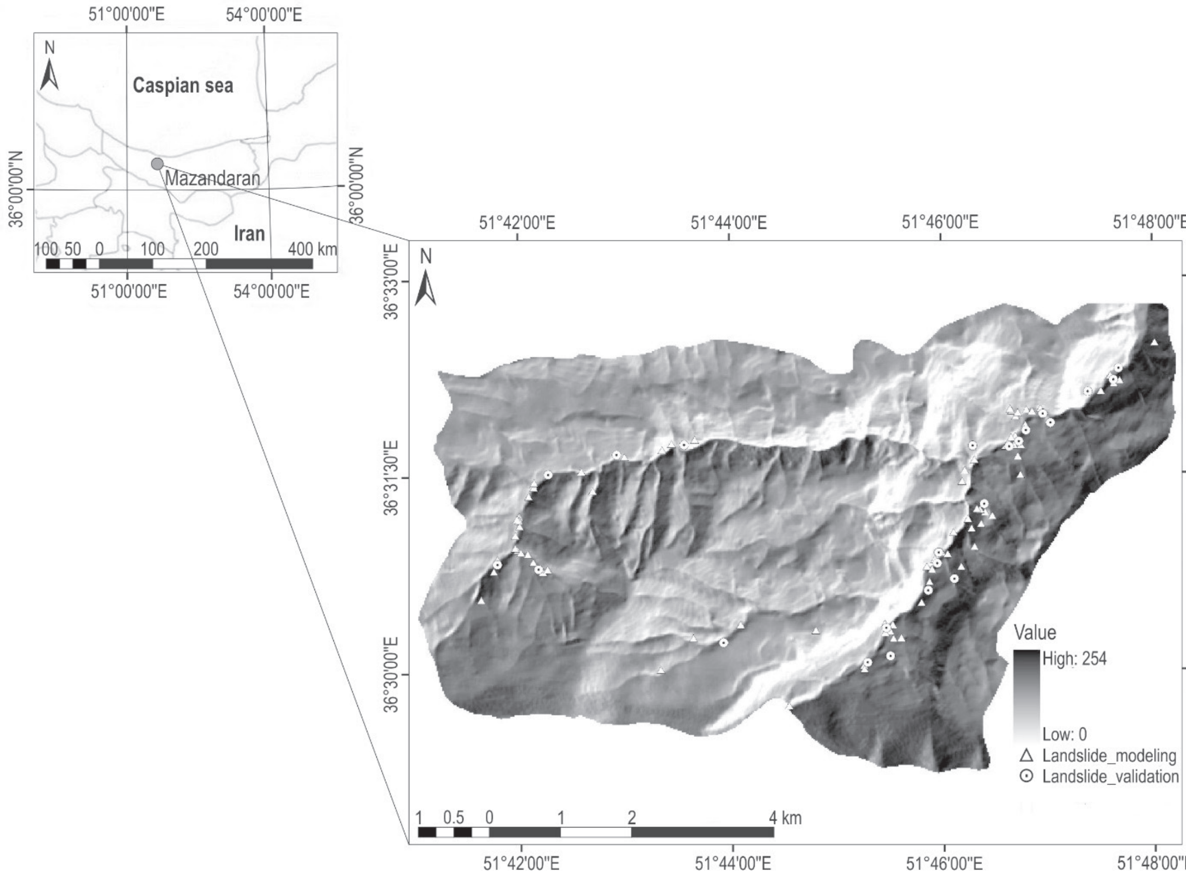

Fig. 1 Location of study area with landslide inventory map

2.2 Spatial database

2.2.1 Landslide inventory map

The landslide inventory map of the study area was compiled by inheriting the landslide locations from interpretation of aerial photographs and field-based inspections. Aerial photographs show that historical landslides could be mapped via breaks in the forest canopy, denuded 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, multiple field surveys and observations were conducted to produce a more detailed and reliable landslide inventory map (Jaafari et al. 2014). Shallow landslides were dominant, but large deep-seated landslides were also observed. In recent years, 103 landslides were detected and mapped within 52 km^2 to assemble a database to evaluate the spatial distribution of slope failures in the study area (Fig. 1).

2.2.2 Slope failure (landslide) conditioning factors

The recognition and mapping of an appropriate set of instability factors related to slope failures requires previous information on the main causes of landslides (Guzzetti et al. 1999). In this study, the

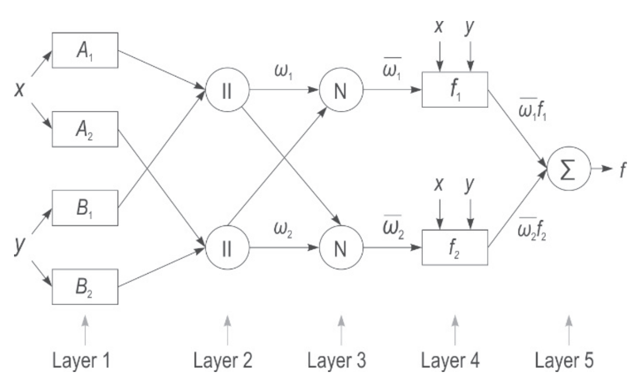

Fig. 2 General structure of ANFIS

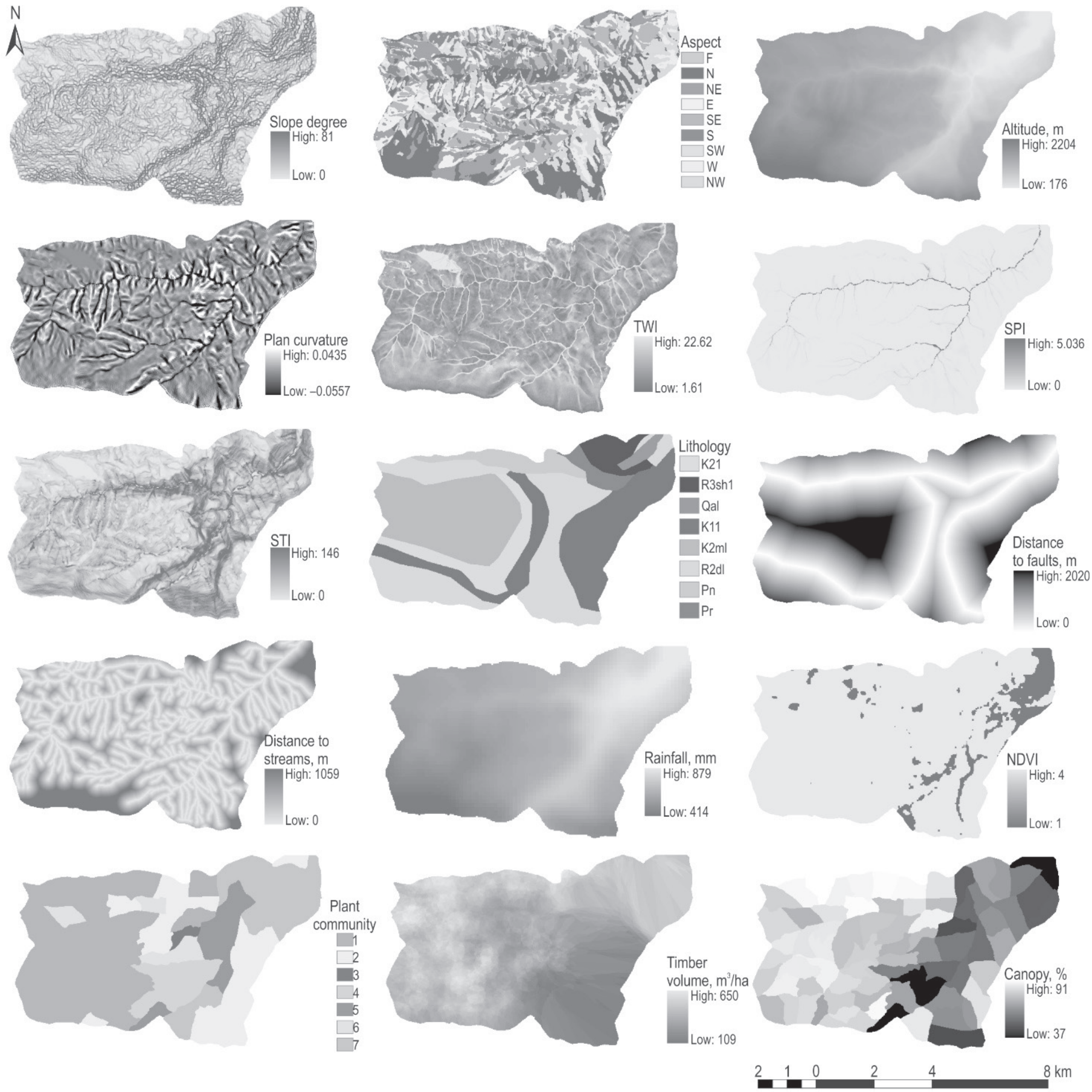

Fig. 3 Geo-environmental parameter maps of the study area: slope degree, slope aspect, altitude, plan curvature, topographic wetness index, stream power index, sediment transport index, lithology, distances to faults, distances to streams, rainfall, normalized difference vegetation index, plant community, timber volume, and canopy

landslide conditioning factors (LCFs) were selected among the most commonly used in the literature to assess slope failures susceptibility; in particular, the results of field surveys suggested that slope degree, slope aspect, altitude, plan curvature, topographic wetness index (TWI), stream power index (SPI), sediment transport index (STI), lithology, rainfall, distance to faults, distance to streams, normalized difference vegetation index (NDVI), forest canopy, forest plant community, and timber volume match very well with the landslide distribution in the study area. The calculation and significance of these factors in landsliding has explicitly been presented in Pourghasemi et al. (2013), Jaafari et al. (2014), Jaafari et al. (2015a), and Wang et al. (2016). Fig. 3 shows the LCFs used in this study.

Slope degree, slope aspect, altitude, plan curvature, TWI, SPI, and STI layers were created from a 20 m Digital Elevation Model (DEM) using ArcGIS and SAGA GIS. The geological map was prepared by GSI on a 1:100,000 scale. Distance to faults and distance to streams were computed using spatial analyst tool of ArcGIS. The rainfall map was prepared using the mean annual precipitation data from the meteorological stations for the study area over the last 20 years (Jaafari et al. 2014). 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. As the raster dataset has enriched the 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 (Bui et al. 2012, Jaafari et al. 2014, Jaafari et al. 2015a) were selected as the mapping unit. This was small enough to capture the spatial characteristics of landslide susceptibility and large enough to reduce computing complexity.

Table 1 The factor list of the datasets from 1 to 5

Factor	Dataset_1 (Model_1)	Dataset_2 (Model_2)	Dataset_3 (Model_3)	Dataset_4 (Model_4)	Dataset_5 (Model_5)
Slope angle	✓	✓	✓	✓	✓
Slope aspect	✓	✓	✓	✓	✓
Altitude, m	✓	✓	✓	✓	✓
Lithology	✓	✓	✓	✓	✓
Rainfall, mm	✓	✓	✓	✓	–
NDVI	✓	✓	✓	✓	–
Plan curvature	✓	✓	✓	–	–
TWI	✓	✓	✓	–	–
SPI	✓	✓	✓	–	–
STI	✓	✓	✓	–	–
Distance to streams, m	✓	✓	–	–	–
Distance to faults, m	✓	✓	–	–	–
Forest canopy,%	✓	–	–	–	–
Timber volume, m^3/ha	✓	–	–	–	–
Plant community	✓	–	–	–	–

A series of tests was also performed considering different input datasets from the LCFs. The purpose of selecting various datasets was to explore the influence of parameter enrichments on the performance of the ANFIS models, and the importance of the added parameter on the landslide assessments (Pradhan 2013). Table 1 shows that dataset_1 includes a maximum number of LCFs, and it continues to narrow down to dataset_5.

The idea behind this kind of grouping came from the nature and the availability of data and resources of each LCF. Some factors, such as forest canopy, timber volume, and plant community, are costly to collect across forestlands in Iran due to the landscape heterogeneity and unavailability of supporting tools such as accurate high-return LiDAR data for all areas and frequent changes over a short time period due to forestry operations. Thus, they were only included in dataset_1. In contrast, the preparatory factors (e.g. slope, aspect, altitude and lithology) that are not expected to change significantly over a short time period (e.g. 50 years) are very easy to quantify using fairly simple GIS operations. These factors were, therefore, considered for inclusion in all datasets. The inclusion of other factors in different datasets also follows this instruction.

2.3 Training and validation dataset

In landslide modeling, the landslide inventory map needs to be split into two subsets for training and validation. Without splitting, it would not be possible to validate the results (Jaafari et al. 2014). When splitting data, there is no rule of thumb for the relative sizes of the two subsets (Pradhan 2013). Here, the inventory map was randomly divided into two datasets. Part_1 that contains 80% of the data (82 landslides) was used in the training phase of the five ANFIS models. Part_2 is a validation dataset with the remaining 20% of the data (21 landslides) used to validate the models and to estimate their accuracy. All 82 landslide locations in the part_1 dataset denote the presence of landslides and were assigned to a 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 LCFs were then extracted to build a training dataset (Bui et al. 2012, Pradhan 2013). This dataset contains a total of 164 points, with one target variable denoting the landslide presence/absence and the 15 LCFs. This dataset was further randomly partitioned into two subsets including: training and checking to develop the ANFIS models. The training set was used to adjust the connections weights, membership functions and model parameters. The checking set was used to check the performance of the model through the training process and to 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% (116 points) of the extracted database was randomly selected as the training dataset, and the remaining 30% (48 points) as the checking dataset. The commercially available Neuframe software (Neusciences 2000) was used to select the datasets at random.

Due to the different scales of the input variables, and in order to increase the speed and accuracy of data processing, input data need to be normalized from 0 and 1 before using them in the ANFIS model. For this purpose, the extracted values from LCFs were normalized using the normalization formula as follows:

$$X_{\mathrm{norm}} = \frac{X_{\mathrm{i}} - X_{\mathrm{min}}}{X_{\mathrm{max}} - X_{\mathrm{min}}} \tag{3}$$

Where:

X_{i} data that should be normalized
X_{max}, X_{min} the maximum and minimum value of original data, respectively
X_{norm} normalized value of X_{i}.

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

In this study, a type_3 ANFIS model (Takagi and Sugeno 1983) was used to produce susceptibility maps of the 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 (Jang 1993). The final output is the weighted average of each rule's output (Buragohain and Mahanta 2008). The general structure of a type_3 ANFIS model with two inputs of x_1 and x_2, and one output of y is shown in Fig. 2 (Erenturk 2009). From this figure, it can be seen that the model contains five layers: the first layer actualizes the fuzziness of inputs, the second layer calculates the firing strength of each rule, the third layer normalizes the firing strengths, the fourth layer determines the consequent parameters of the rule, and the fifth layer computes the output of the fuzzy system by summing the outputs of the fourth layer.

A total of five ANFIS models were constructed to produce LS 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 to generate the initial fuzzy inference system (FIS). The GENFIS1 generates an initial Sugeno-type FIS for ANFIS training using a grid partition, and GENFIS2 uses subtractive clustering to generate the initial Sugeno-type FIS. As proposed by Chiu (1997), due to the large number of input variables considered in this study, the 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 the five ANFIS models, each model was trained by considering 200 epochs. Finally, the output data obtained from the models were converted to a 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. Here, 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. To validate the results of the susceptibility assessment, the AUC of the ROC curve was used (Bui et al. 2012, Pourghasemi et al. 2012, Pradhan 2013, Pourghasemi et al. 2013, Jaafari et al. 2014, Jaafari et al. 2015a, Ezzati et al. 2016). The ROC curve is a graphical representation of the trade-off between the false-negative and false-positive rates for every possible cutoff value. By tradition, the plot shows the false-positive rate (*FPR*) on the *X* axis (Eq. 4) and the true-positive rate (*TPR*) on the *Y* axis (Eq. 5).

$$X = FPR = 1 - \left[\frac{TN}{TN + FP}\right] \tag{4}$$

$$X = TPR = \left[\frac{TP}{TP + FN}\right] \tag{5}$$

Where:

TN (true negative) and *TP* (true positive) are the number of pixels that are correctly classified, whereas *FP* (false positive) and *FN* (false negative) are the numbers of pixels erroneously classified.

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« (Pourghasemi et al. 2013). The best method has a curve with the largest AUC; the AUC varies between 0 and 1, where 1 indicates perfect prediction and, 0.5 indicates random predictions. Larger ROC value suggests 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, moderate; and 0.5–0.6, poor (Hosmer et al. 2013).

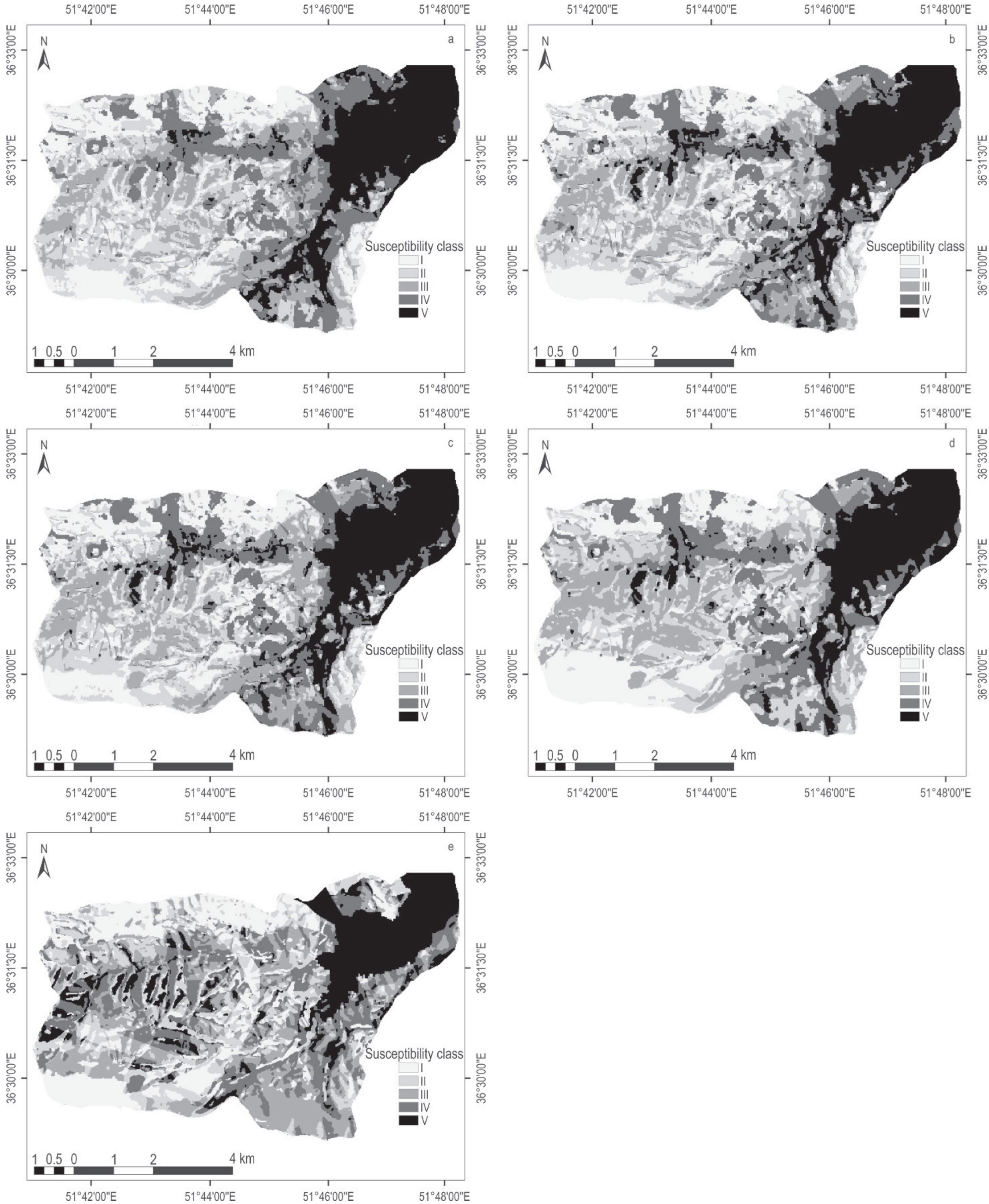

Fig. 4 Susceptibility map produced by: (a) model_1, (b) model_2, (c) mode_3, (d) model_4, (e) model_5

3. Results

The susceptibility maps produced by the five ANFIS models are shown in Fig. 4a–e. In every map, the susceptibility classes of I, II, III, IV and V indicate the likelihood of slope failure (landslide) initiation, ranging from very low to very high susceptibility. A detailed interpretation of susceptibility classification is presented in Table 2.

This shows that each susceptibility class provides a relative ranking of the likelihood of a slope failure following road construction and/or timber harvesting. For example, the first class implies very low susceptibility to slope failure and the area characterized by this class is safe for forestry operations.

The results of validation of the five ANFIS models using ROC-AUC are shown in Figs. 5 and 6. The results show that all the models have good prediction

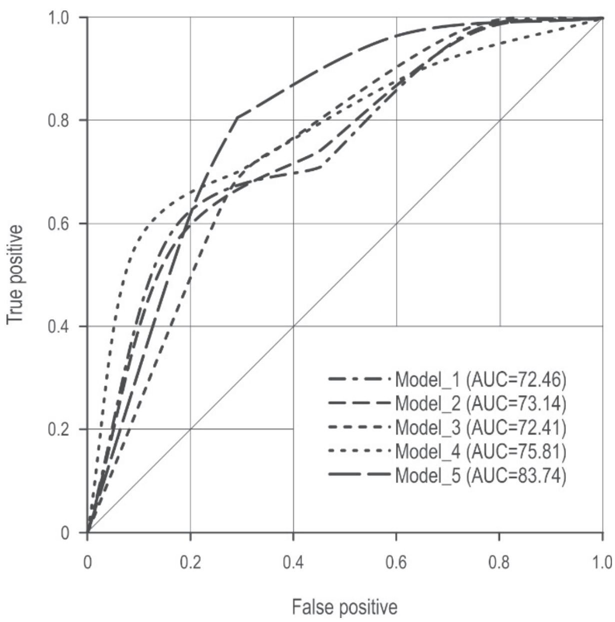

Fig. 5 Prediction rate curves for the susceptibility maps produced in this study

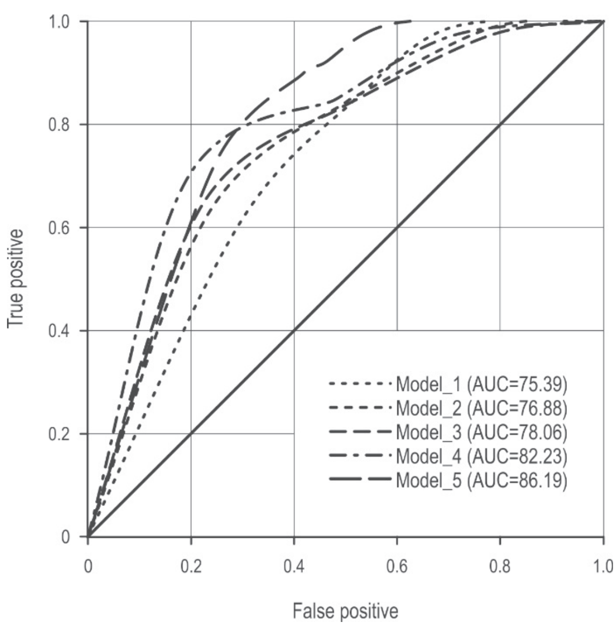

Fig. 6 Success rate curves for the susceptibility maps produced in this study

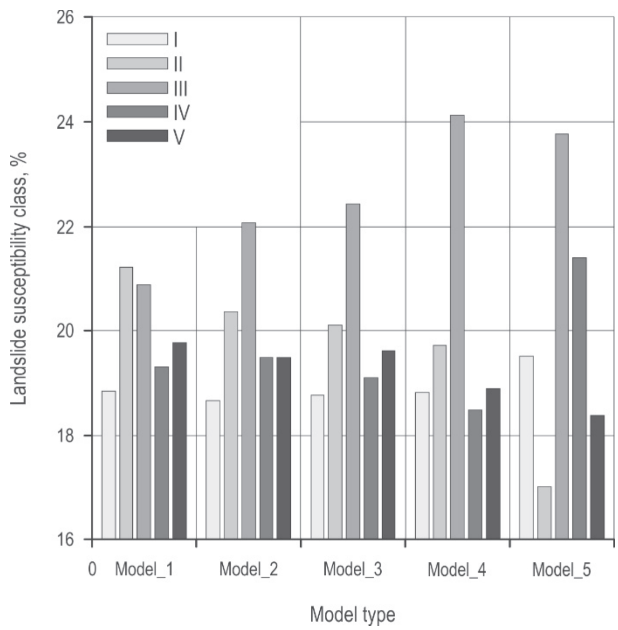

Fig. 7 The landslide susceptibility classes delimited by the five ANFIS models

Table 2 Detailed slope failure susceptibility classification

Interpretation	Susceptibility class
Safe Very low likelihood of failures following road construction or timber harvesting	I
Low instability Normal road construction and timber harvesting will not significantly decrease terrain stability	II
Moderate likelihood of failures following road construction or timber harvesting Minor failures expected in road cuts	III
High likelihood of failures following road construction or timber harvesting	IV
Very high likelihood of failures following road construction or timber harvesting	V

capabilities, with the best results of the model_5 ($AUC_{success\ rate}$=86.19%, $AUC_{prediction\ rate}$=83.74%), followed by the model_4 ($AUC_{success\ rate}$=82.23%, $AUC_{prediction\ rate}$=75.81%).

In addition, a comparison between the five susceptibility classes delimited by the different ANFIS models is presented in Fig. 7. The result suggests that the moderate, high and very high susceptibility classes cover more than 60% of the study area.

4. Discussion

4.1 Landslide susceptibility mapping

Modeling LS across a forestland is challenging because of geological, topographical and environmental complexities. Although various methods for LS assessment have been proposed, the evaluation of predictive ability of these methods in forestlands still lags. This study evaluated the predictive ability of ANFIS for modeling LS across a forestland subjected to forestry operations. Five ANFIS models developed herein offer the possibility to compare the distribution landslide of hazard with different sets of LCFs. When the ROC curves of these five models were considered together, their overall performances were close to each other. Performance validation indicated that the most successful ANFIS model is model_5, which has much fewer attributes than models 1–4. Therefore, it can be concluded that the altitude, slope angle, aspect, and lithology are most suitable LCFs for LS assessment in the study area. Moreover, these results suggest that the other LCFs are a possible source of bias because they decreased the prediction accuracy. There is always a trade-off between the quality of the data, the resources involved, and the reliability of the LS assessment. To achieve the best quality relation, it is very important to invest in landslide inventory and LCFs databases (van Westen et al. 2008).

Selection of LCFs is crucial for the quality of LS models (Irigaray et al. 2007). Although some methods, such as linear correlation, Kolmogorov–Smirnov test and Genetic Algorithm (Irigaray et al. 2007, Kavzoglu, et al. 2015) have been suggested to support the optimal selection of LCFs, the standard guideline is still debated. According to Remondo et al. (2003a, 2003b), the best LS models can be produced only with the DEM-derived factors. They concluded that some of the LCFs, including lithology and 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, the different results reported by Sezer et al. (2011) and Pradhan (2013) suggest that the increase in the number of LCFs has a positive impact on the overall prediction performance of LS assessment using ANFIS. The results are quite different according to various researchers and study areas. This is because there is no common guiding principle for selecting LCFs (Ayalew et al. 2005). They are usually selected based on the landslide types, the failure mechanisms, the map scale of analysis, the characteristics of the study area, and data availability (Glade and Crozier 2005).

4.2 Landslide susceptibility maps for the safety in forestry operations

As pointed out by 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 based on the experience of the experts with the support of 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 this study, each susceptibility map was assigned a set of symbol (I to V) to indicate the likelihood of slope failure (landslide) initiation. A detailed interpretation of susceptibility classification for the relative ranking of the likelihood of slope failures following road construction and/or timber harvesting has also been provided. This interpretation of susceptibility classes can be considered as a safety plan by which safety is managed on the area, as this plan indicates that each part of the area poses certain risks to road construction and timber harvesting.

It is worth pointing out that the assignment and interpretation of the susceptibility classes are subjective and specifically reflect forest management considerations applied by managers who make decisions for management purposes. Therefore, contractors involved in forestry operations must have their own operational safety plans. These plans, which must be updated by contractors on a regular basis, should include safety and health policy, responsibilities, risk assessments and controls (Ryan et al. 2004). Moreover, the nature of the forestry operations implies that there can often be several different operational works close to each other. Therefore, other interpretations can also be added to the susceptibility symbol to support each part of the forestry operations. These may include soil erosion potential, risk of sediment delivery to streams, and the potential for landslide debris to enter streams (BCMOF and BCMOE 1999, Schwab and Geertsema 2010).

Due to the dynamic nature of forestry operations (e.g. a road with steep cuts is constructed in a slope that was considered to be of low susceptibility), the LS maps are subject to change. The single most important contributor to long-term effectiveness of the produced LS maps is the establishment of monitoring systems to observe the changes and note when and how these changes occur. However, given that a monitoring program within a mountain forest is difficult and costly, the results of this study suggest that it be limited to the highly susceptible zones identified here. Moreover, monitoring programs can improve the confidence in predictive ability of the ANFIS models developed here. These investigations were beyond the situation and scope of this study, but they are important components that benefit more efficient planning of forestry operations.

5. Conclusion

This study analyzed the potential of slope failure in a mountain forest using ANFIS models within a GIS environment. The outcome of GIS-based ANFIS application was a set of susceptibility maps, that could be used to predict the stability of slopes from 15 basic factors including slope degree, slope aspect, altitude, plan curvature, TWI, SPI, STI, lithology, rainfall, distance to faults, distance to streams, NDVI, forest canopy, forest plant community, and timber volume. The results of this study suggest that all of the five ANFIS models have performed reasonably well with AUC values over 70%. Therefore, they can be used to develop prudent hazard mitigation plans for safe forestry operations. However, the best model can only be produced with altitude, slope angle, aspect, and lithology. Forest engineers can tailor the use of these models based on their circumstances.

The susceptibility assessment of slope failure is an essential resource of knowledge of the study area for its capacity to support safe forestry operations. Unfortunately, such studies are far from common in the mountainous forestlands subjected to forestry operations. This makes comparative analyses difficult. Thus, it is important to apply the method proposed here to different environmental settings.

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