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Landslide Susceptibility Mapping: an Assessment of the Use of an Advanced Neural Network Model with Five Different Training Strategies

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1. Introduction

Landslide presents a significant constraint to development in many parts of Malaysia which experiences frequent landslides, with the most recent occurring in 2000, 2001, 2004, 2007 and 2008. Damages and losses are regularly incurred because; historically there has been too little consideration of the potential problems in land use planning and slope stability analysis. Landslides are mostly occurred in Malaysia mainly due to heavy tropical rainfall. In recent years greater awareness of landslide problems has led to significant changes in the control of development on unstable land. So far, few attempts have been made to predict these landslides or preventing the damage caused by them. In last few years, landslide susceptibility analysis using GIS and data mining such as fuzzy logic, and artificial neural network methods have been applied by researchers in different countries (Akgun et al., 2008; Ercanoglu & Gokceoglu 2002; Gomez & Kavzoglu, 2005; Pistocchi et al. 2002; Lee et al. 2003a, 2003b, 2004a, 2004b). But their result output can not be directly used in the Malaysian landslide susceptibility analysis. This is due to the changes in the geographical environment set up, litho types and different climatic conditions. The local geographical settings cause different landslide types based on completely different mechanisms and are absolute incomparable. Through scientific analysis of landslides, we can assess and predict landslide-susceptible areas, and thus decrease landslide damage through proper preparation. To achieve this aim, landslide susceptibility analysis techniques have been applied, and validated in the study area using five different training strategies with the aid of artificial neural network.

In landslide literature, there have been many studies carried out on landslide susceptibility and hazard mapping using GIS. There are number of different approaches for the measurement of landslide hazard, including direct and indirect heuristic approaches, and deterministic, probabilistic, statistical and data mining approaches. Recently, there have been studies on landslide susceptibility mapping using GIS, and many of these studies have applied probabilistic models (Baeza and Corominas, 2001; Clerici et al., 2002; Dahal et al., 2008; Dai et al., 2001; Lee & Dan, 2005; Lee & Lee, 2006; Lee & Min, 2001; Lee & Sambath, 2006; Lee, 2004; Lee et al., 2002a, 2002b; Gokceoglu et al., 2000; Lee & Choi, 2003; Lee & Pradhan, 2006, 2007; Nefeslioglu et al., 2008; Santacana et al., 2003; Pradhan et al., 2006; Youssef et al., 2009). One of the multivariate models available, the logistic regression models, has also been applied to landslide susceptibility mapping (Chau & Chan, 2005; Dai & Lee, 2003; Lee, 2005, 2007a; Pradhan, 2010a; 2010c; Pradhan et al., 2008; Pradhan & Lee, 2010a; Pradhan et al., 2010a; Pradhan & Youssef, 2010; Ohlmacher & Davis, 2003; Suzen & Doyuran, 2004a, 2004b). In last few years, a new approach to landslide hazard evaluation using GIS, data mining using fuzzy logic, and artificial neural network, neuro-fuzzy models have been applied (Catani et al., 2005; Caniani et al., 2008; Chang & Chao, 2006; Ercanoglu and Gokceoglu, 2002; Ercanoglu et al., 2004; Ermini et al., 2005; Kanungo et al., 2006; Lee, 2007b; Lee & Evangelista, 2006; Lee et al., 2006, 2007; Neaupane & Achet, 2004; Pradhan, 2010b, 2010d; 2010c; Pradhan et al., 2009; Pradhan et al., 2010a, b, c, d; Pradhan & Buchroithner, 2010; Pradhan & Lee, 2007, 2009, 2010a, 2010b, 2010c; Pradhan & Pirasteh, 2010; Tangestani, 2004; Yesilncar & Topal, 2005).

In recent years, Lee & Pradhan (2006), Lee & Pradhan (2007), and Pradhan & Lee (2010a) investigated the landslide susceptibility in Malaysia. Pradhan & Lee (2010a) evaluated three models for landslide susceptibility analysis using frequency ratio, logistic regression and artificial neural network model. Pradhan & Lee (2010a) analyzed the rainfall precipitation in the Penang area using back-propagation neural networks. However, they could not have a detail landslide hazard analysis due to lack of rainfall intensity data. Slope stability and rainfall intensity is very important factors causing most of the landslides in Malaysia. Besides these two important factors of rainfall and slope, soil weight and distance to drainage are also important factors in some regions. Pradhan et al., (2009) investigated the landslide susceptibility using fuzzy model at Penang Island and they pointed out some important factors, such as topographic slope, topographic aspect, topographic curvature, distance to drainage, lithology, distance to faults, soil texture, landcover, vegetation index and accumulated rainfall intensity.

The objective and motivation of this study is to demonstrate artificial neural network model with five different training strategies for landslide susceptibility mapping with the aid of GIS. In order to get a stable and reliable result, in this paper, nine geological and geomorphological factors including, topographic slope, topographic aspect, topographic curvature, stream power index (spi), distance from drainage;, flow length, flow accumulation, topographic wetness index, distance to road, lithology, distance to the fault lines, soil types, land cover, and ndvi were used to predict landslide susceptible areas. These fourteen factors constructed an ANN using the back propagation algorithm for landslide susceptibility mapping. To meet the objectives, firstly the ANN model was trained using training sites which can be directly utilized for the landslide susceptibility analysis as long as the recorded nine factors are fed into an ANN model. Five different training samples were selected to train the ANN in order to avoid bias effect in the final results. Finally, the results of the landslide susceptibility maps were validated using the existing landslide location data with the aid of receiver operating characteristics (ROC) approaches.

2. Study area characteristics

In this research, a landslide-prone area in the Cameron Highlands in Peninsular Malaysia (Fig. 1) was selected for landslide susceptibility assessment using ANN model. The study area (Fig. 1) falls in the districts of Cameron Highlands which seeing a rapid development with land clearing for housing estate, hotel / apartment causing erosion and landslides. Cameron Highland is a district of Pahang state which is one of the 13 states of the Federation of Malaysia. The District of Cameron Highlands is located in western Pahang bordering the states of Perak and Kelantan. The Pahang – Perak boundary runs approximately in a north – south direction along a sharp divide with numerous high peaks that rise over 1500m above the mean sea level. From north to south along this divide, the following peaks, Gunung Pass (1587m), two unnamed peaks (1501m and 1796m), Gunung Irau (2110m), Gunung Brinchang (2031m), Gunung Ruil (1718m), Gunung Jasar (1704m), Gunung Dungun (1576m) and Gunung Duri (1530m) are present. At Gunung Duri, the divide turns eastwards for about 10km before turning towards the south and southeasterly (Pradhan and Lee, 2010b). The study area covers an area of 285 km² and is located near the northern central part of peninsular Malaysia. It is bounded to the north by Kelantan, west by Perak. Annual rainfall is very high averaging between 2,500 mm to 3,000 mm per year. Two pronounced wet seasons from September to December and February to May. Rainfall peaks between November to December and March to May. The geomorphology of the area consists of undulating plateau stretching about 12 km. The geomorphology of the area is characterized by a rugged topography with the hill ranges varying from 600 m.s.l to over 4800 m. The geology of the Cameron Highlands consists of mostly two types of litho types: igneous and metamorphic rocks. Post-Triassic- Mesozoic granite comprises of most of the granite rocks where as there are few patches of metamorphic rocks mostly comprising of Silurian-Ordovician Schist, phyllite, limestone and sandstone. Several field observations have been carried out in the month of April/ June/ September 2006 and 2007 for collecting ground data.

The landuse in the study area is mainly peat swamp forest, plantation forest, inland forest, scrub, grassland and ex-mining area. The slope angle of the area ranges from 0 degrees to as much as 86 degrees. The relief of the study area varies between 860- 2110 m.s.l.

The annual rainfall of Cameron Highlands, like in all tropical hilly regions, is very high, averaging between 2,500 and 3,000 mm per annum. There are two pronounced wet seasons from September to December and from February to May each year. Rainfall in Cameron

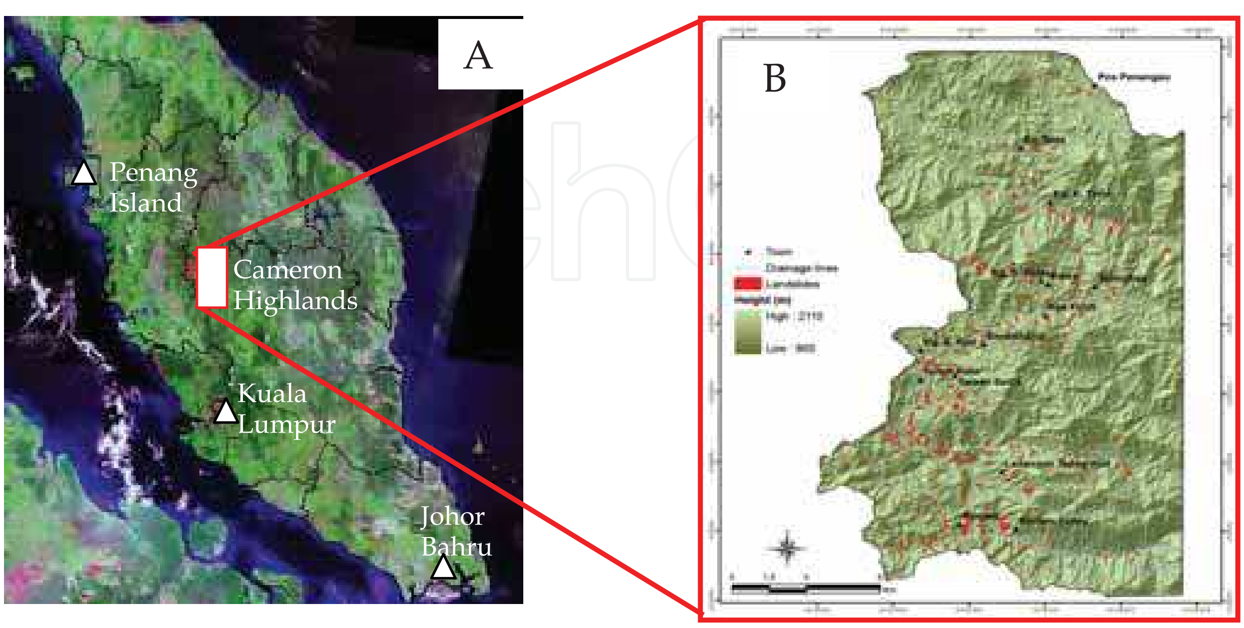


Fig. 1. Location map of the study area

Highlands peaks between March and May and also from November to December. The single-day rainfall high that had been recorded ranged from 87 to 100 mm. It is during such times that many streams and rivers in the Cameron Highlands may overflow, flooding the surrounding areas, and landslides such as debris flow may occur along the river valleys. The intensity of the rain is another factor that affects the fill slopes, causing severe sheet, rill, and gully erosion. During such times, many of the natural and man-made slopes are marginally stable.

3. GIS data used

For the landslide-susceptibility mapping, the main steps were data collection and construction of a spatial database from which the relevant landslide conditioning factors are extracted, followed by assessment of the landslide susceptibility using the relationship between landslide and landslide-conditioning factors, and validation of the results. In the first step, landslides were detected in the study area by interpretation of aerial photographs and extensive field surveys. A landslide inventory map was compiled from 1:10,000 – 1:50,000 scale aerial photographs, and was used to evaluate the frequency and distribution of shallow landslides in the area. In addition, all historical landslide reports, newspaper records, and archived data have been assembled for the period under examination. The source material varies in quality with respect to the precise location of the landslide event. Based on the site description, archived database, and aerial photo interpretation, the locations of the individual landslides were drawn on 1:25, 000 maps, and the location was plotted as close as possible based on the classification scheme proposed by Varnes (1984). Field observations were used to confirm the fresh landslide locations (scars) and types. In the aerial photographs, historical landslides could be observed as breaks in the forest canopy, bare soil, or geomorphological features, like head- and side scarps, flow tracks, and soil- and debris deposits below a scar. These landslides were then classified and sorted out based on their modes of occurrence. The landslide inventory map was very helpful in understanding different triggering factors that control different slope movement types (Cruden & Varnes, 1996). Most of the landslides are shallow rotational, and there are a few translational and flow types. However, during the analyses that were performed in the present study, only the rotational failures are considered, and the other types of failures were eliminated because the occurrence of the other types of failures is rare and ignorable. Consequently, the susceptibility maps that are produced in this paper are valid for the shallow rotational failures. To assemble a database to assess the surface area and number of landslides in the study area, a total of 48 shallow rotational failures were mapped in the study area. The landslide inventory map that was compiled in the present study is shown in Fig. 1b.

In order to develop a method for the assessment of landslide susceptibility, determination of the conditioning factors for the landslides is crucial (Ercanoglu & Gokceoglu, 2002). In fact, the regional landslide assessments should be practical and applicable for the study area. For the first requirement for this statement, the input parameters should be representative, reliable and obtained easily. In this study, we selected the input parameters considering field observations performed on the actual landslides. There were a total of seven landslide conditioning factors considered in the analyses performed. The basic landslide conditioning factors such as altitude, slope angle, plan curvature, distance to drainage, soil texture and stream power index were employed. As a result of the field observations, it was observed that the landslides have a close relation with the distance from the roads. For this reason, the distance to the road was considered as a landslide conditioning factor for the study area, in addition to the basic landslide conditioning factors. All of the factors that were employed in this paper were transformed into a grid-type spatial database using the GIS (Fig. 2).

Topography, soil, and road transport databases were constructed for the analysis (Fig. 2) (Table 1). Maps relevant to landslide occurrences were constructed from a vector-type spatial database using Arc/ Info GIS software (ESRI). These included 1:25,000 scale topographic maps (National Mapping Agency, Malaysia) and 1:100,000 scale soil maps (Department of Irrigation and Drainage, Malaysia). For the digital elevation model (DEM) creation, 20-m interval contours, spot heights and survey base points showing the elevation values were extracted from the 1:25, 000-scale topographic maps. This is used to generate the DEM with 10-m pixel size and triangulated irregular network from which the altitude, slope angle, aspect, curvature and stream power index are derived [Fig. 2(a)–(d)]. The accuracy of the DEM was quantitatively accessed based on the several field-surveyed points using GPS and total station points (Pradhan et al., 2010d). A total of 130 GPS check points were used are used to evaluate the vertical accuracy of the DEM. As a quality assurance of DEM, the vertical accuracy of a set of terrain points is first determined by its root mean square error (RMSE), the square root of the average of the set of squared differences between two points. The RMSE between the "true" values and estimated values is defined as in Eq. (1):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Z_{fieldi} - Z_{DEMi}\right)^2}{n}} \tag{1}$$

where n is the number of field reference points, Z_{field} is the terrain height of points measured by GPS, Z_{DEM} is the height obtained from the DEM. In addition, the height differences between the DEM for the surveyed-check points were analyzed using standard statistical mean and standard deviation to determine the error. The analysis results (Table 2) revealed that the RMSE error for the obtained DEM was ± 2.39 m which is within the acceptable limit (Toz & Erdogan, 2008). Validation results of DEM revealed that, significant differences were not observed from the RMSE values which only differ slightly on each checking locations.

Classification	Sub-Classification	GIS Data Type	Scale
Geological Hazard	Landslide	Polygon coverage	1:25,000
Basic Map	Topographic Map	Point, Line and Polygon coverage	1:25,000
	Geological Map	Polygon coverage	1:63,300
	Drainage	Line coverage	1: 25,000
	Land Cover	GRID	2.50 m × 2.5 m
	Soil Map	GRID	1:100,000
	Normalised Differentiated Vegetation Index (ndvi)	GRID	2.5 m × 2.5 m

Table 1. List of data used in this study

In the present study, substantial attention has been given for slope conditions, because there is a physical relation between the landslide occurrence and slope gradient. Increase in slope gradient results in increase of driving forces. For this reason, slope configuration and steepness plays an important role on the susceptibility of a slope to landsliding. This makes slope an important factor in preparing the landslide susceptibility map. The slope map was reclassified into four classes following the standard classification scheme set by the Ministry of Science, Technology and Environment Malaysia for hill land: (1) < 15 degrees, (2) 16 – 25 degrees, (3) 26 – 35 degrees, and (4) > 35 degrees (Fig. 2a) (Pradhan & Lee, 2010c). In the case of aspect layer, eight directions are shown for the different direction of slope (Fig. 2b).

Average error (m.)	1.58 m
Absolute average error (m.)	1.81 m
RMSE (m.)	± 2.39 m

Table 2. Errors of the DEM for the study area

The term curvature is generally defined as the curvature of a line formed by intersection of a random plane with the terrain surface (Ercanoglu & Gokceoglu, 2002). The influence of plan curvature on the land degradation processes is the convergence or divergence of water during downhill flow. In addition, this parameter constitutes one of the main factors controlling the geometry of the terrain surface where landslides occur (Ercanoglu & Gokceoglu, 2002). In the case of the curvature negative curvatures represent concave, zero curvature represent flat and positive curvatures represents convex surface. The plan curvature map was prepared using the avenue routine in ArcView 3.2 (Fig. 2c).

The fourth parameter considered in the present study is stream power index (SPI) and is shown in Fig. 2d. According to the Moore et al., (1991), SPI is a measure of erosive power of water flow based on the assumption that discharge (q) is proportional to specific catchment area A_s (Equation 2).

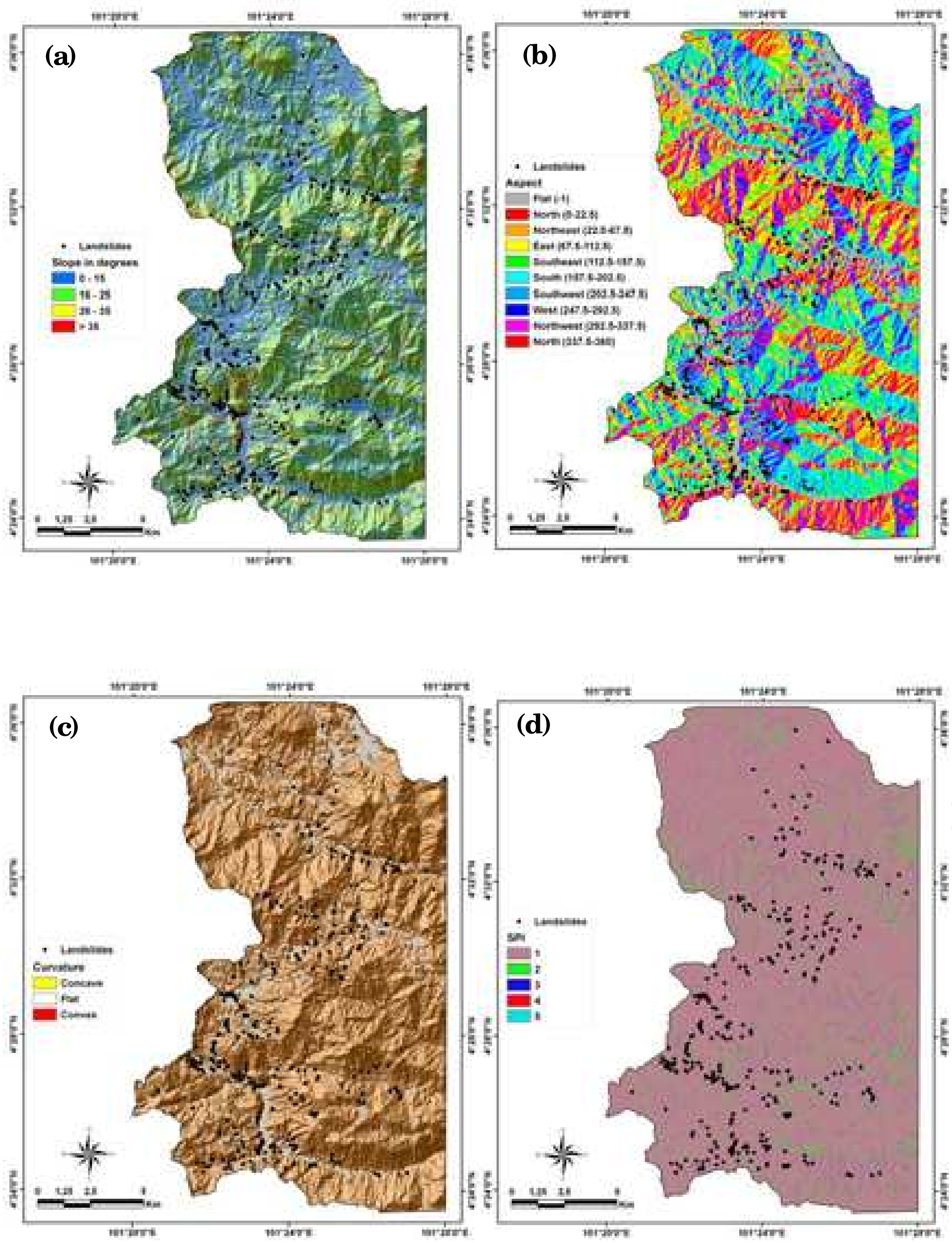
$$SPI = A_s \tan\beta \tag{2}$$

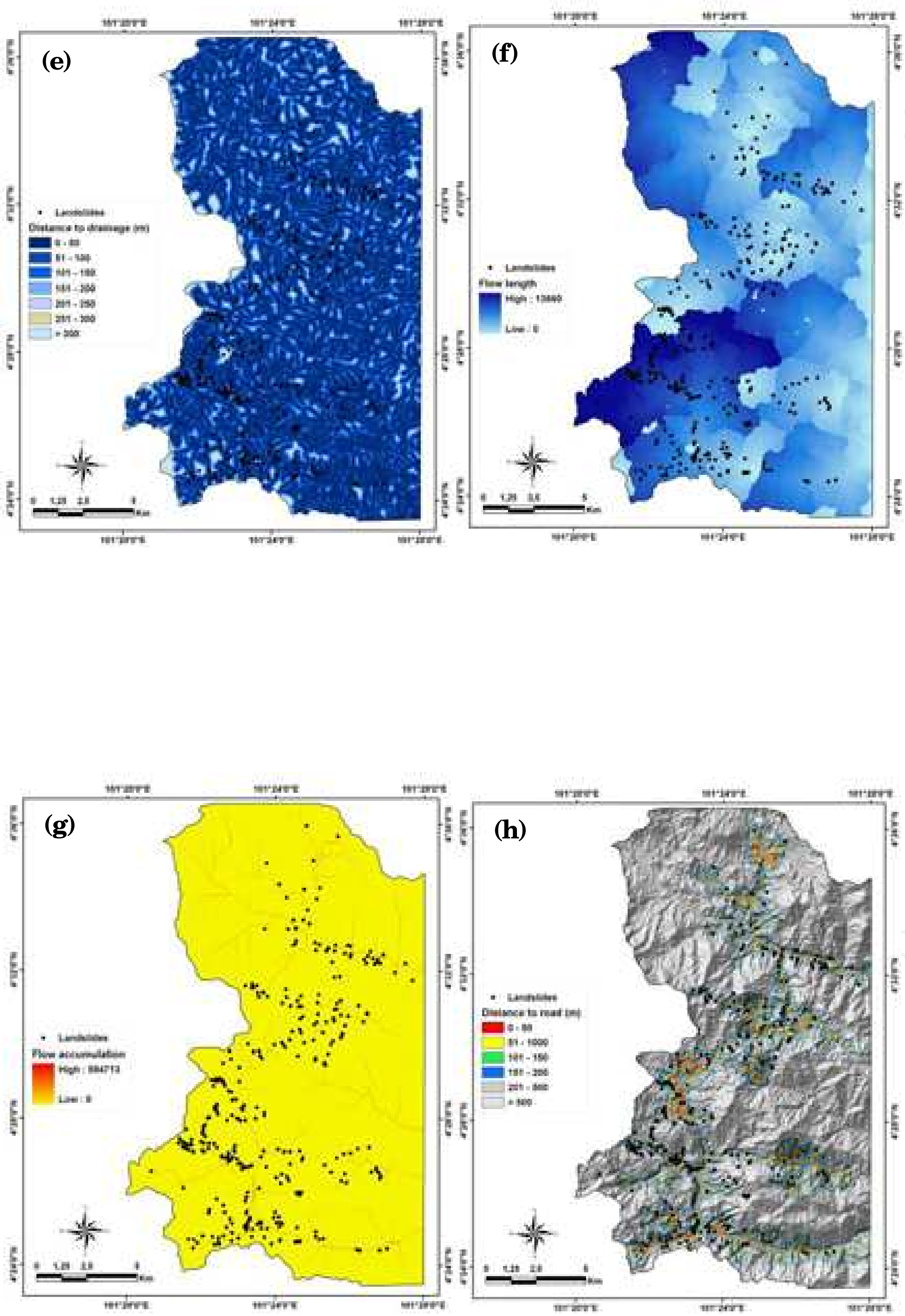
where A_s is the specific catchment area (m2m-1) while β is the slope gradient in degree.

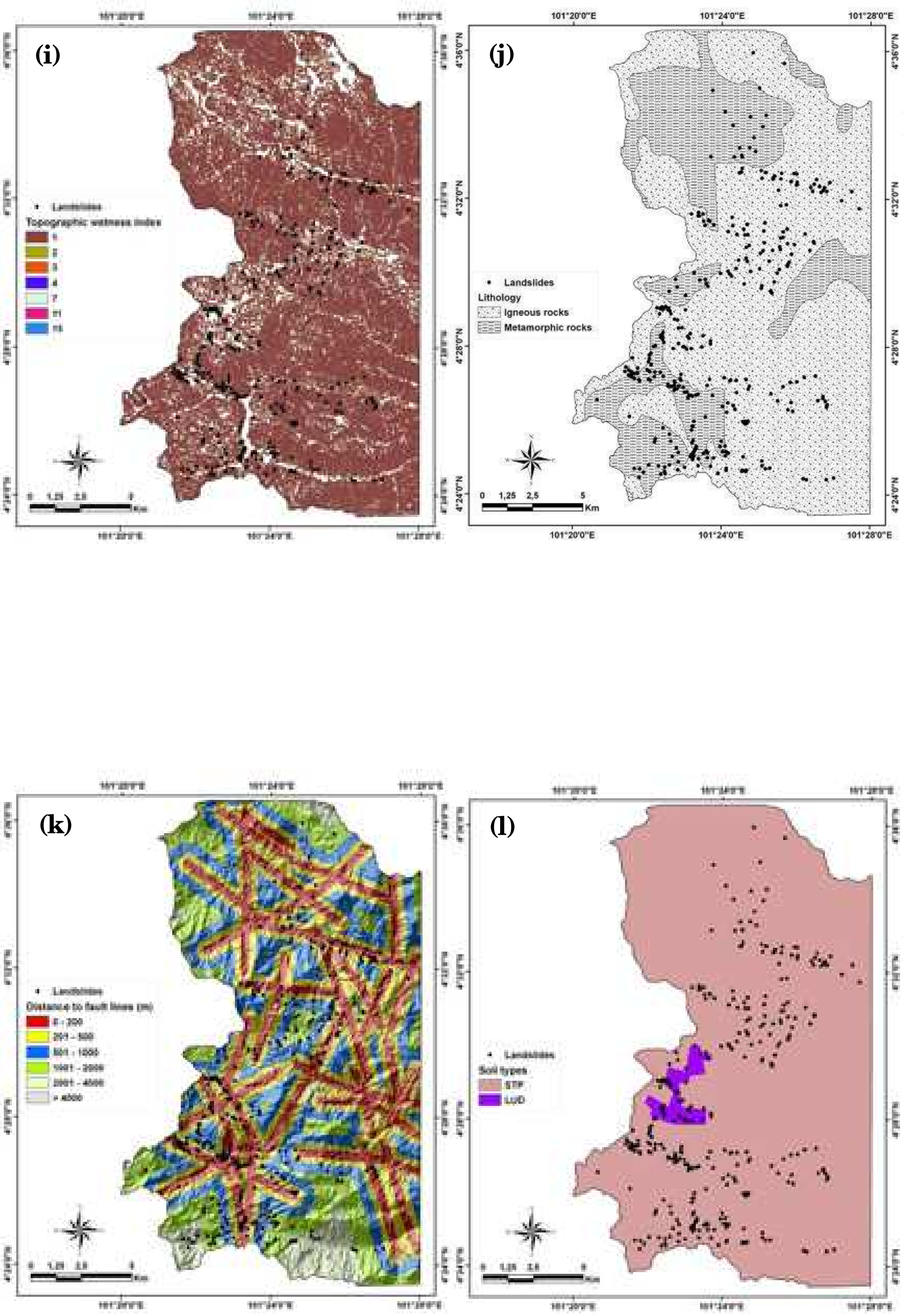
In addition, the distance from drainage was calculated using the topographic database. The drainage buffer was calculated based on Euclidean distance method at 50 m intervals as shown in Fig. 2e. The sixth and seventh parameters used in the study are flow length and flow accumulation which were derived from the digital elevation model in ArcGIS (Fig. 2f, 2g). Road-cuts are usually sites of anthropologically instability. A given road segment may act as a barrier, a net source, a net sink or a corridor for water flow, and depending on its location in the area (Ercanoglu & Gokceolgu, 2002). It usually, serves as a source of landslides. The road map is derived from the topography map. From the field observation, it has been noticed that most of the landslides have occurred along the cut-slopes and roads. The distance to road buffer is selected based on the occurrence of landslides to the proximity of the road. Therefore, a 50 m buffer zone is calculated based on the Euclidean distance method in ArcGIS 9.0 (Fig. 2h). Subsequently, the topographic wetness index map was prepared in the ArcGIS (Fig. 2i). The lithology map was prepared from the hardcopy geology map (Fig. 2j). The proximity to major fault lines is calculated based on Euclidean distance method in ArcGIS 9.0 (Fig. 2k). The soil texture map was prepared from a

1:100,000-scale soil map (Fig. 2l), which is the only existing soil map for the studied area. The landcover map was extracted from the Spot 5 satellite images using supervised classification techniques (Fig. 2m). Finally, the normalised difference vegetation index map (ndvi) was also prepared from the Spot 5 satellite image (Fig. 2n).

All the fourteen landslide conditioning factors were converted to a raster grid with 10 m × 10 m cells with 2418 rows by 1490 columns for the application of the ANN model. GIS ArcGIS 9.0 version software package and MATLAB was used as the basic analysis tools for spatial management and data manipulation.




(e)
(f)
(g)
(h)


(i)
Landslides
Topographic wetness index
(j)
Landslides
Lithology
Igneous rocks
Metamorphic rocks
101°20'0"E
101°24'0"E
101°28'0"E
4°24'0"N
4°28'0"N
4°32'0"N
4°36'0"N
0 1,25 2,5 5 Km
(k)
Landslides
Distance to fault lines (m)
(l)
Landslides
Soil types
STP
LUD

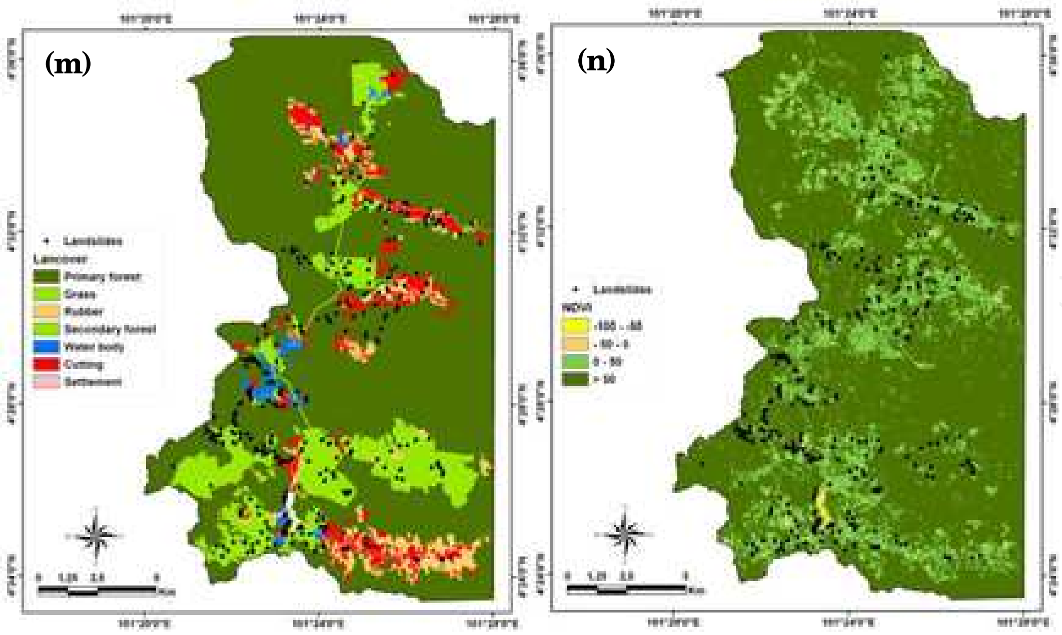


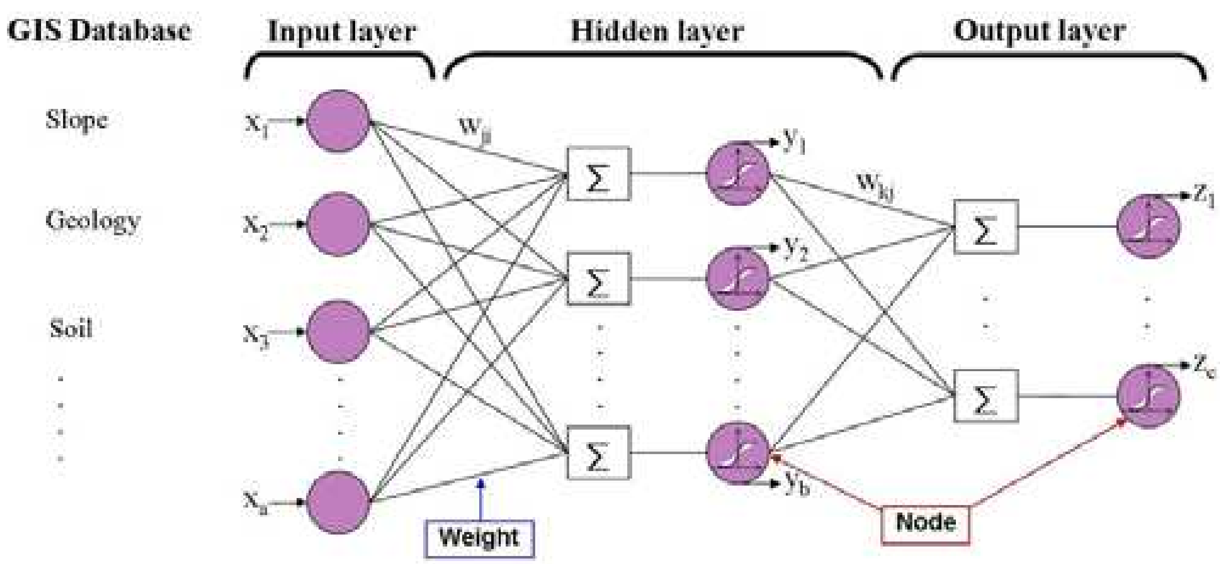
Fig. 2. Input data layers (a) Slope; (b) Aspect; (c) Curvature; (d) Stream power index (spi); (e) Distance from drainage; (f) Flow length; (g) Flow accumulation; (h) Topographic wetness index; (i) Distance to road; (j) Lithology; (k) Distance to the fault lines; (l) Soil types; (m) Land cover; and (n) Vegetation index (NDVI)

4. Artificial Neural Network model: preview

The artificial neural network approach has many advantages compared with other statistical methods (Basheer & Hajmeer, 2000). Firstly, the artificial neural network method is independent of the statistical distribution of the data and there is no need for specific statistical variables. Neural networks allow the target classes to be defined in relation to their distribution in the corresponding domain of each data source (Zhou, 1999), and therefore integration of remote sensing data or GIS data is convenient. An artificial neural network is a "computational mechanism able to acquire, represent, and compute a mapping from one multivariate space of information to another, given a set of data representing that mapping" (Atkinson & Tatnall, 1997). Most ANN models share a number of characteristics. These will be identified before proceeding to describe particular models (Moody & Katz, 2003). First, unlike expert systems, ANNs are not initialized with any external rule base. Rather the goal of the ANN is to internally identify a set of rules for matching input data to output conclusions. An ANN is composed of a set of nodes and a number of interconnected processing elements. ANN uses learning algorithms to model knowledge and save this knowledge in weighted connections, mimicking the function of a human brain (Turban & Aronson, 2001; Schalkoff, 1997). One of the most commonly used ANN models is the feed-forward back-propagation ANN. This is a supervised, pattern recognition model that needs to be trained using a data set for which both the input values (x) for a set of predictors and the correct output values (y) are known for a set of examples. The architecture of this ANN is based on a structure known as the Multi-Layer Perceptron (MLP). The MLP, as the name implies, consists of a set of layers, each of which is composed of a set of nodes (alternatively referred to as "processing elements", "units", "processing units", or "neurons"). The MLP with the back-propagation algorithm is trained using a set of examples of associated input and output values (Hines, 1997). The purpose of an artificial neural network is to build a model of the data-generating process, so that the network can generalize and predict outputs from inputs that it has not previously seen. This learning MLP algorithm is trained with the "Back-Propagation algorithm", which consists of an input layer, hidden layer, and an output layer.

The first layer of the network, or input layer, contains a node for each of l input variables (Fig. 3). The l input variables are analogous to the independent variables in multiple regressions. When a given set of l input values for one of the n samples in the training data set is presented to the input nodes, we say that the network is presented with an input pattern ($x_{i,l}p$=$x_{i,1}$,$x_{i,2}$,……,$x_{i,3}$, where $i=1$ to n). The superscript indicates terms that consists of or refer to a given pattern of values (Moody & Katz, 2003).

The last layer of the network, or output layer, contains nodes, one for each output type (Fig. 3). In this case, there are nine input nodes (one each for slope, aspect, curvature, stream power index (spi), distance from drainage;, flow length, flow accumulation, topographic wetness index, distance to road, lithology, distance to the fault lines, soil types, land cover, and ndvi). Sandwiched between the input and output layers is one "hidden" layer which will allow complexities to develop in the mapping functions. In this case, a three tired ANN architecture model is used. The hidden layer, like the input and output layer, consists of nodes.



$$y_j = f(net_j) = f\left(\sum_{i=1}^{a} w_{ji} x_i\right)$$

$$z_k = f(net_k) = f\left(\sum_{j=1}^{b} w_{kj} y_j\right)$$

Where...
i = 1, 2, ...a; a = number of input variables;
j = 1, 2, ...b; b = number of hidden nodes;
k = 1, 2, ...c; c = number of output nodes;

Fig. 2. Three tiered architecture of feed-forward, back-propagation neural network (multilayer perception).

The hidden and output layer neurons process their inputs by multiplying each input by a corresponding weight, summing the product, and then processing the sum using a nonlinear transfer function to produce a result. An artificial neural network "learns" by adjusting the weights between the neurons in response to the errors between the actual output values and the target output values. At the end of this training phase, the neural network provides a model that should be able to predict a target value from a given input value.

There are two stages involved in using neural networks for multi-source classification: the training stage, in which the internal weights are adjusted; and the classifying stage. Typically, the back-propagation algorithm trains the multi-layered until some targeted minimal error is achieved between the desired and actual output values of the network. Once the training is complete, the network is used as a feed-forward structure to produce a classification for the entire data (Paola & Schwengerdt, 1995; Swingler, 1996). For this study, the neural networks were simulated in the neural network module of Mathworks MATLAB (The MathWorks Inc. 1999). The back propagation multilayer perceptron (MLP) is a commonly used and widely available neural network structure in geospatial analysis and was used in this study.

5. Landslide susceptibility mapping using the Artificial Neural Network model

5.1 Application of frequency ratio model

Frequency ratio approaches are based on the observed relationships between distribution of landslides and each landslide-related factor, to reveal the correlation between landslide locations and the factors in the study area. Using the frequency ratio model, the spatial relationships between landslide-occurrence location and each factors contributing landslide occurrence were derived. The frequency is calculated from analysis of the relation between landslides and the attribute factors (Lee & Pradhan, 2006). In the relation analysis, the ratio is that of the area where landslides occurred to the total area, so that a value of 1 is an average value. If the value is greater than 1, it means a higher correlation, and value lower than 1 means lower correlation.

To calculate the Landslide Susceptibility Index (HSI), each factor's frequency ratio values were summed to the training area as in equation (3). The landslide susceptible value represents the relative susceptibility to landslide occurrence. So the greater the value, the higher the susceptible to landslide occurrence and the lower the value, the lower the susceptible to landslide occurrence.

$$HSI = Fr1 + Fr2 + \ldots\ldots + Frn \quad (3)$$

(HSI: Landslide Susceptibility Index; Fr: Rating of each factors' type or range)

5.2 Application of logistic regression model

Logistic regression allows one to form a multivariate regression relation between a dependent variable and several independent variables. Logistic regression, which is one of the multivariate analysis models, is useful for predicting the presence or absence of a characteristic or outcome based on values of a set of predictor variables. The advantage of logistic regression is that, through the addition of an appropriate link function to the usual linear regression model, the variables may be either continuous or discrete, or any combination of both types and they do not necessarily have normal distributions. In the case of multi-regression analysis, the factors must be numerical, and in the case of a similar statistical model, discriminant analysis, the variables must have a normal distribution. In the present situation, the dependent variable is a binary variable representing presence or absence of landslide. Where the dependent variable is binary, the logistic link function is applicable (Atkinson & Massari, 1998). For the present study, the dependent variable must be input as either 0 or 1, so the model applies well to landslide possibility analysis. Logistic regression coefficients can be used to estimate ratios for each of the independent variables in the model.

Quantitatively, the relationship between the occurrence and its dependency on several variables can be expressed as:

$$p = 1 / \ (1 + e\text{-}z) \tag{4}$$

where p is the probability of an event occurring. In the present situation, the value p is the estimated probability of landslide occurrence. The probability varies from 0 to 1 on an S-shaped curve and z is the linear combination. It follows that logistic regression involves fitting an equation of the following form to the data:

$$z = b0 + b1x1 + b2x2 + \ldots + bnxn \tag{5}$$

where b0 is the intercept of the model, the bi (i = 0, 1, 2, …, n) are the slope coefficients of the logistic regression model, and the xi (i = 0, 1, 2, …, n) are the independent variables. The linear model formed is then a logistic regression of presence or absence of landslides (present conditions) on the independent variables (pre-failure conditions).

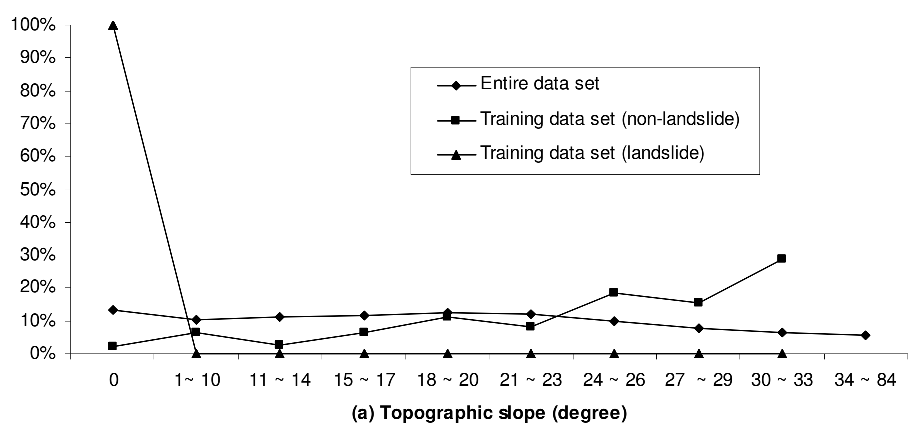
Using the logistic regression model, the spatial relationship between landslide-occurrence and factors influencing landslides was assessed. The spatial databases of each factor were converted to ASCII format files for use in the statistical package, and the correlations between landslide and each factor were calculated. Though there were two cases, in the first case only one factor was used. Besides, logistic regression mathematical equations were formulated for each case. Finally, the probability that predicts the possibility of landslide-occurrence was calculated using the spatial database, equations (4) and (5). However, in the second case all factors were used logistic regression mathematical equations were formulated as shown in equations (4) and (5) for each case. Using formula (4) and (5), the landslide susceptibility index was calculated.

6. Landslide susceptibility mapping using Artificial Neural Network model

The probabilities of occurrence of landslides were calculated based on (a) the various input attributes that have been listed in table 1 and their cumulative influence (weightage values were derived from ground-based information) and (b) knowledge based classification. Before running the artificial neural network program, the training site should be selected. So, the landslide-prone (occurrence) area and the landslide-not-prone area were selected as training sites. Pixels from each of the two classes were randomly selected as training pixels, with 327 pixels denoting areas where landslide not occurred or occurred. First, areas where the landslide was not occurred were classified as “areas not prone to landslide” and areas where landslide was known to exist were assigned to an “areas prone to landslide” training set. Training sites were selected based on landslide location as prone training site and with a varying slope values as non-prone training site and then the MLP trained back propagation algorithm was computed. Five different training sites were selected randomly to produce five susceptibility maps.

The MLP trained with the Back-Propagation algorithm was then applied to the input attribute layers by modifying the number of hidden nodes and the learning rate. Distribution of hidden layers and entire training dataset is shown in Fig. 3. Hidden layers were selected two times of input attribute layers. So obviously, the output will have both "existing" and "non-existing" landslide areas. Some of the input attributes layers are continuous and others categorical in nature. Therefore, these data were converted to raster grid in order to apply the ANN model. Three-layered feed-forward network was implemented using the MATLAB software package. Here, "feed-forward" denotes that the interconnections between the layers propagate forward to the next layer. The number of hidden layers and the number of nodes in a hidden layer required for a particular classification problem are not easy to deduce. In this study, a 9 x 19 x 2 structure was selected for the network, with input data normalized in the range 0.1-0.9. The nominal and interval class group data were converted to continuous values ranging between 0.1 and 0.9. Therefore, all the layers were normalized in the range 0.1- 0.9. The categorical data and their interval class group were converted to a continuous values ranging 0.1 - 0.9. In this way, the continuous values became nominal for back propagation modeling.

The learning rate was set to 0.01, and the initial weights were randomly selected between 0.1 and 0.3. The MLP trained back-propagation algorithm was used to minimize the error between the predicted output values and the calculated output values. The algorithm



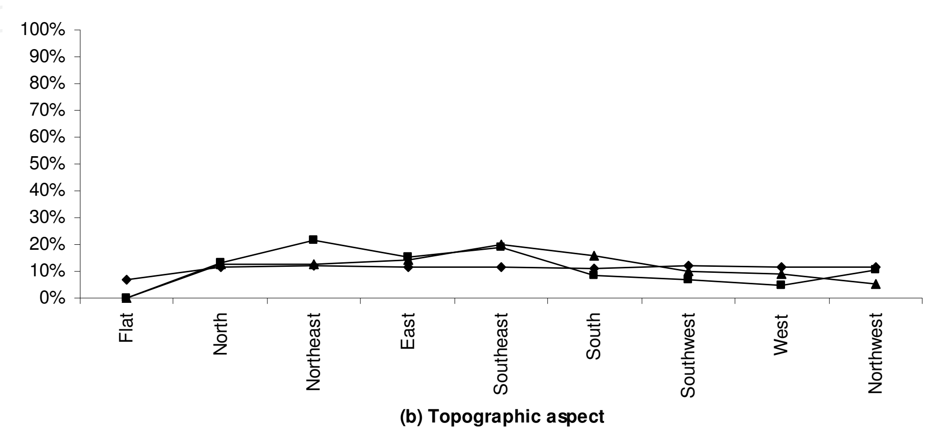
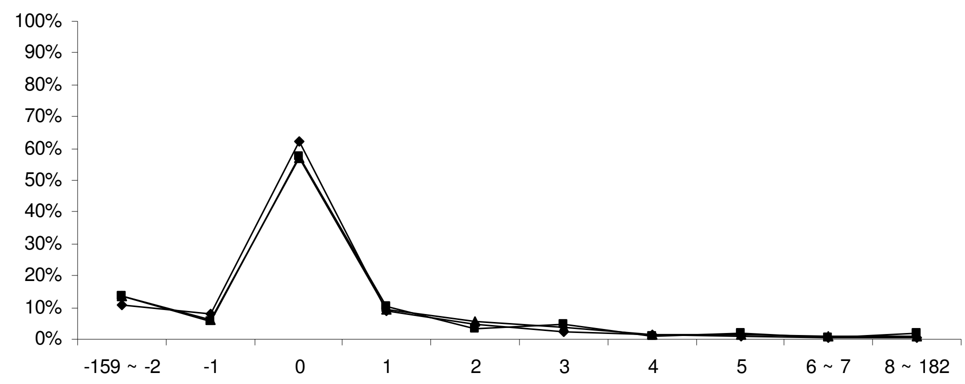
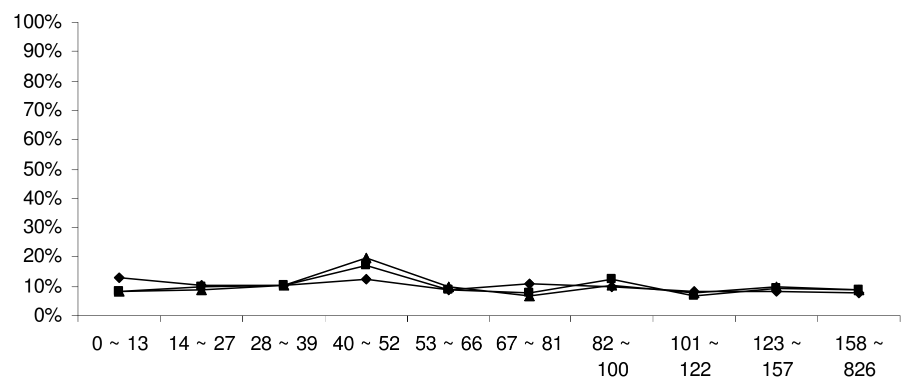


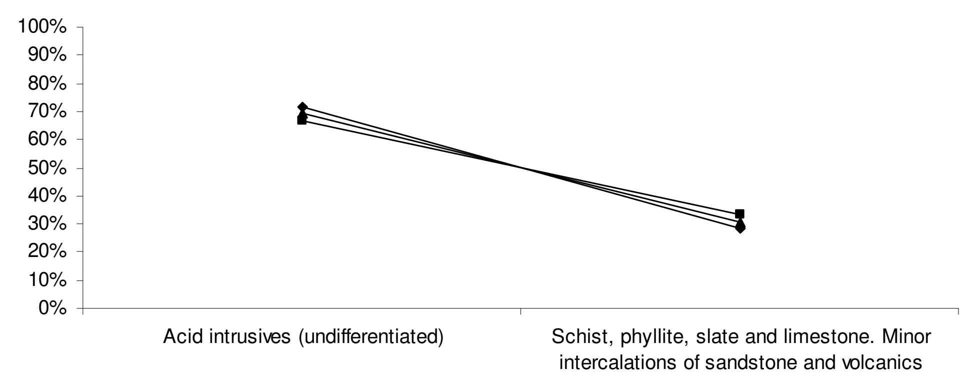
Fig. 3. Distribution of entire and training data set (continued next page)



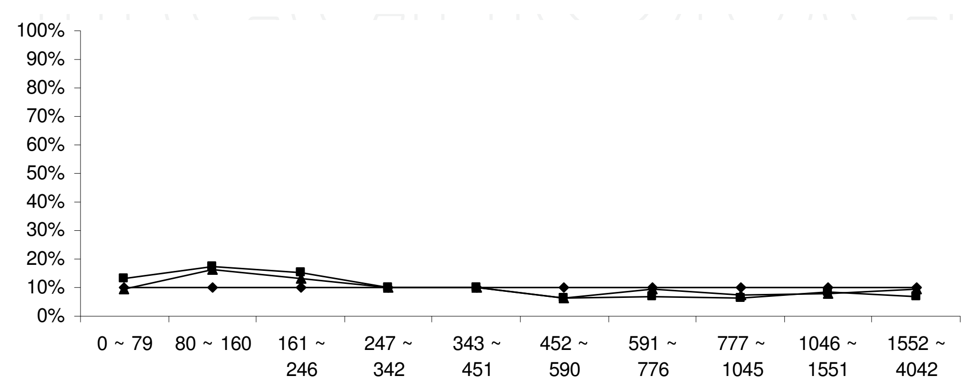
(c) Topographic curvature



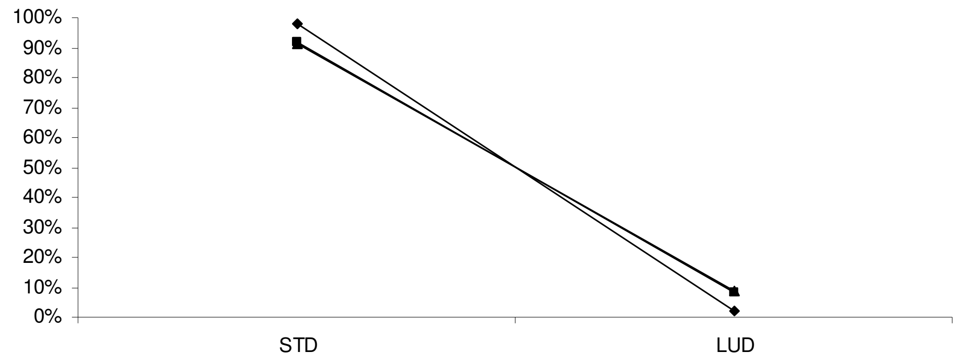
(d) Distance from drainage (m)



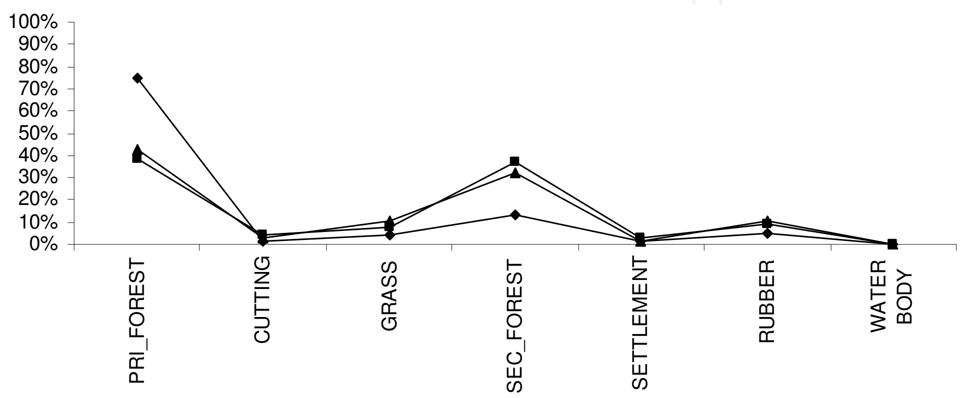
(e) Lithology (types)



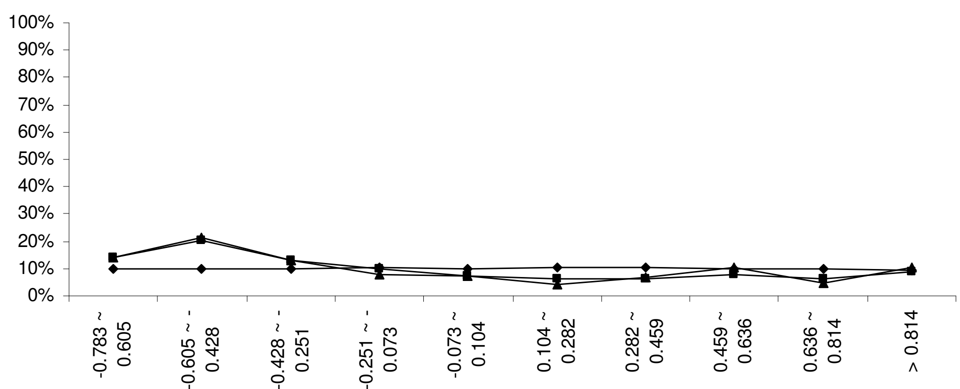
(f) Distance from lineaments (m)



(g) Soil types



(h) Landcover types



(i) NDVI values

propagated the error backwards iteratively by adjusting the weights. The number of epochs was set to 2,500, and the root mean square error (RMSE) value used for the stopping criterion was set to 0.01. Most of the training datasets met the 0.01 RMSE goal. The results of the learning rate for the training datasets are shown in Figure 3. However, if the RMSE value was not achieved, then the maximum number of iterations was terminated at 2,000 epochs. When the latter case occurred, then the maximum RMSE value was 0.213. Finally, the landslide susceptibility maps were generated using the five training sites (Fig. 4- 8). The values were classified by equal areas and grouped into four classes (highest 10%, second 10%, third 20% and reminding 60%) based on equal area classification for visual interpretation.

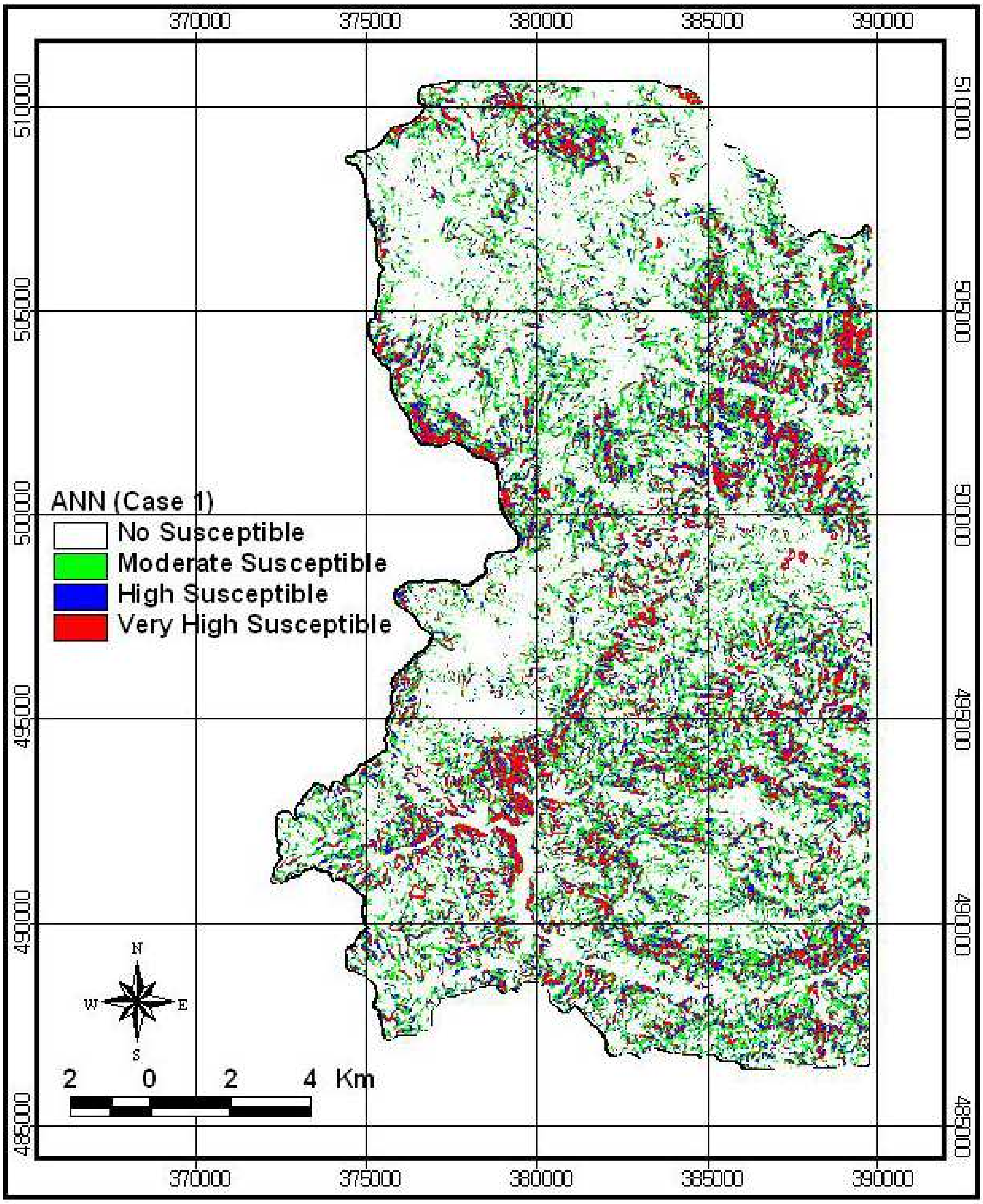


Fig. 4. Landslide susceptibility map using Case 1: Use of landslide location as prone training site and slope is 0 as non-prone training site

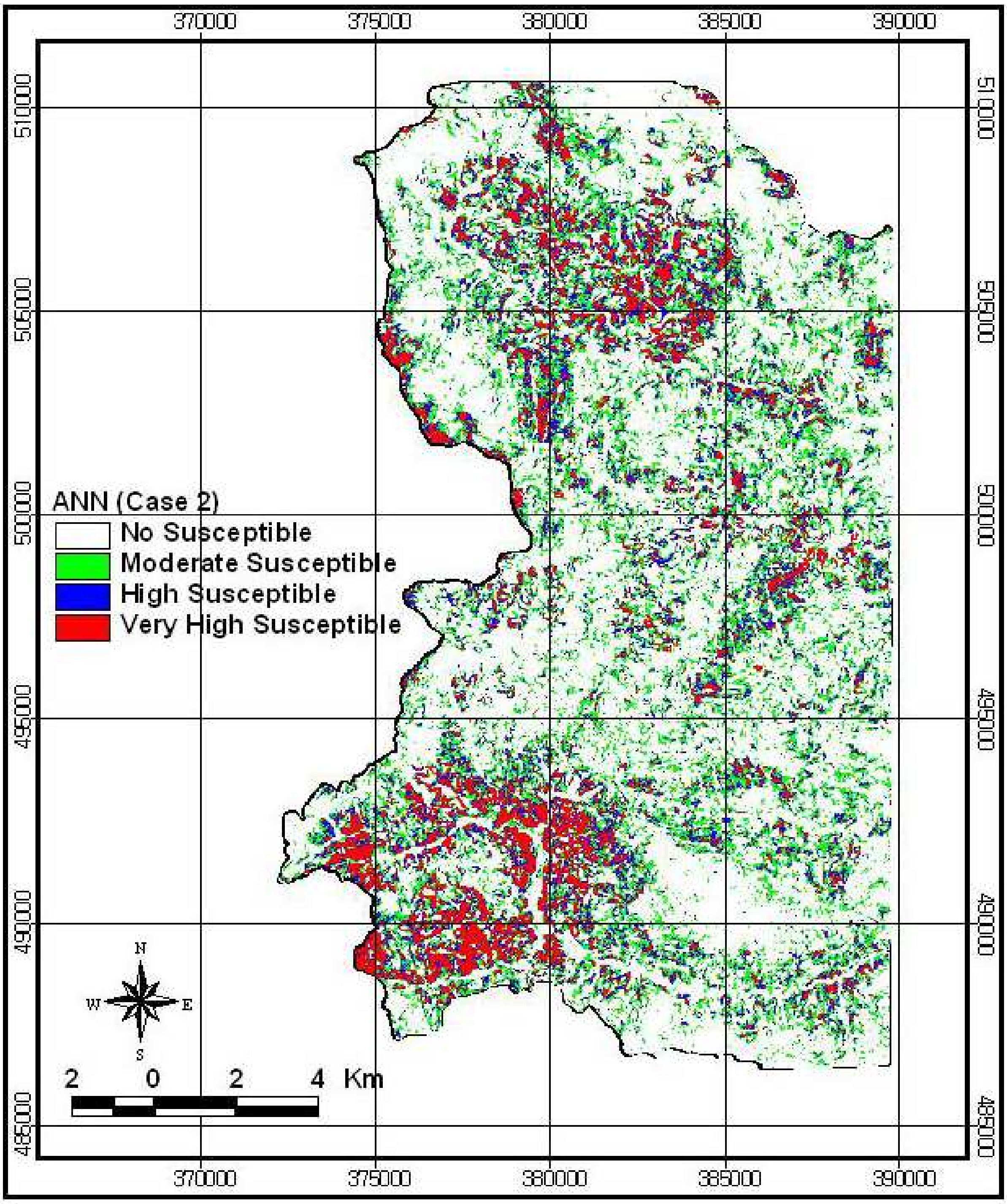


Fig. 5. Landslide susceptibility map using case 2: use of landslide location as prone training site and result from likelihood ratio as non- prone training site

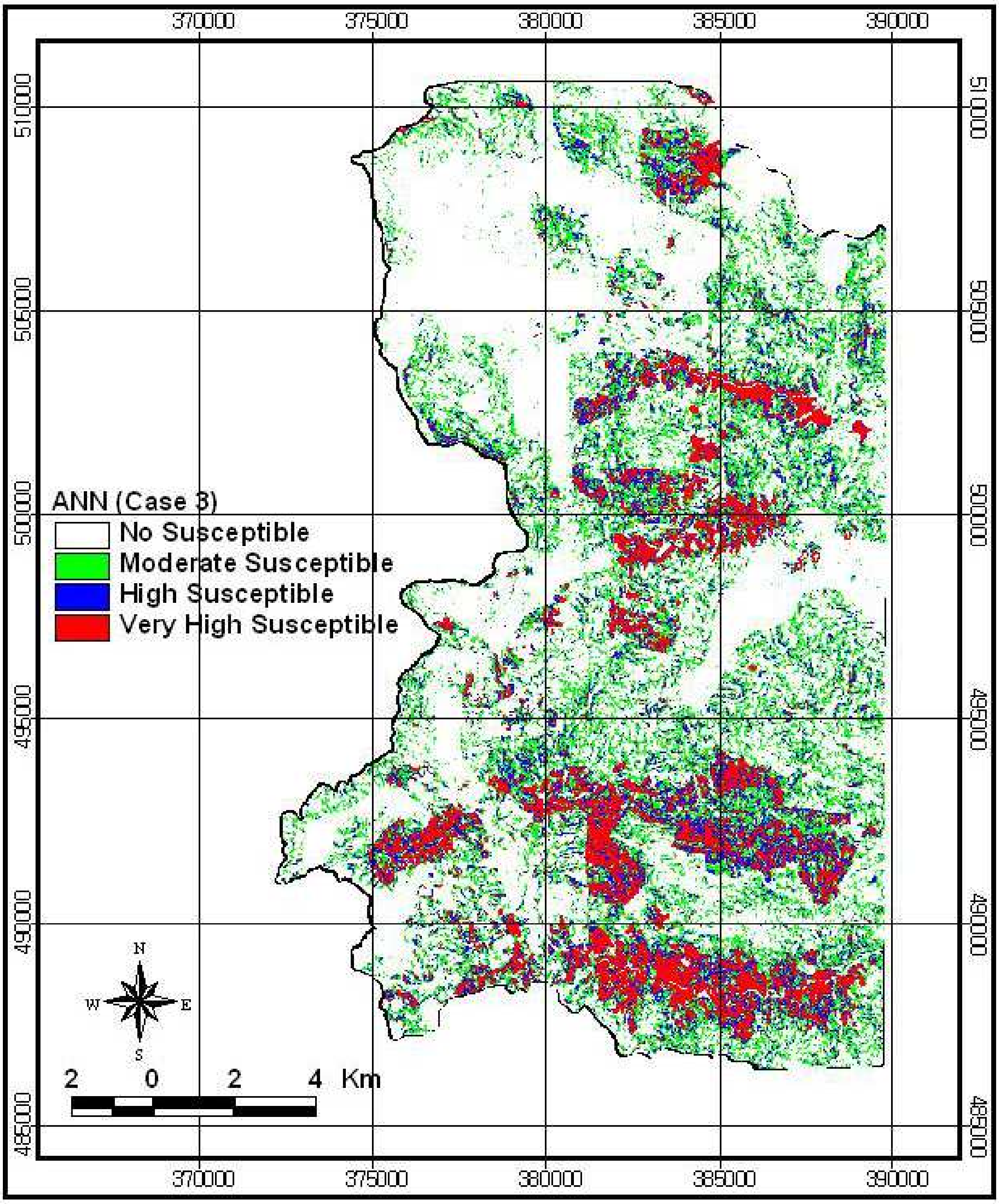


Fig. 6. Landslide susceptibility map using case 3: use of landslide location as prone training site and result from logistic regression as non- prone training site

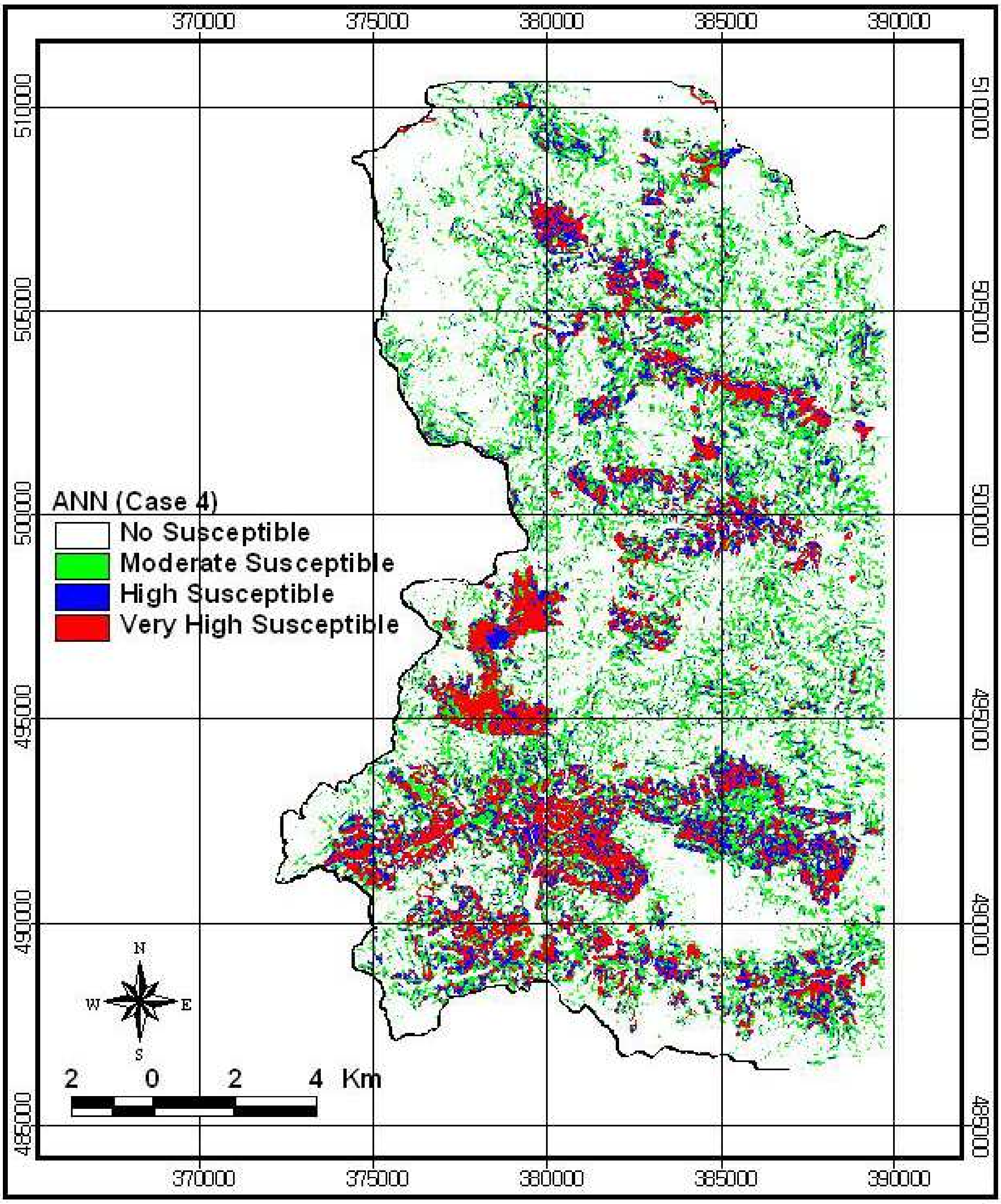


Fig. 7. Landslide susceptibility map using case 4: use of result from likelihood ratio as prone training site and result from likelihood ratio as non-prone training site

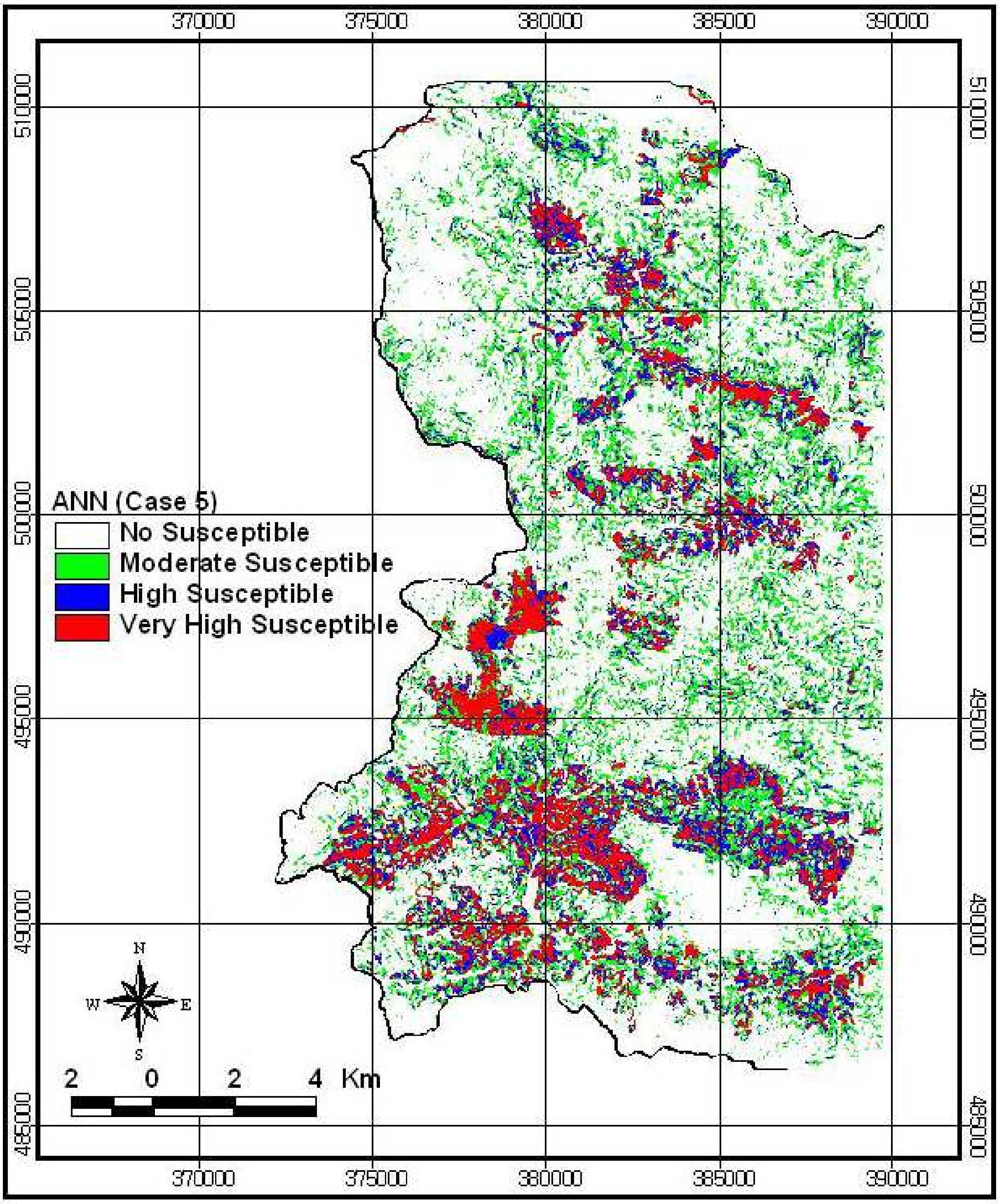


Fig. 8. Landslide susceptibility map using case 5: use of result from logistic regression as prone training site of result from logistic regression as non-prone training site

7. Accuracy assessment and comparison of susceptibility maps

The landslide susceptibility analysis result was verified using landslide test locations which were not used during the modelling process. Global Positioning System data for landslide locations has been collected for various parts of study area. 32 active landslides have been recorded and added to the inventory to be used for the validation of the neural network model output. The rate curves were created and its areas of the under curve were calculated for all cases. The rate explains how well the model and factor predict the landslide. So, the area under curve can assess the prediction accuracy qualitatively. To obtain the relative ranks for each prediction pattern, the calculated index values of all cells in the study area were sorted in descending order. Then the ordered cell values were divided into 100 classes, with accumulated 1% intervals. The rate verification results appear as a line in Fig. 9. For example, in the case of all factor used, 90 to 100% (10%) class of the study area where the landslide susceptibility index had a higher rank could explain 35% of all the landslides. In addition, the 80 to 100% (20%) class of the study area where the landslide susceptibility index had a higher rank could explain 58% of the landslides. To compare the result quantitative, the areas under the curve were re-calculated as the total area is 1 which means perfect prediction accuracy. So, the area under a curve can be used to assess the prediction accuracy qualitatively.

Validation results show that in the training site 1 (case 1) where slope equal to "zero" used for susceptibility map, the area ratio was 0.6935 and the prediction accuracy was 69%. In the training site 2 (case 2) for high frequency ratio values, the area ratio was 0.7465 and the prediction accuracy was 75%. In the training site 3 (case 3) for low frequency ratio values, the area ratio was 0.7030 and the prediction accuracy was 80%. In the training site 4 (case 4) for high logistic regression values, the area ratio was 0.8345 and the prediction accuracy was 83%. In the training site 5 (case 5) for low logistic regression values, the area ratio was 0.8670 and the prediction accuracy was 87%. So from the prediction accuracy graphs (Fig 9), it is quite evident that, training site 5 shows the best prediction accuracy of 87%, where as training site 1 shows the least prediction accuracy of 69% with difference is about 18%. Therefore, one can conclude that the selection of training site is very important for the landslide susceptibility mapping.

8. Concluding remarks

Landslides present a significant constraint to development in Malaysia, notably through the inadvertent reactivation of ancient inland landslides. A series of Government funded research projects has provided much background information and identified suitable methods for the use of landslide susceptibility information in land use planning. However, a number of significant problems remain over the use of this information. In this study, a neural network approach with weights derived from frequency ratio and logistic regression model to estimating the susceptible area of landslides using GIS and remote sensing is presented.

An artificial neural network approach has been used to estimate areas susceptible to landslides using a spatial database for a Cameron Highland. Five different sampling strategies employing different training sites were used for comparison purposes. The results using result from logistic regression as prone training site and result from logistic regression as non-prone training site (Case 5) and result from likelihood ratio as prone training site and result from likelihood ratio as non-prone training site (Case 4) were better than the other

three estimation cases, with the results using of landslide location as prone training site and result from likelihood ratio as non- prone training site being the worst.
The back-propagation training algorithm presents difficulties when trying to follow the internal processes of the procedure. The method also involves a long execution time, has a heavy computing load, and there is the need to convert the database to another format. However, landslide susceptibility can be analyzed qualitatively. In addition to using a multi-faceted approach to a solution, they enable the extraction of reliable results for a complex problem, and for continuous and discrete data processing.
Decision making under uncertainty is closely related to susceptibility analysis. Landslide susceptibility map will help for decision making for planners. These decisions are usually in the form of technical countermeasures, regulatory management or combinations of the two. Classic examples of regulatory management are zoning maps which, for instance, exclude some areas from habitation. Regulatory management is often quite intricate in prescribing different permit procedures which may include detailed evaluations and additional exploration or even go so far to prescribing particular slope designs (slope grades e.g.). The latter is actually a combination of regulatory and technical management. Technical mitigating measures range from a variety of stabilizing measures to protective measures such as rock fall galleries to warning devices. One of the most important steps of developing a hazard mitigation plan is assessing risks, or estimating potential losses to the people and properties within the landslide prone area.

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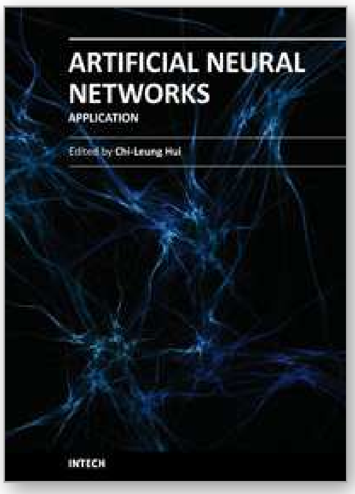

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