Approaches for Delineating Landslide Hazard Areas Using Different Training Sites in an Advanced Artificial Neural Network Model

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Abstract The current paper presents landslide hazard analysis around the Cameron area, Malaysia, using advanced artificial neural networks with the help of Geographic Information System (GIS) and remote sensing techniques. Landslide locations were determined in the study area by interpretation of aerial photographs and from field investigations. Topographical and geological data as well as satellite images were collected, processed, and constructed into a spatial database using GIS and image processing. Ten factors were selected for landslide hazard including: 1) factors related to topography as slope, aspect, and curvature; 2) factors related to geology as lithology and distance from lineament; 3) factors related to drainage as distance from drainage; and 4) factors extracted from TM satellite images as land cover and the vegetation index value. An advanced artificial neural network model has been used to analyze these factors in order to establish the landslide hazard map. The back-propagation training method has been used for the selection of the five different random training sites in order to calculate the factor’s weight and then the landslide hazard indices were computed for each of the five hazard maps. Finally, the landslide hazard maps (five cases) were prepared using GIS tools. Results of the landslides hazard maps have been verified using landslide test locations that were not used during the training phase of the neural network. Our findings of verification results show an accuracy of 69%, 75%, 70%, 83% and 86% for training sites 1, 2, 3, 4 and 5 respectively. GIS data was used to efficiently analyze the large volume of data, and the artificial neural network proved to be an effective tool for landslide hazard analysis. The verification results showed sufficient agreement between the presumptive hazard map and the existing data on landslide areas.

Keywords artificial neural network; landslide hazard; GIS; Malaysia

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Introduction

In recent years, Lee and Pradhan (2006), Lee and Pradhan (2007), and Pradhan and Lee (2009) investigated the landslide susceptibility in Malaysia¹⁻³. Pradhan and Lee (2009) evaluated three models for landslide susceptibility analysis using frequency ratio,
logistic regression and artificial neural network model\cite{3}. Pradhan and Lee (2009) analyzed the rainfall precipitation in the Penang area using back-propagation neural networks\cite{3}. However, they could not have a detailed landslide hazard analysis due to lack of rainfall intensity data. Slope stability and rainfall intensity are very important factors causing most of the landslides in Malaysia\cite{4}. Besides these two important factors of rainfall and slope, soil weight and distance to drainage are also important factors in some regions\cite{4}. Pradhan and Lee (2008), investigated the landslide susceptibility in Selangor area and they pointed out some important factors, such as topographic slope, topographic aspect, topographic curvature, distance to drainage, lithology, distance to faults, soil texture, land-cover, vegetation index and accumulated rainfall intensity \cite{5}. Further, Pradhan et al. (2009) presented a fuzzy model for landslide susceptibility\cite{6}. In landslide literature, there have been many studies carried out on landslide hazard evaluation using GIS. There are a 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 hazard evaluation using GIS, and many of these studies have applied probabilistic models\cite{7-19}. One of the multivariate models available, the logistic regression models, has also been applied to landslide hazard mapping \cite{20-28}. In the last few years, a new approach for landslide hazard evaluation using GIS, data mining using fuzzy logic, and artificial neural network models have been applied worldwide\cite{29-33}.

The objective and motivation of this study is to demonstrate a data mining model for the landslide hazard analysis with the aid of GIS. In order to get a stable and reliable result, in this paper we analyzed various geological and environmental parameters and chose ten factors including rainfall precipitation, topographic slope, topographic aspect, topographic curvature, distance to drainage, lithology, distance to faults, soil texture, land-cover and normalized difference vegetation index (NDVI) to predict landslide susceptible areas. These ten factors constructed an ANN using the back propagation algorithm for landslide susceptibility analysis. To meet the objectives,
central part of Peninsular Malaysia. It is bounded to the north by Kelantan, west by Perak. Annual rainfall is very high averaging between 2500 mm to 3000 mm per year. Two pronounced wet seasons are 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 geology of the Cameron Highland consists of mostly quaternary and Devonian granite. Many landslides have been recorded through the field work along streams scouring the sides of the streams which are shown in Fig. 2.

Fig.2 Field photographs illustrating the characteristic and types of landslides in various parts of the study area

2 Artificial neural network model

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”[55]. The back-propagation training algorithm is the most frequently used neural network method and is the method used in this study. The back-propagation training algorithm is trained by using a set of examples of associated input and output values. 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 algorithm is a multi-layered neural network, which consists of an input layer, hidden layers and an output layer. 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 [34].

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 network 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 [34].

A neural network consists of a number of interconnected nodes. Each node is a simple processing element that responds to the weighted inputs it receives from other nodes. The arrangement of the nodes is referred to as the network architecture (Fig. 3).

![Topography, Geology, Landcover, Soil](image)

Fig.3 Three tiered architecture of neural network

The receiving node sums the weighted signals from all the nodes that it is connected to in the preceding layer. Formally, the input that a single node receives is weighted according to Eq. (1).

\[
net_j = \sum_i w_{ij} \cdot o_i
\]  

where \( w_{ij} \) represents the weights between nodes \( i \) and \( j \), and \( o_i \) is the output from node \( i \), given by

\[
o_j = f(net_j)
\]  

The function \( f \) is usually a non-linear sigmoid function that is applied to the weighted sum of inputs before the signal propagates to the next layer. One advantage of a sigmoid function is that its derivative can be expressed in terms of the function itself:

\[
f'(net_j) = f(net_j)(1 - f(net_j))
\]  

The network used in this study consisted of three layers. The first layer is the input layer, where the nodes were the elements of a feature vector. The second layer is the internal or “hidden” layer. The third layer is the output layer that presents the output data. Each node in the hidden layer is interconnected to nodes in both the preceding and following layers by weighted connections [35-36].

The error, \( E \) for an input training pattern, \( t \) is a function of the desired output vector, \( d \) and the actual output vector, \( o \) given by:

\[
E = \frac{1}{2} \sum_k (d_k - o_k)
\]  

The error is propagated back through the neural network and is minimized by adjusting the weights between layers. The weight adjustment is expressed as:

\[
w_{ij}(n+1) = \eta(\delta_j \cdot o_i) + \alpha \Delta w_{ij}
\]  

where \( \eta \) is the learning rate parameter (set to \( \eta = 0.01 \) in this study), \( \delta_j \) is an index of the rate of change of the error, and \( \alpha \) is the momentum parameter (set to \( \alpha = 0.01 \) in this study).

The factor \( \delta_j \) is dependent on the layer type. For example, for hidden layers,

\[
\delta_j = (\sum \delta_k w_{jk}) f'(net_j)
\]  

and for output layers,

\[
\delta_j = (d_j - o_j) f'(net_j)
\]  

This process of feeding forward signals and back-propagating the error is repeated iteratively until the error of the network as a whole is minimized or reaches an acceptable magnitude.

Using the back-propagation training algorithm, the weights of each factor can be determined and may be used for classification of data (input vectors) that the network has not seen before. From Eq. (2), the effect of an output, \( o_j \) from a hidden layer node, \( j \) on the output, \( o_k \) from an output layer (node \( k \)) can be represented by the partial derivative of \( o_k \) with respect to \( o_j \) as

\[
\frac{\partial o_k}{\partial o_j} = f'(net_j) \cdot \frac{\partial (net_k)}{\partial o_j} = f'(net_j) \cdot w_{jk}
\]  

Eq. (8) produces both positive and negative values. If the effect’s magnitude is all that is of interest, then the importance (weight) of node \( j \) relative to another
node \( j_0 \) in the hidden layer may be calculated as the ratio of the absolute values derived from Eq. (8):

\[
\frac{\partial o_k}{\partial o_j} = \left| \frac{f'(net_j) \cdot w_{jk}}{f'(net_{jk})} \right| = \left| w_{jk} \right|. \tag{9}
\]

We should mention that \( w_{jk} \) is simply another weight in \( w_{j} \) other than \( w_k \).

For a given node in the output layer, the results of Eq. (9) show that the relative importance of a node in the hidden layer is proportional to the absolute value of the weight connecting the node to the output layer. When the network consists of output layers with more than one node, then Eq. (9) cannot be used to compare the importance of two nodes in the hidden layer.

\[
w_{jk} = \frac{1}{J} \cdot \sum_{j=1}^{J} \left| w_{jk} \right| \tag{10}
\]

\[
t_{jk} = \frac{\left| w_{jk} \right|}{\frac{1}{J} \cdot \sum_{j=1}^{J} \left| w_{jk} \right|} = \frac{J \cdot \left| w_{jk} \right|}{\sum_{j=1}^{J} \left| w_{jk} \right|} \tag{11}
\]

Therefore, with respect to node \( k \), each node in the hidden layer has a value that is greater or smaller than unity, depending on whether it is more or less important, respectively, than an average value. All the nodes in the hidden layer have a total importance with respect to the same node, given by

\[
\sum_{j=1}^{J} t_{jk} = J \tag{12}
\]

Consequently, the overall importance of node \( j \) with respect to all the nodes in the output layer can be calculated by

\[
t_j = \frac{1}{K} \cdot \sum_{j=1}^{K} t_{jk} \tag{13}
\]

Similarly, with respect to node \( j \) in the hidden layer, the normalized importance of node \( j \) in the input layer can be defined by

\[
s_j = \frac{\left| \phi_j \right|}{\frac{1}{J} \cdot \sum_{j=1}^{J} \left| \phi_j \right|} = \frac{1}{\sum_{j=1}^{J} \left| \phi_j \right|} \tag{14}
\]

The overall importance of node \( i \) with respect to the hidden layer is

\[
s_i = \frac{1}{J} \cdot \sum_{j=1}^{J} s_j \tag{15}
\]

Correspondingly, the overall importance of input node \( i \) with respect to output node \( k \) is given by

\[
st_i = \frac{1}{J} \cdot \sum_{j=1}^{J} s_j \cdot t_j \tag{16}
\]

3 Data using GIS and remote sensing

The GIS and remote sensing data used in the present study are shown in Table 1. The accurate detection of the location of landslides is very important for probabilistic landslide hazard analysis. The application of remote sensing methods, such as aerial photographs and satellite images, is used to obtain significant and cost-effective information on landslides. In this study, 1:25000–1:50000-scale aerial photographs were used to detect the landslide locations. These photographs were taken during the period 1981-2000, and the landslide locations were detected by photo interpretation and the locations verified by fieldwork. Recent landslides were observed in aerial photographs from breaks in the forest canopy, bare soil, or other geomorphic characteristics typical of landslide scars, for example, head and side scarps, flow tracks, and soil and debris deposits below a scar.

| Classification       | Sub-classification | GIS data type       | Scale      |
|----------------------|--------------------|---------------------|------------|
| Geological hazard    | Landslide          | Point coverage      | 1:25000    |
| Topographic map      | Line and point coverage | 1:25000          |
| Geological map       | Polygon coverage   | 1:63300             |
| Drainage             | Line coverage      | 1:25000             |
| Basic map            |                    |                     |            |
| Land cover           | Grid               | 30 m × 30 m         |
| Soil map             | Grid               | 10 m × 10 m         |
| Vegetation Index (NDVI) | Grid             | 10 m × 10 m         |
| Precipitation amount | Grid               |                     |
There were ten factors considered for the landslide hazard analysis, and these factors were extracted from the constructed spatial database. These factors were transformed into a vector-type spatial database using GIS. A digital elevation model (DEM) was created first from the topographic database. Contour and survey base points that had elevation values from the 1:25000-scale topographic maps were extracted, and a DEM was constructed with a resolution of 10 m. Using this DEM, the slope angle, slope aspect and slope curvature were calculated. In the case of the curvature, the negative curvatures represent concave, the zero curvature represents flat and the positive curvatures represent convex. The curvature map was prepared by using the avenue routine in ArcView 3.2. In addition, the distance from drainage was calculated by using the topographic database. The drainage buffer was calculated in 100 m intervals. Using the geology database, the types of lithology were extracted, and the distance from lineament were calculated. The lithology map was obtained from a 1:63300-scale geological map, and the distance from lineament map was calculated in 100 m intervals. Land cover data was classified by using a Landsat TM image employing an unsupervised classification method and was verified by field survey. The nine classes identified, such as urban, water, forest, agricultural area, tin mines, rubber and palm oil plantation were extracted for land cover mapping. Finally, the normalized difference vegetation index (NDVI) map was obtained from spot satellite images. The NDVI value was calculated by using the formula $\text{NDVI} = (\text{IR} - \text{R}) / (\text{IR} + \text{R})$, where IR value is the infrared portion of the electromagnetic spectrum, and R-value is the red portion of the electromagnetic spectrum. The NDVI value denotes areas of vegetation in an image. The precipitation amount was calculated by using the historical rainfall data for the years 1987-2007 for all stations in Peninsular Malaysia obtained from the Malaysian meteorological department. Then the rainfall amount for each of the weather station was interpolated by using the IDW interpolation in ArcView 3.2. The precipitation amount measured in mm denotes the average historical rainfall amount in the study area. All the above mentioned landslide inducing factors were converted to a raster grid with 10 m×10 m cells for application of the artificial neural network.

4 Landslide hazard analysis using the artificial neural network

Before running the artificial neural network program, the training site should be selected. Therefore, the landslide-prone (occurrence) area and the landslide-not-prone area were selected as training sites. The cells from each of the two classes were randomly selected as training cells in five different cases (see Fig.4). First, areas where landslide does not occur and slope is zero were classified as “non-landslide prone area” and areas where landslide is known to exist were assigned to “landslide prone area” training set.

The back-propagation algorithm was then applied to calculate the weights between the input layer and the hidden layer, and between the hidden layer and the output layer, by modifying the number of hidden node and the learning rate. Three-layered feed-forward network was implemented by 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 9×28×2 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, the continuous values were not ordinal data, but the nominal data, and the numbers denote the classification of the input data.

The learning rate was set to 0.01, and the initial weights were randomly selected to values between 0.1 and 0.3. The weights calculated from 10 test cases were compared to determine whether the variation in the final weights was dependent on the selection of the initial weights. The back-propagation algorithm was used to minimize the error between the predicted output values and the calculated output values. The algorithm propagated the error backwards, and iteratively adjusted the weights. The number of epochs was set to 2000, and the root mean square error (RMSE) value used for the stopping criterion was set.
to 0.01. Most of the training data sets met the 0.01 RMSE goal. 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. For easy interpretation, the average values were calculated, and these values were divided by the average of the weights of some factor that had a minimum value. Finally, the weights were applied to the entire study area, and the landslide hazard maps were created for all five different training cases (Fig. 5). The values were classified by equal areas and grouped into four classes for visual interpretation. The possibility was classified into four classes (highest 10%, second 10%, third 20% and reminding 60%) based on area for visual and easy interpretation.
Fig. 5 Cumulative frequency diagram showing landslide hazard index rank occurring in cumulative percent of landslide occurrence

5 Verification of susceptibility map

The landslide hazard analysis result was verified by using known landslide locations. Verification was performed by comparing the known landslide location data with the landslide hazard map. The rate curves were created and its areas under the curve were calculated for all cases. The rate explains how well the model and factor predict the landslide. Therefore, the area under the curve can assess the model validation 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 0.1% intervals. The rate verification results appear as a line. For example, in the case of all factor used, 0.9 to 1% (10%) class of the study area where the landslide hazard index had a higher rank could explain 35% of all the landslides. In addition, the 0.8 to 1% (20%) class of the study area where the landslide hazard index had a higher rank could explain 58% of the landslides. To compare the result quantitatively, the areas under the curve were re-calculated as the total area is 1 which means perfect prediction accuracy. Therefore, the area under a curve can be used to assess the prediction accuracy qualitatively. The area ratio was 0.8345, which shows the prediction accuracy of 83.45%.

6 Discussions and conclusion

The occurrence of landslide makes 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 hazard information in land use planning. However, a number of significant problems remain over the use of this information. In this study, a data mining approach to estimating the susceptible area of landslides using GIS and remote sensing has been presented. From the application of artificial neural networks, the relative importance, weight between factors was calculated. Using the weights, the landslide hazard map was created and verified. The result of verification showed 83.45% prediction accuracy. The verification result has somewhat high value.

Landslide hazard maps are of great help to planners and engineers for choosing suitable locations to implement developments. These results can be used as basic data to assist slope management and land-use planning, but the models used in the study are valid for generalized planning and assessment purposes, although they may be less useful at the site-specific scale where local geological and geographic heterogeneities may prevail. For the model to be more generally applied, more landslide data are needed, as well as application to more regions.

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Notes to Contributors

Contributions are welcomed on one of the following subjects or in related areas:

★ GIS ★ Geodynamic ★ Physical geo-surveying
★ GPS ★ Geo-surveying ★ Engineering surveying
★ RS ★ Photogrammetry ★ Mapping apparatus
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