Journal of Applied Sciences Research, 8(3): 1608-1611, 2012
ISSN 1819-544X
This is a refereed journal and all articles are professionally screened and reviewed

ORIGINAL ARTICLES

Application of GIS for Landslide Hazard Assessment Using Neural Network

SeyedmajidMousavi

Islamic azad university, science and research branch Faculty of Agriculture and Natural Resources

ABSTRACT

A landslide or landslip is a geological phenomenon which includes a wide range of ground movement, such as rock falls, deep failure of slopes and shallow debris flows. Landslides occur frequently in some of area and seriously affect local livelihoods and living conditions. Therefore, it is necessary to analyze and assess landslide hazard analysis. The goal of this paper is to use neural network with GIS to assess Landslide Hazard. In this research at first factors is recognized and then,these factors were analyzed using an advanced artificial neural network model to generate the landslide hazard map. Each factor’s weight was determined by the back-propagation training method. Landslide locations were used to verify results of the landslide hazard map and the verification results showed 83.2% accuracy. The

Key words: GIS, Landslide Hazard, Assessment, multivariate statistical analysis, neural network

Introduction

Landslides may occur as a consequence of a number ofdetermining and triggering factors (Abdel-Salam, M.M., 1982; Bull, W.B., 1996; Aleotti, P., Chowdhury, R., 1999)]. In order to assess hazard from landslidesit is therefore necessary to identify and analyze the mostimportant determining factors leading to slope failure.

There have been many studies that have been carried out on landslide hazard evaluation using GIS, for example, reference (Ballard, T.M., Willington, R.P., 1975) summarized many landslide hazard evaluation studies. Recently, there have been studies on landslide hazard evaluation using GIS, and many of these studies have applied probabilistic models (Benda, L.E., Cundy, T.W., 1990; Bolt, B.A., *et al.*, 1975). One of the statistical models available, the logistic regression model, has also been applied to landslide hazard mapping (Bozzano, F., et al., 1996), as well as the geotechnical model and the safety factor model (Brabb, E.E., 1984). As a new approach to landslide hazard evaluation using GIS, data mining using fuzzy logic, safety factor and artificial neural network models have been applied.

Approaches to landslide hazard assessment using GIShave been reported by, among others, reference (Brabb, E.E., 1984; Anbalagan, R., 1992; Carrara, A., 1991; Cevik, E., Topal, T., 2003). The applicability of various GIS methods withrespect to the characteristics of the study area, the landslidetype and extension, the type of data available andthe mapping scale has been discussed by Soeters& VanWesten.

Within the spatial analysis, GIS with its analytical data storage and cartographic capacities allows a relatively quick and easy landslide hazard assessment for the given region. Therefore, it has been applied extensively to landslide hazard research studies, particularly those undertaken over the last decade. The most often applied approaches using GIS techniques are based on statistic methods especially based on statistical method such as "Statistical index” method and “Multiple linear regression” method of Van Westen (1993) and Carrara (1983).The purpose of this study is to develop an integrated approach for landslide hazard assessment using GIS and Neural network.

Material And Method

Neural network:

An artificial neural network (ANN), usually called neural network (NN), is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. The network considered in the paper is a feedforward network of sigmoidal units with supervised learning algorithms. The number of layers is $L+1$, including the input, the hidden and output layers. Henceforward the layers will be indicated with k ($k=0, 1, \dots, L$), where $k=0$ is the input layer, $k=1$ is the first hidden layer and $k=L$ is the output layer. The inputs, weights and biases are real values. $n=\mathrm{config}(k-1)$ is the total number of neurons

Corresponding Author: SeyedmajidMousavi, Islamic azad university, science and research branch Faculty of Agriculture and Natural Resources

in layer $k-1$, $w_{j,i(k)}$is the weight from neuron i (i=1, …, n), belonging to layer $k-1$, to neuron j (j=1, …, config(k)), belonging to layer k, and bias$j$(k) is the bias current of the jth neuron of layer k.

The aim of this section is to illustrate the learning algorithm we used to improve fault tolerance in the multilayer network when used in classification problems. It is essentially based on the traditional back-propagation algorithm, with the introduction of some modifications to distribute the weight values in each layer in a more uniform fashion. The aim is to distribute the absolute weight values in a generic layer uniformly around the average absolute value.

This section comprises two subsections. The first illustrates the considerations behind the strategy we propose, the second is a detailed illustration of the algorithm proposed. In this second subsection, we also give some numerical examples of how the algorithm works. Our concluding considerations will then show that the modifications made to the original backpropagation algorithm do not reduce the functionality of the multilayer network trained by it.The learning strategy proposed in the paper is essentially based on the idea that fault tolerance in a multilayer network increases if the absolute values of the weights are uniformly distributed around the average absolute value, so that the absolute value of each weight belonging to a generic layer is as close as possible to the average absolute value for that layer. This applies in particular to the weights in the output layer, which play an essential role in the performance of a multilayer network on the occurrence of faults.

Integration GIS and NNA:

The data used is come from a project in Vietnam (Chung, C.F., *et al.*, 1995). Accurate detection ofthe location of landslides is very important for probabilisticlandslide hazard analysis. In this study, 1:25,000–1:50,000-scale aerialphotographs were used to detect the landslide locations. Recentlandslides were observed in aerial photographs from breaks inthe forest canopy, bare soil, or other geomorphiccharacteristics typical of landslide scars, for example, headand side scarps, flow tracks, and soil and debris depositsbelow a scar. To assemble a database to assess the surface areaand number of landslides in each of the three study areas, atotal of 327 landslides were mapped in a mapped area of8,179.28 km2.

The statistical approach is an indirect method in which either a predictive function or index is derived from a combination of weighted factors. The relative contribution of each factor is obtained by means of statistical analyses (bivariate and multivariate). Using GIS makes these over layering operations much easier and largely explains the increasing popularity of the statistical approach, which closely parallels the ever-increasing application of GIS techniques. There were 10 factors that were considered, and the factorswere extracted from the constructed spatial database. Thefactors were transformed into a vector-type spatial databaseusing the GIS, and landslide-related factors were extractedusing the database. A digital elevation model (DEM) wascreated first from the topographic database. Contour andsurvey base points that had elevation values from the1:25,000-scale topographic maps were extracted, and a DEMwas constructed with a resolution of 10 m.

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. Cells from each of the two classes were randomly selected as training cells, with 327 cells denoting areas where landslide did not occur or occurred. First, areas where the landslide did not occur 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.

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 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 × 19 × 2 structure was selected for the network, with input data normalized in the range of 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 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 2000 epochs. When the latter case occurred, the maximum RMSE value was 0.213. The final weights between layers acquired during training of the neural network and the contribution or importance of each of the nine factors used to predict landslide hazard are shown in Table 1.

Table 1: Weights of each factor estimated by neural network considered in this study

Factor	Weight Normalized	Weight
Slope (unit: degree)	2.009	0.193
Aspect	1.301	0.125
Curvature (unit: unit less)	1.557	0.149
Distance from drainage (unit: m)	1.619	0.155
Geology	1.452	0.139
Distance from lineament (unit: m)	1.456	0.139
Soil	1.042	0.100
Land cover	0.073	1.003

Result And Discussion

The landslide hazard analysis result was verified 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 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 the 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. For example, in the case of all factors used, 90 to 100% (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 80 to 100% (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. So, the area under a curve can be used to assess the prediction accuracy qualitatively. The area ratio was 0.8292 and the prediction accuracy is 82.92%.

Conclusion:

This study was carried out by combining Remote Sensing technology and GIS models with neural network.Land sliding presents a significant constraint on development in Malaysia, notably through the inadvertent reactivation of ancient inland landslides. A series of government-funded research projects have 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 is presented.

Reference

Abdel-Salam, M.M., 1982. *Some institutional aspects and future prospects of the SudanGezira Scheme*. DSRC seminar series; discussion paper 26. Khartoum, Development Studiesand Research Centre Faculty of Economic and Social Studies University of Khartoum.

Bull, W.B., 1996. Prehistorical earthquakes on the Alpine fault, New Zealand. Journal of geophysical research, 101: 6037-6050.

Aleotti, P., R. Chowdhury, 1999. Landslide hazard assessment: summary review and newperspectives. Bulletin engineering geology and environment, 58: 21-44.

Ballard, T.M., R.P. Willington, 1975. Slope instability in relation to timber harvesting in the Chilliwack Provincial Forest. The forestry chronicle, 51: 59-62.

Benda, L.E., T.W. Cundy, 1990. Predicting deposition of debris flows in mountain channels. Canadian Geotechnical Journal, 27: 409-417.

Bolt, B.A., W.L. Horn, G.A. MacDonald, R.F. Scott, 1975. Geological Hazards, 328 pp. Springer-Verlag, New York, pp: 328.

Bozzano, F., M. Floris, G. Valentini, 1996. Ilruolodellepioggenelleinstabilità di pendiosulversanteionicodella Basilicata: Primirisultati. Proc. of the International Conference ALBA 1996, Prevention of Hydrogeological Hazards: The Role of Scientific Research, November 5-7, 1996, Alba, Italy, I: 357-367.

Brabb, E.E., 1984. Innovative approaches to landslide hazard and risk mapping. In Proc. 4th Inter. Sym. on Landslides, Toronto, Ont. J. Seychuk (editor). 30: 307-324.

Anbalagan, R., 1992. Landslide hazard evaluation and zonation mapping in mountainousterrain. Engineering geology, 32: 269-277.

Carrara, A., 1991. GIS techniques and statistical models in evaluating landslide hazard. Earth Surf. Proc. and Landforms., 5: 427-445.

Cevik, E., T. Topal, 2003. GIS-based landslide susceptibility mapping for a problematic segment of the natural gas pipeline, Hendek (Turkey). Environmental geology, 44: 949–962.

Chung, C.F., A.G. Fabbri, C.J. Van Westen, 1995. Multivariate regression analysis forlandslide hazard zonation. Geographical information systems in assessing natural hazards (A.Carrera and F.Guzzetti, editors, Kluwer Academin Publishers, Dordrecht, The Netherlands): 107-133.

Chung, C.F., A.G. Fabbri, 1998. Three Bayesian prediction models for landslide hazard. In:A. Buccianti, (ed.) Proceedings of International Association for Mathematical Geology 1998129Annual Meeting (IAMG 98), Ischia, Italy, October 3-7, 1998, eds. A. Buccianti, R. Potenza, &G. Nardi, 204-211.

Chung, C.F., A.G. Fabbri, 1999. Probabilistic prediction models for landslide hazardmapping. Photogrammetric Engineering & Remote Sensing, 65(12): 1389-1399.

Nguyen QuocKhanh, 2009. Vietnam, LANDSLIDE HAZARD ASSESSMENT IN MUONGLAY, VIETNAM APPLYING GIS AND REMOTE SENSING