

Data Acquisition and Analysis for Land Slide susceptibility mapping using Geographical Information System (GIS) at Nilgiris district, India.

S.PRABU¹ PROF. DR.S.S.RAMAKRISHNAN² PROF.DR.R.VIDYA³

Institute of Remote Sensing, College of Engineering Guindy,
Anna University,
Chennai, Tamil Nadu,
India

Abstract: The purpose of this study is to develop technique for landslide susceptibility mapping using artificial neural networks and then to apply the technique to the selected study area at Nilgiris district in Tamil Nadu. Landslide locations are identified by interpreting the satellite images and field survey data, and a spatial database of the topography, soil, forest, and land use. Then the landslide-related factors are extracted from the spatial database. These factors are then used with an artificial neural network to analyze landslide susceptibility. Each factor's weight is determined by the back-propagation training method. Different training sets will be identified and applied to analyze and verify the effect of training. The landslide susceptibility index will be calculated by back propagation method and the susceptibility map will be created with a GIS program. The results of the landslide susceptibility analysis are verified using landslide location data. In this research GIS is used to analysis the vast amount of data very efficiently and an ANN to be an effective tool to maintain precision and accuracy. Finally the artificial neural network will prove it's an effective tool for analyzing landslide susceptibility.

Keywords: Landslide susceptibility mapping, Geographical Information System, Digital Photogrametry, Artificial Neural Networks.

1 Introduction

The main goal of the analysis of landslide susceptibility is to reduce the impact of landslides by determining the areas at risk. Natural hazard mapping includes the formation of natural events such as landslide, flood, earthquake, and volcanic eruption that happened in the past and the estimated future occurrence. There has been rapid

progress in the preparation of landslide susceptibility maps because of the development in technology. Geographical Information Systems (GIS) and Remote Sensing (RS) techniques have proved to be very valuable in preparing these kinds of maps. Data is easily gathered and analyzed using RS techniques and according to mathematical and statistical criteria it is possible to store,

process, and analyze a large amount of complex data easily, and in a very short time using GIS techniques.

Today, the need for new residential areas and for new engineering buildings has increased rapidly because of the increase in population. In developed countries, an extensive search is carried out to find the most appropriate location for new construction. One of the most important parameters that should be taken into account is the risk of natural hazards. Following the investigation the selection is made by evaluating the related data selected from qualitative or quantitative parameters such as the geological structure related with the area, distance from large faults, relationship between structural elements and slope, form of the slope of the hill, direction of the slope of the side, the potential of the land cover, rain, and seismicity.

2 Problem Formulation

Preparation of landslide inventory and susceptibility maps is one of the most important stages in landslide hazard mitigation. These maps provide important information to support decisions for urban development and land use planning. Also, effective utilization of these maps can considerably reduce damage potential and other cost effects of landslides. However, landslides and their consequences are still a great problem for many countries, particularly in India. In our country with the rapidly increasing populations, are facing the problem arising from increasing demand for urban lands, at the same time as their limited financial resources hinder mitigation efforts, which should be performed before landslide events

occur. To date, a number of different methods have been developed to predict landslide hazards. They can be divided into two groups as qualitative methods and quantitative methods. These vary from experience-based analyses to complex mathematical, logical, and/or computer-based systems to analyze landslide susceptibility, hazard, and risk. Geomorphologic analyses and direct field mapping methods are considered qualitative methods because they don't yield numeric output with reference to landslide assessment. On the other hand, quantitative methods such as deterministic analyses, probabilistic approaches, statistical methods, and artificial intelligence techniques closely rely on mathematical models and produce numeric outputs. However, no general agreement has yet been reached about the best method for producing landslide hazard assessment maps. Although all known methods have their advantages and disadvantages, utilization of quantitative methods has become preferred and more commonly used in recent years. In addition, utility of GIS (Geographical Information Systems) has been emphasized in nearly every landslide study published in recent years. Therefore, it can be concluded that the general trend related to landslide assessments is the utilization of quantitative methods and specifically, GIS based ones.

The work presented here is aimed at evaluating landslide inventory and susceptibility in a selected landslide-prone area in the Nilgiris District of Tamil Nadu, India. To achieve this, first a detailed landslide inventory map is prepared by extensive field assessment and air photo interpretations. Secondly,

input parameter maps are produced and analyzed together with the landslide inventory map. Since the complex nature of the landslide mechanism and its ability to reflect nonlinearities and complexity, Artificial Neural Network (ANN) is chosen to assess landslide susceptibility, and is then used to evaluate areas susceptible to landslides using a GIS based system. Lastly, performance of the resulting susceptibility map was evaluated.

In recent years, with an increasing interest, several papers have been published concerning with ANN applications and landslide assessment in the literature (e.g. Lee *et al.*, 2001, 2003; Ermini *et al.*, 2005; Gomez and Kavzoglu, 2005; Yesilnacar and Topal, 2005). With this study, it is expected to satisfy the lack of landslide inventory in some part of Tamil Nadu region, at least for the study area, and to predict susceptible areas to landslides with an Artificial Neural Network Back propagation implementation.

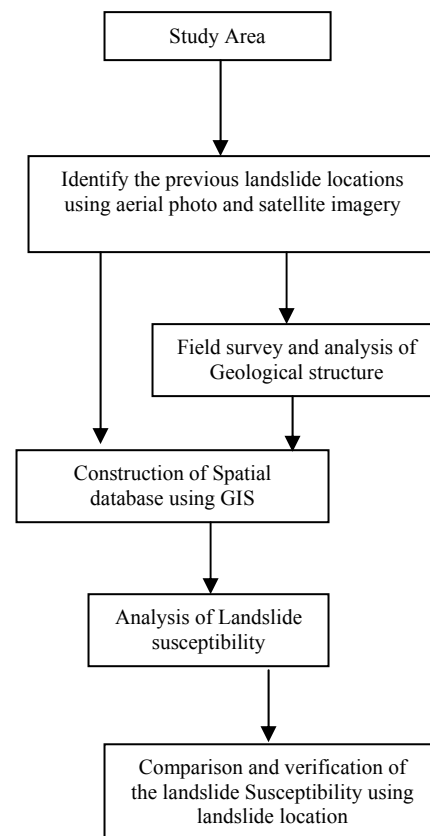
3 Problem Solution

For the landslide susceptibility analysis of this study, the landslide occurrence areas are detected by interpretation of satellite images and field survey data. Maps are constructed in a vector format spatial database for the GIS and these data are then used in the application of artificial neural network methods. These included topographic maps, soil maps and forest maps. From the spatial database, landslide causing factors are calculated and extracted for landslide susceptibility analysis: slope, aspect, curvature, topographic type, soil texture, soil material, forest type and land use. Then the landslide

susceptibility is analyzed using an artificial neural network program that was partially modified from an original version developed by Hines (1997) in the MATLAB software package.

Landslide susceptibility is mapped using the trained back-propagation neural network. The results predicted by the artificial neural network are converted into grid data, and a landslide susceptibility map is generated using the GIS. Finally, these forecast results were verified using actual landslide locations.

3.1 Methodology Flowchart



3.2 The Artificial Neural Networks

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". 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 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.

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.

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. 1). 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 Equation (1).

$$\text{net}_j = \sum W_{ij} O_i \quad (1)$$

Where W_{ij} represents the weights between nodes i and j , and o_i is the output from node i , given by

$$O_j = f(\text{net}_j) \quad (2)$$

The function f is usually a nonlinear 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:

$$f'(\text{net}_j) = f(\text{net}_j) \cdot (1 - f(\text{net}_j)) \quad (3)$$

The network used in this study consisted of three layers. The first layer is the input layer, where the nodes are 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.

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

$$E = 1/2 \sum (d_k - o_k)^2 \quad (4)$$

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

$$W_{ij}(n+1) = \eta (\delta_j o_i) + \alpha W_{ij} \quad (5)$$

Where η is the learning rate parameter (set to $\eta = 0.01$ in this study), δ_j is an index of the rate of change of the error, and α is the momentum parameter.

The factor δ_j is dependent on the layer type. For example,

$$\text{For hidden layers, } \delta_j = \left(\sum \delta_k w_{jk} \right) f'(\text{net}_j) \quad (6)$$

And for output layers,

$$\delta_j = (d_k - O_k) f'(net_k) \quad (7)$$

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 Equation (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 ok with respect to oj as

$$\frac{\partial O_k}{\partial O_j} = f'(net_k) \times \frac{\partial (net_k)}{\partial o_j} = f'(net_k) \times W_{jk} \quad (8)$$

Equation (8) produces both positive and negative values.

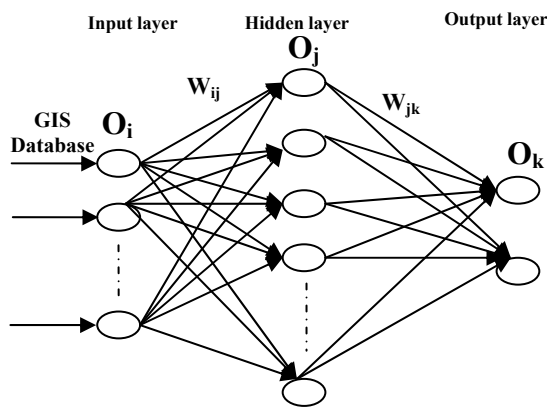


Figure 1 Architecture of artificial neural network.

3.3 Spatial Database Using GIS

To apply the artificial neural network, a spatial database is created that took

landslide-related factors such as topography, soil, forest, and land use into consideration (Table 1). Landslide occurrence areas are detected from both Indian Remote Sensing (IRS) and field survey data. In the study area, rainfall triggered debris flows and shallow soil slides are the most abundant. Maps relevant to landslide occurrence are constructed in a vector format spatial database using the GIS ARC/INFO or Arc Map software package.

3.4 Data Requirement

Classification		GIS Data Type		Scale Or Resolution	
Spatial Database	Factor	Spatial Database	Factor	Spatial Database	Factor
Landslide	Landslide	ARC/INFO Polygon coverage	ARC/INFO GRID	1:50,000	10 × 10 m
Topographic Map	Slope	ARC/INFO Line and Point Coverage		1:50,000	
Soil Map	Aspect Curvature Texture	ARC/INFO Polygon coverage		1:50,000	
Forest Map Type	Topographic Type	ARC/INFO Polygon coverage		1:50,000	
Land Use	Land Use	ARC/INFO GRID		30 × 30 m	

Table 1: Data layers required for the study area.

Landslide occurrence areas are detected in the Nilgiris District, Tamil Nadu, from both Indian Remote Sensing (IRS) and field survey data. In the study area, rainfall triggered debris flows and shallow soil slides are the most abundant. Maps relevant to landslide occurrence are constructed in a vector format spatial database using the GIS

ARC/INFO software package. These included 1:50,000 scale topographic maps, 1:50,000 scale soil maps, and 1:50,000 scale forest maps. Contour and survey base points that had an elevation value read from a topographic map are extracted, and a digital elevation model (DEM) is constructed. The DEM has a 10 m resolution and will be used to calculate the slope, aspect, and curvature. Soil texture, parent material, drainage, effective thickness, and topographic type will be extracted from the soil database. Forest type, timber age, timber diameter, and timber density will be extracted from forest maps. Land use was classified from Landsat TM satellite imagery.

Both the calculated and extracted factors are converted to form a 10×10 m² grid (ARC/INFO grid type), and then it will be converted to ASCII data for use with the artificial neural network program.

3.5 Landslide Susceptibility Forecast Mapping and Verification

The calculated landslide susceptibility index values computed using back propagation is converted into an ARC/INFO grid. Then a landslide susceptibility map is created. The final landslide susceptibility maps are prepared.

Verification is performed by comparing existing landslide data with the landslide susceptibility analysis results of the study area.

4 CONCLUSIONS

Landslides are one of the most hazardous natural disasters, not only in India, but around the world.

Government and research institutions worldwide have attempted for years to assess landslide hazards and their associated risks and to show their spatial distribution. An artificial neural network approach will be used to estimate areas susceptible to landslides using a spatial database for a selected study area.

In this neural network method, it is difficult to follow the internal processes of the procedure. There is a need to convert the database to another format, such as ASCII, the method requires data be converted to ASCII for use in the artificial neural network program and later reconverted to incorporate it into a GIS layer. Moreover, the large amount of data in the numerous layers in the target area cannot be processed in artificial neural network programs quickly and easily. Using the forecast data, landslide occurrence potential can be assessed, but the landslide events cannot be predicted. However, landslide susceptibility can be analyzed qualitatively, and there are many advantages, such as a multi-faceted approach to a solution, extraction of a good result for a complex problem, and continuous and discrete data processing. To capitalize on these advantages, the artificial neural network methods have to be improved by further application and upgrading of the programs. Moreover, for the advanced analysis of landslide susceptibility, the calculated weights have to be applied with rating and the susceptibility result has to be verified.

Reference

[1] Lee, C. F., Ye, H., Yeung, M. R., Shan, X., and Chen, G.: *AIGISbased methodology for natural terrain*

- landslide susceptibility mapping in Hong Kong*, Episodes, 24, 150–179, 2001.
- [2] Lee, S., Ryu, J. H., Lee, M. J., and Won, J. S.: *Use of an artificial neural network for analysis of the susceptibility to landslides at Boun, Korea*, Env. Geol., 44, 820–833, 2003.
- [3] Ermini, L., Catani, F., and Casagli, N.: *Artificial neural networks applied to landslide susceptibility assessment*, Geomorphology, 66, 327–343, 2005.
- [4] Gomez, H. and Kavzoglu, T.: *Assessment of shallow landslide susceptibility using artificial neural network in Jabonosa River basin, Venezuela*, Eng. Geol., 78, 11–27, 2005.
- [5] Yesilnacar, E. and Topal, T.: *Landslide susceptibility mapping: a comparison of logistic regression and neural networks methods in a medium scale study, Hendek region (Turkey)*, Eng. Geol., 79, 251–266, 2005.
- [6] P.M. Atkinson, A.R.L. Tatnall, “Introduction neural networks in remote sensing”, *International Journal of Remote Sensing* vol. 18, no. 4, pp. 699-709, 1997.
- [7] J.W. Hines, “*Fuzzy and Neural Approaches in engineering*”. John Wiley and Sons, Inc. New York: 210 p., 1997.
- [8] Saro Lee, Joo-Hyung Ryu, Joong-Sun Won, Hyuck-Jin Park, “Determination and application of the weights for landslide susceptibility mapping using an artificial neural network”, *Engineering Geology* vol. 71, pp. 289–302, 2004