Sensitivity analysis in ANN models landslide susceptibility, Guantánamo, Cuba

Abstract

While Artificial Neural Networks ANNs have been proved to be a promising method in landslide susceptibility modelling, their application is still depending on the difficulty to interpret the results and the influences of each conditioning factor on landslide occurrence. This contribution proposes the application of a graphical method [1] to analyse the function computed by a Multi-Layer Perceptron (MLP) network. This approach allowed us to qualitatively investigate the degree of interaction among the conditioning factors. The experimental results were obtained in the Guantánamo province



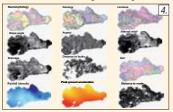


This study area (Fig. 1) is the most eastern province of Cuba with 75% of mountainous area, 6186 km2, and 516,311 inhabitants (2006). The

territory is frequently affected by different types of landslides (Fig. 2 and 3) with casualties and economic damage. The results coming out from the sensitivity analysis show an increase of landslide susceptibility with increasing slope angle, internal relief, rainfall and peak ground acceleration. Other variables have shown linear and non linear interaction with other variables.

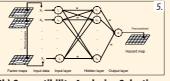
1) Selection of the Input Data

We have used 186 photo-interpreted landslide events and 12 conditioning factors (Fig. 4)



2a) Susceptibility Analysis – Selection of the Network

The analysis was performed by using the Levenberg-Marquardt algorithm to train the MLP network and the early stopping technique to improve its generalization capability

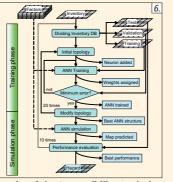


2b) Susceptibility Analysis - Selection of the Topology and Analysis

The database was subdivided into three subsets: a training set used to optimise the weights, a validation set used to stop the training before the network starts learning noise in the data, and a test set to evaluate the prediction capability of the network. In order to obtain results representative of the whole data and not conditioned by a specific subdivision of the dataset, a 10-fold cross-validation procedure was used in the analysis. The network was trained increasing the number of neurons in the hidden layer. For each increment of number of neurons, the training was repeated 10 times with different initialisation of the weights and stopped by using the early stopping technique. The described procedure (Fig. 6) allows for selecting the best topology for each database subdivision.

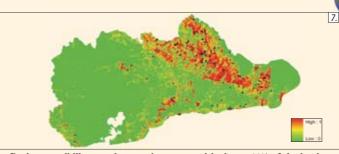
3) Sensitivity Analysis

The sensitivity analysis was carried out by evaluating the differences in the network output obtained when each input variable at the time is set at the baseline (in this case 0). This graphical method consists of plotting the delta of the network output versus the current variable. In order to better interpret the results, each point in the plots is visualised according to the value of the . partial derivative



Results of the Susceptibility Analysis

The results of the analysis (i.e., best topology and prediction capability) are shown in Table 1 for each of the database subdivision. We selected the network with the best accuracy (i.e. subdivision 9) to produce the susceptibility map in Fig. 7. Table 1 shows the selected topology and the performance measurements for each of the database subdivision. The performance measurements calculated on the test sets are sensitivity (Sen), specificity (Spe), and overall accuracy (Acc)



The final susceptibility map has good accuracy with almost 90% of the landslides correctly classified

The most susceptible areas are located over ophiolites and metavulcanites in the northeast part of the province or they are related to steep slopes in the coastal terraces and less frequently inland

Results of the Sensitivity Analysis

The sensitivity analysis detected a positive trend (Fig. 8) between rainfall and the output of the network. The same trend was found for slope, internal relief, and peak ground acceleration. Fig. 9 shows a linear relationship and interaction with other variables for the aspect variable, whereas Fig. 10 displays a non linear behaviour and interaction for the drainage variable.

Fig. 11 shows the interaction between the peak ground acceleration and the rainfall. The variable rainfall is represented in the plot with four colours depending on its value: 150-325 mm \rightarrow black, 325-500 mm \rightarrow blue, 500-675 mm \rightarrow green, 675-850 mm \rightarrow red. The model discriminates landslides triggered by rainfall from landslides triggered by earthquakes.For other variables it was not possible to detect any interaction. In Fig. 12 the variable slope is represented with four colours depending on its value: 0-12° -> black, 12-24° -> blue, 24-36° -> green, 36-48° -> red. This means that more than one variable is involved in the interaction.

Conclusions

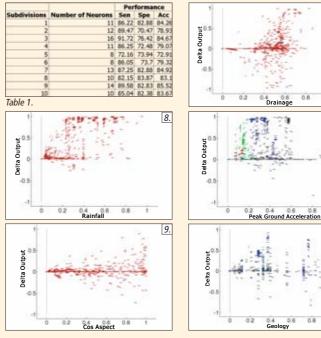
The graphical sensitivity analysis has shown to be a useful tool in understanding the function computed by a neural network. It has also detected interactions and non linear behaviours, confirming the necessity to use complex and non linear models in the susceptibility analysis.

Reference: [1] Plate, T., Bert, J., Band, P., 2000. Visualizing the function computed by a feed-forward neural network. Neural Computation, 12, 6, 1337-135

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