Development and application of artificial neural network for landslide susceptibility mapping and its verfication at Janghung, Korea

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Abstract : The purpose of this study is to develop landslide susceptibility analysis techniques using artificial neural network and to apply the developed techniques to the study area of janghung in Korea. Landslide locations were identified in the study area from interpretation of satellite image and field survey data, and a spatial database of the topography, soil, forest and land use were consturced. The 13 landslide-related factors were extracted from the spatial database. Using those factors, landslide susceptibility was analyzed by artificial neural network methods, and the susceptibility map was made with a GIS program. For this, the weights of each factor were determinated in 5 cases by the backpropagation method, which is a type of artificial neural network method. Then the landslide susceptibility indexes were calculated using the weights and the susceptibility maps were made with a GIS to the 5 cases. A GIS was used to efficiently analyze the vast amount of data, and an artificial neural network was turned out be an effective tool to analyze the landslide susceptibility.

INTRODUCTION

In Korea, frequent landslides often result in significant damage to people and property. In the study area, Janghung in Korea, much damage was caused on these occasions. The site lies between the latitudes 36 °25' 21'' N and 36° 30' 00'' N, and longitudes 127° 39' 36'' E and 127° 45' 00'' E, and covers an area of 68.43km^2.

For the landslide susceptibility analysis, first, the study area was selected, then landslide-related databases were collected, artificial neural network were trained, weights were determinated landslide susceptibility was analyzed, the result was verified, and the landslide susceptibility map was created.

To analze and verify the effect of training site, the 5 cases with different training site were applied. When the weights converged to reasonable values, the weight that satisfied the stopping criterion during the training, landslide susceptibility was analyzed using the weights modified by back propagation between neural network layers. The analysis results were converted to grid data and the landslide susceptibility map was made using GIS. Finally, the analysis forecast was verified using landslide location.

ARTIFICIAL NEURAL NETWORK

The most frequently used neural network method and used method in the study is the backpropagation-learning algorithm. This is a learning algorithm of 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 of their inputs by the corresponding weights, summing the product, then processing the sum using a nonlinear transfer function to produce a result. Artificial neural network " learns" by adjusting the weights between the neurons in response to the errors between actual output values and target output values. At the end of this training phase, the neural network represents a model, which should be able to predict a target value given an input value.

The Multi-layer Perceptron (MLP) can separate data that are non-linear because it is ' multi-layer' , and it generally consists of three types of layers. The first layer is the input layer, where the nodes are the elements of a feature vector. The second type of layer is the internal or ' hidden' layer since it does not contain output unit. The third type of layer is the output layer and this presents the output data. Each node in the network is interconnected to the nodes in both the preceding and following layers by connections. These connections have associated with them weights (Atkinson and Tatnall, 1997).

SPATIAL DATABASE CONSTRUCTION USING GIS

Landslide occurrence areas were detected in the Janghung area, Korea, by interpretation of IRS (Indian Remote Sensing) and field survey data. Topography, soil, and forest databases were also constructed. Maps relevant to landslide occurrence were constructed in a vector format spatial database using the GIS software ARC/INFO. These included 1:25,000 scale topographic maps, 1: 50,000 scale soil maps and 1:25,000 scale forest maps. Contour and survey base points that have an elevation value read from the topographic map were extracted, and a DEM (Digital Elevation Model) was made. The DEM has the 10m resolutions. Using the DEM, the slope, aspect and curvature were calculated. Soil texture, parent material, drainage, effective thickness, and topographic type were extracted from the soil database. Forest type, timber age, timber diameter, and timber density were extracted from the forest map. Lithology was extracted from the geological database, and land use was classified from Landsat TM satellite imagery To achieve this, the calculated and extracted factors were converted to a 10 m × 10 m grid (ARC/INFO GRID type), and then converted to ASCII data for use with the artificial neural network program. The analysis results were converted to grid data using GIS.

LANDSLIDE SUSCEPTIBILITY ANALYSIS USING ARTIFICIAL NEURAL NETWORK

The weights were applied to the entire study area and the landslide susceptibility index value was calculated. The calculated index values were converted into an ARC/INFO GRID using the GIS. Then the landslide susceptibility map was created using the GRID data.

LANDSLIDE SUSCEPTIBILITY FORECAST MAPPING AND VERIFICATION

Verifications were performed by comparing the forecast with existing landslide data, and the result of this is shown in Fig. 8. For verification of landslide susceptibility calculation methods, two basic assumptions are needed. One is that landslides are related to spatial information such as topography, soil, forest, geology and land use, and the other is that future landslides will be precipitated by a specific impact factor such as rainfall or earthquake (Chung and Fabbri, 1999). In this study, the two assumptions are satisfied because the landslides are related to the spatial information and the landslides were precipitated by one cause, heavy rainfall in the left and right sides of the study area.

The verification method was performed by comparison of existing landslide data and landslide susceptibility analysis results for the left side of the study area. The success rates in Fig. 1. 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 set to Y-axis, with accumulated intervals in X-axis.

CONCLUSIONS AND DISCUSSION

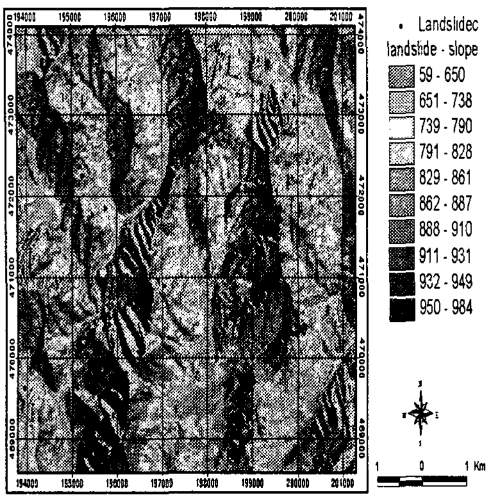
In this neural network method, it is difficult to follow the internal processes of the procedure, and the method entails a long execution time and has a heavy computing load. There is a need to convert the database to another format such as ASCII.

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.

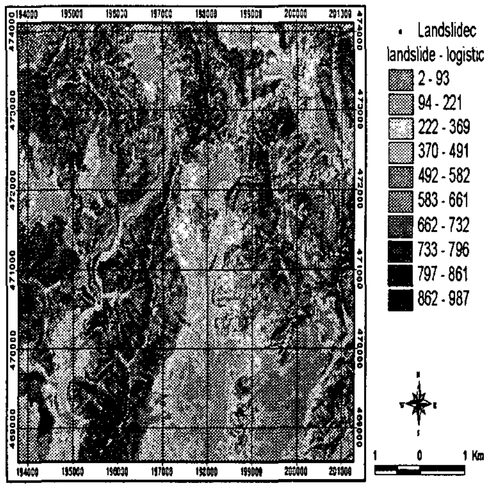
The landslide susceptibility maps made from the susceptibility index values are of great help to planners and engineers for choosing suitable locations to undertake projects. The results can be used as basic data to assist slope management and land-use planning. For the method to be more generally applicable, more landslide data are needed, as well as the program being applied to more regions.

Table1. Weight of facter

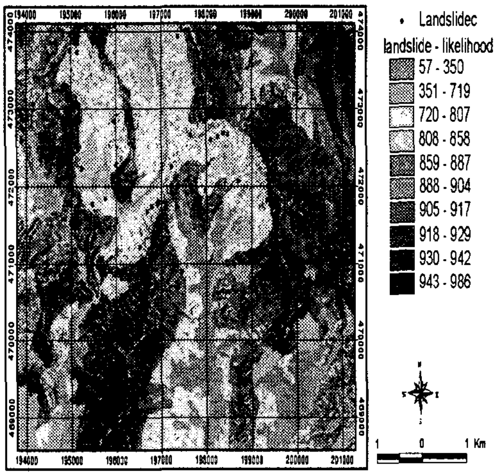
Methods / Factors	landslide-slope			landslide-likelihood			lnadslide-logistic			like-like			logis-logis		
	Average	Standard Deviation	**Weight**	Average	Standard Deviation	**Weight**	Average	Standard Deviation	**Weight**	Average	Standard Deviation	**Weight**	Average	Standard Deviation	**Weight**
Slope	0.106	0.009	**1.554**	0.105	0.007	**1.540**	0.123	0.007	**1.916**	0.109	0.011	**1.635**	0.116	0.010	1.765
Aspect	0.117	0.007	**1.716**	0.071	0.008	**1.035**	0.071	0.007	**1.116**	0.069	0.010	**1.031**	0.070	0.010	1.074
Curvature	0.071	0.005	**1.046**	0.068	0.008	**1.000**	0.066	0.010	**1.035**	0.067	0.005	**1.000**	0.066	0.008	1.003
Topgraphic Type	0.069	0.010	**1.008**	0.068	0.011	**1.000**	0.072	0.012	**1.119**	0.071	0.010	**1.068**	0.081	0.009	1.231
Soil Texture	0.069	0.006	**1.018**	0.073	0.009	**1.073**	0.064	0.009	**1.000**	0.073	0.010	**1.092**	0.071	0.009	1.089
Soil Drainage	0.072	0.010	**1.053**	0.087	0.007	**1.279**	0.082	0.011	**1.277**	0.101	0.010	**1.515**	0.079	0.010	1.207
Soil Effetive Thickness	0.071	0.009	**1.049**	0.069	0.006	**1.013**	0.067	0.010	**1.050**	0.073	0.008	**1.096**	0.066	0.008	1.003
Soil Material	0.068	0.009	**1.006**	0.070	0.009	**1.017**	0.067	0.012	**1.042**	0.070	0.013	**1.042**	0.071	0.010	1.082
Forest Type	0.073	0.009	**1.070**	0.073	0.005	**1.064**	0.086	0.007	**1.337**	0.068	0.006	**1.015**	0.085	0.011	1.299
Timber Diameter	0.074	0.010	**1.093**	0.102	0.012	**1.499**	0.087	0.009	**1.358**	0.079	0.014	**1.189**	0.086	0.014	1.313
Forest Density	0.073	0.011	**1.068**	0.071	0.011	**1.036**	0.073	0.011	**1.137**	0.076	0.010	**1.134**	0.066	0.011	1.000
Timber Age	0.068	0.009	**1.000**	0.075	0.012	1.100	0.075	0.013	**1.178**	0.073	0.011	**1.092**	0.076	0.008	1.157
Land Use	0.069	0.008	**1.018**	0.067	0.011	0.978	0.068	0.009	**1.055**	0.071	0.007	**1.070**	0.067	0.012	1.016



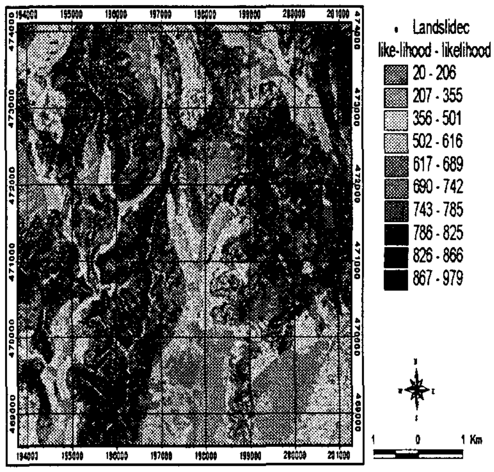
(a) Case 1: Use of landslide location as occurrence training site and slope is 0 as not-occurrence training site



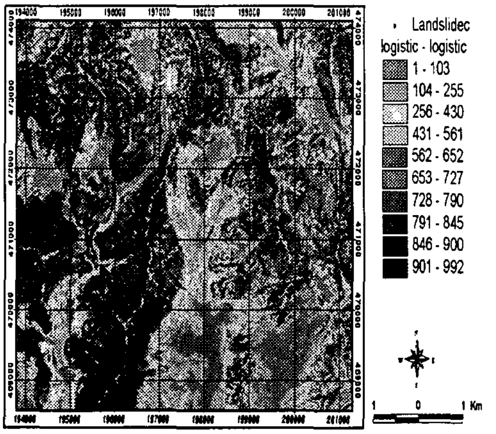
(c) Case 3: Use of landslide location as occurrence training site and result form logistic regression as not-occurrence training site



(b) Case 2: Use of landslide location as occurrence training site and result form likelihood ratio as not-occurrence training site



(d) Case 4: Use of result from likelihood ratio as occurrence training site and result form likelihood ratio as not-occurrence training site



(e) Case 5: Use of result from logitsic regression as occurrence training site of result from logitsic regression as not-occurrence training site

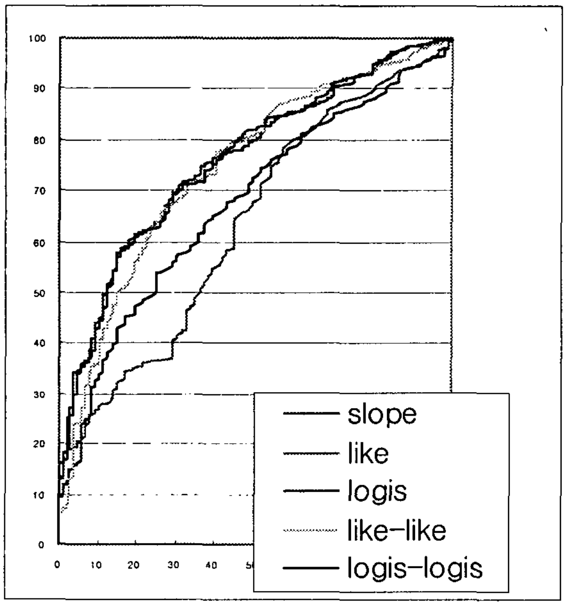


Figure1 . Sucess curve of each cases..

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