# THE CROSSING APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO LANDSLIDE SUSCEPTIBILITY MAPPING AT KANGNEUNG, KOREA

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**Abstract:** The purpose of this study is to reveal the spatial relationship between landslides and geospatial data set and to map the landslide susceptibility using this relationship, and the landslide occurrence data in Kangneung area in 2002. Landslide locations were identified from interpretation of satellite images. Landslide susceptibility was analyzed using an artificial neural network. The weights of each factor were determined by the back-propagation training method. Susceptibility maps were constructed from Geographic Information System (GIS). The cases were overlaid and cross overlaid for landslide susceptibility mapping in each study area in Kangneung.

**Keywords:** Landslide, Susceptibility, GIS, Artificial neural network, Korea

## 1. Introduction

A Geographic Information System (GIS) is a useful and efficient tool for landslide hazard analysis and there are many recent studies of landslide hazard evaluation using GIS. Artificial neural network methods have previously been applied to land use and cover classification using satellite imagery In particular, the multi-layer perceptron method using a back propagation algorithm was used widely in a supervised classification with training area data. In this study, the GIS and artificial neural network methods were combined and applied to develop a new technique for landslide susceptibility analysis.

## 2. Spatial database construction using GIS

Landslide locations were identified from interpretation of satellite images using change detection method and field survey data. The instability factors include the lithology and geological structure, bedding altitude, seismicity, slope steepness and morphology, stream evolution, groundwater conditions, climate, vegetation cover, land use, and human activity. The availability of thematic data varies greatly, depending on the type, scale, and method of data acquisition. In this study, geomorphologic, lithologic, soil, forest and land-use data were available for the entire area.

Maps relevant to landslide occurrence were constructed in a vector format spatial database using the GIS software ARC/INFO for Kangneung areas. These included 1:5,000 scale topographic maps, 1:25,000 scale soil maps, 1:25,000 scale forest maps, and 1:50,000 scale geological maps and 30 m resolution land-use data from TM (Thematic Mapper) satellite images. From the maps, 16 factors (slope, aspect, curvature, topographic type, soil texture, soil material, soil drainage, soil effective thickness, timber type, timber age, timber diameter, timber density, geology and land cover, Lineament, Drainage lineament) used for landslide susceptibility analysis were extracted. In this analysis, the study area was divided into a 5 m × 5 m pixel grid for Boun(ARC/INFO GRID type), which were converted to ASCII format for use in the artificial neural network program. There are 1586 X 1209(Sagimakri) and 505 X 768(Samkyori) cells in the each Kangneung area.

## 3. Landslide susceptibility analysis using an artificial neural network

The training sites were selected from the landslide-related factors. The back-propagation algorithm was applied to calculate weights between the input layer and the hidden layer and between the hidden layer and the output layer by modifying the number of hidden layers and the learning rate. All 14 factors were used for calculating the weights. the structure 16 (input layer) × 32 (hidden layer) × 2 (output layer) was selected for the network, with input data normalized to the range 0.1 to 0.9. Nominal and interval class group data were converted to continuous values between 0.1 and 0.9.

## 4. Calculation of the susceptibility index and mapping

The landslide-susceptibility index value was calculated from the weights determined from back-propagation and the spatial database. The index values were between 0.1 and 0.9 for each cell. The output indices were converted to GIS Grid data. Using the values, the landslide susceptibility indices (LSI) were determined and used to create the landslide susceptibility maps. This is case of distribution of the landslide-susceptibility map, as indicated in Figures 1, 2. Figure 1, 2 is the case where 16 factors were used. The value is classified by equal area and grouped into five classes for easy visual inter pretation of landslide susceptibility. With an increase in the index, the landslide susceptibility also increases for all the cases.

Also, the weights were applied to the other study area, Kangneung, Sagimakri area of the weight are crossed application Samkyori area. And Samkyori area of the weight is crossed application Sagimakri area. The landslide- susceptibility map of the Kangneung area was made using the LSI values and crossing application each area. as shown in Figure 3, 4.

Table 1. Case of cross application

| | Area | Weight |
|---|---|---|
| Case1 | Sagimakri | Sagimakri |
| Case2 | Samkyori | Samkyori |
| Case3 | Sagimakri | Samkyori |
| Case4 | Samkyori | Sagimakri |

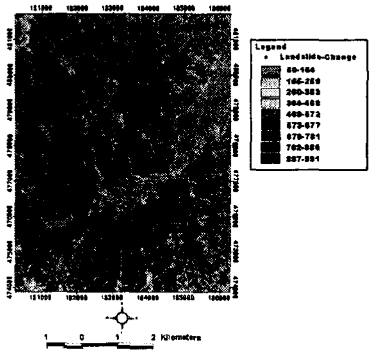

**Figure 1. Case1**

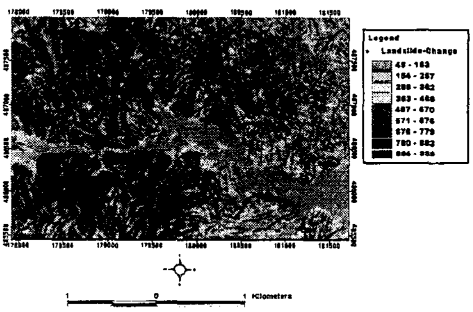

**Figure 2. Case2**

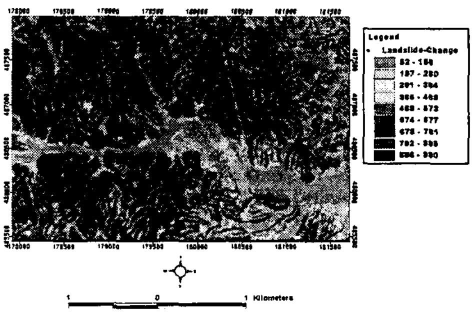

**Figure 3. Case3**

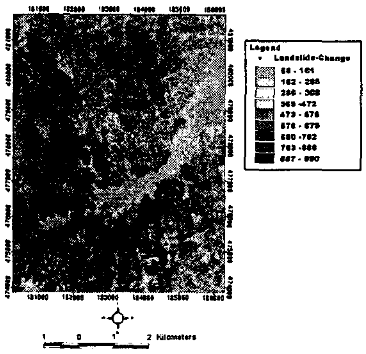

**Figure 4. Case4**

## 5. Landslide susceptibility verification and comparison

To obtain the relative ranks for each prediction pattern, the calculated index values of all cells in the Kangneung areas were sorted in descending order. Then, the ordered cell values were set on the Y-axis, with accumulated intervals on the X-axis. and calculate case of success rate curva measure percent.

All Cases were used by 16 factors. According to the success-rate verification result that is shown in Figure 5 and Table 4. case1 is 95.0%, case2 is 98.3%, case3 is 97.7% and case4 is 94.9%. the case2 is the height other cases. Case1 and Case4 showed similar results in the success rate curva measure percent.

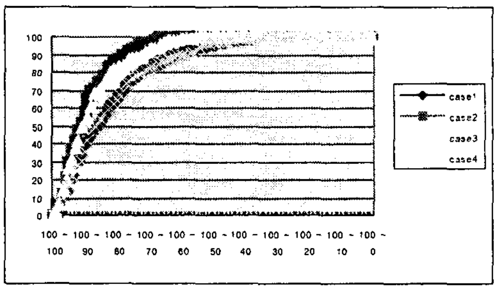


Figure 5 Sucess rate curva of Case 1 ~ 4

**Tables 4-15 Each case of success rate curva measure percent.**

| | |
|---|---|
| Case1 | 95.0% |
| Case2 | 98.3% |
| Case3 | 97.7% |
| Case4 | 94.9% |

## 6. Conclusions and discussion

The results demonstrate that GIS and the neural network can be used to produce a landslide-susceptibility index and, consequently, to manage landslide hazards effectively.

In the neural network method, it is difficult to follow the internal processes of the procedure and the method requires a long execution time and so a heavy computing load. Landslide susceptibility can be analyzed qualitatively, and there are 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. In addition, artificial neural network models are adaptive and capable of generalization. They can handle imperfect or incomplete data, and can capture non-linear and complex interactions among variables of a system.

## 7. References

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