Development of Artificial Neural Network Techniques for Landslide Susceptibility Analysis
산사태 취약성 분석 연구를 위한 인공신경망 기법 개발

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SYNOPSIS: The purpose of this study is to develop landslide susceptibility analysis techniques using artificial neural networks and to apply the newly developed techniques for assessment of landslide susceptibility to the study area of Yongin in Korea. Landslide locations were identified in the study area from interpretation of aerial photographs and field survey data, and a spatial database of the topography, soil type and timber cover were constructed. The landslide-related factors such as topographic slope, topographic curvature, soil texture, soil drainage, soil effective thickness, timber age, and timber diameter were extracted from the spatial database. Using those factors, landslide susceptibility and weights of each factor were analyzed by two artificial neural network methods. In the first method, the landslide susceptibility index was calculated by the back propagation method, which is a type of artificial neural network method. Then, the susceptibility map was made with a GIS program. The results of the landslide susceptibility analysis were verified using landslide location data. The verification results show satisfactory agreement between the susceptibility index and existing landslide location data. In the second method, weights of each factor were determinated. The weights, relative importance of each factor, were calculated using importance-free characteristics method of artificial neural networks.

1. Introduction

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 the back propagation algorithm was used widely in a supervised classification with training data [1]. In the study, for landslide susceptibility analysis, two artificial neural network methods are applied in a Geographic Information System (GIS) environment. In the first artificial neural networks method, for the landslide-susceptibility analysis, the study area was selected, landslide-related databases were constructed, artificial neural networks were trained,landslide susceptibility was analyzed, the result was verified, and the landslide susceptibility map was created. In the second artificial neural networks method, for the determination of weights of each factor to landslide susceptibility, study area was selected, landslide-related databases were constructed, artificial neural networks were trained and weights of each factor were determinated (Figure 1.).

The artificial neural network program can allow analysis of landslide susceptibility, but it is inconvenient for management of spatial data, and modification of its input data is difficult. A GIS has no default function for artificial neural network analysis, but has many functions for database construction, display, printing, management and analysis. Therefore, it is necessary to integrate the GIS and artificial neural networks to reduce the restrictions of using the two applications separately, so the benefits of integrating GIS and artificial neural networks are efficiency and ease of management, input, display and analysis of spatial data for landslide susceptibility analysis. Moreover, the artificial neural networks have many advantages compared with statistical methods. The artificial neural network method is independent of the statistical distribution of the data, so, integration of remote sensing data or GIS data is convenient. Moreover, there is no need statistical variable and accurate analysis is possible through training data is a few. However, resultant values do not accurately coincide with the correct values because of the random initial weights, variables have to be selected empirically, and the execution time is too long.

2. Stduy area and spatial database

The study area, Yongin in Korea area had considerable landslide damage following heavy rains in 1991, and was consequently selected as a suitable case to evaluate susceptibility to landslides. Landslide location, topography, soil, and forest spatial databases were used for the analysis. These included 1:5,000 scale topographic maps, 1:25,000 scale soil maps, and 1:25,000 scale forest maps. From the maps, seven factors used for landslide susceptibility analysis were extracted. The factors involved are topographic slope and curvature derived from the topography database soil texture, drainage, and effective thickness from the soil database and timber diameter and timber age from the forest database.

The study area was divided into a 10 m 10 m pixel grid (ARC/INFO GRID format), which was converted to ASCII format for usein the artificial neural network program. There were 658,790 pixels in the study area, and 11,735 of them had landslides.

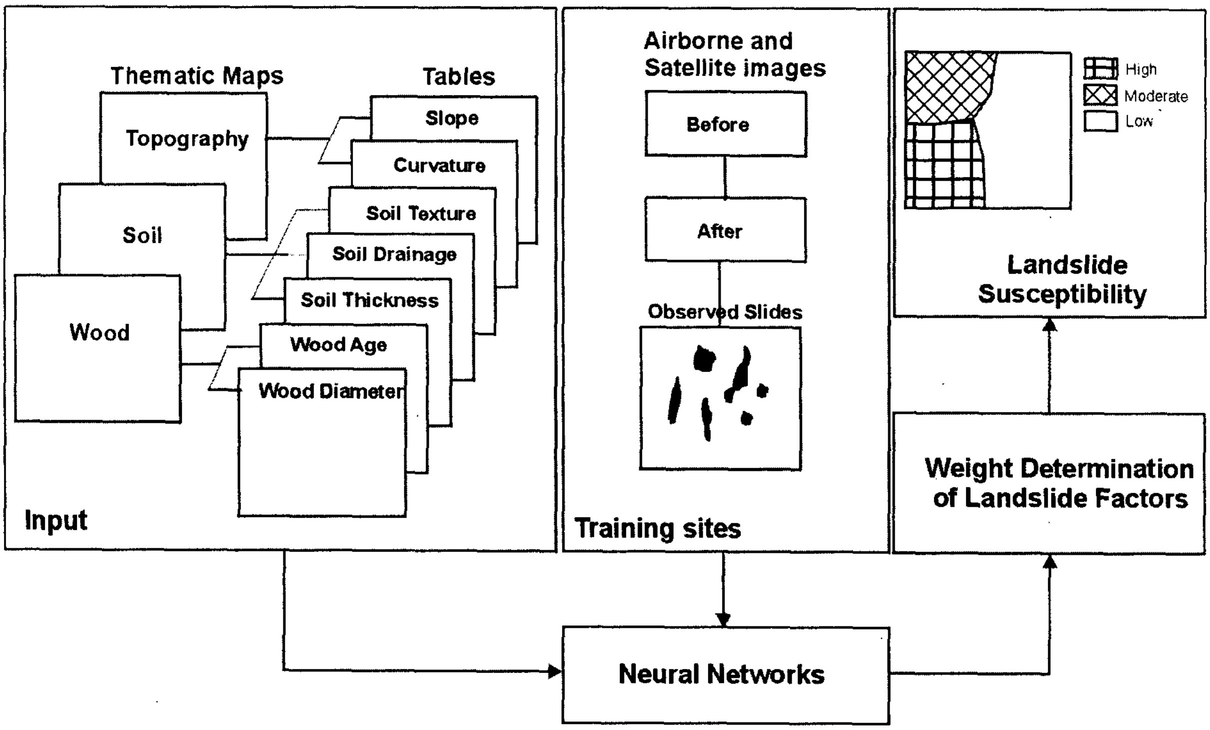

Figure 1. Landslide analysis using a neural network

3. Landslide susceptibility mapping using artificail neural networks

In the land use and cover classification, the supervised classification is assigned at the site where the information is well known this training site is classified by analysis of the input data for the site. By this process, landslide susceptibility data were analyzed using artificial neural network methods (Figure 2). A GIS spatial database was used as input data and landslide locations were used as training sites. The constructed landslide related factors do not have a Gaussian distribution and are not statistically related or distributed for the supervised classification, so the back propagation neural network method was used. In the artificial neural network method, seven factors such as topographic slope, topographic curvature, soil texture, soil drainage, soil effective thickness, timber age, and timber diameter, were used. The program developed by Hines [2] was partially modified and upgraded for the landslide analysis. It was enhanced in the input and output areas, and in the calculation algorithm for faster execution because artificial neural network program needs a high computational load.

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 three-layered feed forward network was implemented on the basis of the framework and the structure of 7x5x2 was selected for the networks with input data normalized to the range 0.1 to 0.9. The learning rate was set to be 0.01, and the initial weights were randomly selected. From each of the two classes, 200 pixels per class were selected as training pixels. The landslide prone (occurrence) locations and the landslide non-prone locations were selected as training sites. To lessen the error between the predicted output values and the actually calculated output values, the back propagation algorithm was used. The algorithm propagates the weights backwards and then controls the weights. The landslide susceptibility index value was acquired by calculating the weights determined from back propagation and the spatial database. The acquired index values were two values such as(0.11, 0.89) for each cell. The first value represents the no-landslide probability and the second value represents landslide possibility. For example, (0.11, 0.89) represents a high possibility of landslide. In this study, the second values were used only for landslide susceptibility analysis, but if the two values were used together, a more accurate analysis would be possible.

The landslide susceptibility was analyzed using the second value. The value was assigned to landslid esusceptibility index. Then verification was performed by comparing the forecast with existing landslide data, and the index value. The range is classified into 30 classes, by area, each equal to about 3.3% of the total area. The verification was performed by dividing the cell ratio (%) where landslides occurred, by the total cell ratio (%) per landslide susceptibility index range such as TABLE 1. Thus, the greater the ratio divided value, the more the area is susceptible to landslides and the index average value is 1.

The ratio increases with the landslide susceptibility value. For an index value below 0.095, the occurrence ratio is very low, with a value of 0.005, but for an index value above 0.930, the occurrence ratio is very high at 2.162 (recall that the average value is 1). The verification results show satisfactory agreement between the susceptibility index and existing landslide location data.

The index value can be divided into five ranges to classify the landslide hazard map according to the ratio value change such as very low (below 0.255), low (0.256-0.675), medium (0.676-0.897), high (0.898-0.923) and very high (above 0.924). Using the classification, a landslide susceptibility hazard map was made with landslide locations (Figure 3). The map was divided into the five classes.

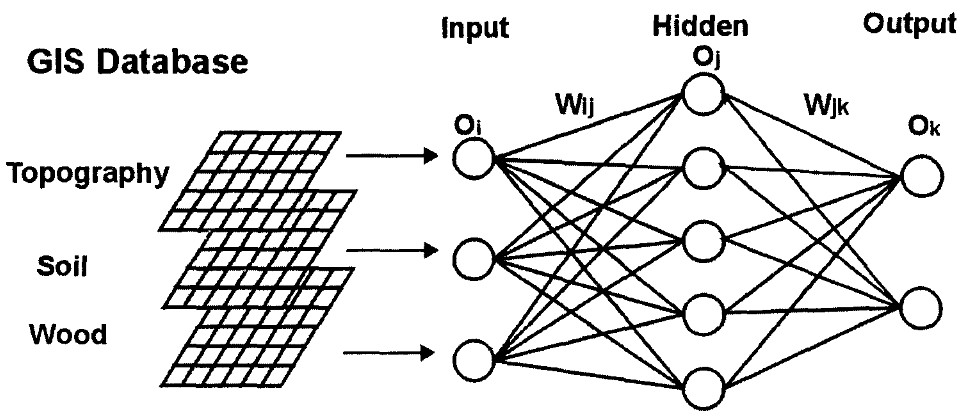

Figure 2. The architecture of the artificial neural network (Wang and Rahman, 1999)

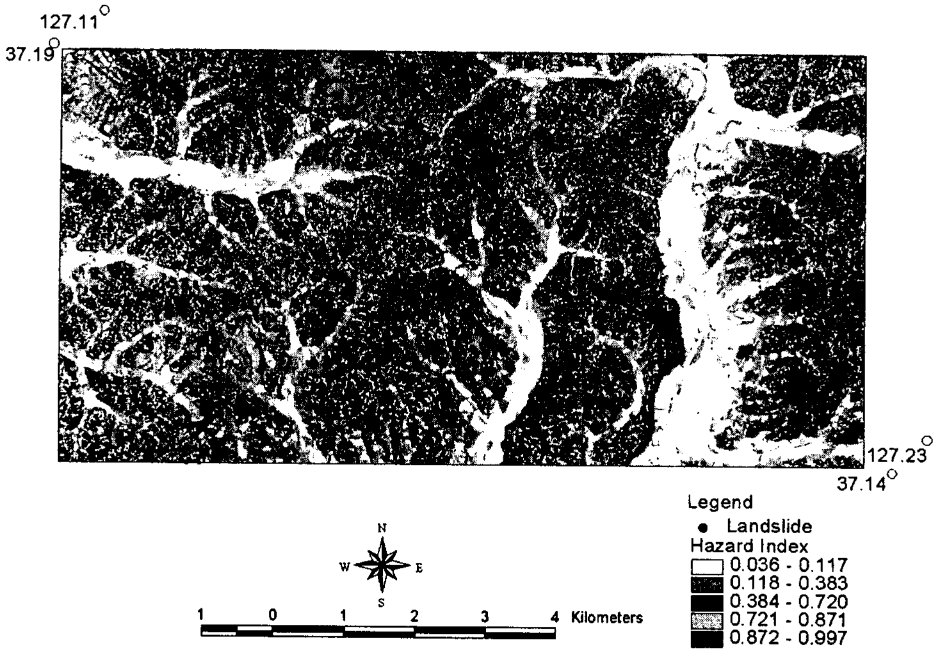

Figure 3. Landslide susceptibility map using neural network method

4. Determination of weights for landslide susceptibility analysis

For the determination of the each factor's weights, relative importance of each factor, importance-free characteristics method of artificial neural networks was used and three-layer feed-forward networks were implemented on the basis of the framework provided by Hines [2] also. The structure of 7152 is selected for the networks with input data normalized to the range 0.1 to 0.9. The learning rate is set to be 0.01 and the initial weights are randomly selected. From each of the 2 classes, 200 pixels are selected as training pixels. The calculation repeated 10 times and the mean value and mean/min value were acquired such as TABLE 2.

The topographic slope had the highest value 5.33 and the topographic curvature had the lowest value 1.00. The weights can be applied to landslide susceptibility analysis with rating that is represents relative susceptible value to landslide in each factor.

Table 1. Weight of each factor estimated by neural networks proposed in this study.

Factor	No. of Test	1	2	3	4	5	6	7	8	9	10	Mean	Std.	Normalized Weight*
Topo	Slope(TS)	0.35	0.33	0.34	0.35	0.32	0.29	0.32	0.37	0.38	0.24	0.32	1.1	5.33
	Curvature (TC)	0.07	0.06	0.06	0.05	0.08	0.08	0.06	0.06	0.07	0.08	0.06	0	1.00
Soil	Drainage (SD)	0.11	0.10	0.10	0.11	0.10	0.11	0.12	0.11	0.08	0.11	0.11	0.3	1.83
	Effective thickness (SE)	0.11	0.10	0.11	0.12	0.10	0.12	0.13	0.12	0.10	0.12	0.11	0.4	1.83
	Texture (ST)	0.08	0.08	0.07	0.05	0.08	0.09	0.07	0.07	0.08	0.07	0.07	0.1	1.17
Wood	Diameter (WD)	0.15	0.15	0.16	0.17	0.18	0.15	0.15	0.13	0.16	0.18	0.16	0.4	2.67
	Age(WA)	0.10	0.13	0.12	0.12	0.10	0.12	0.11	0.10	0.10	0.17	0.12	0.4	2.00

* Normalized weight with respect to topography curvature

5. Conclusion and discussion

For landslide susceptibility analysis, two artificial neural network methods are applied in a GIS. In the first method, the landslide-susceptibility analysis was performed and in the second method, weights of each factor to landslide susceptibility were determinated using artificial neural networks.

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 continuousand 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 hasto be verified.

6. References

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