Determination and application of the weights for landslide susceptibility mapping using an artificial neural network

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ABSTRAT : The purpose of this study is the development, application and assessment of probability and artificial neural network methods for assessing landslide susceptibility in a chosen study area. As the basic analysis tool, a Geographic Information System (GIS) was used for spatial data management. A probability method was used for calculating the rating of the relative importance of each factor class to landslide occurrence. For calculating the weight of the relative importance of each factor to landslide occurrence, an artificial neural network method was developed. Using these methods, the landslide susceptibility index was calculated using the rating and weight, and a landslide susceptibility map was produced using the index. The results of the landslide susceptibility analysis, with and without weights, were confirmed from comparison with the landslide location data. The comparison result with weighting was better than the results without weighting. The calculated weight and rating can be used to landslide susceptibility mapping.

INTRODUCTION

Landslides are a recurrent problem throughout most of Korea. The most common type of landslide in Korea is triggered by heavy rainfall, but little attempt is made to predict them, or to prevent damage arising from them. The object of this study is that weight is determinated using artificial neural network method and applied for landslide susceptibility mapping in GIS. The difference of this study from the other studies is to apply the artificial neural network for determination of weight value. Moreover the objective and scientific weight and rating are essential to the standardization of landslide hazard mapping in Korea. The rating was determinated using probability method in Lee and Min (2001) study in the same study area, so the rating was used for this study.

The study area was Yongin of Korea, It's lies between the latitudes 37.156° N and 37.174° N, and the longitudes 127.146° E and 127.169° E and covers an area of 66 km^2.

DETERINATION OF THE WEIGHTS OF FACTORS USING THE NEURAL NETWORK METHOD

The basic element of a neural network is the processing node. This sum is then passed through an activation function to produce the node's output value. An enhancement is to add a constant input to the summation at each processing node.

A neural network consists of a number of interconnected nodes. Each node is a simple processing element that responds to the weighted inputs it received from other nodes. The arrangement of the nodes is referred to as the network architecture The receiving node sums the weighted signals from all nodes to which it is connected in the preceding layer. Formally, the input that a single node j receives is weighted according to Eq. (1):

$$net_j = \sum_i w_{ij} \cdot o_i \tag{1}$$

where w_{ij} represents the weight between node i and node j, and o_i is the output from node i such as Eq. (2):

$$o_j = f(net_j) \tag{2}$$

The valued produced by hidden node j, o_j, is the activation function, f, evaluated at the sum produced within node j, NET_j. NET_j, in turn, is a function of the weights between the input and hidden layer, w_{ij}, and the outputs of the input layer nodes, o_i . The function f is usually a non-linear sigmoid function that is applied to the weighted sum of inputs before the signal processes proceeds to the next layer. Advantage of the sigmoid function is that its derivative can be expressed in terms of the function itself such as Eq. (3):

$$f'(net_j) = f(net_j)(1 - f(net_j)) \tag{3}$$

The error, E, for one training pattern for input layer, t, is a function of the desired output vector, d, and the actual output vector, o, given by Eq. (4).

$$E = \frac{1}{2}\sum_{k}(d_k - o_k)$$

(4)

The error back propagated through neural network and the error is minimized by changing the weight between layers. So, the weight can be expressed by Eq. (5):

$$w_{ij}(n+1) = \eta(\delta_j \cdot o_i) + \alpha\Delta w_{ij}$$

(5)

where η is the learning rate parameter, δj is an index of the rate of change of the error, and α is the momentum parameter. 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.

WEIGHT DETERMINATION USING BACKROPAGATION ALGORITHM

Using the backpropagation, the weight of each factor can be recognized and it can be used to weight determination for landslide susceptibility. Zhou (1999) described the method of determination of the weight using backpropagation. From Eq. (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 o_k with respect to o_j such as Eq. (6):

$$\frac{\partial o_k}{\partial o_j} = f'(net_k) \cdot \frac{\partial(net_k)}{\partial o_j} = f'(net_k) \cdot w_{jk}$$

(6)

The Eq. (6) equation can produce values with both positive and negative signs. If only the magnitude of the effects is of interest, the importance of node j relative to another node $j0$ in the hidden layer can be calculated as the ratio of the absolute values from the Eq. (6):

$$\frac{|\partial o_k|}{|\partial o_j|} / \frac{|\partial o_k|}{|\partial o_{j0}|} = \frac{|f'(net_k) \cdot w_{jk}|}{|f'(net_k) \cdot w_{j0k}|} = \frac{|w_{jk}|}{|w_{j0k}|}$$

(7)

The Eq. (7) shows that, with respect to a particular node k in the output layer, the relative importance of a node j in the hidden layer is proportional to the absolute value of the weight on its connection to the node k in the output layer. When more than one node in the output layer is concerned, the Eq. (7) equation cannot be used to compare the importance of two nodes in the hidden layer. In other words, the relative importance of a node must somehow normalized to make it more comparable with that of other nodes. One choice is to let, in (7):

$$w_{j0k} = \frac{1}{J} \cdot \sum_{j=1}^{J} |w_{jk}|$$

(8)

to obtain the normalized importance of node j with respect ton node k

$$t_{jk} = \frac{|w_{jk}|}{\frac{1}{J} \cdot \sum_{j=1}^{J} |w_{jk}|} = \frac{J \cdot |w_{jk}|}{\sum_{j=1}^{J} |w_{jk}|}$$

(9)

Therefore, with respect to the node k, each node in the hidden layer has a value greater or smaller than one, depending on whether it is more or less important than the average, respectively. With respect to the same node k, all the nodes in the hidden layer have a total importance such as Eq. (10):

$$\sum_{j=1}^{J} t_{jk} = J$$

(10)

Consequently, with respect to all nodes in the output layer, to which connected to hidden layer, the overall importance of node j can be calculated as Eq. (11):

$$t_j = \frac{1}{K} \cdot \sum_{k=1}^{K} t_{jk}$$

(11)

Similar to Eq. (9), with respect to the node j in the hidden layer, the normalized importance of the node i in the input layer can be defined as Eq. (12).

$$s_{ij} = \frac{|w_{ij}|}{\frac{1}{I} \cdot \sum_{i=1}^{I} |w_{ij}|} = \frac{I \cdot |w_{ij}|}{\sum_{i=1}^{I} |w_{ij}|}$$

(12)

With respect to the hidden layer, the overall importance of node i is done by Eq (13):

$$s_i = \frac{1}{J} \cdot \sum_{j=1}^{J} s_{ij}$$

(13)

Correspondingly, the overall importance of the input node i with respect to the output node k is given by Eq. (14):

$$st_i = \frac{1}{J} \cdot \sum_{j=1}^{J} s_{ij} \cdot t_j$$

(14)

APPLICATION

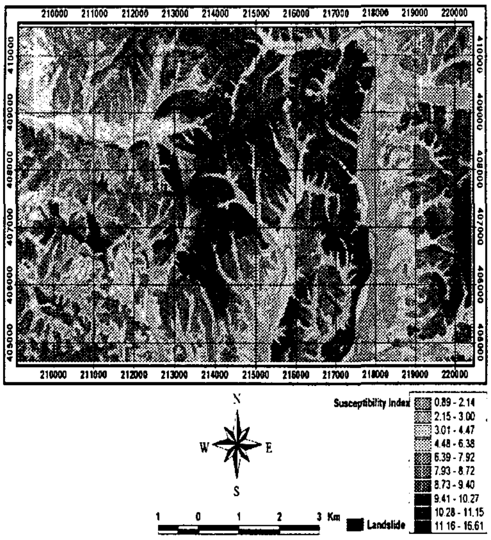
The factors were inputted to a MATLAB based application program that we had developed. Using the 7 × 15 × 2 (number of input, hidden and output layers) structure. The input data normalized to the range 0.1 to 0.9, learning rate was set to be 0.01, and the initial weights were randomly selected. From each of the two classes (landslide and not-landslide), 200 pixels per class were selected as training pixels randomly. The 10 training sites were selected randomly for influence of the training site and the training sites were processed 10 times literately for recognizing the change of initial weight.

After training, the weights were determined, as shown in Table `. As the initial weights were assigned random values, the results were not the same. Therefore, in this study, the calculation was repeated 10 times, and the results revealed similar values. The topographic curvature value used was the minimum value, 1.00, and the topographic slope used was the maximum value, 5.33.

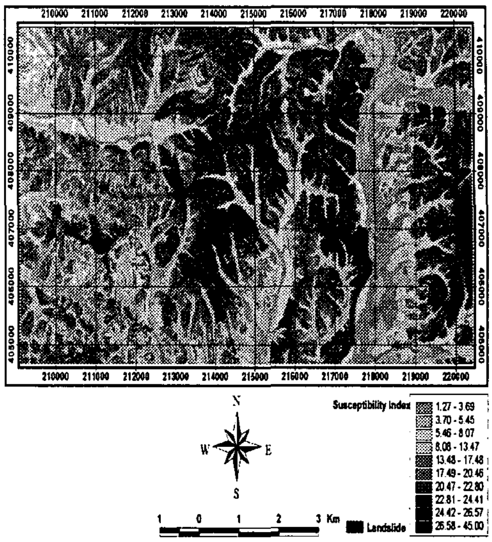
CONCLUSION AND DISCUSSION

In the Yongin area, landslide occurrence locations were formed into a GIS database. Various maps were constructed of the landslide-related factors derived from the database. Among the factors, the topographic slope, topographic curvature, soil drainage, soil effective thickness, soil texture, wood diameter, and wood age were used for the determination of the weights. Using these factors, probability methods with and without weights were applied to analyze the landslide susceptibility. The weight was determined using an artificial neural network method. The analyzed results were used to reconstruct a GIS database, and mapped. The results were verified and compared by calculating the correlation observed between landslide occurrence location and the results. The verification results showed a satisfactory agreement between the susceptibility map and landslide location data. The comparison result with weighting was better than the results without weighting.

The objective and scientific weight and rating are essential to the landslide hazard mapping and the weights can be applied to an area that needs weighting and rating such as groundwater pollution assessment and soil loss assessment. Landslide susceptibility maps are very helpful to planners and engineers for choosing suitable locations to carry out developments. However, the methods used in this study are valid for generalized planning and assessment purposes, although they may be less useful at the site-specific scale, where local geological and geographic heterogeneities may prevail. For the method to be applied in general, more landslide location data are needed, as well as its application to more regions. Fortunately, the landslide-related spatial database for topography, soil, forest, and geology is already available for most areas of Korea, so the landslide analysis can be performed quickly and cheaply for all of Korea.



(a)without Weighting



(b) With Weighting

Factors \ Number of test		1	2	3	4	5	6	7	8	9	10	Mean	Std.	Normalized Weight*
Topography	Slope	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	0.07	0.06	0.06	0.05	0.08	0.08	0.06	0.06	0.07	0.08	0.06	0.0	1.00
Soil	Drainage	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	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	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
Timber	Diameter	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	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

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