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Landslide susceptibility mapping using geological data, a DEM from ASTER images and an Artificial Neural Network (ANN)

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ABSTRACT

An efficient and accurate method of generating landslide susceptibility maps is very important to mitigate the loss of properties and lives caused by this type of geological hazard. This study focuses on the development of an accurate and efficient method of data integration, processing and generation of a landslide susceptibility map using an ANN and data from ASTER images. The method contains two major phases. The first phase is the data integration and analysis, and the second is the Artificial Neural Network training and mapping. The data integration and analysis phase involve GIS based statistical analysis relating landslide occurrence to geological and DEM (digital elevation model) derived geomorphological parameters. The parameters include slope, aspect, elevation, geology, density of geological boundaries and distance to the boundaries. This phase determines the geological and geomorphological factors that are significantly correlated with landslide occurrence. The second phase further relates the landslide susceptibility index to the important geological and geomorphological parameters identified in the first phase through ANN training. The trained ANN is then used to generate a landslide susceptibility map. Landslide data from the 2004 Niigata earthquake and a DEM derived from ASTER images were used. The area provided enough landslide data to check the efficiency and accuracy of the developed method. Based on the initial results of the experiment, the developed method is more than 90% accurate in determining the probability of landslide occurrence in a particular area.

1. Introduction

The occurrence of landslides is the result of the interaction of complex and diverse environmental factors. These factors are divided into the trigger and the primary cause. Landslide occurrence triggers include weathering, earthquakes, rainfall and snow melting. Human activity like construction of roads and buildings on steep slopes and dispersal of water from supply systems and sewers could also trigger the occurrence of the phenomena (Cubito et al., 2005). Important primary causes include geomorphic and geologic features, rock outcropping, rock types and vegetative cover (Zêzere et al., 1999a; Fernandes et al., 2004; Cubito et al., 2005; Moreiras, 2005). Primary causes of landslides could include a wide range of factors like flow accumulation and distance to roads (Dahal et al., 2008), topographic-wetness and stream-power indices (Gokceoglu et al., 2005) and land use, presence of old landslides and human activity (Zêzere et al., 1999b). Studies on the dynamics and interactions of the different factors affecting landslide occurrence are very important for successful landslide risk assessment. Several studies have been conducted to determine the relationship between various environmental factors and landslide occurrences (Anbalagan, 1992; Lee and Min, 2001; Iwahashi et al., 2003; Ayalew and Yamagishi, 2005).

Landslides are one of the most destructive geological hazards affecting Japan every year. Major landslides are normally triggered by strong earthquakes, like the ones that devastated Niigata Prefecture in Honshu Island in 2004. Several studies have been conducted on landslides after the 2004 earthquake. Some of them concentrated on the contribution of the geologic and geomorphic factors to landslides (Chigira and Yagi, 2006; Yagi et al., 2007). Yagi et al. (2007) found a strong relationship between landslide occurrence and geologic and geomorphic factors (slope and aspect) in landslide concentrated areas. However, analyzing the results of these studies for predicting future occurrence of landslides using conventional statistical analytical tools is very important. Indeed, landslide occurrence prediction requires a quantitative methodology to model these complex phenomena from past events using data gathered in the field or in the laboratory (Melchiorre et al., 2006). However, the complicated non-linear relationships between landslide occurrence and its contributing factors require the use of a complex modeling method for more accurate prediction.

Artificial Neural Network (ANN) has recently been an analytical tool for a wide range of applications in the fields of natural sciences. These applications include speech recognition (Bengio, 1993), human face recognition (Soulie et al., 1993), satellite image classification (Civco, 1993; Atkinson and Tatnall, 1997; Bandibas and Kohyama, 2001) and

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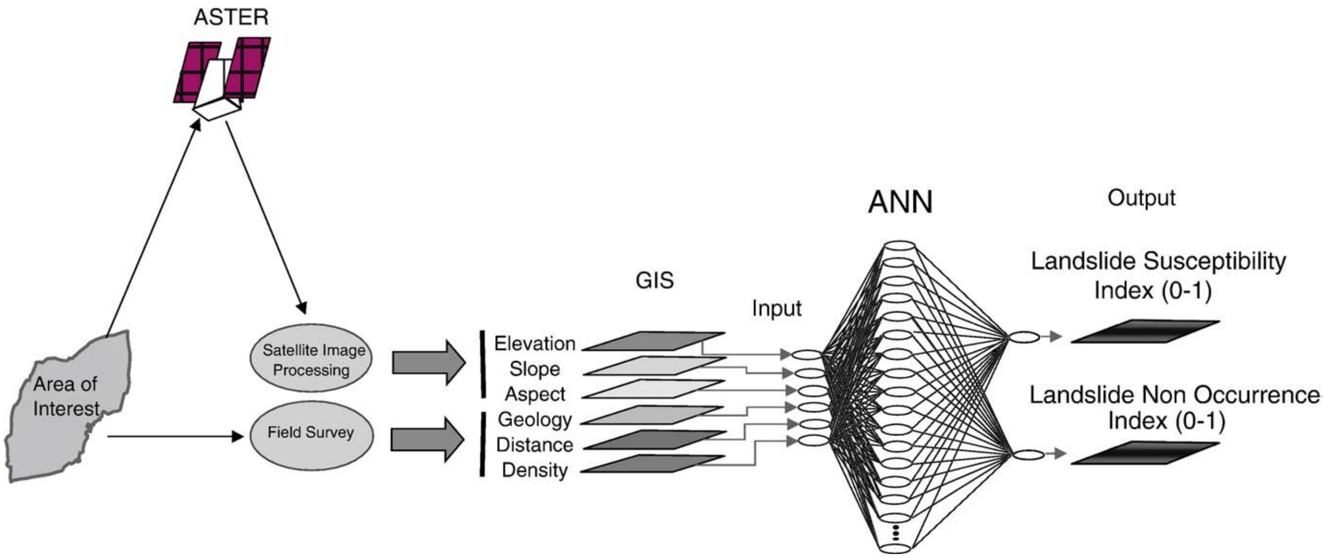

Fig. 1. Landslide susceptibility mapping system using Artificial Neural Network (ANN), ASTER satellite based geomorphic data and geological factors.

shape and texture recognition (Khotanzad and Lu, 1991). One of the advantages of using an ANN for qualitative modeling of natural phenomena is that it can handle data at any measurement scale ranging from nominal, ordinal to linear and ratio, and any form of data distribution (Wang et al., 1995). In addition, it can easily handle qualitative variables making it widely used in integrated analysis of spatial data from multiple sources for prediction and classification. A number of authors have described the basic principles and applications of ANNs for pattern recognition (Rumelhart et al., 1986; Alexander and Morton, 1990; Sethi and Jain, 1991; Guyon and Wang, 1993; Nigrin, 1993; Haykin, 1994). ANNs are data-driven models and universal non-linear function approximators. Consequently, ANNs have been important modeling tools for landslide susceptibility zonation (Lee et al., 2003; Lu and Rosenbaum, 2003; Ermini et al., 2005; Gomez and Kavzoglu, 2005). ANNs' ability to learn non-linear functions from the data is an important feature in the problem of classifying landslide-prone areas (Melchiorre et al., 2006).

This study focuses on the use of an ANN to quantitatively model the relationship between landslide occurrence and geologic/geomorphic factors and to accurately and efficiently generate landslide susceptibility maps. Data obtained from the landslide areas in Niigata Prefecture, Japan, were used in this study. This research also aims to determine the feasibility of developing an efficient method of generating landslide susceptibility mapping system by using the data gathering system of Japan's Advanced Spaceborne Thermal Emission Radiometer (ASTER) satellite (Fig. 1). This research uses ASTER images to generate important inputs such as geomorphic information for landslide modeling.

2. Methods: ANN

2.1. Error Back-Propagation ANN computing

Neural computing is the study of networks of adaptable nodes which, through a process of learning from task examples, store experiential knowledge and make it available for use (Alexander and Morton, 1990). The aim of ANN computing is to build a new model of the data generating process so that it can generalize and predict outputs from inputs (Atkinson and Tatnall, 1997). One of the most important neural computing methodologies is the Error Back-Propagation Neural Network (EBPNN) computing. In this method, neurons are organized as sequential layers, each composed of one or more neurons: the input layer, middle layer(s) and output layer. It is a feed forward network where each path has a weight assigned to it that dictates the scale of relationships between neurons. Weights can take positive or negative values and their distribution within an ANN determines its information processing behavior. To process information, a set of patterns is given to its input layer, which has one input and several output paths for each neuron N_i. Results from the input layer are processed by the middle (hidden) layer(s) where there are several input and output paths for each neuron N_j. It is through the middle layer that the ANN has an internal representation of the problem. The output layer with several input paths, but just one output path for each neuron N_k, processes the results of the middle layer to give the output pattern. The use of ANN for modeling information patterns involves two stages: the training stage, wherein the weights of the connection between neurons are adjusted; and the classification stage wherein the trained ANN uses input patterns to predict outputs. Fig. 2 shows an example of feed forward EBPNN. It has b and c numbers of neurons in the input and output layers, respectively.

Training of a feed forward neural network involves the iterative alteration of weights between neurons. This alteration is done with training patterns, a list of inputs and desired outputs that serves as examples. Pattern probabilities are equal, which means that no pattern is more "important" than others in the representation of the problem. Initially, weights between neurons are determined randomly. A pattern is presented to the network and the computed results (output) are compared with the desired results. Obviously, the initial outputs will not be similar to the desired ones and we have an error proportional to the

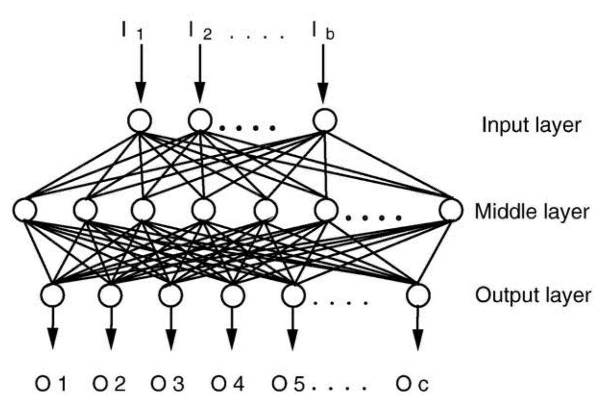

Fig. 2. A 3-layered feed forward Artificial Neural Network with b and c number of neurons in the input and output layers, respectively.