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GIS and ANN model for landslide susceptibility mapping

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Abstract: Landslide hazard is as the probability of occurrence of a potentially damaging landslide phenomenon within specified period of time and within a given area. The susceptibility map provides the relative spatial probability of landslides occurrence. A study is presented of the application of GIS and artificial neural network model to landslide susceptibility mapping, with particular reference to landslides on natural terrain in this paper. The method has been applied to Lantau Island, the largest outlying island within the territory of Hong Kong. A three-level neural network model was constructed and trained by the back-propagate algorithm in the geographical database of the study area. The data in the database includes digital elevation modal and its derivatives, landslides distribution and their attributes, superficial geological maps, vegetation cover, the raingauges distribution and their 14 years 5-minute observation. Based on field inspection and analysis of correlation between terrain variables and landslides frequency, lithology, vegetation cover, slope gradient, slope aspect, slope curvature, elevation, the characteristic value, the rainstorms corresponding to the landslide, and distance to drainage line are considered to be related to landslide susceptibility in this study. The artificial neural network is then coupled with the ArcView3.2 GIS software to produce the landslide susceptibility map, which classifies the susceptibility into three levels: low, moderate, and high. The results from this study indicate that GIS coupled with artificial neural network model is a flexible and powerful approach to identify the spatial probability of hazards.

GIS and ANN model for landslide susceptibility mapping XU Zeng-wang (State Key Laboratory of Resources and Environment Information System, Institute of Geographic Sciences and Natural Resources Research, CAS, Beijing 100101, China) 1 Introduction The population growth and the expansion of settlements and life-lines over hazardous areas exert increasingly great impact of natural disasters both in the developed and developing countries. In many countries, the economic losses and casualties due to landslides are greater than commonly recognized and generate a yearly loss of property larger than that from any other natural disasters, including earthquakes, floods and windstorms. Landslides in mountainous terrain often occur as a result of heavy rainfall, resulting in the loss of life and damage to the natural and/or for human environment. Potential sites that are prone to landslides should therefore be identified in advance to reduce such damages. In this regard, landslide hazard mapping can provide much of the basic information essential for hazard mitigation through proper project planning and implementation. Earth sciences, and geomorphology in particular, may play a relevant role in assessing area at high landslide hazard and in helping to mitigate the associated risk, providing a valuable aid to a sustainable progress. Tools for handling and analyzing spatial data (i.e. GIS) may facilitate the application of quantitative techniques in landslide hazard assessment and mapping[1]. Landslide hazard was defined by Varnes[2] as the probability of occurrence of a potentially damaging landslide phenomenon within a specified period of time and within a given area. The probability of landslide depends on its geographical environment around it, that is, the geographical factors determining the landslides and their intensity. Dai[3] has grouped the factors which determine the landslide hazard of an area into two categories, the quasi-static and dynamic variables. The spatial distribution of the quasi-static variables within a given area determines the spatial distribution of the landslide susceptibility in the region[1]. Up to now, most of the studies have focused on the indirect mapping of landslide susceptibility rather than on landslide hazard as defined by Varnes (1984). These studies have been largely based on the general principle that "the past and the present are the keys to the future", i.e. future slope failures will be more likely to occur under those conditions which led to past and present landslides[1,4,5]. Many method s and techniques for assessing landslide hazards have been proposed or tested. Statistical models were used in the statistical determination of the combinations of variables that have led to past landslides. Quantitative or semi-quantitative estimates are then made for areas currently free of landslides, but with similar conditions. Both simple and multivariate statistical approaches have been widely used in such an indirect mapping of landslide susceptibility [1,5-11]. Statistical techniques are generally considered as the most appropriate approach for landslide susceptibility mapping at scales of 1:20,000 to 1:50,000, because at such a scale range it is possible to map out in detail the occurrence of past landslides, and to collect sufficient information on the relevant variables that are considered to be relevant to the occurrence of landslides[11]. GIS has provided various functions of handling, processing, analyzing, and reporting of geo-spatial data[12]. The overlay operation commonly applied within GIS is useful in both heuristic and statistical approaches[1,8,10,13-15]. An important aspect of the statistical methods is the capability to supply probabilistic forecasts. However, there are several difficulties with the method such as the identification of all the relevant triggering factors that will be used as ´explanatory´ variables for each landslide. An artificial neural network (ANN) is believed to process information in a manner similar in some ways to that of the human brain, although their processing capability is much lower than that of the human brain. The artificial neural network consists of a set of simple processing units arranged in a defined architecture and connected by weighted channels which act to transform the environmental factors into a susceptibility level. An artificial neural network model use a small training sets and, once being trained, it is rapid computationally, which will be of value in processing the large dataset. According to French[15], there are several advantageous characteristics of the neural network approach to modeling, designing, or problem solving as follows: (1) the problem or task addressed may be either poorly defined or understood, and observations of the process may be difficult or impossible to perform; application of a neural network does not require a priori knowledge of the underlying process; (2) one may not recognize all of the existing complex relationships between aspects of the process under investigation; through a training procedure the neural network incorporates the role of all necessary relationships controlling the process; (3) a standard optimization approach or statistical model provides a solution only when being allowed to run to the completion; the neural network always converges to an optimal (or suboptimal) solution and need not run to any prespecified solution condition; (4) neither constraints nor an a priori solution structure is necessarily assumed or strictly enforced in the NN development. These characteristics eliminate, at least to some degree, the difficulties concerning regression-based methodologies: primarily the need for the forecaster to select the explanatory variables and the dependence on an understanding of the local conditions. We introduce the geographical environment of the Lantau Island and provide descriptive statistics of the landslide pertinent factors in Section 2. The technological scheme incorporates the GIS and artificial neural network model to mapping landslides susceptibility is presented in Section 3. Section 4 provides a specific description of the back propagate artificial neural network model adopted in this study. A landslide susceptibility map has been provided through the using of the trained neural network model in Section 5. Finally the results of the research of coupling GIS and intelligent model are discussed.

2 Description of the study area

2.1 Geographical environment

Lantau Island, situated in the southwestern part of Hong Kong with a total land area of about 143 km2, has been selected as the study area in this research. Lantau Island, the largest outlying island within the territory of Hong Kong, is virtually undeveloped and uninhabited, mainly because of the steep natural terrain, with slope angles generally between 20o and 40o. The ground generally rises at about 30o from sea level everywhere on the island. Elevation ranges from the sea level to over 900 m above sea level and changes abruptly. The only flat land exists as occasional small coastal patches. The bedrock geology of the study area consists of volcanic rocks and the younger granitic suite of rocks. Deposits of younger superficial materials that are generally colluvial, alluvial or littoral in character, sometimes overlie the bedrock materials, which are often heavily weathered in-situ to form deep residual deposits. The oldest rocks are the sandstones and siltstones. These are sedimentary rocks that occur as a small outcrop. Extensive deposits of colluviums probably blanketed the landscape as a result of numerous individual episodes of mass wasting and erosion during Quaternary. In recent times, the alluvium and raised beach sediments were deposited under the combined influence of higher sea levels and fluctuating climatic conditions[16,17]. The foot slope terrain is generally covered by natural woody forest, whereas dense bushes or grass covers the mid-slopes. Bedrock outcrops occur on the steep terrain with gradients exceeding 40o, and on mountain peaks. The climate is sub-tropical and monsoonal, with mild, dry winters and hot, humid summers. Rainfall is high, and occasionally intense during the rainstorms and typhoons. Given the steep natural terrain mantled with a layer of superficial deposits and the frequent intense rainfall, it is not surprising that landslides commonly occur on such natural terrains. On 4-5 November 1993, the late-season passage of typhoon Ira dumped over 400 mm rainfall in 24 hours ending at 10:00 am on 5 November for most parts of Lantau Island, wi th a maximum of over 700 mm in the Tung Chung area where the rainfall was most intense[18]. As a result of intense rainfall, over 893 landslides occurred on the natural terrain of Lantau Island. The locations of all observable natural terrain landslides in the study area that took place during and prior to November, 1993, rainstorms were identified with the use of 6000 feet aerial photographs by the Geotechnical Engineering Office (GEO), Hong Kong[19], resulting in an average density of 6.1 landslides/km2 that year .The locations of the crowns of the landslides are shown in Figure 1. Site inspections indicates that the landslides have the following characteristics: (1) the volume of failure generally ranged from tens of cubic meters to over a thousand cubic meters; (2) the failures generally occurred along the colluviums-bedrock contact, and predominant failure mode is translational based on the shape of the failure surface; and (3) most landslides started as slides and quickly converted to flows because of the water involved and the steep terrain below the debris sources[19,20]. 2.2 Descriptive statistics of pertinent factors There are 5670 landslides throughout the island. According to the year inventory, the distribution of landslide number is described in Figure 1. The inventory began in 1945, so all the landslides before are labeled as 1945. There are 5670 landslides spread 22 years from 1945 to 1994. Figure 1 Distribution of landslides in Lantau Island according to the years of inventory 3 Procedure The procedure of landslide susceptibility mapping adopted here begins with the definition of terrain variable using the data of landslide inventory on the basis of terrain conditions. Two classes of samples indicating that landslide has occurred and not occurred respectively are used to obtain variables of statistically meaningful and to develop an artificial neural network model with input layer, hidden layer and output layer. The model is trained by back propagation method then coupled with the Arcview GIS software to map landslide susceptibility. A flowchart of the methodology is presented in Figure 2. Figure 2 Flow chart of the methodology 4 Artificial neural network model Neural networks are mathematical models of theorized mind and brain activity which attempt to exploit the massively parallel local processing and distributed storage properties believed to exist in the brain. Neural networks are also referred to ad connectionist systems or parallel distributed processors. The areas addressed by NN approaches include data compression, optimization, pattern matching, system modeling, and function approximation[21]. When a NN is used to address a complex non-linear problem, such as the task at hand, it must first learn the mapping of input to output. The learning process, or training, forms the interconnections (correlations) between neurons and its accomplished using known inputs and outputs, and presenting these to the NN in some ordered manners. The strength of these interconnections is adjusted using an error convergence technique, so that a desired output will be produced for a given input. Once formed, the interconnections remain fixed and the NN is used to carry out the intended task. In this section, the structure of the NN is explained by describing the path followed by the trained NN in performing a computation. Figure 3 Structure of the back propagate artificial neural network model with three layers The neural network was developed as a three-layer learning network, consisting of an input layer, a hidden layer and an output layer as shown in Figure 3. Each layer is made up of several units, and layers are interconnected by sets of correlation weights. The units receive input from either outside the model (the initial inputs) or from the interconnections. Units operate on the input transforming it to produce an analogue output called the firing rate. The weights function to multiply an incoming firing rate prior to its arrival at the next layer. Figure 4 A typical artificial neural network unit. The weighted inputs to the unit are summed to derive the net input to the unit (netj) and this is passed through the unit´s activation function (f) to determine the magnitude of the output from the unit where is the weight of the interconnection channel to unit from unit (or input) and is the output of unit (or external input). This net input is then transformed by the activation function to produce an output ( ) for the unit. The transformation associated with each unit is a sigmoid function defined as, where is a gain parameter, which is often set to 1, and a bias weight are often used. The values for the weighted channels between units are not set by the analyst for the task at hand but rather determined by the network itself during training. Conventionally a backpropagation learning algorithm is used which iteratively minimizes an error function over the network outputs and a set of target outputs, taken from a training data set. Training begins with the entry of the training data to the network, in which the weights connecting network units were set randomly. These data flow forward through the network to the output units. Here the network error, the difference between the desired and actual network output, is computed. This error is then fed backward through the network towards the input layer with the weights connecting units changed in proportion to the error. The whole process is then repeated many times until the error rate is minimized or reaches an acceptable level. Conventionally the overall output error is defined as half the overall sum of the squares of the output errors, which for the pth training pattern is, where is the desired output and the actual network output of unit , and the total epoch error is, On each iteration back propagation recursively computes the gradient or change in error with respect to each weight, , in the network and these values are used to modify the weights between network units. The weights are changed b y, where is the change for the weight which connects the th with its th incoming connection, is a constant that defines the learning rate, is the computed error and the value of the th incoming connection. For training by epoch an overall correction to a weight is made after the presentation of all the training data and is, The calculation of the error, , varies for output and hidden units. Since the desired output is known for the training data the error for the output units may, assuming the use of a sigmoid activation function with , be calculated from, whereas for a hidden unit, whose outputs are connected to k other units, the error is defined in proportion to the sum of the errors of all k units as modified by the weights connecting these units by, Once the overall output error has declined to an acceptable level, which is typically determined subjectively, training ceases. 5 Susceptibility mapping The ANN model is coupled with GIS to map the susceptibility of natural landslide on Lantau Island. A three-level classification scheme, ranging from low to high susceptibility, was employed for the produced probability. The final product of the anslysis is shown in Figure 5. It should be noted that the complexity of the failure processes means that any evaluation of stability contains a considerable amount of uncertainty. The method in the analysis is limited in this specific research. Because different pilot regions might provide different quality of triggering factors. But the ANN model can provide not only a computing schema, but a conceptual model to use the non-linearity and optimized method in the risk assessment with GIS. Figure 5 Landslides susceptibility map produced by ANN model 6 Conclusions and discussion Artificial neural networks are not, however, a panacea. There are a series of problems and limitations in the use of an artificial neural network. For instance, the definition of the network architecture and selection of a learning algorithm are largely subjective and interpretation of the results restricted as the trained network is semantically poor. References

关键词： GIS; artificial neural network model; landslide susceptibility mapping