MINERAL POTENTIAL MAPPING AND VERIFICATION OF LIMESTONE DEPOSITS USING GIS AND ARTIFICIAL NEURAL NETWORK IN THE GANGREUNG AREA, KOREA

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ABSTRACT : The aim of this study was to analyze limestone deposits potential using an artificial neural network and a Geographic Information System (GIS) environment to identify areas that have not been subjected to the same degree of exploration. For this, a variety of spatial geological data were compiled, evaluated and integrated to produce a map of potential deposits in the Gangreung area, Korea. A spatial database considering deposit, topographic, geologic, geophysical and geochemical data was constructed for the study area using a GIS. The factors relating to 44 limestone deposits were the geological data, geochemical data and geophysical data. These factors were used with an artificial neural network to analyze mineral potential. Each factor's weight was determined by the back-propagation training method. Training area was applied to analyze and verify the effect of training. Then the mineral deposit potential indices were calculated using the trained back-propagation weights, and potential map was constructed from GIS data. The mineral potential map was then verified by comparison with the known mineral deposit areas. The verification result gave accuracy of 87.31% for training area.

KEY WORDS: Limestone, Mineral potential mapping, GIS, Artificial neural network, Korea

1. INTRODUCTION

Modern exploration is a multidisciplinary task requiring the simultaneous consideration of numerous disparate geological, geochemical and geophysical datasets. GIS methods for processing and combining data within maps are useful in exploration for deposits. This study uses GIS to integrate and analyze a variety of geoscientific data, including geology, and geochemical and geophysical anomalies. This application builds a model using observations about the association of mineral occurrences with various geological features in a qualitative manner. The degree of accuracy of the final mineral potential map relies mainly on the validity of the model, the knowledge of the geologist and on the quality of the data collected.

The objective of this study was to evaluate the spatial relationship between various datasets and generate a limestone potential map using artificial neural network in the Gangreung area of Korea. Especially, the selecting of training site is important in artificial neural network.

The study area is bounded by latitudes 37°00′–38°00′ N and longitudes 127°45′–129°35′ E and lies in the east-center of the Korean Peninsula (Fig. 1). This region has many mineral deposits and geological, geochemical and geophysical survey data are available.

Many probabilistic and statistical models have been proposed for mineral resource assessment; for example, weights of evidence (Bonham-Carter et al., 1994), logistic regression (Agterberg, 1988), fuzzy logic (Knox-Robinson, 2000) and artificial neural network (Brown et al., 2000). Most of these approaches have been successfully applied to mineral resource appraisal.

Figure 1. Study area.

2. DATABASE

The preparation of mineral potential maps using GIS was accomplished in four major steps: (1) Assembly of a spatial database. (2) Processing the data from the database. (3) Application of a weight to generate a mineral potential map. (4) Verification of the mineral potential map using known mineral deposits.

The mineral deposit map (Koh et al., 2003) was based on the classification of mineral variety and deposit type. A total of 44 limestone deposits of sedimentary type were used to create a spatial database using GIS. The geological, geochemical and geophysical maps were similarly treated. The factors related to limestone mineral occurrence are the geological data(Kim et al., 2001) of lithology and fault structure (Fig. 2), geochemical data (Lee et al., 1998), including the presence of As, Ba, Ca, Cd, Cl^-, Co, Conductivity, Cr, Cu, Eh, F^-, Fe, K, Li, Mg, Mn, Mo, Na, Ni, NO_2^-, NO_3^-, Pb, pH, PO_4^{2-}, Si, SO_4^{2-}, Sr, V, W and Zn, and the geophysical data(Koo et al., 2001) on the Bouguer and magnetic anomalies. All of these factors were used within a spatial database with a pixel size of 100 m^2. The numbers of rows and columns were 1122 and 1505, respectively.

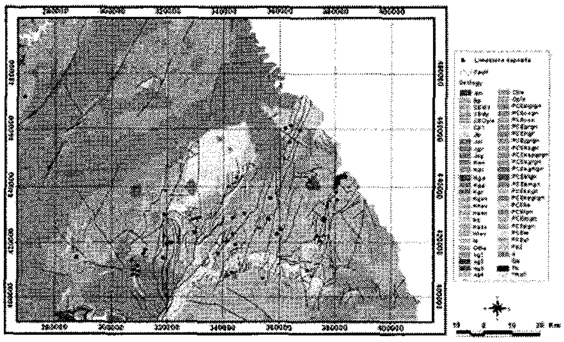
Figure 2. Geological map with mineral deposits.

3. ARTIFICIAL NEURAL NETWORK

The 36 factors were used as the input data. The mineral deposit locations and the non-mineral deposit locations were selected as training area. Pixels from each of the two classes were selected as training pixels, with 44 pixels denoting areas where mineral deposits occurred. If the analysis selected more than 44 sites with the same value, then the sites were selected randomly.

The back-propagation algorithm was applied to calculate the weights between the input layer and the hidden layer, and between the hidden layer and the output layer, by modifying the number of hidden node and the learning rate. A three-layered feed-forward network was implemented using the MATLAB software package based on the framework provided by Hines (1997). 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 36 x 72 x 2 structure was selected for the network, with input data normalized in the range 0.1-0.9. The learning rate was set to 0.01, and the initial weights were randomly selected to values between 0.1 and 0.3. The weights calculated from 5 test cases were compared to determine whether the variation in the final weights was dependent on the selection of the initial weights. The results show that the initial weights did not have an influence on the final weight under the conditions used. The back-propagation algorithm was used to minimize the error between the predicted output values and the calculated output values. The algorithm propagated the error backwards, and iteratively adjusted the weights. The number of epochs was set to 3,000, and the root mean square error (RMSE) value used for the stopping criterion was set to 0.01. Most of the training data sets met the 0.01 RMSE goal. However, if the RMSE value was not achieved, then the maximum number of iterations was terminated at 3,000 epochs. When the latter case occurred, then the maximum RMSE value was <0.2.

The final weights between layers acquired during training of the neural network and the contribution or importance of each of the 36 factors used to predict mineral deposit potential are shown in Table 1. The results were not the same, as the initial weights were assigned random values. Therefore, in this study, the calculations were repeated 5 times, to allow the results to achieve similar values. Finally, the weights were applied to the entire study area, and the mineral deposit potential map was created for training area (Fig. 3).

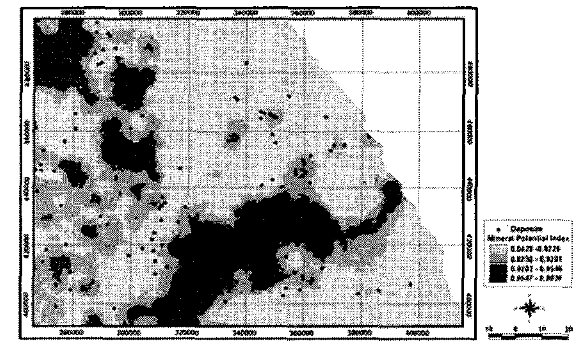
Figure 3. Limestone mineral potential maps based on artificial neural network model.

4. VERIFICATION

The result of the mineral potential analysis was verified by comparing known deposit location data with the mineral potential map. Rate curve was drawn and the areas under the curve were determined in the case. The rate shows how well the model and factors predict the mineral deposit occurrence; thus, the area beneath the curve qualitatively assesses the prediction accuracy.

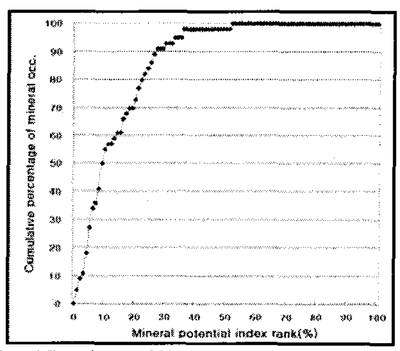

Figure 4. Verification of limestone mineral potential map.

To obtain the relative ranking for each prediction pattern, the calculated index values of all the pixels in the study area were sorted in descending order. The ordered pixel values were then divided into 100 classes with accumulated 1% intervals. The rate verification results appear as a line in Fig. 4. The graph was selected what showed the best prediction accuracy among the 5 running.

To compare the result quantitatively, the areas under the curve were re-calculated as if the total area were one, which indicates perfect prediction accuracy. The area beneath a curve can therefore be used to assess the prediction accuracy qualitatively. The area ratio was 0.8731 and we determined that the prediction accuracy was 87.31%.

Table 1. Weight of artificial neural network.

Run / Factors	Run1	Run2	Run3	Run4	Run5	Ave.	S.D	N.V.*
Al	0.030	0.027	0.026	0.030	0.025	0.028	0.003	1.043
Alkal.	0.029	0.026	0.030	0.028	0.026	0.028	0.002	1.055
As	0.024	0.028	0.029	0.028	0.029	0.028	0.002	1.043
Ba	0.027	0.028	0.025	0.029	0.029	0.028	0.001	1.042
Boug.	0.026	0.028	0.030	0.026	0.025	0.027	0.002	1.016
Ca	0.028	0.032	0.028	0.028	0.027	0.029	0.002	1.081
Cd	0.025	0.024	0.034	0.026	0.029	0.027	0.004	1.039
Cl^-	0.028	0.028	0.024	0.027	0.026	0.027	0.002	1.017
Co	0.033	0.026	0.025	0.028	0.024	0.027	0.003	1.029
Cond.	0.024	0.032	0.028	0.030	0.032	0.029	0.003	1.102
Cr	0.028	0.027	0.024	0.027	0.028	0.027	0.001	1.017
Cu	0.027	0.030	0.028	0.027	0.028	0.028	0.001	1.055
Eh	0.028	0.028	0.022	0.029	0.033	0.028	0.004	1.066
F^-	0.029	0.025	0.026	0.027	0.024	0.026	0.002	1.001
Fault	0.034	0.026	0.028	0.027	0.028	0.028	0.003	1.074
Fe	0.027	0.026	0.028	0.027	0.026	0.026	0.001	1.000
Geol.	0.023	0.033	0.029	0.027	0.031	0.029	0.004	1.081
K	0.030	0.026	0.031	0.024	0.029	0.028	0.003	1.060
Li	0.027	0.028	0.027	0.029	0.027	0.028	0.001	1.045
Mag.	0.027	0.026	0.027	0.029	0.029	0.028	0.002	1.045
Mg	0.027	0.030	0.027	0.027	0.024	0.027	0.002	1.025
Mn	0.025	0.029	0.027	0.032	0.031	0.029	0.003	1.088
Mo	0.030	0.030	0.030	0.027	0.032	0.030	0.002	1.121
Na	0.027	0.029	0.027	0.027	0.029	0.028	0.001	1.054
Ni	0.031	0.025	0.028	0.027	0.025	0.027	0.002	1.037
NO_2^-	0.031	0.031	0.025	0.025	0.026	0.027	0.003	1.038
NO_3^-	0.029	0.027	0.031	0.031	0.025	0.028	0.003	1.071
Pb	0.028	0.027	0.030	0.032	0.028	0.029	0.002	1.102
pH	0.024	0.027	0.032	0.031	0.026	0.028	0.004	1.059
PO_4^{2-}	0.025	0.025	0.031	0.025	0.030	0.027	0.003	1.024
Si	0.031	0.029	0.025	0.024	0.026	0.027	0.003	1.024
SO_4^-	0.027	0.029	0.033	0.029	0.027	0.029	0.002	1.098
Sr	0.030	0.029	0.028	0.030	0.029	0.029	0.001	1.099
V	0.028	0.025	0.027	0.031	0.031	0.028	0.003	1.079
W	0.029	0.026	0.025	0.023	0.030	0.026	0.003	1.003
Zn	0.026	0.032	0.026	0.029	0.029	0.028	0.002	1.076

5. CONCLUSIONS AND DISCUSSIONS

In the study, the mineral potential map of limestone was made using the artificial neural network. As the results, prediction accuracy showed 87.31%. A number of areas within the study area have been identified as having high limestone potential. Many of these areas coincide with areas of known deposits. Others, however, are enigmatic and await follow-up exploration.

The GIS is not only capable of routine display, but also offer great potential by providing a range of tools to query, manipulate, visualize and analyze geological, geochemical and geophysical data in mineral exploration applications. The artificial neural network is useful for providing a quantitative measure of the weights among the factors for deposit prospects. Furthermore, the maps generated by the models, not only predict known areas of mineral occurrence, but also identify areas of potential mineralization where no known deposit occurs.

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