The Use of a Multilayer Feedforward Neural Network for Mineral Prospectivity Mapping

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Abstract

This paper reports a pilot study on the use of an artificial neural network in conjunction with a Geographic Information System (GIS) for the integration large multi-source data sets used in regional mineral exploration and prediction of mineral prospectivity. A multilayer feedforward neural network, trained with the error-backpropagation algorithm, is used to estimate the favourability for gold deposits from a raster GIS database for the Tenterfield 1:100,000 sheet area, NSW. To validate and assess the effectiveness of the neural-network method, mineral prospectivity maps were also prepared using the empirical weights of evidence and the conceptual fuzzy logic methods. The neural network produces a geologically-plausible mineral prospectivity map similar, but superior, to the fuzzy logic and weights of evidence maps. The results of this study indicate that neural networks have several advantages over existing methods.

1. Introduction

The development of faster, more efficient and objective Geographic Information System (GIS)-based methods for integration and analysis of regional exploration data sets has a potentially important role in supporting the decision-making process for geologists in ground acquisition and selection of exploration targets.

Neural networks have the ability to extract underlying patterns in a data set without pre-existing knowledge (e.g., a deposit model), and to operate at acceptable accuracy with noisy data. This suggests that they could be well suited to the integration of mineral exploration data and could be trained to recognise the geological and geophysical signatures of mineral systems in order to predict the location of new deposits.

2. Previous Work

Mineral prospectivity maps represent one way of combining the geological, geophysical, geochemical maps used in regional-scale exploration. Areas are ranked according to their potential to host mineral deposits of a particular type. An empirical or data-driven approach to the prospectivity mapping involves the statistical analysis of the spatial relationships of map features (e.g., faults, lithological units) to mineral deposit locations. The range of techniques used includes logistic regression [1], Boolean algebra, the index-overlay method [2], and weights of evidence [3]. Knowledge-driven or conceptual methods feature in later work and employ a range of artificial-intelligence computing techniques, such as fuzzy logic [4], evidential-belief theory [5], and expert systems [6].

Although neural networks have been applied to petroleum exploration [7,8], there are very few studies that describe the application of artificial neural networks to mineral exploration [9,10,11]. The use of neural networks for mineral prospectivity mapping has been described in only two previous studies [12,13].

3. GIS Database

3.1 GIS Thematic Layers

The GIS database for the trial study corresponds to the area of the Tenterfield 1:100,000 sheet (map 9339, Fig. 1), and was compiled by the Geological Survey of New South Wales [14]. The database comprises the following thematic layers; solid geology, regional-scale faults, airborne total magnetic intensity (classed image data), airborne gamma-ray spectrometry (U, Th, K and total count, classed image data) and deposit locations. The mineral deposit layer includes mineral occurrences, and small and medium-sized deposits. Each cell in the grid data represents a 200 metre square on the ground.

3.2 Geology

The area of the Tenterfield 1:100,000 sheet is located in the southern portion of the New England Orogen (Fig. 1). The highly fractionated Late Permian to Early Triassic leucogranites are the most important hosts to gold mineralisation. The mid-Triassic Stanthorpe Adamellite, appearing as a semi-circular body east of the Demon Fault in the north of the study area, hosts large, low-grade, primary, disseminated and secondary alluvial deposits. Numerous alluvial gold occurrences are scattered across the Bungulla Porphyritic Adamellite, which forms an arcuate body on the eastern margin of the Stanthorpe Adamellite [14].

Forty-seven secondary, thirteen primary, and five spatially-associated, granitoid-hosted gold deposits of unknown form were selected from the GIS deposit thematic layer for this study.

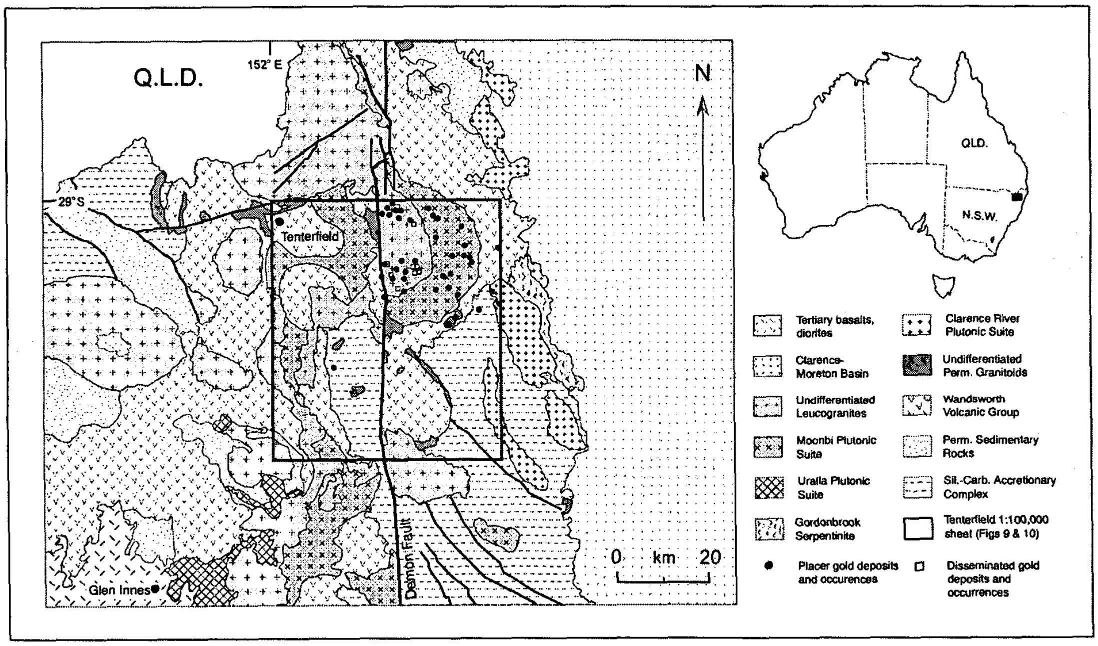


Figure 1. Location and simplified geology of the Tenterfield 1:100,000 sheet area adapted from an unpublished regional digital map supplied by the Geological Survey of New South Wales.

4. Methods

4.1 Data processing

A Multilayer Perceptron (MLP) neural network, trained using the error-back-propagation algorithm [15], was chosen for this study because it performs very well for a large variety of problem types and has powerful function-approximation capabilites [16].

Pre-Processing

All thematic layers in the GIS database were converted to raster format prior to further processing. The original solid geology layer contained 41 rock units, many of which contain zero or very few deposits. Consequently, units belonging to the same rock suite or stratigraphic group were combined, resulting in a simplified geology layer consisting of 12 rock units. The GIS database layer containing regional faults was converted to a grid in which the cell values indicate the distance to the nearest fault.

At each cell location in the Tenterfield 1:100,00 sheet grid, values from each thematic layer were combined to form a feature vector. Linear scaling was applied to both input feature vectors and the target values.

Input Coding, Network Topology and Network Parameters

A one-of-n coding scheme was applied to the solid geology layer so that each rock type was assigned a separate input unit. A single input unit was assigned to the magnetic, four gamma-ray, and fault-proximity layers. Binary coding was used for the single output unit, with one and zero representing the presence and absence of deposits, respectively. The number of units in the hidden layer of the network was determined experimentally, resulting in an 18-2-1 network topology. The learning rate and momentum were set to 0.5 and 0, respectively. Weights were randomly initialised in the range [-0.5,+0.5] and were updated incrementally.

Training Data Set Selection and Training

Training data were randomly divided into training, validation and test sets. (There were an insufficient number of deposit and occurrence points available to allow a third of the data to be reserved as a test data set in the statistically-based weights of evidence method.) Approximately equal numbers of deposit and non-deposit vectors were selected for each of the data sets. Since there are only 63 gold deposits of the required type in the Tenterfield area compared with 69,377 non-deposit cells, the size of the data sets used for training were limited by the number of deposits available. The training, validation and test data sets were each randomly assigned one third of the available deposit vectors (21 each), and two non-deposit vectors from each of the 12 main rock units, giving a total of 24 non-deposit vectors in each training set. The training patterns were presented to the network in a randomly permutated order.

Ten networks, using a different random set of initial weights, were trained. Training was stopped at the number of epochs corresponding to the minimum TSS error for the validation data set. The neural network giving the lowest error for the validation data set was used to process the input vectors for the whole Tenterfield grid.

Post-Processing

Output values produced by the trained network for the complete Tenterfield data set were re-scaled and classed to produce a multiclass prospectivity map.

4.2 Comparing Mineral Prospectivity Map Quality

Prospectivity maps depict areas ranked according to their potential to host mineral deposits of a particular type and therefore do not represent a classification of some extensive category, such as agricultural crop type, that can be readily checked. Instead, the following statistics were used to compare the quality of different mineral prospectivity maps:

1) conditional probabilities of the occurrence of known mineral deposits for each prospectivity map class were calculated using the numbers of grid cells, assuming that the deposits occupy a single cell each.

2) a high prospectivity map class should define an area in which a high proportion of the known deposits are predicted in a small proportion of the total map area. This can be expressed as the following ratio:

$$\frac{n(D_A)/n(D_{total})}{n(A)/n(T)} = \frac{P(D/A)}{P(D)} \qquad (1)$$

where $n(D_A)$ represents the number of deposits in map class A, $n(D_{total})$ is the total number of deposits, $n(A)$ is the area of map class A, $n(T)$ is the total area, $P(D/A)$ is the conditional probability of a deposit, given a particular prospectivity map class, and $P(D)$ is the probability of a deposit for the map area as a whole. In the highest group of prospectivity classes, the probability of finding a deposit should be significantly upgraded and the ratio should be greater than one.

3) the Chi-square statistic is used as a measure of the extent to which observed and expected numbers of deposits differ.

Applying similar reasoning as above, the observed number of deposits in the map classes with the highest favourability should be much higher than the number that would be expected if the distribution of deposits with respect to map classes were random.

4) Spearman's and Kendall's rank correlation coefficients are used to assess the degree to which the conditional probability of occurrence of known mineral deposits increases with increasing map-prospectivity class.

4.3 Preparation of weights of evidence and fuzzy logic prospectivity maps

As a basis for validating and comparing the performance of the neural network method, mineral prospectivity maps were prepared using both an empirical method, based on statistics and Bayesian probability, known as weights of evidence, and a conceptual method, based on fuzzy-logic.

Weights of Evidence Method

The weights of evidence method is based on the concept of prior and posterior probabilities and employs a log-odds formulation of Bayes rule [3]. The method results in some loss of information in the original data, since multiclass maps must be converted to binary maps prior to analysis and requires an assumption that parameters in the binary evidence maps are conditionally independent with respect to deposits. A full description of the weights of evidence method is given by Bonham-Carter [2].

Fuzzy Logic Method

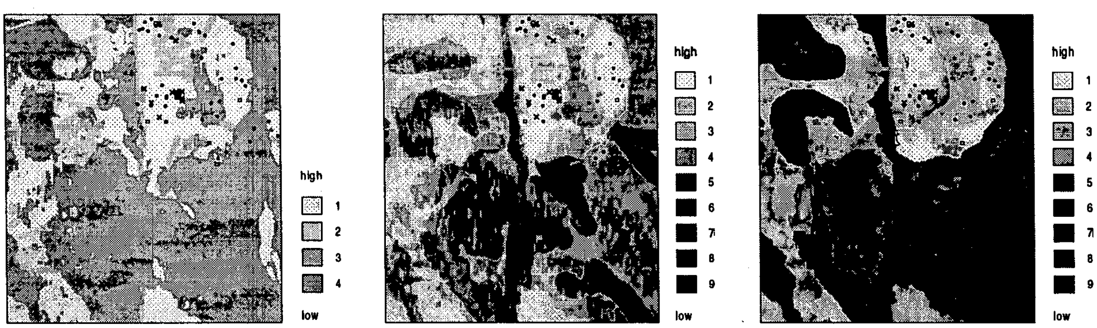
The degree to which the value of a GIS database parameter belongs to the fuzzy set "favourable for mineralisation" is expressed as a real number in the interval [0,1]. Fuzzy membership values were assigned to each parameter value stored in the GIS thematic layers according to subjective judgement. Fuzzy membership values from different layers were combined using a variety of different operators and fuzzy-logic inference nets. The prospectivity map that best accounted for the known deposit points while minimising the area of the highest prospectivity classes was chosen as the final fuzzy logic map. The gamma fuzzy operator with a value of 0.95 gave the best results. The fuzzy gamma operator is given by;

$$\mu_{comb} = \left[1 - \prod_{i=1}^{N}(1-\mu_i)\right]^{\gamma} \left(\prod_{i=1}^{N}\mu_i\right)^{1-\gamma} \qquad (2)$$

where $\gamma = [0,1]$ and μ_i is the fuzzy membership value for the i^{th} data set. Detailed descriptions of fuzzy operators are given by Zimmermann [17], An et al. [4], and Bonham-Carter [2]. Processing for the weights of evidence and fuzzy logic method was performed using the GEODIPS GIS prospectivity analysis package [18].

5. Results

Mineral prospectivity maps are shown together with known gold occurrence and deposit points in Figure 2.



a) b) c)

Figure 2. Prospectivity maps. a) Weights of evidence method. b) Fuzzy logic method. c) Neural network method. Crosses, dots and open squares represent known primary, alluvial and undifferentiated gold deposits and occurrences, respectively.

Both the neural network and fuzzy logic favourability results are divided into nine equal classes. Due to the necessity of combining several input maps to avoid problems of conditional dependence, the weights of evidence map contains only three discrete probability levels. Classifying these values results in a four-class prospectivity map in which one of the classes does not correspond to any cells on the map.

The values of the map quality indices presented in Table 1 are all higher for the neural network map than those for the other two maps.

Table 1. Statistical measures of prospectivity map quality.

Statistic	Method		
	Weights of Evidence	Fuzzy Logic	Neural Network
Chi-square	66	63	83
Spearman's ρ	0.80	0.50	0.93
Kendall's τ	0.67	0.53	0.83

The value of the Chi-square statistic is significantly higher for the neural network map than the weights of evidence and fuzzy logic maps, indicating greater differences between the observed numbers of deposits and the numbers expected due to chance. Both the Spearman's and Kendall's rank correlation coefficients show the degree to which the conditional probability of occurrence of known deposits, P(D/A), increases with increasing prospectivity map class. These statistics are also significantly higher for the neural network map than for the weights of evidence and fuzzy logic maps.

The probability and probability ratio measures of map quality (Table 2) indicate that the highest prospectivity map classes in the neural network map are stronger predictors of deposits than in the fuzzy logic map and slightly stronger than in the weights of evidence map.

The upper part of Table 2 shows the conditional probability that a cell contains a known deposit, given that the area of interest is restricted to a particular prospectivity class. The lower part of Table 2 shows the ratio of conditional probability to probability for the study area as a whole. The nine-class fuzzy logic and neural network maps were reclassified into four-class maps to enable a direct comparison with the weights of evidence map.

Table 2. Probability and probability ratio measures of prospectivity map quality.

Map Class	Method		
	Weights of Evidence	Fuzzy Logic	Neural Network
$P(D/A) \times 10^4$			
1	2.52	2.85	2.60
2	0.00	1.65	2.15
3	8.67	6.89	11.66
4	23.45	18.91	26.74
P(D/A)/P(D)			
1	0.28	0.31	0.29
2	0.00	0.18	0.24
3	0.96	0.76	1.29
4	2.58	2.08	2.95

6. Conclusions

1) A neural network approach, using a simple implementation of the most commonly-used neural network architecture is successful in integrating geological and geophysical data sets representative of those used in a regional exploration program to produce a mineral prospectivity map.

2) The similarity of the neural network map to the empirical weights of evidence and conceptual fuzzy logic map indicates that the neural network map is consistent with both the spatial relationships in the data, and with geological knowledge about factors important for gold mineralisation in the Tenterfield area, respectively.

3) The neural network method has several advantages over existing methods, including the ability to: a) respond to critical combinations of parameters, rather than automatically increasing the prospectivity due to all favourable parameters, b) combine data sets without

the loss of information inherent in the weights of evidence method, c) overcome problems related to conditional independence in the weights of evidence method, and d) produce results that are relatively unaffected by redundant data, spurious data and data containing multiple populations.

4) Statistical measures used to compare map quality indicate that the neural network method performs as well, or better, than existing methods, while using approximately a third less data than the weights of evidence method. (Approximately one third of the available data was reserved as a test data set in the neural network method and was not used in training.)

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8. References

[1] Reddy, R. K. T., Agterberg, F. P. & Bonham-Carter, G. F., "Application of GIS-based logistic models to base-metal potential mapping in Snow Lake area," *In: Proceedings of Canadian Conference on GIS*, Ottawa, pp. 607-618, 1991.

[2] Bonham-Carter, G. F., "Geographic Information Systems for Geoscientists: Modelling with GIS," Pergamon Press, New York, 1994.

[3] Bonham-Carter, G. F., Agterberg, F. P. & Wright, D. F., "Integration of geological datasets for gold exploration in Nova Scotia," *Photogrammetric Engineering and Remote Sensing*, vol. 54, no. 11, pp. 1585-1592, 1988.

[4] An, P., Moon, W. M. & Rencz, A., "Application of fuzzy set theory to integrated mineral exploration," *Canadian Journal of Exploration Geophysics*, vol. 27, no. 1, pp. 1-11, 1991.

[5] Moon, W, M., "Integration of geophysical and geological data using evidential belief function," *IEEE Transactions, Geoscience and Remote Sensing*, vol. 28, no. 4, pp. 711-720, 1990.

[6] Katz, S. S., "Emulating the Prospector expert system with a raster GIS," *Computers and Geosciences*, vol. 17, no. 7, pp. 1033-1050, 1991.

[7] Osborne, D. A., "Neural networks provide more accurate reservoir permeability," *Oil and Gas Journal*, vol. 90, no. 39, pp. 80-83, 1992.

[8] Wong, P. M., Taggart, I. J. & Gedeon, T. D., "Use of neural network methods to predict porosity and permiability of a petroleum reservoir," *AI Applications*, vol. 9, no. 2, pp. 27-37, 1995.

[9] Singer, D. A. & Kouda, R., "Classification of mineral deposits into types using mineralogy with a probabilistic neural network," *Nonrenewable Resources*, vol. 6, no. 1, pp. 27-32, 1997.

[10] An, P., Chung, C. J. F. & Rencz, A. N., "A preliminary study of alteration mapping from airborne geophysical and remote sensing data using feed-forward neural networks," *In: Society of Exploration Geophysicists 64th Annual International Meeting; Technical Program Abstracts*, vol. 64, pp 837-840, 1994.

[11] Gong, P., "Integrated analysis of spatial data from multiple sources: using evidential reasoning and artificial neural network techniques for geological mapping," *Photogrammetric Engineering and Remote Sensing*, vol. 62, no. 5, pp. 513-523, 1996.

[12] Singer, D. A. & Kouda, R., "Application of a feedforward neural network in the search for Kuroko deposits in the Hokuroku District, Japan," *Mathematical Geology*, vol. 28, no. 8, pp. 1017-1023, 1996.

[13] Clare, A., Bolt, G. & Daneel, G., "The use of neural analysis as an exploration tool," *In: Proceedings of the 12th International Conference on Applied Geologic Sensing*, Environmental Research Institute of Michigan (ERIM), Ann Arbor, vol 2, pp. 199-205, 1997.

[14] Barnes, R. G., Henley, H. F. & Henley, J. E., "Exploration data package for the Tenterfield and Coaldale 1:100,000 sheet areas," *Geological Survey Report No. GS1995/004*. Geological Survey of New South Wales, 1995.

[15] Rummelhart, D. E., Hinton, G. E. & Williams, R. J., "Learning representations by back-propagating errors," *Nature*, vol. 323, 9 October, pp. 533-536, 1986.

[16] Hornik, K., "Approximation capabilities of multilayer feedforward networks," *Neural Networks*, vol. 4, no. 4, pp. 251-257, 1991.

[17] Zimmermann, H. J., "*Fuzzy Set Theory and its applications*," Kluwer Academic Publishing, Boston, 1985.

[18] Jusmady & Taylor, G.R.T., "Geological Data Integration and Processing System (GEODIPS) software package, Version 1.03," Department of Applied Geology, University of New South Wales, 1997.