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Research Paper

Recognizing Porphyry Copper Mineralization Targets in Chahar-Gonbad Area of Kerman Province Using Extreme Learning Intelligent Method

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Abstract: Selection of training sites is an important and critical undertaking in the modeling procedure of mineral exploration targets using artificial intelligence approaches. This is because application of improper training algorithms results in exploration targeting models that carry bias and uncertainty. The present study aims to model exploration targets of porphyry copper mineralization in Chahar-Gonbad area, Kerman province, Iran, using artificial neural networks. In this regard, continuous weighted evidence maps of exploration criteria including proximity to intrusive contacts, fault density, multi-element geochemical signature and proximity to iron-oxide and argillic alterations were generated and applied as inputs to the neural network. Subsequently, 16 points with known mineral deposits and 16 points without mineralization were used to train the neural network through extreme learning algorithm. The ensuing exploration targeting model was compared with a model obtained by using geometric average integration method through prediction-area plot. The overall efficiency of the models are 0.34 and 0.27, respectively. Evaluation of the models demonstrated that the areas with high copper mineralization potential, marked as exploration targets, are in good conformity with known copper occurrences as well as with geological indicator features. Thus, the targets can be planned for further exploration programs.

Keywords: Continuous weighting method, Logistic function, Chahar-Gonbad area, Artificial neural networks, Exploration targets.

INTRODUCTION

Mineral potential models are generated at any exploration scale, from regional to local, to delineate mineral exploration targets [1]. Many mineral deposits are hidden and buried, and so, do not show direct visible evidence. Thus, discovering ore deposition sites has been always an exploration challenge [2,3]. In this regard, according to the presence of geological indicator features and spatial proxies of mineralization such as alterations, geochemical anomalies, and structural features, the possible occurring of mineralization events are investigated through mineral prospectivity analysis [4-6].

General methods of generating weighted evidence layers for use in mineral exploration targeting are categorised into knowledge-driven, data-driven, hybrid and logistic-based continuous approaches [1-3,7]. The knowledge-driven methods are used in areas where there are no or a few number of known deposits [8]. If there are sufficiently known deposits in an area, data-driven modelling methods can be used to determine exploration targets [2,3,7,8]. In continuous weighting methods, the spatial positions of mineralization events, or so called as training points, are not used in the modelling procedure [8]. Furthermore, the exploration spatial data, representing mineralization, are not discretised using arbitrary intervals. As a result, this method overcomes the bias and uncertainty in the weighting procedures [9].

Extreme Learning Machine (ELM) was developed to address previous shortcomings of supervised methods and was found to be significantly more efficient than other algorithms. Huang et al. used three algorithms, including Back Propagation (BP), Support Vector Machine (SVM), and ELM, to process satellite imagery to study plants and diabetes, and the results showed that the ELM algorithm is significantly more efficient than others [10]. Luo et al. used Timeliness Managing Extreme Learning Machine (TMELM), On-line Sequential Extreme Learning Machine (OSELM) and, ELM algorithms to investigate possible coal mine accidents during mineral production [11]. The results proved the superiority of ELM algorithm over two other algorithms. Wang et al. examined the data of a coal mine located in western China, using Principal Component Analysis (PCA) and the ELM algorithm, to investigate and determine the model of deposit thickness, and observed that the accuracy of the ELM algorithm is high in generalization and education [12].

Following the above-mentioned researches, this paper aims to evaluate the efficiency of ELM training algorithm in prospectivity analysis and data integration for exploration targeting through artificial neural network and to compare its effectiveness with geometric average integration method [6].

METHODS

In this research, a nonlinear logistic function was applied to generate continuously-weighted evidence maps for modelling exploration targets. For this five weighted layers including proximity to host rock, fault density, geochemical signature, and proximity to Iron oxide and argillic alterations were generated. The weighted maps were then integrated with two different methods, geometric average (without using training samples) [5] and artificial neural network (using training samples) [10]. Finally the models were compared by prediction-area plot [8]. In order to better illustrate and evaluate the methods used in this paper, exploration data of porphyry copper deposits in Chahar-Gonbad region of Kerman province, Iran, were applied (Figure1).

FINDINGS AND ARGUMENT

Continuous weighting methods, unlike the existing conventional data-driven, knowledge- driven and hybrid approaches, do not require classification and then weight allocation to the classes of spatial data [1]. Thus, by using the continuous weighting methods, the drawbacks of the conventinal methods are modulated. In the continuous weighting method, fuzzy weights are assigned to the continuous exploration values using logistic functions [5]. Figure 2 shows the continuous weighted maps in this study. In this method, the known deposit locations and expert's opinion are not used for weighting [4]. After generation of the continuousely-weighted evidence layers, they were integrated by geometric average function (Figure 3A) and neural network method (Figure 4A). The exploration targeting models were then classified for prioritization of the area for further exploration progranms (Figures 3B and 4B) [13].

To assess the ability of the two models generated, in terms of predicting undiscoverd mineralization, location of 16 known mineral deposits and 16 non-deposit locations (without mineralization) were applied two make the prediction-area plots (Figure 5) [5,14]. In this plot, there are three curves, namely the curve of (1) the prediction rate of mineral deposit corresponding to the prospectivity classes (MDL), (2) the percentage of the areas occupied by the corresponding classes of mineral prospectivity (Area), and (3) the prediction rate of non-deposit locations corresponding to the prospectivity classes (NDL) [5,14]. The comparison demonstrated that the potential model produced with the use of neural network data-driven method with an overall efficiency of 0.34 is better than the potential model produced using the geometric average method with an overall efficiency of 0.27. It should be emphasized that the geometric average method does not require training data and can work well in areas without known mineral deposits.

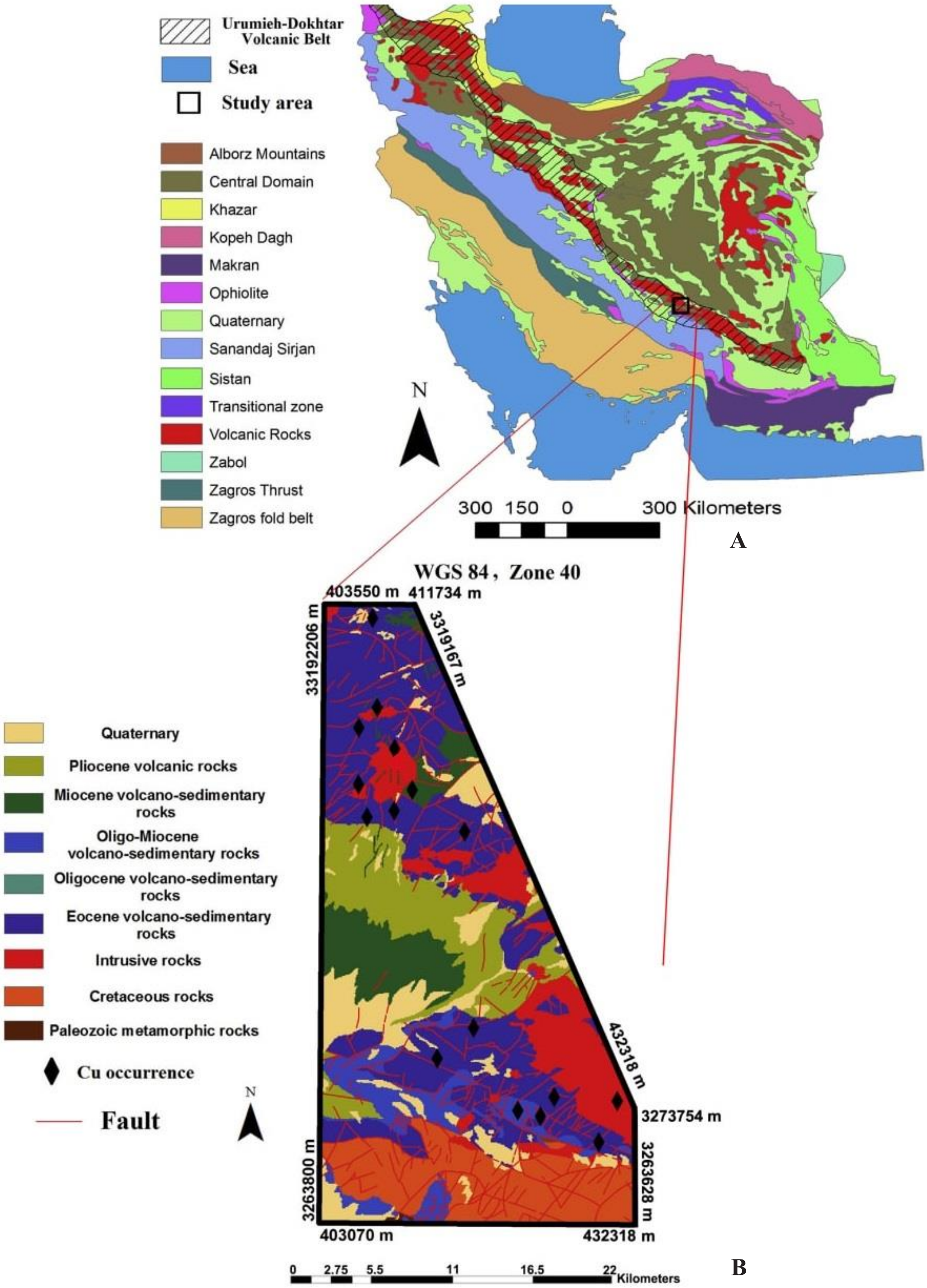


Figure 1. A: Location of the study area in Iran and **B:** its simplified geological map

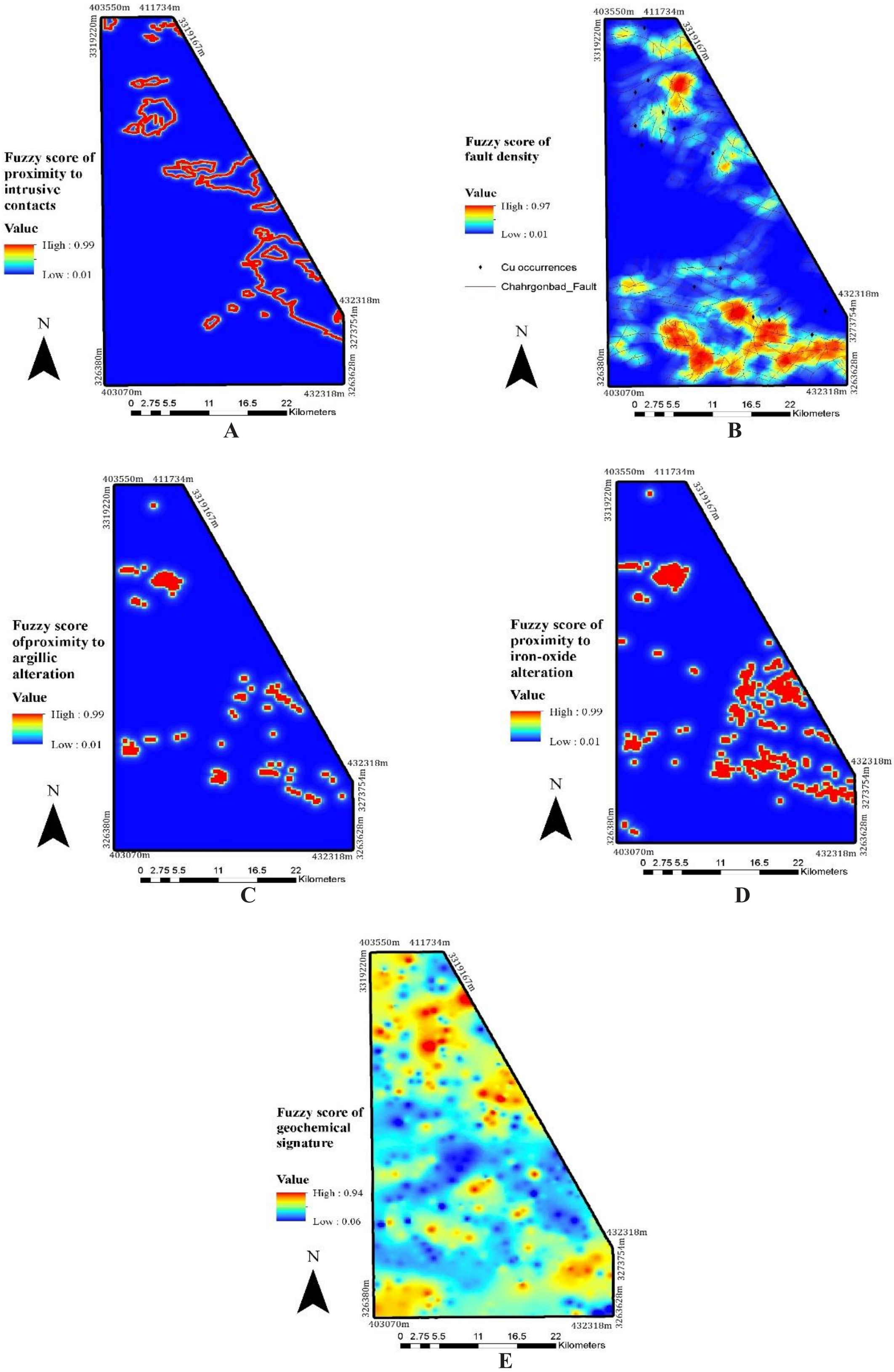
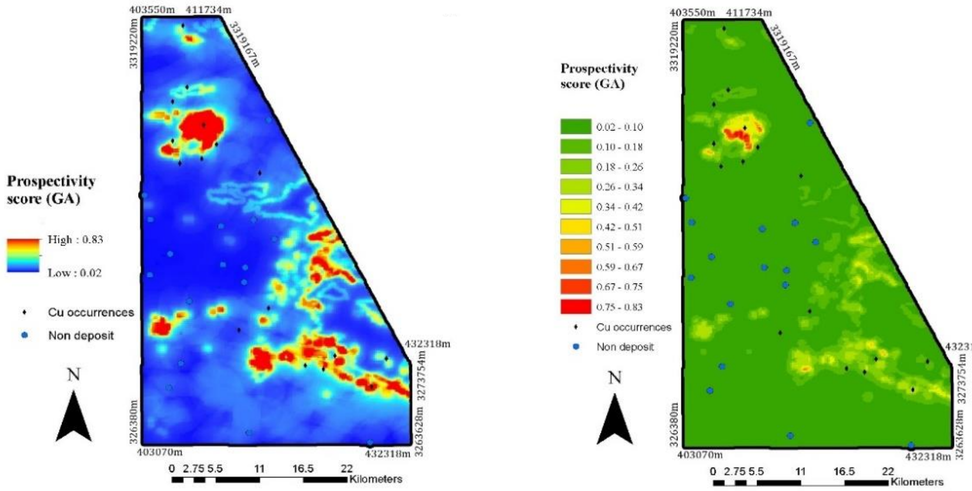
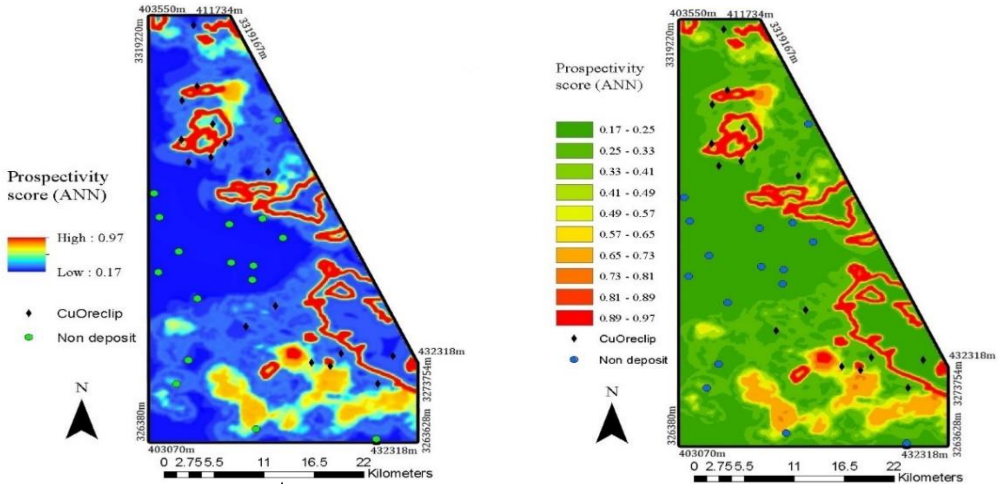


Figure 2. Continuously-weighted evidence layer of **A:** proximity to intrusive rocks, **B:** fault density, **C:** proximity to argillic alteration, **D:** proximity to iron-oxide alteration, and **E:** multi element geochemical signature



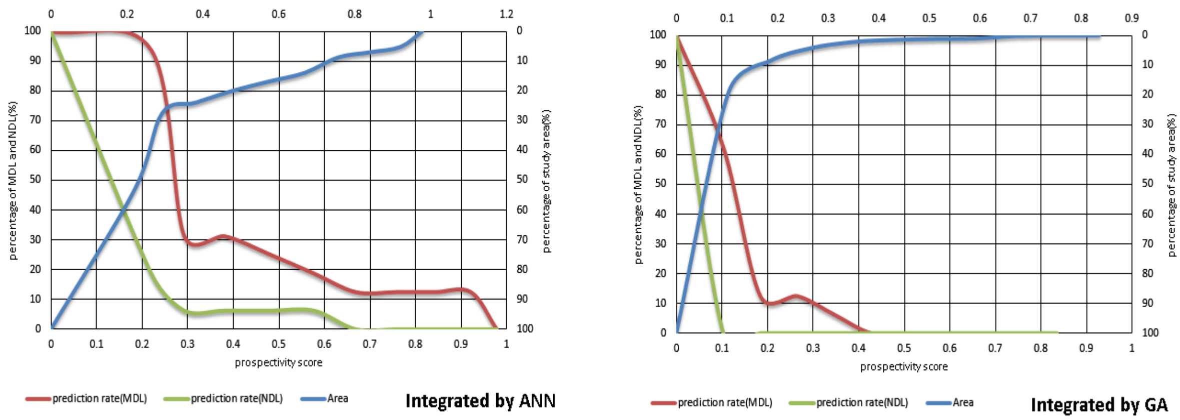
A B

Figure 3. A: Geometric average exploration targeting model and **B:** model of the ensuing classified targets



A B

Figure 4. A: Artificial neural network exploration targeting model and **B:** model of the ensuing classified targets



A B

Figure 5. Prediction-area plot for exploration targeting model using **A:** the geometric average and **B:** artificial neural network methods

CONCLUSIONS

Findings of this paper can be remarked as below:

- Extreme learning machine can efficiently be used to train artificial neural networks for the purpose of increasing the exploration success of targeting models. That is due to the various activation functions, strong ability in data analysis, high accuracy in generalization and training, and fast processing time of the ELM algorithm.

- It is suggested to design further exploration programs by focusing on the targets generated in the present study in order to vectoring towards undiscovered mineral deposit sites.

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