-RESEARCH PAPER-

International Journal of Mining and Geo-Engineering IJMGE

IJMGE 57-4 (2023) 405-412 DOI: 10.22059/IJMGE.2023.361593.595080

Investigating the performance of continuous weighting functions in the integration of exploration data for mineral potential modeling using artificial neural networks, geometric average and fuzzy gamma operators

Esmaeil Bahri [a, *], Andisheh Alimoradi [a], Mahyar Yousefi [b]

[a] *Department of Mining and Petroleum Engineering, Faculty of Engineering, Imam Khomeini International University, Ghazvin, Iran.*
[b] *Faculty of Engineering, Malayer University, Malayer, Iran.*

Article History:
Received: 02 July 2023.
Revised: 22 July 2023.
Accepted: 14 August 2023.

ABSTRACT

In mineral exploration programs, reducing uncertainty and increasing exploration success have always been challenging issues. To modulate the above-mentioned uncertainty and increase exploration accomplishment, integration, and prospectivity analysis techniques are used for mineral exploration targeting. This paper aims to model the mineral potential of porphyry copper deposits in the Jiroft region, Kerman province. To achieve this goal and overcome the aforementioned issues resulting from the operation of complex ore-forming geological processes, continuous weighting methods through logistic functions were used while training points and analyst's opinions were not contributed to the weighting procedure. Then, to generate exploration targets, the weighted layers were combined with three different integration methods namely, artificial neural network, geometric average, and fuzzy gamma operators. The comparison of the model obtained from the application of an artificial neural network with those obtained by the geometric average and the fuzzy gamma operators using prediction rate-area plots indicated that all the models have good overall performance and acceptable prediction rate. However, the performance of the artificial neural network model is slightly less than that of the other two models. Thus, the targets generated using the geometric average and fuzzy gamma operators are more reliable for planning further exploration programs.

Keywords: *Artificial neural network, Exploration targets, Fuzzy gamma, Geometric average, Porphyry copper deposits.*

1. Introduction

The need to explore new mineral deposits at greater depths has been a challenge for industries. Therefore, more precise and cutting-edge exploration methods have been developed to identify new mineral deposits. These methods have been developed due to the wide variety of mineralization types, the characteristics of the explored mineralization as well as the diversity of natural conditions prevalent in complex geological environments. Efforts have always been made to develop methods that minimize the error in identifying promising areas. For this purpose, since the late 20th century, attempts have been conducted to compare and integrate the results of different exploration methods, called mineral potential modelling, to identify areas that require further exploration [1]. In general, the set of processes for analyzing different exploration data, extracting and identifying geological complications representing mineralization, and production of weighted control layers predicting mineralization, and finally combining spatial evidence to identify the target and promising areas for the exploration of unknown mineralization is called mineral potential modelling. The output of the mineral potential model is a map in which the possible presence of mineral deposits is predicted [2].

A variety of methods have been developed for assigning weights to exploration evidence data and combining them to model mineral potentials. The methods are divided into some general categories including knowledge-driven, data-driven, hybrid, user-defined functions and continuous methods using logistical functions [4,3]. Knowledge-based methods are used at the preliminary stages of mineral exploration in areas with suitable geological conditions but limited previous exploration experience. These methods are generally used in areas where there are no or few known mineral deposits [5]. Data-driven approaches are applied in areas where there is enough exploration data and knowledge to implement supervised modelling methods [5]. In hybrid methods, which are a combination of data- and knowledge-driven approaches, the results of data-driven methods are generally used to allocate weights in the knowledge-based method or vice versa [2]. In user-defined functions, weights are assigned to classes (patterns) of evidence maps in which the functions' parameters are determined by expert judgments and trial and error practice [6]. In continuous weighting methods, sigmund (S-shaped) logistic functions are used to assign weights to mineral exploration data, resulting in fuzzified exploration layers. In this method, the values of logistic function parameters such as slope and inflection point are obtained without the intervention of experts through solving mathematical equations and calculations [7]. Each of these methods has its own advantages and disadvantages. Knowledge-based, data-driven, hybrid methods and user-defined functions introduce bias and uncertainty due to the weighting process [6,5]. In the continuous weighting method using logistic

* Corresponding author. *E-mail address:* esmaeil.bahri.1995@gmail.com (E. Bahri).

functions, none of the mentioned disadvantages exist and it is an efficient way for weighting the data, resulting in significantly reduced uncertainty in the outcomes [7]. In this regard, the purposes of this study are 1) to produce a model of mineral potential for porphyry copper deposits in the Jiroft region, Kerman province, using continuous weighting methods and 2) to evaluate and compare the performance of artificial neural network, geometric average and fuzzy gamma integration approaches.

2. The Geology of the study area and exploration data

The Jiroft region is located on the Urumieh-Dokhtar magmatic arc within the southern part of Kerman province, Iran [9,8]. One of the characteristic geological features of this region is the existence of a huge volume of intrusive and volcanic rocks with the Jurassic to Oligo-Miocene age range [10]. The intrusive masses in the study area are moderately granular and their main minerals are plagioclase and clinopyroxene. The lithological composition of these massifs varies from granite to granodiorite. The main texture of these rocks is granular, but, subophitic, intergranular, and granophyric can also be seen in them [9]. In some parts of the study area, there are sedimentary rocks ranging from Triass to Oligo-Miocene, which are mainly composed of sandstone and limestone schists. A small part of the area also contains sedimentary-metamorphic rocks of Paleozoic age. Most of the southern part of the study area is covered by Quaternary rocks [10]. The geological map of the Jiroft region is shown in Figure 1. There are nine known porphyry copper deposits in the study area that were used for training and evaluation purposes. In this study, the 1: 100000 geological map of the study area and the results of chemical analysis of 584 stream sediments geochemical samples, prepared by the Geological Survey and Mineral Exploration of Iran, were used as input data.

3. The conceptual model of ore deposit of the type sought

The first step in the process of building a mineral potential model is to define the conceptual or descriptive model of the deposit type sought, or more precisely, to define the conceptual genetic model for the targeted deposit. Prediction of mineral locations is mostly based on experimental relationships obtained from descriptive models of known deposits. A descriptive model of a type of mineral deposit based on the characteristics of a number of similarly known deposits is a guide to finding new deposits of the same type. When using GIS to prepare mineral potential maps, descriptive models of deposits play an important role in selecting and adapting forecast maps and assigning weight to them [5].

Defining a conceptual model for a type of deposit requires information and data from different types of geological processes related to mineral deposits as well as the type of deposit being explored. Therefore, the study and review of discovered reservoir models, the similar explored deposits in the study area, and related geological environments that describe the geological characteristics of a particular type of mineralization (to be explored), are extremely important. Given that the formation and occurrence of a large number of deposits and minerals (not all of them) depend on plate tectonics, it is necessary to study the structural and geological assemblages of the study area when designing a conceptual model. In addition, it is useful to study and review the findings related to certain geological processes that control mineralization (such as faults and other geological features) [16, 15, 14, 13, 12, 11]. In addition, the analysis of spatial distribution and dispersion of mineral deposits of the same type as the target deposits, as well as the analysis of the association and spatial dependencies and dispersion of prospective mineral deposits and specific geological structures is also useful and should be considered [20, 19, 18, 17]. According to the above explanations and studies, the conceptual model of porphyry copper deposits is defined as follows:

- Porphyry copper deposits result from the activity of hydrothermal processes after magmatism and are associated with granitoid intrusive rocks [23, 22, 21, 20, 19]. Therefore, in porphyry copper deposits, the mineral is spatially and genetically related to porphyry intrusions, so a wide range of intrusive rocks with diorite to granite composition including diorite, granodiorite, monzonite, and quartz monzonite play the role of metal sources and heat sources in the formation of porphyry copper deposits [24].
- Mineral-rich solutions take the least resistant path and move through cracks and fractures that facilitate the passage and circulation of hydrothermal fluids. Fault zones act as conduits for deep melt sources and hydrothermal fluids [20]. Therefore, fault zones are used to identify possible locations for porphyry deposits [28, 27, 26, 25].
- Porphyry copper deposits are often associated with anomalies of trace elements or mineralizing agents such as Sb, As, Pb, Zn, Ag, Au, Mo, Cu, or their halos in rocks, sediments, and soils [6].

4. Methods

4.1. Generation of weighted maps for mineralization controlling factors

Using the available data, the distribution maps of the lines and intrusive masses in the region were extracted. Then, control maps of the density of the lines and the proximity to the intrusive masses were made in a GIS environment. In order to analyze and process geochemical data from stream sediments, to construct a geochemical control layer, the factor analysis method was used, which is a statistical method for analyzing the information in the dataset, particularly useful when dealing with a large number of variables with unknown relationships. In this method, the variables are placed into factors, so that the percentage of variance is reduced from the first factor to the next factor. Therefore, the variables that are in the first factor are the most influential [29]. In this paper, using the stepwise factor analysis method and Geochemical Mineralization Probability Index (GMPI), which is an approach for mapping geochemical anomalies, the geochemical signatures were weighted. In addition, using the GMPI, the prediction ability of every geochemical sample is evaluated in terms of prospecting the targeted mineral deposit [30]. The GMPI is obtained by Equation (1) [30]:

$$\mathrm{GMPI} = \frac{e^{Fs}}{1+e^{Fs}} \tag{1}$$

Where Fs is the value of the factor score for each geochemical sample. In order to construct a weighted geochemical controlling map, the stepwise factor analysis was performed on a dataset of eight indicator elements of mineralization, comprising Zn, Pb, Ag, Cu, As, Sb, Ba, and Au. The results are presented in Table 1.

Table 1. Obtained factor values from the rotated principal component analysis.

	Components		
	1	2	3
Zn	-.711	.276	.101
Pb	-.075	-.893	.002
Ag	.864	.316	-.098
Cu	-.568	.028	-.229
As	.851	.232	-.066
Sb	-.625	.295	.071
Ba	.905	.208	-.018
Au	-.043	.007	.968

According to the values in Table 1, it can be seen that the elements silver, arsenic, and barium in the first column of the components of factor analysis have values above the threshold, so these three elements were considered together and another stage of analysis was conducted on them and then their weighted geochemical map was prepared using Equation 1. Also, the elements zinc, copper, and antimony, in the first column of the components of factor analysis had their absolute values above the threshold. Another step of factor analysis was performed on them and finally using equation 1, their weighted geochemical maps were made. Lead and gold elements, according to their values in the second and third columns of the table of components of factor analysis, respectively, were studied as a single element and their map was drawn. Using the GMPI relation, the resulting maps were weighted. Finally, four weighted geochemical maps obtained from the four aforementioned factors were combined through the function of Yousefi et al., 2012 [30] to make a stronger geochemical controlling signature, and the final porphyry copper geochemical evidence map was generated (Figure. 2). More details about these methods can be found in Yousefi et al. (2012 and 2014) and Yousefi (2017) [32,31,30]. In order to produce weighted maps of fault density and proximity to the intrusive body, equation (2) was used [33]:

$$F_{EV} = \frac{1}{1+e^{-s(EV-i)}} \quad (2)$$

Where F_{EV} is a score between 0 and 1, EV is the value of each cell in the control map, and i and s are the inflection point and slope parameters of the function, respectively. Equations (3) and (4) were used to find the values of i and s [33]:

$$S = \frac{9.2}{EVmax - EVmin} \quad (3)$$

$$i = \frac{EVmax + EVmin}{2} \quad (4)$$

Where EVmin and EVmax are the maximum and minimum values of exploration data in the input maps, respectively.

In this method, as previously stated, the values of i and s are calculated through the formula and there is no uncertainty due to the application of expert opinion in the selection of parameters i and s. weighted control maps of linear density and proximity to intrusive masses are shown in Figures 3 and 4.

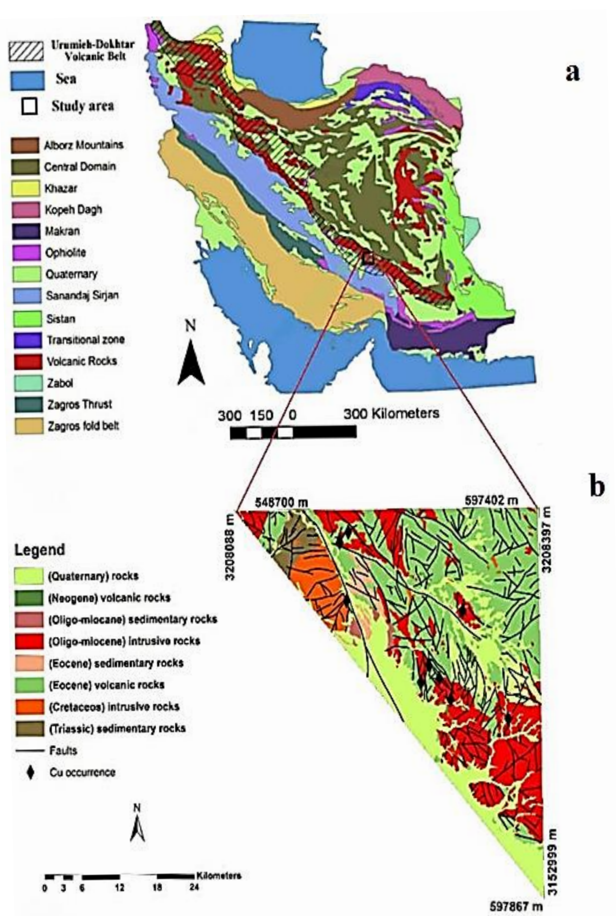

Figure 1. a) The location of the study area on the structural geological map of Iran b) The geological map of the study area with faults and the location of known porphyry copper ore occurrences and mines.

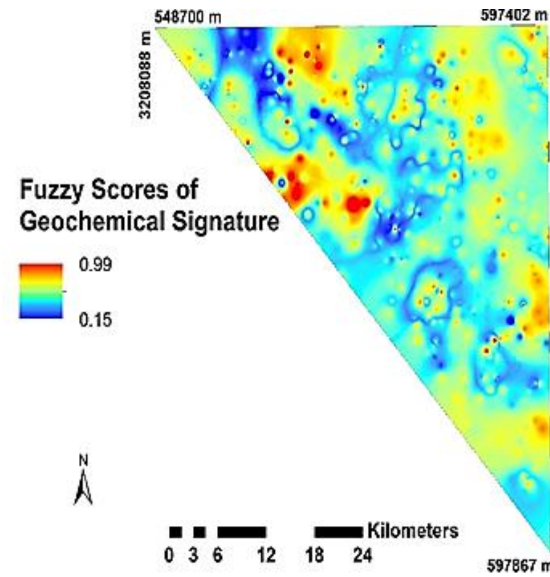

Figure 2. The weighted geochemical control map.

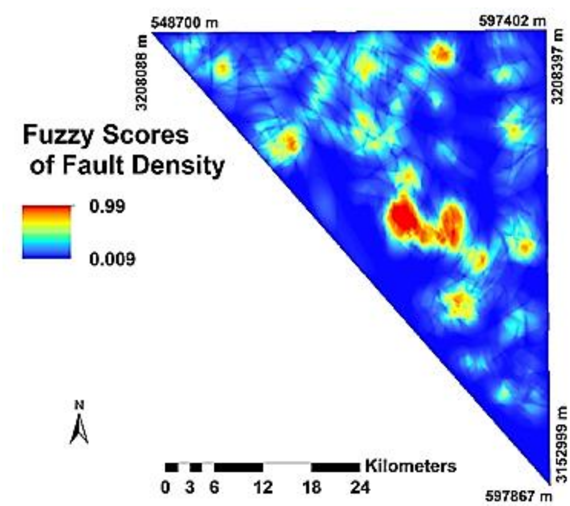

Figure 3. The weighted control map of the density of faults and lines.

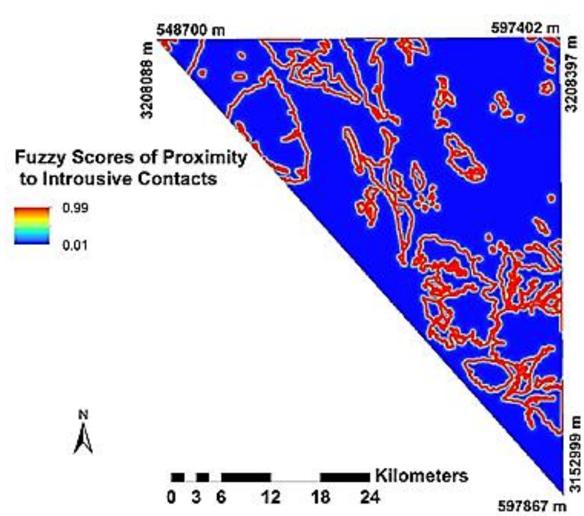

Figure 4. Weighted control map proximity to intrusive contacts.

4.2. Combining weighted control maps

4.2.1. Fuzzy gamma method

In this section, using the fuzzy gamma (=0.9) operator, three weighted controlling maps: fault density, proximity to intrusions, and geochemical anomalies were combined and a model of the mineral potential of porphyry copper deposits in the study area was produced (Figure 5).

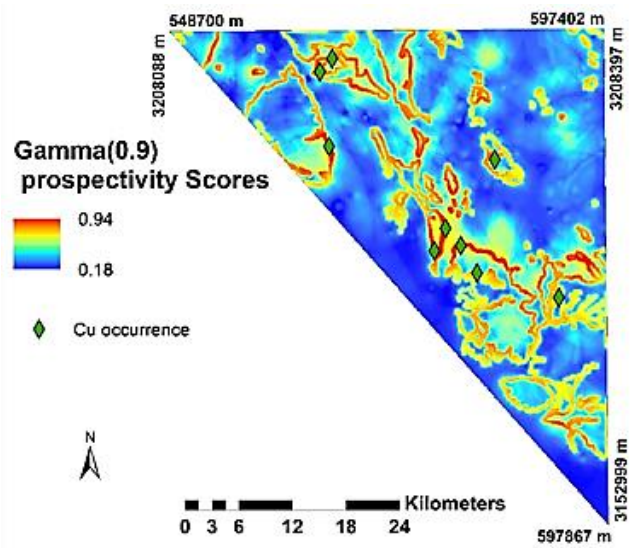

Figure 5. The final model with gamma fuzzy operator along with the known copper ore occurrences in the study area.

4.2.2. Geometric average method

In this section, according to the previous part, weighted control maps were combined with each other to produce the mineral resource potential model of the search, using the geometric average method and equation (5) [6]:

$$GA(F1 \times F2 \times \ldots \times Fn) = (\prod_{i=1}^{n} Fi)^{1/n} = \sqrt[n]{F1 \times F2 \times \ldots \times Fn} \quad (5)$$

GA is the geometric average value of each cell in the final map, Fi is the weight of each cell in the control i map (assigned by the logistic function) and n is the number of weighted control maps.

The mineral potential model of porphyry copper deposits made by the geometric average method is shown in Figure 6.

4.2.3. Artificial neural network method

Artificial neural networks (ANNs) are a method of artificial intelligence that is made by modelling the human nervous system and is widely used in engineering sciences to model the behavior and function of the human brain in a situation that requires the use of intelligence [34]. Using ANNs, nonlinear relationships between complex natural environment variables in which physical processes are not directly observed can be described [35]. While linear and ordinary mathematical methods cannot be used to model complex and ambiguous systems [36].

Each neural network consists of three stages: training, generalization, and execution. In the training phase, the network learns the patterns in the inputs within the training datasets that each neural network uses a specific rule to learn. Generalization means the power of the neural network to create acceptable structures for inputs that are not part of the training datasets. In the execution phase, the neural network is used to perform the function for which it was designed [37].

In exploratory studies and the identification of target areas, how mineral resources are arranged, their structure, and location are due to the complex interactions of various geological processes, so that the effect of these processes is indirectly on the characteristics and evidence of geology that are associated with mineral deposits. These geological properties, which are in fact identification criteria, are described by their response in one or more sets of control spatial data, which will be used in mineral potential modelling. It is difficult to describe the dependencies between these control variables and mineral deposits due to the great variety of natural conditions affecting mineralization and their modelling using linear methods is practically impossible. Therefore, considering the capabilities of ANNs, they can be effectively used in modelling mineral potential [36]. In order to train an ANN, a series of numerical data is needed. Here, the location of nine known copper occurrences in the study area and nine locations without copper storage were used for network training. Non-deposit locations were selected based on the following criteria [38]:

A) The places without mineral deposits must have a random distribution.

B) They are not located on the host rock of porphyry copper mineralization.

C) They need to be located far away from known indexes.

In the results of other methods, porphyry copper mineralization has been introduced as areas with very weak mineralization potential.

The training process of ANNs, which is the first step in using this method, is performed by various training algorithms. Here, the extreme learning machine (ELM) training algorithm was used to train the desired neural network. Because there was a problem of data shortage in this region (nine known occurrences in the region), and the ELM algorithm works better than other ANN training algorithms in conditions where available data is limited [39]. The ELM algorithm is a new training algorithm for Single-hidden-Layer Feedforward Networks ($SLFN_S$).

Unlike the old training algorithms for $SLFN_S$, the ELM algorithm has the lowest error rate in training and output weights. Also, the training speed in the ELM algorithm is nearly 1000 times faster than other $SLFN_S$ training algorithms, including BP (back-propagation). However, the performance of the ELM algorithm is much higher [40].

ELM algorithm output function with training set

$$N = \{(x_i, t_i), x_i \in R^n, t_i \in R^m, i = 1, 2, \ldots, N\} \quad (6)$$

The number of hidden nodes L and the hidden node function g (w, b, and x) are in equation (7) [40]:

$$f(x) = \sum_{j=1}^{L} \beta_j \, g(w_j \, b_j \, x) = h(x)\beta \quad (7)$$

Where $\beta = [\beta_1, \beta_2, \ldots, \beta_L]^T$ is the vector of output weights between the hidden layer with L node and the output node, and $h(x)=[g(w_1, b_1, x), \ldots, g(w_L, b_L, x)]$ is the output row vector of the hidden layer corresponding to input x. The value of b can be calculated from equation (8) [40]:

$$\beta = H^T T \quad (8)$$

Where $T=(t_1, t_2, \ldots, t_N)^T$ and H^T is the output matrix of the hidden layer (H).

To train the ELM training algorithm, a training data matrix including four columns and 18 rows (target variable, here known mineral deposit sites) were used. Thus, its 4th column includes numerical values (0 and 1) for known deposit locations and non-deposit locations (18 in total). while its first, second and third columns include numerical values (fuzzy values between 0 and 1) corresponding to the weighted control maps.

The network specifications used for training with the ELM training algorithm were considered as follows:

- The network used is the feeder type and its training mode is supervisor.
- 80% of the available data were randomly allocated for training and 20% for testing.

Two regression criteria (R) and Root Min Square Error (RMSE) were used to evaluate the performance of training and network testing.

In an optimal mode of network training, the network parameters were as follows:

- The number of hidden (middle) layer neurons in the network is 40.
- The training and testing processes are repeated 20 times.
- The values of parameters C1 and C2 (i.e., learning coefficients) are 2.5 and 3, respectively.

Finally, the network was trained in this optimal mode with the parameters mentioned above, and then this trained network was used to combine weighted control maps as follows:

- Fuzzy numerical values of all cells of weighted control maps were extracted and arranged in three separate columns for each control map, in a matrix.
- In the next step, to find the fourth column of this matrix, which is the network output vector and the final answer of the ANN, the above-trained network was used.
- Finally, the numerical values obtained from the output vector of the neural network were mapped in the GIS. The final map integrated by the data-driven method of ANN is in Figure 7.

5. The evaluation of models

Mineral potential models made by different methods, to evaluate their efficiency and accuracy of estimation, should be evaluated and compared by different methods. In mineral potential modelling, the identified target areas should represent the actual spatial relationships between evidence and spatial patterns associated with the mineral deposits of the type being searched for. Therefore, the locations of known mineral deposits can be used to evaluate the weights assigned to evidence and spatial patterns as well as models produced, which is done by juxtaposing the locations of known mineral deposits [41,30].

Also, to determine the probability of the presence of mineral deposits, the ratio can be used by dividing the weight of different classes using the area occupied by that class. This means that if two different classes of spatial control maps with different areas have the same weight, the probability of finding undiscovered deposits in a class with a smaller area is higher than in another class [43,42].

Each of these two criteria can be used to evaluate the performance of a model. This means that if one class of the control map occupies less space than the other classes of the control map, it is easier to find undiscovered deposits in that class. Besides, if a control map class has a larger number of known deposits than other control map classes, that class has a stronger potential for finding undiscovered deposits than other classes. In this regard, Yousefi and Karanza 2015 used both of the above criteria to evaluate the models simultaneously and proposed a Prediction Rate – Area diagram (P-A) to evaluate the models with the intersection of two curves serving as the criterion for evaluating models [46, 45, 44, 43, 6]. When evaluating mineral potential models, another criterion that should be considered is the share of undeposited locations in the evaluation of models. Accordingly, areas that have been identified as mineral potential areas in the models should have the least overlap with non-deposit sites where there is no geological evidence and favorable exploration criteria [7]. In this regard, researchers proposed a receiver performance characteristic curve to evaluate the models [49,48,47]. Using the Receiver Operating Characteristics (ROC), both the locations of mineral deposits and the locations without deposits are used to evaluate the models. However, the important criterion of the area occupied by the classes is not included in these curves. Therefore, to consider all the above criteria in the form of a single method for evaluating mineral potential models, an improved rate-area diagram was used here [50]. The overall performance of the model (Oe) is obtained from equation 9[50]:

$$O_e = P_m - P_n \tag{9}$$

Pm and Pn are the values of the curves: the forecast rate of known deposits and the prediction rate of non-deposit locations at the intersection with the occupied area curve, expressed as a percentage. The result of the above relation will be a number in the range of 1 to -1, which a larger number indicating higher efficiency and performance of the evaluated model. Also, positive and negative numbers indicate the efficiency and inefficiency of the evaluated model, respectively, for use in the next stages of exploration of the prospecting deposit in the study area. In order to evaluate three models for the mineral potential of porphyry copper deposits made in the previous sections, first all three models were discretely classified by equal distances. Then, using the predicted rate-area diagram, the models were evaluated. The results of this evaluation are shown in Figures 8 to 13 and Table 2. Examining both the forecast-area rate graphs for all three final models and the data obtained from these graphs as shown in Table 2, it can be seen that the prediction rate of known mineral deposits (Pm) for the fuzzy gamma model is 0.8 equal to that of the geometric average model. However, the Pm for the ANN-based model is 0.75. So, it can be concluded that in this regard, the model obtained from the ANN method is slightly weaker (5%) than the obtained models operated by the geometric average and fuzzy gamma methods. In contrast, by examining the prediction rate of non-deposit locations (P_n), it is observed that for the models obtained using the fuzzy gamma and geometric average methods, the values are 0.4, but as can be seen, the P_n for the model generated by the ANN method is 0.38. Therefore, it can be concluded that the models obtained from the fuzzy gamma method and the geometric average are slightly weaker (by 2%) than the model obtained from the ANN method.

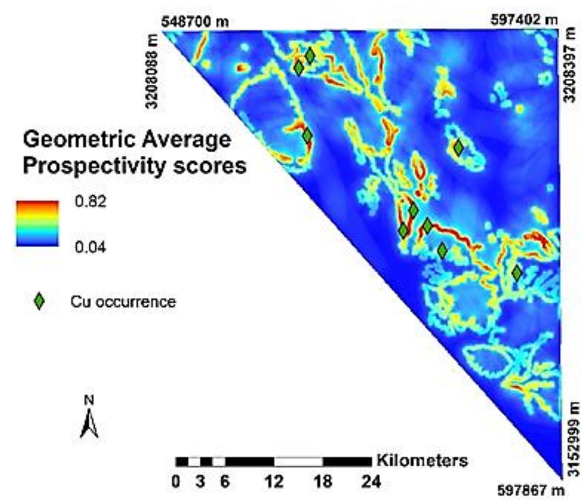

Figure 6. The Final model produced by the geometric average method with the known occurrences and known porphyry copper mines in the study area.

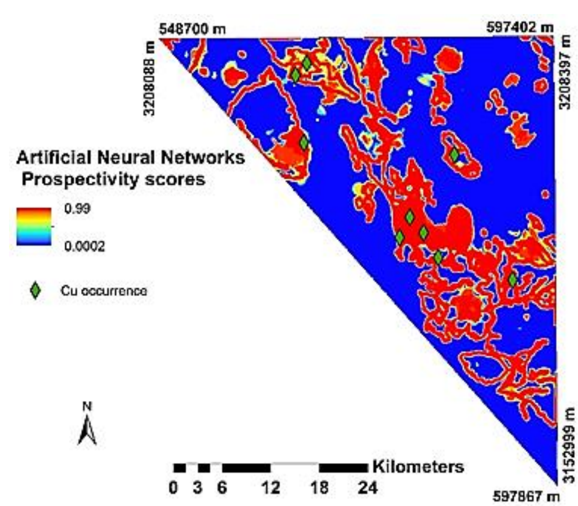

Figure 7. The final model from the method of ANNs with the known porphyry copper occurrences in the study area.

Finally, by examining the overall performance (O_e) of the models, it is concluded that the models combined with the methods, namely fuzzy

Table 2. The values of P_m, P_n and O_e for the three mineral potential models.

Models	P_m	P_n	O_e
Gamma (0.9)	0.80	0.40	0.40
Geometric Average	0.80	0.40	0.40
ANNs	0.75	0.38	0.37

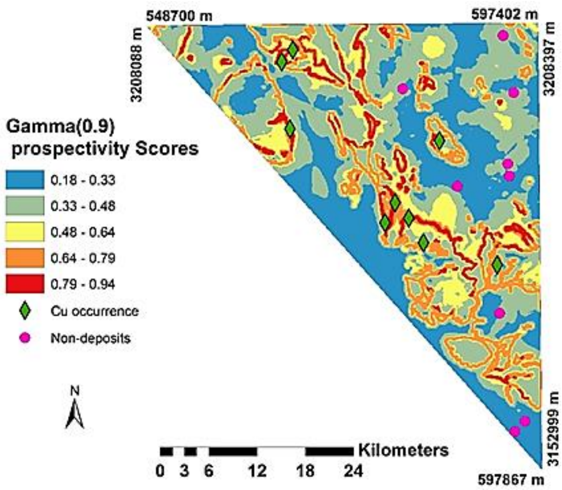

Figure 8. The final classified model (integrated with the fuzzy gamma method).

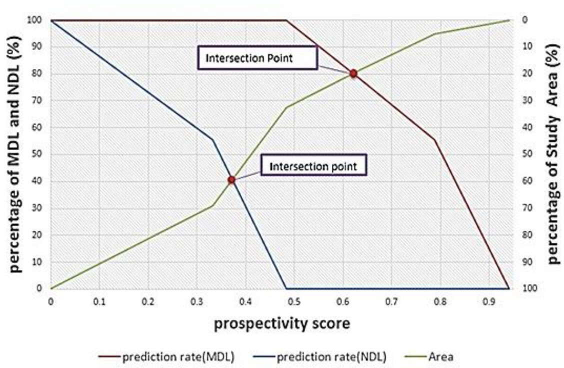

Figure 9. The P-A diagram of the fuzzy gamma model.

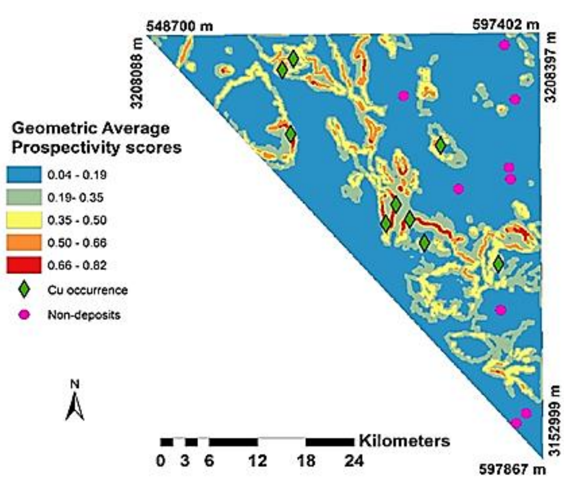

Figure 10. The final classified model (combined by the geometric average method).

gamma and geometric average with an overall performance of 40% are similar to each other and stronger than the model obtained by ANNs with 37% overall performance. Thus, these models are relatively more efficient.

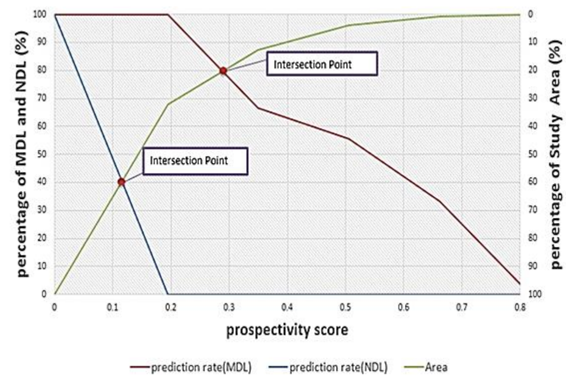

Figure 11. P-A diagram of the geometric average model.

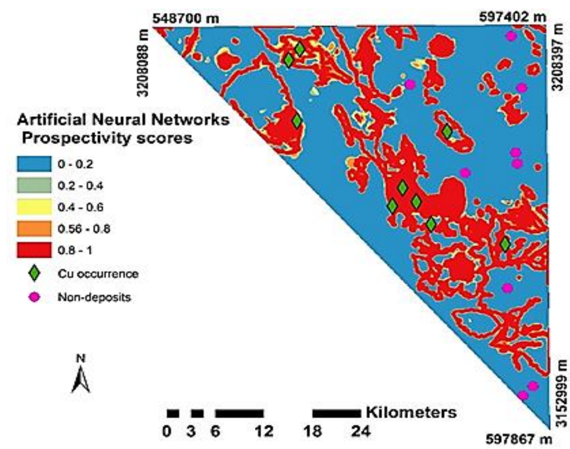

Figure 12. Final classified model (integrated by artificial neural network method).

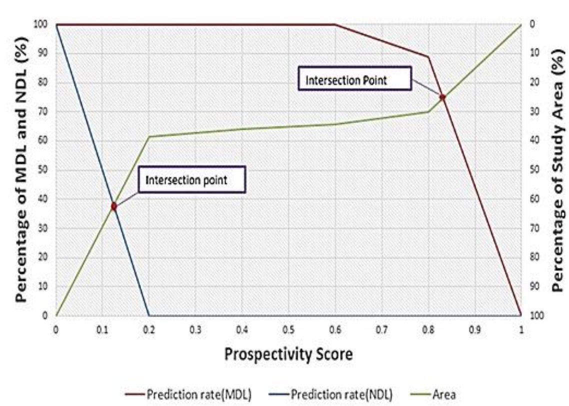

Figure 13. P-A diagram of the artificial neural network model.

6. Discussion

The ANN method, which was used to combine weighted control maps and construct a mineral resource potential model in the present study, is a data-driven method and the results depend on the number of data used in the network training process [2]. In this case, the small number of training data has a negative effect on the results, while the methods of geometric average and fuzzy gamma are not actually data-driven operators, and the results of combining control maps through these functions are independent of training samples and the known deposit location in the study area. Therefore, in the results of evaluating the final models obtained from three methods of geometric average, fuzzy gamma, and ANN, the ANN model showed lower overall performance and a lower prediction rate than the other two models due to the small amount of data used for network training. The fuzzy gamma models and geometric average showed general performance as well as high and similar prediction rates, and were found to be more suitable and reliable in the next stages of exploration in the study area. To study the data-driven method of ANN more accurately in mineral potential modelling, it is suggested to use other ANN training algorithms or other methods based on artificial intelligence, such as support machining and random forest for integration of weighted control maps and production of the mineral potential model of porphyry copper deposits in the Jiroft region. Also, the processing of satellite images and preparation of alteration maps [51] of the study area, as well as the use of appropriate geophysical data in the process of combining weighted control layers, can further limit the exploration objectives and increase the efficiency of the final models obtained in the next tasks. These improvements will be applicable and doable. It is also recommended to examine recently-developed exploration data analysis approaches on the dataset of the present study and compare the results [54, 53, 52].

7. Conclusion

Although, the number of training points for training the ANN was limited, but the fast learning machine algorithm trained the network well, and the model produced by the ANN method showed a high and acceptable prediction rate. So, the rapid learning machine algorithm is a powerful and efficient algorithm for training ANNs in the stage of combining control maps and building mineral potential models, even in conditions where training points are very limited.

- Models produced by the geometric average and fuzzy gamma methods both provide the same and acceptable forecast rate, and both models are efficient for use in the next stages of copper exploration in the study area.
- By comparing the prediction rate of models produced by the geometric average and fuzzy gamma methods with the model produced by the ANN method, this result is obtained. Although all three models have a high and acceptable prediction rate, but the model produced by the ANN method is slightly weaker and the models produced by the methods of geometric average and fuzzy gamma, because of the location and the number of known copper occurrences in the study area are independent, show a relatively better performance. Therefore, they are recommended for use in later stages of exploration and for more detailed exploration of porphyry copper deposits in the Jiroft region of Kerman province.

REFERENCES

[1] Yousefi, M., Kreuzer, O.P., Nykänen, V., Hronsky, J.M.A., 2019. "Exploration information systems—a proposal for the future use of GIS in mineral exploration targeting". Geology Reviews 111, 103005.

[2] Afzal, P., Yousefi, M., Mirzaei, M., Ghadiri-Sufi, E., Ghasemzadeh, S., Daneshvar Saein, L., 2019. "Delineation of podiform-type chromite mineralization using Geochemical Mineralization Prospectivity Index (GMPI) and staged factor analysis in Balvard area (southern Iran). Journal of Mining and Environment 10: 705-715.

[3] Yousefi, M., Kreuzer, O.P., Nykänen, V., Hronsky, J.M.A., 2019. "Exploration information systems—a proposal for the future use of GIS in mineral exploration targeting". Ore Geology Reviews 111, 103005.

[4] Yousefi, M., E.J.M., Carranza, Kreuzer, O.P., Nykänen, V., Hronsky, J.M.A., Mihalasky, M., J., 2021. "Data analysis methods for prospectivity modelling as applied to mineral exploration targeting: State-of-the-Art and Outlook". Journal of Geochemical Exploration 229, 106839.

[5] Carranza, E. J. M. 2008. "Geochemical Anomaly and Mineral Prospectivity Mapping in GIS" Handbook of Exploration and Environmental Geochemistry. Vol. 11, Elsevier, Amesterdam.

[6] Yousefi, M., Carranza, M. J. M. 2015. "Fuzzification of Continouse- value spatial evidence for mineral prosprctivity mapping" Computers & Geosciences 74: 97-109.

[7] Yousefi, M., Carranza, M. J. M. 2017. "Union score and fuzzy logic mineral prospectivity mapping using discretized and continuous spatial evidence values" Journal of African Earth Sciences 128: 47-60.

[8] Berberian, F., Muir, I.D., Pankhurst, R.J., Berberian, M., 1982. "Late cretaceous and early miocene andean-type plutonic activity in northern Makran and central Iran". J. Geol. Soc. Lond. 139, 605e614.

[9] Badrzadeh, Z., Aghazadeh, M., 2014. "Geochemistry and Structural Geology of Intrusive Masses of South-Western Part of Jiroft" Geochemistry Journal, 2, Payame Noor University

[10] Hezarkhani, A. 2006. "Mineralogy and fluid inclusion investigations in the Reagan Porphyry System, Iran, the path to an uneconomic porphyry copper deposit" Journal of Asian Earth Sciences 27: 598–612.

[11] Roberts, R. G., Sheahan, P., Cherry, M. E. 1998. " Ore Deposit Models" Geoscience Canada Reprint Series 3, Geological Association of Canada, Newfoundland.

[12] Berger, B. R., Drew, L. J. 2002. "Mineral – deposit models: new developments in: A.G. Fabbri, Gaal, G., Mccammon, R.B. (Eds.), Deposit and Geoenvironmental models for Rsource Exploration and Environmental Security" NATO Science Series 2, 80: 121-134.

[13] Pirajno, F. 1992. "Hydrothermal Mineral Deposits, Principles and Fundamental Concepts for the Exploration Geologists" Springer- verlag, Berlin.

[14] Robb, L. 2004. "Introduction to Ore- foming Processes" Blackwell, Oxford.

[15] Carlson, C. A. 1991. "Spatial distribution of ore depisits" Geology 19: 111-114.

[16] Vearcombe, J., Vearcombe, S. 1999. "The spatial distribution of mineralization: applications of Fry analysis" Economic Geology 94: 475- 486.

[17] Bonham – Carter, G. F. 1985. "Statistical association of gold occurrences with Landsat – derived lineaments, Timmins-Kirkland Lake area, Ontario, Canadian" Journal of Remote sensing 11: 195-211.

[18] Carranza, E. J. M, Hale, M. 2002. "Spatial association of mineral occurrence and curvi-linear geological features" Mathematical Geology 34: 199-217.

[19] Sillitoe, R. H. 1972. "A plate tectonic model for the origin of porphyry copper deposits" Econ. Geol. 67: 184-197.

[20] Sillitoe, R. H. 1997. "Characteristics and controls of the largest porphyry copper-gold and epithermal gold deposits in the circum-Pacific region" Aust. J. Earth Sci. 44: 373-388.

[21] Sillitoe, R. H., 2010." Porphyry copper systems" Econ. Geol. 105: 3-41.

[22] Arribas, A. J. 1995. "Contemporaneous formation of adjacent porphyry and epithermal Cu-Au deposits over 300 ka in northern Luzon, Philippines" Geology, 23: 337–340.

[23] Singer, D. A., Berger, V. I., Moring, B. C. 2005. "Porphyry copper deposits of the world: Database, map, grade and tonnage models" U.S. Geological Survey. Open-File Report : 1005–1060.

[24] Hezarkhani, A. 2006. "Mineralogy and fluid inclusion investigations in the Reagan Porphyry System, Iran, the path to an uneconomic porphyry copper deposit" Journal of Asian Earth Sciences 27: 598–612.

[25] Guillou-Frottier, L., Burov, E. 2003. "The development and fracturing of plutonic apexes: Implications for porphyry ore deposits" Earth and Planetary Science Letters 214: 341–356.

[26] Qu, X., Hou, Z., Zaw, K., Youguo, L. 2007. "Characteristics and genesis of Gangdese porphyry copper deposits in the southern Tibetan Plateau: Preliminary geochemical and geochronological results" Ore Geology Reviews 31: 205–223.

[27] Ghasemi, A., Talbot, C. J. 2006. "A new tectonic scenario for the Sanandaj–Sirjan Zone (Iran)" Journal of Asian Earth Sciences 26: 683–693.

[28] Meshkani, S. A., Mehrabi, B., Yaghubpur, A., Sadeghi, M. 2013. "Recognition of the regional lineaments of Iran: Using geospatial data and their implications for exploration of metallic ore deposits" Ore Geology Reviews 55: 48–63.

[29] Zare Chahooki, M. A., 2010. "Moltivariate Analysis in SPSS" University of Tehran.

[30] Yousefi, M., Kamkar-Rouhani, A., Carranza, M. J. M. 2012. "Geochemical mineralization probability index (GMPI): A new approach to generate enhanced stream sediment geochemical evidential map for increasing probability of success in mineral potential mapping" Journal of Geochemical Exploration 115 : 24–35.

[31] Yousefi, M., Carranza, E. J. M., Kamkar-Rouhani, A. 2014. "Weighted drainage catchment basin mapping of stream sediment geochemical anomalies for mineral potential mapping".Journal of Geochemical Exploration 128:88–96.

[32] Yousefi, M. 2017. "Recognition of an enhanced multi-element geochemical signature of porphyry copper deposits for vectoring into mineralized zones and delimiting exploration targets in Jiroft area, SE Iran" Ore Geology Reviews 83: 200–214.

[33] Yousefi, M., Nykänen, V. 2016. "Data-driven logistic-based weighting of geochemical and geological evidence layers in mineral prospectivity mapping" Journal of Geochemical Exploration 164: 94–106.

[34] Nykanen, V. 2008. " Radial basis functional link nets used as a prospectivity mapping tool for orogenic gold deposits within the Central Lapland Greenstone Belt, Northern Fennoscandian Shield" Natural Resource Research 17: 29-48.

[35] Zadeh, L. A. 1997. "Introduction to hybrid artificial intelligence systems" in Tsoukalas, L. H., and Uhrig, R. E., eds., fuzzy and Neural Approaches in Engineering: john and sons. Inc., New York, p. 1-7.

[36] Porwal, A., 2006. "Mineral Potential Mapping with Mathematical Geological Models" ph.D. Thesis, University of Utrecht, The Netherlands, ITC(International Institute for Geo-Information Science and Netherlands, ITC(International Institute for Geo-Information Science and Earth Observation) Publication No. 130, Enschede, 289pp.

[37] Fathi, M., Alimoradi, A., Hemati Ahooi, R. 2021 "optimizing extreme learning machine algorithm using particle swarm optimization to estimate iron ore grade"journal of Mining and Environment 12 (2), 397-411.

[38] Carranza, E. J. M., Laborte, A. G. 2016. "Data-driven predictive modeling of mineral prospectivity using random forests: A case study in Catanduanes Island (Philippines)" Natural Resources Research 25:35–50.

[39] Chen, Y., Wu, W., 2017. "Mapping mineral prospectivity using an extreme learning machine regression" Ore Geology Reviews 80 : 200–213.

[40] Huang, G. B., Zhu, Q. Y., Siew, C. K., 2006. "Extreme learning machine: theory and applications" Neurocomputing 70 : 489–501.

[41] Carranza, E. J. M., Woladi, T., Chikambwe, E. M. 2005. "Application of data-driven evidential belief functions to prospectivity mapping for aquamarine-bearing pegmaties, Lundazi District, Zambia" Natural Resource Deposits 14: 47-63.

[42] Bonham-Carter, G. F., Agterberg, F. P., Wright, D, F. 1989. "Weigh of evidence modeling: a new apprpach to mapping mineral potential In: Agterberg, F. P., Bonham-Carter, G. F. (Eds.), Statistical Applications in the Earth Science" Geological Survey of Canada 89: 171-183.

[43] Yousefi, M., Carranza, M. J. M. 2015. "Prediction – area (P- A) plot and C-A fractal analysis to classify and evaluate evidential maps for mineral prospectivity modeling"Computers & Geosci Computers & Geosciences 83:72–79.

[44] Nezhad, S. G., Mokhtari, A. R., Rodsari, P. R. 2017. "The true sample catchment basin approach in the analysis of stream sediment geochemical data" Ore Geology Reviews 83; 127–134.

[45] Zhang, N., Zhou, K., Du, X. 2017. "Application of fuzzy logic and fuzzy AHP to mineral prospectivity mapping of porphyry and hydrothermal vein copper deposits in the Dananhu-Tousuquan island arc, Xinjiang, NW China" Journal of African Earth Sciences 128: 84–96.

[46] Du, X., Zhou, K., Cui, Y., Wang, J., Zhang, N., Sun, W. 2016. "Application of fuzzy Analytical Hierarchy Process (AHP) and Prediction-Area (PA) plot for mineral prospectivity mapping: A case study from the Dananhu metallogenic belt, Xinjiang, NW China" Arabian Journal of Geosciences 9: 298.

[47] Nykanen, V., Lahti, I., Niiranen, T., Korhonen, K. 2015. "Receiver operating characteristics (ROC) as validation tool for prospectivity models—A magmatic Ni–Cu case study from the Central Lapland Greenstone Belt, Northern Finland" Ore Geology Reviews 71: 853–860.

[48] Parsa, M., Maghsoudi, A., Yousefi, M. 2017. "A receiver operating characteristics-based geochemical data fusion technique for targeting undiscovered mineral deposits" Natural Resources Research 27: 15–28.

[49] Zuo, R. 2018. "Selection of an elemental association related to mineralization using spatial analysis" Journal of Geochemical Exploration 184: 150–157.

[50] Roshanravan, B., Aghajani, H., Yousefi, M., Kreuzer, O. 2018b. "An Improved Prediction-Area Plot for Prospectivity Analysis of Mineral Deposits" Natural Resources Research. 28:1089-1105.

[51] Mars, J. C., & Rowan, L. C. (2006). Regional mapping of phyllic- and argillic-altered rocks in the Zagros magmatic arc, Iran, using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data and logical operator algorithms. Geosphere, 2(3), 161-186.

[52] Yousefi, M., Hronsky, J.M.A., 2023. "Translation of the function of hydrothermal mineralization-related focused fluid flux into a mappable exploration criterion for mineral exploration targeting". Applied Geochemistry 149, 105561.

[53] Yousefi, M., Yousefi, S., Kamkar Rouhani, A. G., 2023a. "Recognition coefficient of spatial geological features, an approach to facilitate criteria weighting for mineral exploration targeting". International Journal of Mining and Geo-Engineering.

[54] Yousefi, M., Barak, S., Salimi, A., Yousefi, S., 2023b. "Should geochemical indicators be integrated to produce enhanced signatures of mineral deposits? A discussion with regard to exploration scale". Journal of Mining and Environment.