

Comparison of subjective and objective methods for the spatial estimation of the porphyry Cu potential in Ahar-Arasbaran area, north-western Iran

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ABSTRACT Geographic Information System (GIS) are very useful tools for managing, checking, and organizing spatial information from many sources and of many types in thematic layers. In this paper, using GIS, we describe and compare different models for the estimation of porphyry copper potential maps in Ahar-Arasbaran zone, north-western Iran. Final potential mapping of the study area was assessed according to the advantages and disadvantages of each method and a combination of them. The results demonstrate that the Analytic Hierarchy Process (AHP) method provides the best output with the lowest potential area and the highest point validation coverage, and highlights a new potential area of porphyry copper mineralization confirmed by field check.

Key words: potential mapping, porphyry, Ahar-Arasbaran, GIS.

1. Introduction

The presence of mineral resources is an important guarantee for a country to experience a sustainable and fast development of its national economy. It has been a significant scientific topic for research, among scientists all over the world, to obtain a clear view of these resources (Guangsheng *et al.*, 2007). The preliminary quantitative prediction and assessment for mineral resource exploration is based on multi-information (geology, physical geography, geochemistry, and remote sensing), synthetic technology, and metallogenetic theory (Gongwen and Jianping, 2008). Geographic Information Systems (GIS) are very useful tools for managing spatial information and are frequently used to evaluate mineral potential in exploration districts and provide tools to deal with multiple data sets, or layers, of diverse character from various sources (Bonham-Carter, 1994; Pan and Harris, 2000; de Araujo and Macedo, 2002; Roy *et al.*, 2006; Carranza, 2008; Carranza *et al.*, 2008; Pazand *et al.*, 2011, 2012a). Before the construction of a predictive model, which can be defined as representing the favourability or probability of a mineral deposit of the type/style sought to occur, a schematic subdivision has to be drawn depending on the type of inference mechanism considered. The two model types are: 1) knowledge-driven, and 2) data driven (Feltrin, 2008). The former means that evidential weights are estimated subjectively based on one or more expert opinions about the spatial association of target deposits with certain geologic features, whereas the latter means that evidential weights are quantified objectively with respect to locations of known target deposits (Bonham-Carter,

1994; Moon, 1998; Cheng and Agterberg, 1999; Carranza and Hale, 2001; Porwal *et al.*, 2004; Carranza *et al.*, 2008).

Several methods exist for mineral potential mapping. There are no better or worse techniques, but due to the geological complexity, condition, and data for an area, some techniques are better suited to potential mapping than others. In this paper, several methods of both knowledge-driven and data-driven types, such as fuzzy logic, Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Weights Of Evidence (WOE), neural network, and a hybrid of the methods, are used to build a mineral potential mapping for porphyry Cu mineralization in Ahar-Arasbaran zone. The Ahar-Arasbaran area has been studied for several decades because of its mineral potential for metallic ores, especially copper (skarn and porphyry types) and gold sulphide (Hezarkhani and Williams-Jones, 1996; Hezarkhani *et al.*, 1997, 1999; Mollai *et al.*, 2004, 2009; Hezarkhani, 2006, 2008). The aim of this work is to demonstrate the capabilities of these different methods to provide a porphyry copper prospective map, to determine advantages and disadvantages of each, as well as to choose the best method for providing porphyry copper potential mapping in the study area. Finally, using a combination of all the maps, final and optimal potential mapping was obtained.

2. Study area

The Ahar-Arasbaran area is located in the east Azarbaijan province, north-western Iran, in the northern part of the Cenozoic Urumieh-Dokhtar magmatic arc (Fig. 1) with an arial extent

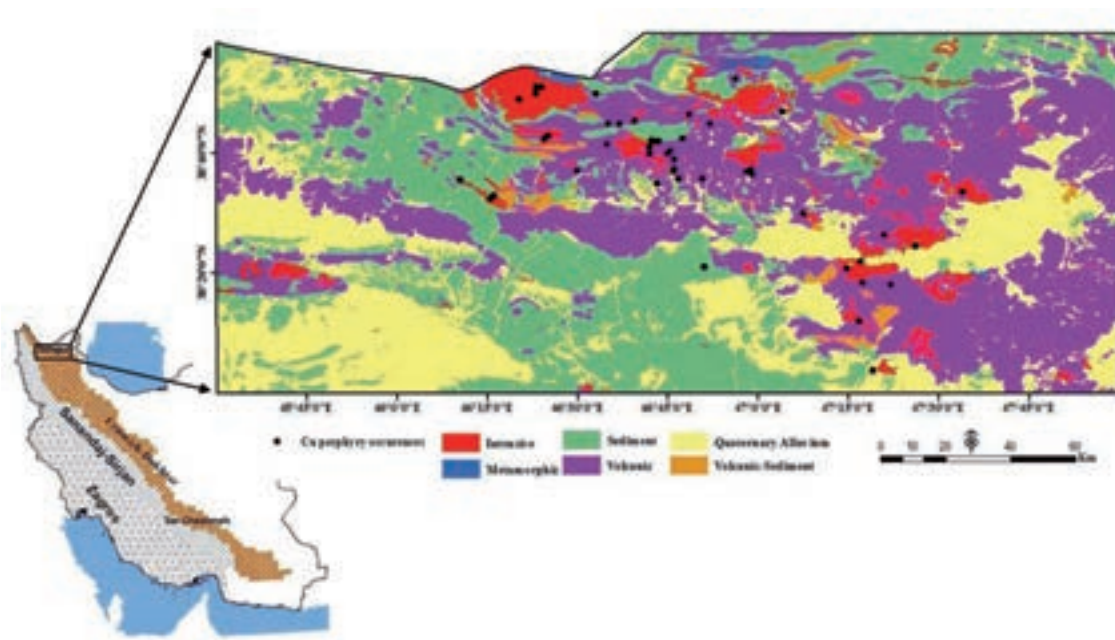


Fig. 1 - Major structural zones of Iran (after Nabavi, 1976) and a modified and simplified geologic map of the study area (after Mahdavi, 1988; Babakhani and Nazer, 1991; Mehrpartou *et al.*, 1992; Asadian, 1993; Amini, 1994; Asadian *et al.*, 1994; Mehrpartou, 1997, 1999; Faridi and Haghfarshi, 2006). The map also indicates the locations of the Cu porphyry deposits (black dots).

of about 23,135 km². Continental collision between the Afro-Arabian continent and the Iranian micro-continent during the closure of the Tethys ocean in the Late Cretaceous resulted in the development of the Urumieh-Dokhtar magmatic arc (Mohajjel and Fergusson, 2000; Babaie *et al.*, 2001; Karimzadeh Somarin, 2005). All of the entire known porphyry copper mineralization in Iran occurs in the Urumieh-Dokhtar orogenic belt (Fig. 1). This belt was formed by subduction of the Arabian plate beneath central Iran during the Alpine orogeny (Berberian and King, 1981; Pourhosseini, 1981) and hosts two major porphyry copper deposits: 1) the Sarcheshmeh deposit and 2) the Sungun deposit. In the Ahar-Arasbaran area, there are 47 occurrences of economical and sub-economical porphyry copper deposits and all are associated with mid- to late-Miocene diorite/granodiorite to quartz-monzonite stocks (Pazand *et al.*, 2012a).

In the Arasbaran region, two intrusive magmatic cycles were recognized (Jamali and Mehrabi, 2014): Cycle I is of shoshonitic affinity and is not associated with significant mineralization, Cycle II, consisting of two cycles during the Upper Oligocene-Lower Miocene and Upper Miocene-Pliocene, is the significant metallogenic magmatic cycle. The earlier sub-cycle is dominantly associated with Cu-Mo porphyry mineralization, while the late sub-cycle is associated with porphyry Cu-Au and epithermal Au mineralization (Jamali and Mehrabi, 2014).

3. Database

Five main types of geological data (input layers in the GIS) have been considered relevant for Cu porphyry exploration. They include airborne magnetic, stream sediment geochemical data, geology, structural data, and alteration zone (Pazand *et al.*, 2012a). All data are managed in a GIS environment as an input shapefile, and are considered as a proxy variable of Cu porphyry deposits.

The magnetic anomalies identified by the airborne magnetic surveys may reflect the increased concentration of secondary magnetite in potassic alteration zones, or magnetite destruction in other peripheral styles of alteration, or high magnetite in the original intrusive plutons responsible for mineralization (Daneshfar, 1997). Airborne magnetic data were also used to identify magnetic lineation, faults, and intrusive bodies. The map of the total magnetic intensity was classified and coded into ten main classes.

Geological data inputs to the GIS are derived and compiled from the geologic map of 1:100,000 scale, and lithologic units were hand-digitized into vector format. Each polygon was labeled according to the name of each litho-stratigraphic formation, and a host rock evidence map was prepared including intrusive and volcanic rock as two sub-criteria.

The geochemical analysis of stream sediment samples using Atomic Absorption Spectrophotometry (AAS) provided the concentrations of some elements considered as pathfinders of Cu porphyry mineralization (Cu, Mo, Pb, Zn, As, Sb, Ba).

After normalization, the geochemical data were assigned to five classes. Values equal to or less than the mean value were considered low background. Values between the mean and mean plus one standard deviation ($+\sigma$) are threshold. Values between ($+\sigma$) and ($+2\sigma$) are slightly anomalous. Values between ($+2\sigma$) and ($+3\sigma$) are moderately anomalous, and values greater than ($+3\sigma$) are highly anomalous (Pazand *et al.*, 2012a). The geochemical evidence maps for each of the elements were prepared as geochemical sub-criteria. Porphyry-Cu deposits in the Urumieh-Dokhtar belt of

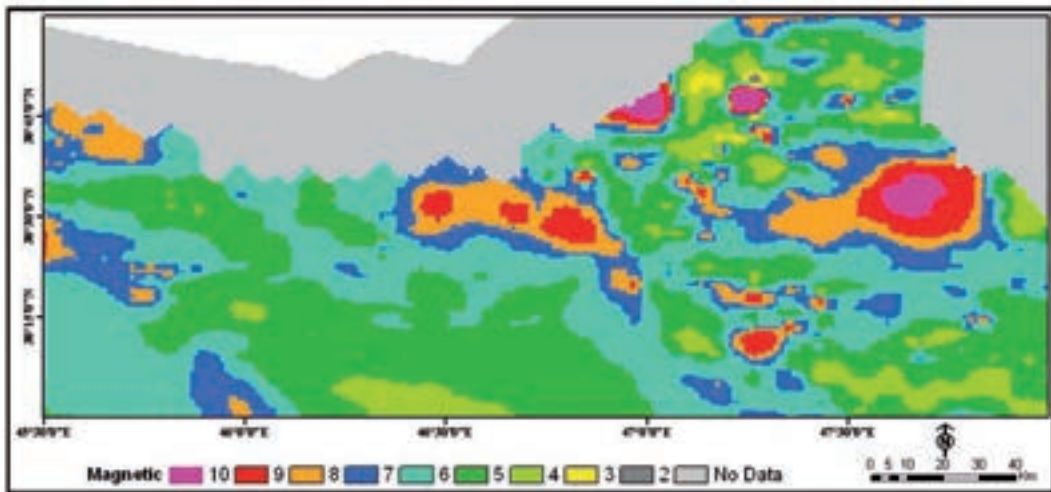


Fig. 2 - Evidence layer of total magnetic intensity.

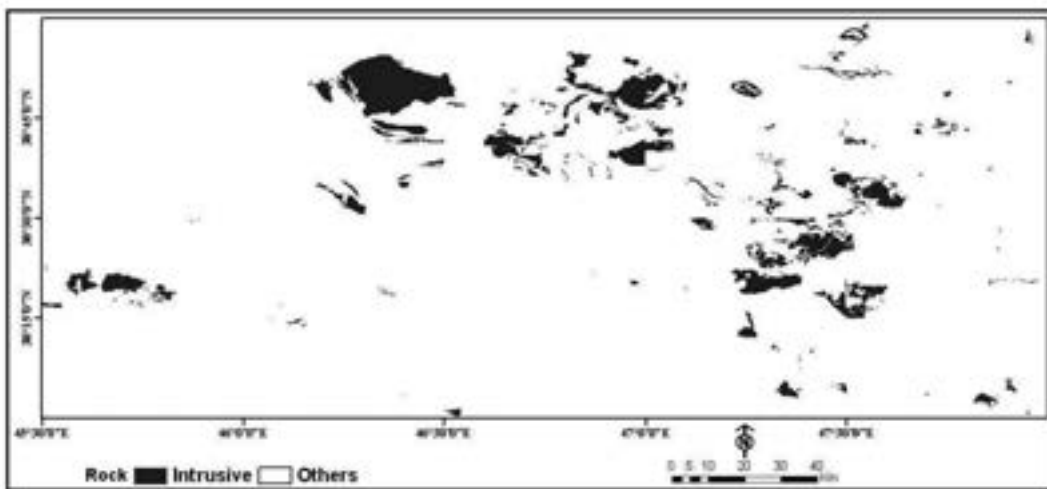
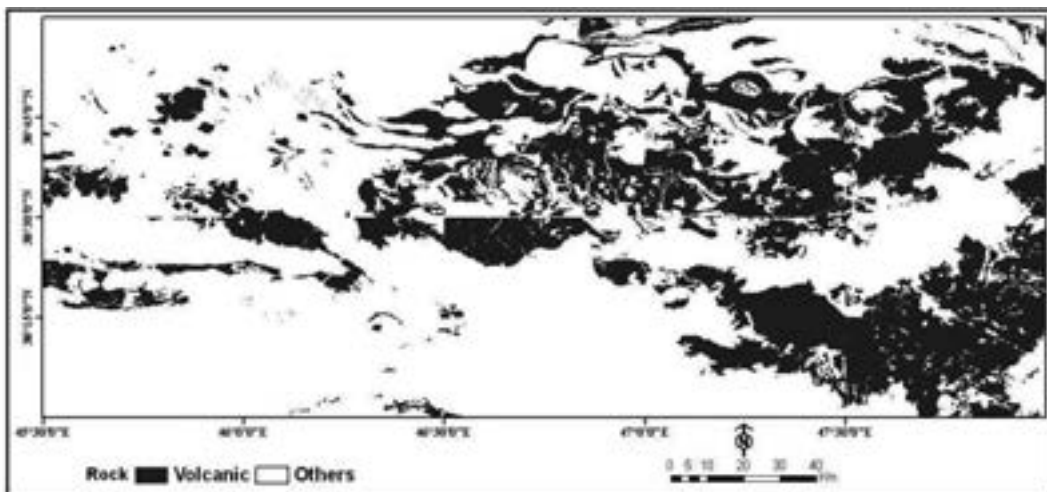


Fig. 3 - Evidence layers of intrusive and volcanic rocks.

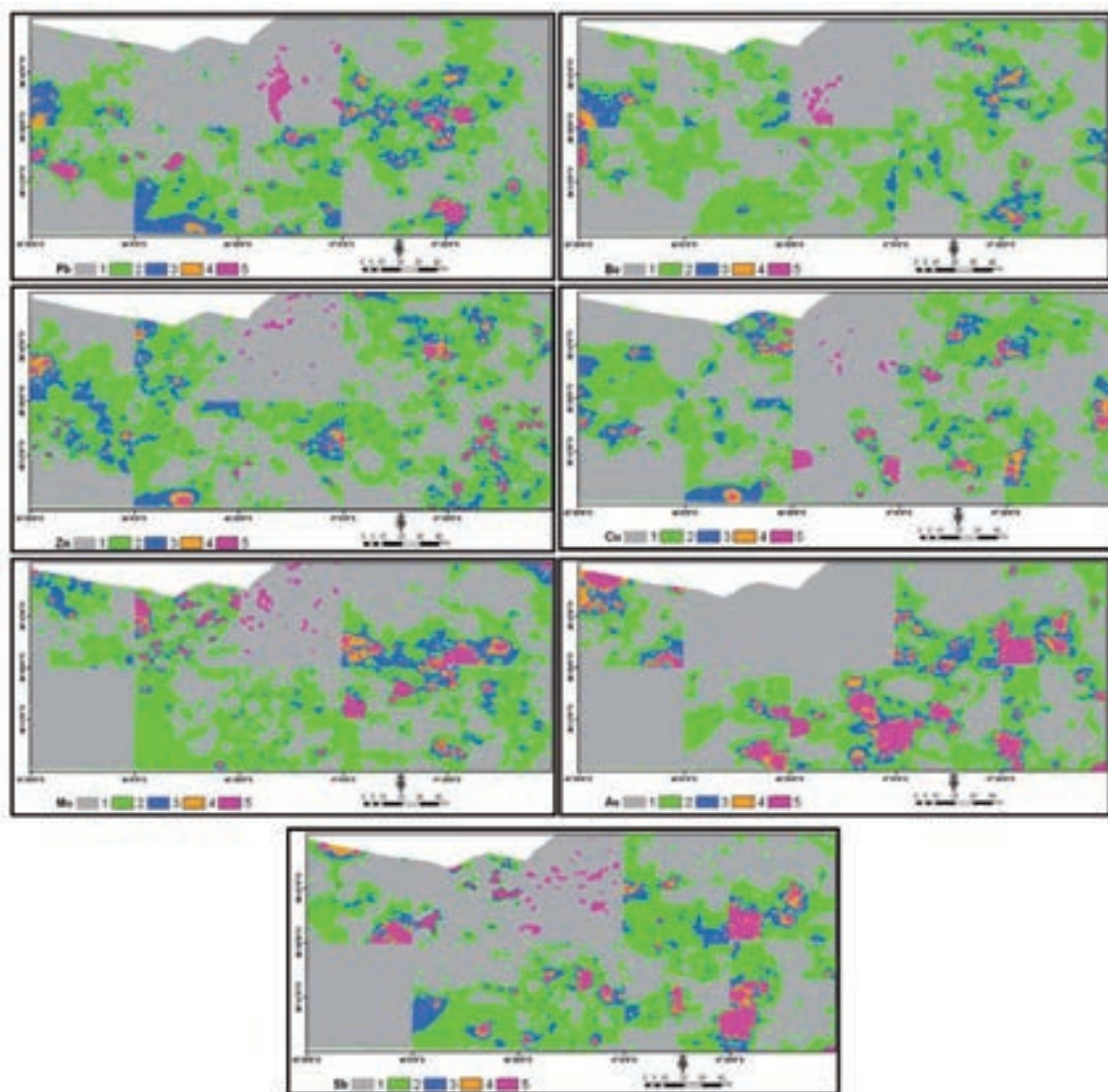


Fig. 4 - Geochemical evidence layers of Cu, Mo, Ba, Zn, Sb, As, and Pb.

Iran show geochemical halos of indicator elements, mainly Cu, Mo, Au, Ag, Zn, Pb, As, and Sb (Yousefi and Carranza, 2014).

Linear structural features interpreted from aeromagnetic data and remotely sensed data were combined with faults available in the geological map to generate a structural evidence map as follows:

$$FD = a/A + b/B + c/C \quad (1)$$

where FD is the fault density, a is the number of lines in the cell, b is the number of intersections in the cell, c is the length of the linear in the cell, and A, B, C are averages of a, b, c parameters in the study area respectively (Hardcastle, 1995). The map provided in this layer was classified and coded into ten main classes according to their density per unit of area. Mirzaie *et al.* (2015) study

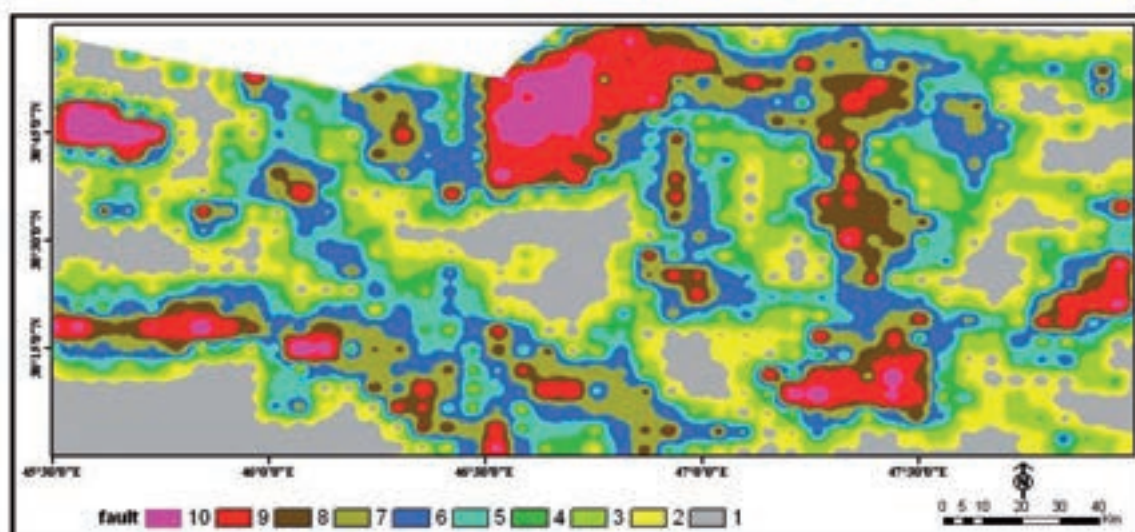


Fig. 5 - Evidence layer of faulting density.

about fault control on Cu mineralization in kerman porphyry copper belt (south-eastern Iran) revealed that the fractal analysis of structural features, such as drainages and faults coupled with detailed structural analysis in target zones, can be used to indicate the location of the potential Cu mineralization.

Remote sensing data (ASTER) were used for the identification of argillic, phyllic, prophylic, and iron oxide alteration layer (Pazand *et al.*, 2012b), as four alteration sub-criteria, and for preparing an alteration evidence map. Each evidence map was converted to raster with cell size 100×100 m by ArcGIS software.

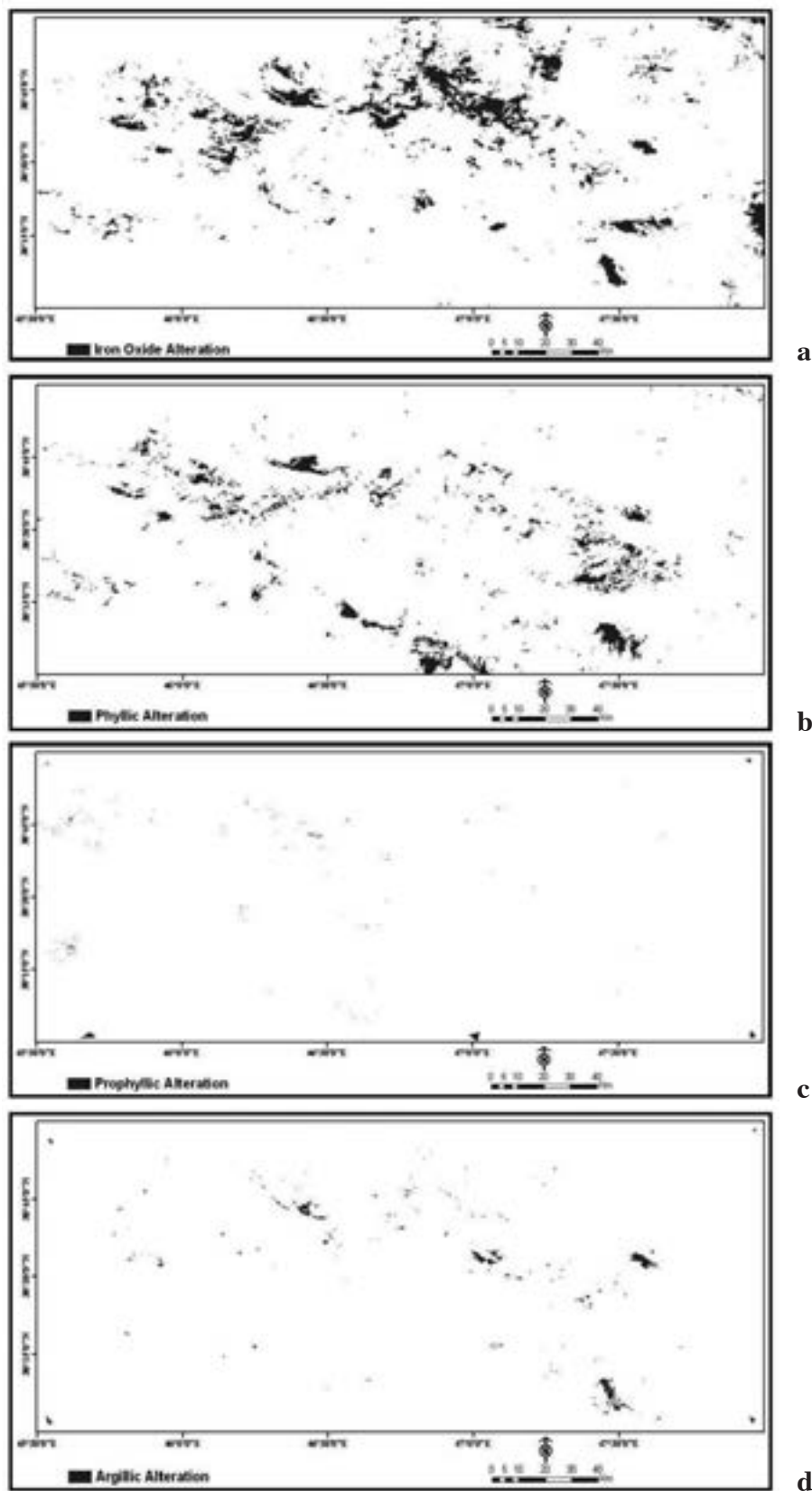
4. Porphyry copper potential mapping

Mineral prospectivity modelling involves the following three procedures: i) conceptual modelling and identification of input predictor maps, ii) construction of appropriate predictor maps, and iii) integration of the predictor maps using mathematical models (Porwal and Carranza, 2015).

After selecting the above-mentioned mineralization factors (porphyry copper), the most important task is to determine the appropriate score for each factor. Each technique will use different approaches and will provide different maps. Some of the techniques will weight selected proxies by using expert knowledge, while others make use of the spatial associations among known deposits to calculate optimal weights for selected proxies. Accordingly, they have been broadly classified into knowledge-driven and data-driven (Asadi *et al.*, 2015).

5. Knowledge-driven methods

Knowledge-driven approaches rely on the input from a geologist or team of geologists to weight the importance of each proxy variable and the relative importance of different map layers



a

b

c

d

Fig. 6 - Alteration: evidence layers of: a) iron oxide, b) phyllic, c) prophyllitic, and d) argillic.

as they relate to the particular exploration model being used. This approach is more subjective but has the advantage of incorporating the knowledge and expertise of one or more geologists in the modelling process (Harris *et al.*, 2015).

6. Fuzzy logic

In the fuzzy logic method, maps (fuzzy membership) based on the significance distance of features are weighted (for each pixel or spatial position, a particular weight between 0 to 1 is appointed). A number of set operators based on fuzzy mathematics were defined: the most widely used operators in fuzzy modelling are the fuzzy AND, fuzzy OR, the complement, the algebraic sum, the algebraic product, and the Gamma operator (Zimmerman, 1991; Ghanbari *et al.*, 2012; Pazand *et al.*, 2013). The evidence map can be formulated in a series of steps by using an inference network. The inference network is an important means of simulating the logical thought processes of an expert (Fig. 7). The fuzzy favorability maps produced by using a Gamma value of 0.85 as best value were then defuzzified using 0.5 as the threshold. The resulting binary favorability map is shown in Fig. 8. The results were validated by overlaying the known mineral deposits on the binary favorability map (Fig. 8). It can be seen that the favorable areas, which occupy 1437.7 km², contain 36 of the 47 known Cu porphyry deposits in the study area. Thus the model predicts 76.5% of the known Cu porphyry deposits, while at the same time reducing the search area to less than 6.2% of the total area.

7. Similarity to ideal solution (TOPSIS)

According to this technique, the best alternative would be the one that is nearest to the positive ideal solution and farthest from the negative ideal solution (Ataei *et al.*, 2008). The ideal solution

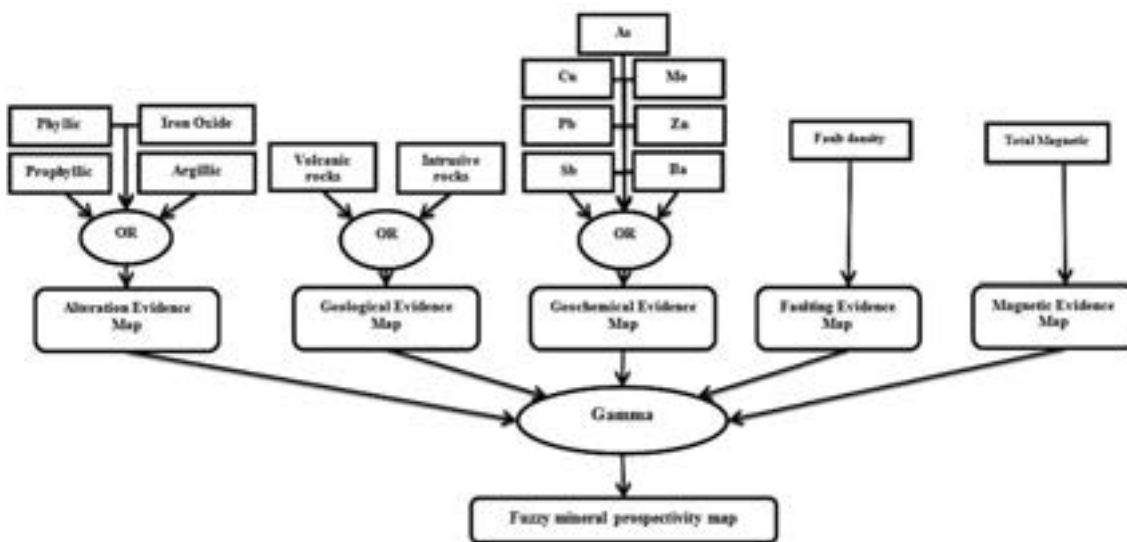


Fig. 7 - Simplified network used for predicting Cu porphyry mineralization using the fuzzy logic method.

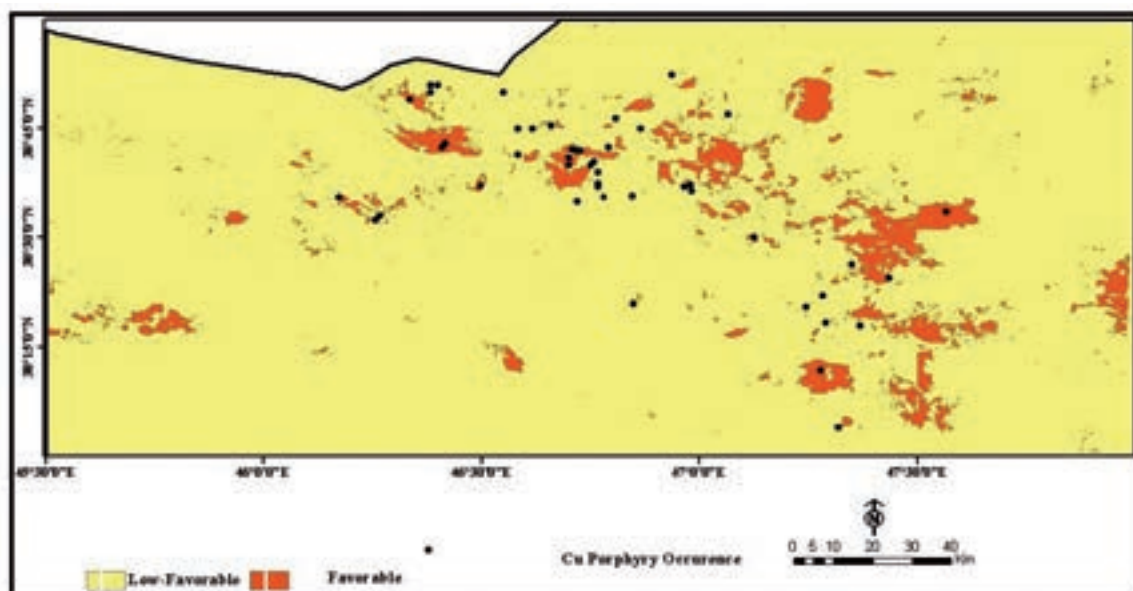


Fig. 8 - Potential mapping for Cu porphyry mineralization in Ahar-Arasbaran area according to the fuzzy logic method.

(also called the positive ideal solution) is a solution that maximizes the benefit criteria/attributes and minimizes the cost criteria/attributes, whereas the negative ideal solution (also called the anti-ideal solution) maximizes the cost criteria/attributes and minimizes the benefit criteria/attributes (Pazand *et al.*, 2012a). The TOPSIS method consists of the following steps (Dagdeviren *et al.*, 2009; Pazand *et al.*, 2012a):

1. establish a decision matrix for the ranking;
2. calculate the normalized decision matrix;
3. calculate the weighted normalized decision matrix by multiplying the normalized decision matrix by its associated weights;
4. determine the positive-ideal and negative-ideal solutions;
5. calculate the separation measures, using the n-dimensional Euclidean distance, i.e.: the separation of each alternative from the positive-ideal and negative-ideal solution;
6. calculate the relative closeness to the idea solution and rank the performance order.

The mapping of potential for porphyry copper mineralization in the Ahar-Arasbaran area was prepared by TOPSIS equations (Pazand *et al.*, 2012a) by using ArcGIS software. The score of the prediction criteria are provided by geologists who are experienced in copper exploration and metallogeny characteristics of the study area. Pazand *et al.* (2012a) used the TOPSIS method to create a Cu porphyry mineral prospectivity map for Ahar-Arasbaran area. The areas with greater than threshold value ($+ \sigma$) were introduced as a binary favorability map. From 48 known porphyry copper occurrences in the region, 34 occurrences were located in areas with high potential; this means that the model predicts 72.34% of the known porphyry copper deposits, and the ability and the accuracy of the method is confirmed (Fig. 9).

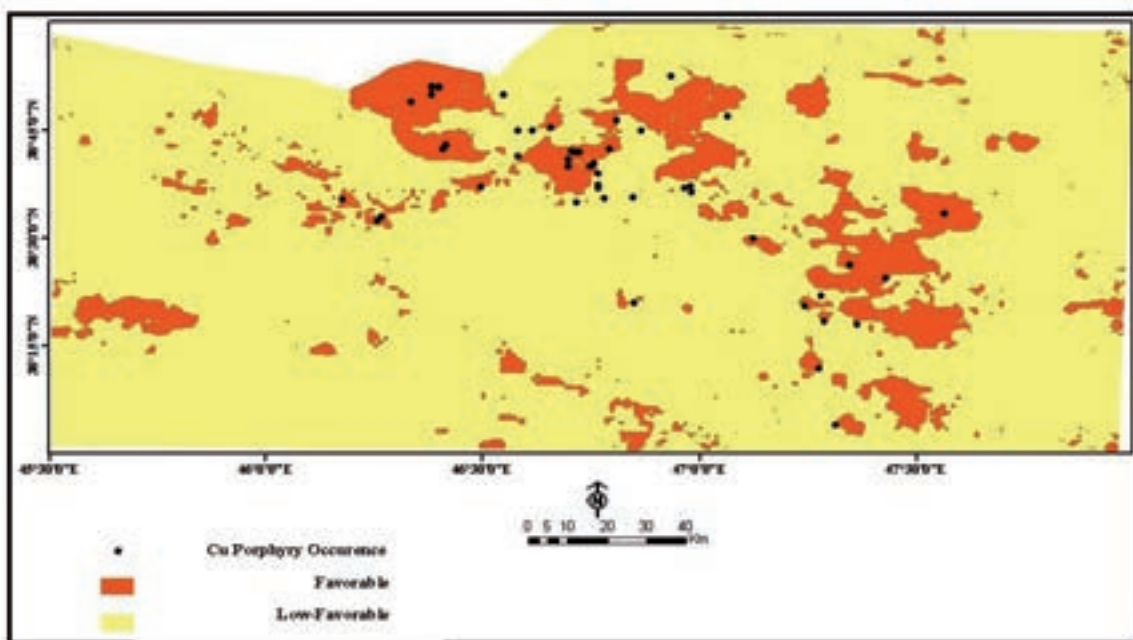


Fig. 9 - Potential mapping for Cu porphyry mineralization in Ahar-Arasbaran area according TOPSIS method.

8. Analytic Hierarchy Process (AHP)

AHP is a mathematical decision-making technique that allows for the rational evaluation of weightings (Pazand *et al.*, 2011). It determines an optimal solution through the use of simple representation of a hierarchical model. AHP relies on three fundamental assumptions (Hosseinali and Alesheikh, 2008):

1. preferences for different alternatives depend on separate criteria which can be reasoned about independently and given numerical scores;
2. the score for a given criteria can be estimated from sub-criteria. That is, the criteria can be arranged in a hierarchy and the score at each level of the hierarchy can be calculated as a weighted sum of the lower-level scores;
3. at a given level, suitable scores can be calculated only from pair-wise comparisons.

Let C_1, \dots, C_m be the m performance factors and $W = (w_1, \dots, w_m)$ be their normalized relative importance weight vector, which is to be determined by using pairwise comparisons and which has to satisfy the normalization condition (Dambatta *et al.*, 2009):

$$\sum_{j=1}^m W_j = 1 \quad \text{with } w_j \geq 0 \text{ for } j = 1, \dots, m \tag{2}$$

The pairwise comparisons between the m decision factors can be conducted by asking questions of experts or decision-makers like “which criterion is more important with regard to the decision goal?” The answers to these questions form an $m \times m$ pairwise comparison matrix as follows (Pazand *et al.*, 2011):

$$A = (a_{ij})_{m \times m} = \begin{bmatrix} a_{11} & \dots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{m1} & \dots & a_{mm} \end{bmatrix} \tag{3}$$

where a_{ij} represents a quantified judgment on w_i/w_j with $a_{ij} = 1$ and $a_{ij} = 1/a_{ji}$ for $i, j = 1, \dots, m$. If the pairwise comparison matrix $A = (a_{ij})_{m \times m}$ satisfies $a_{ij} = a_{ik} a_{kj}$ for any $i, j, k = 1, \dots, m$, then A is said to be perfectly consistent; otherwise, it is said to be inconsistent. From the pairwise comparison matrix A , the weight vector W can be determined by solving the following characteristic equation:

$$AW = \lambda_{max} W \tag{4}$$

where λ_{max} is the maximum eigenvalue of A (Bernasconi *et al.*, 2011). Such a method for determining the weight vector of a pairwise comparison matrix is referred to as the principal right eigenvector method (Saaty, 1980). The pairwise comparison matrix A should have an acceptable consistency, which can be checked by the following consistency ratio (CR):

$$CR = \frac{(\lambda_{max} - n) / (n - 1)}{RI} \tag{5}$$

where RI is the average of the resulting consistency index depending on the order of the matrix. If $CR \leq 0.1$, the pairwise comparison matrix is considered to have an acceptable consistency; otherwise, it is required to be revised (Saaty, 1980; Hsu *et al.*, 2008). Finally, the third step of the AHP method computes the entire hierarchic weight. In practice, AHP generates an overall ranking of the solutions using the comparison matrix among the alternatives and the information on the ranking of the criteria. The alternative with the highest eigenvector value is considered to be the first choice (Saaty, 1996; De Feo and De Gisi, 2010; Pazand *et al.*, 2011).

As mentioned above, geologists were invited to give scores to the prediction criteria. The scores are arranged in a matrix and the weights for each of the compared elements are calculated using various methods, such as eigenvector. This gives a weight for each element

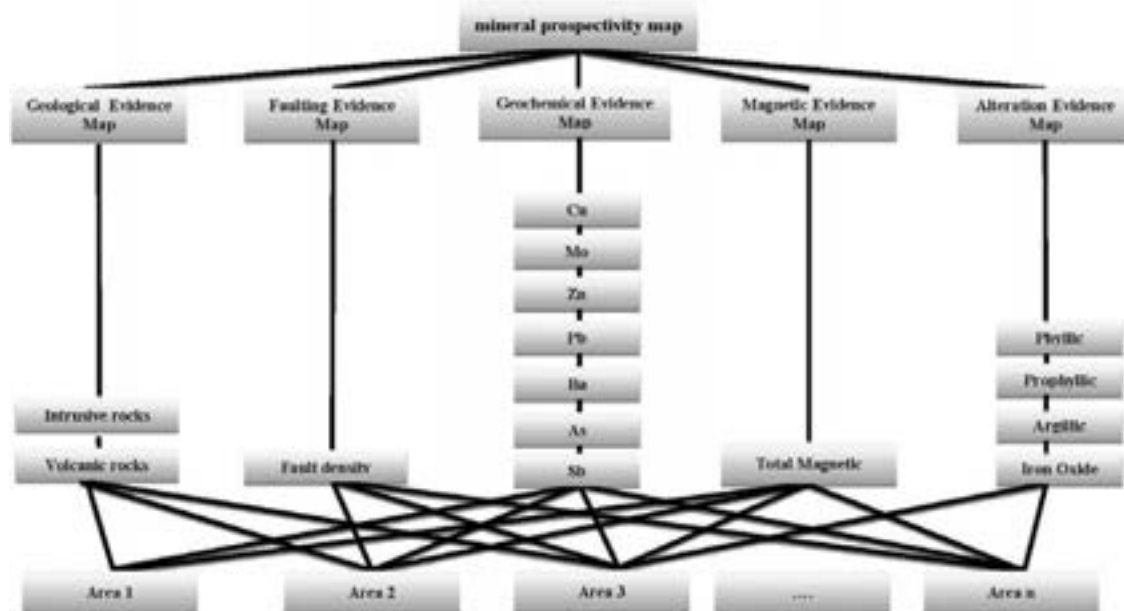


Fig. 10 - The hierarchic structure of the AHP framework for predicting Cu porphyry mineralization.

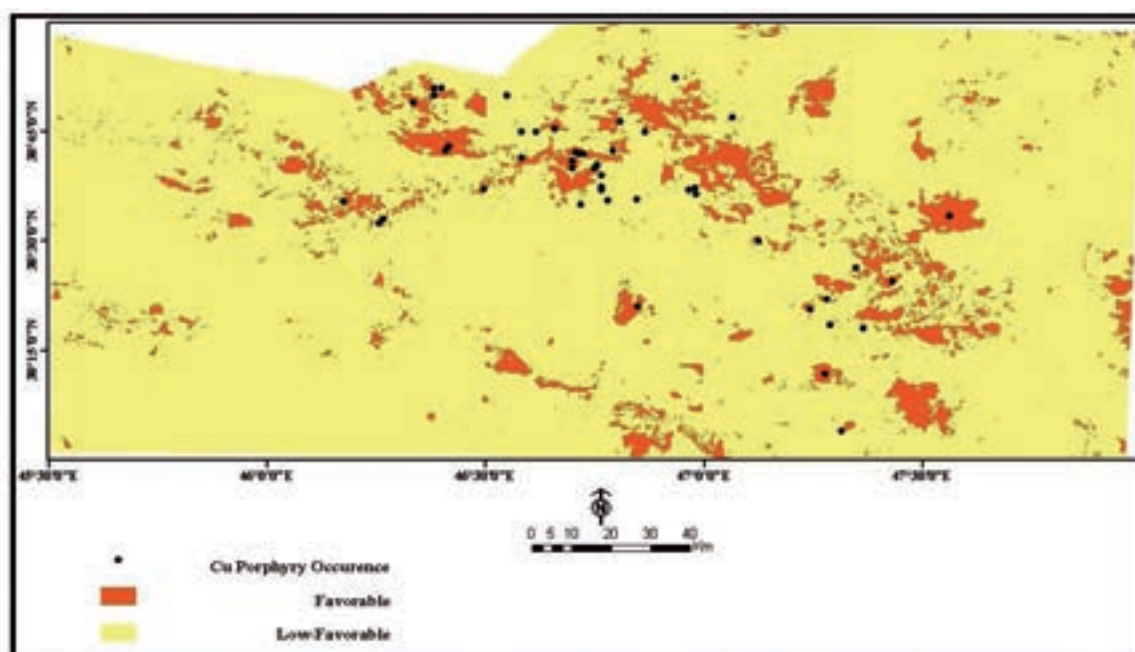


Fig. 11 - Potential mapping for Cu porphyry mineralization in Ahar-Arasbaran area according AHP method.

within a cluster, as well as an inconsistency ratio (Hosseinali and Alesheikh, 2008; Pazand *et al.*, 2011). In the map of the potential for porphyry copper mineralization in the Ahar-Arasbaran area prepared by the AHP method (Fig. 10), the areas with values greater than the threshold value ($+ \sigma$) (2083.72 km², about 9% of the total area) are the most favorable to host copper mineralization. From 48 known porphyry copper mineralizations in the region, 40 were located in areas with high potential; this means that model predicts 86.95% of the known porphyry copper deposits (Fig. 11).

9. Fuzzy AHP

The pure AHP model has some shortcomings. It creates and deals with a very unbalanced scale of judgement and does not take into account the uncertainty associated with the mapping of human judgement to a number by natural language. The ranking of the AHP method is rather imprecise, and the subjective judgements by perception, evaluation, improvement, and selection derived of decision-makers have great influence on the AHP results. To overcome these problems, several researchers integrate fuzzy theory with AHP to improve the uncertainty (Sun, 2010). Most of the basic steps involved in fuzzy AHP are similar to discrete AHP. However, the use of fuzzy numbers instead of discrete numbers and the process of extracting priorities from the pair-wise comparison matrices differentiate fuzzy AHP from discrete AHP (Pazand *et al.*, 2014).

Pazand *et al.* (2014) used the fuzzy AHP method to create Cu porphyry mineral prospectivity map for the Ahar-Arasbaran area and used a workflow like AHP (Fig. 10).

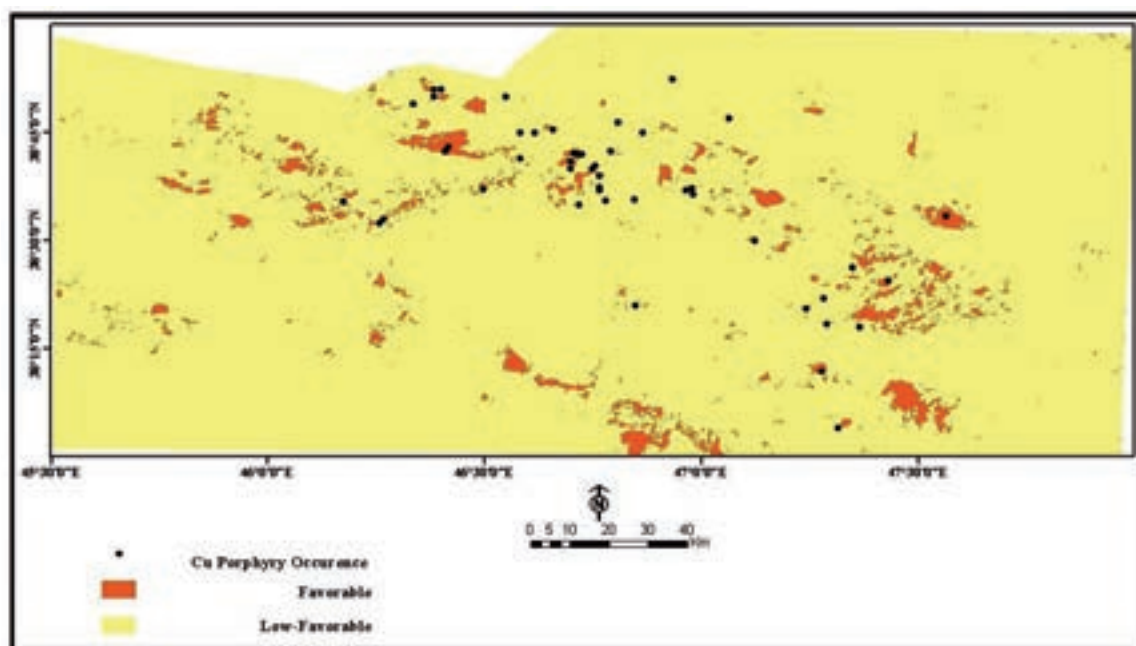


Fig. 12 - Potential mapping for Cu porphyry mineralization in Ahar-Arasbaran area according to fuzzy AHP method.

The potential map of the porphyry copper mineralization, calculated by using the Fuzzy AHP method with a threshold value greater than $x+s$, highlights an area of 962.27 km² (4.15% of the total area). From 48 known porphyry copper occurrences in the region, 32 occurrences were located in areas with high potential; this means that the model predicts 68.08% of the known porphyry copper deposits (Fig. 12).

10. AHP-TOPSIS method

The AHP-TOPSIS model for the porphyry Cu potential area selection problem, composed of AHP and TOPSIS methods, consists of three basic stages: 1) identify the criteria to be used in the model, 2) AHP computations, 3) evaluation of the study area with TOPSIS and the determination of the potential area (Pazand and Hezarkhani, 2015). AHP and TOPSIS are practical and useful techniques for determining, respectively, the relative importance of the criteria and the ranking and selection of a number of externally determined alternatives through distance measures. The AHP method is employed to determine the importance weights of evaluation criteria, then the TOPSIS technique is used for selection and ranking of the study area. The mapping of potential for porphyry copper mineralization in the study area with greater than threshold value ($+σ$) by the AHP-TOPSIS method occupies 2812.35 km², and is equal to 12.15% of the total area. From 48 known porphyry copper occurrences in the region, 34 occurrences were located in areas with high potential; this means that the model predicts 70.83% of the known porphyry copper deposits (Fig. 13).

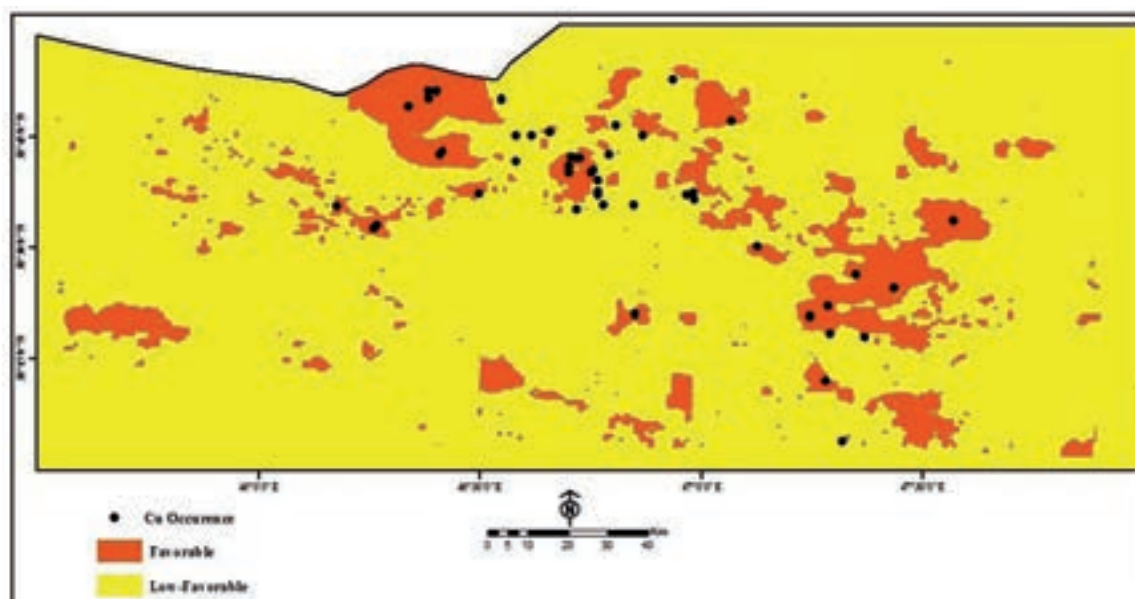


Fig. 13 - Potential mapping for Cu porphyry mineralization in Ahar-Arasbaran area according to AHP-TOPSIS method.

11. Data-driven methods

In data-driven techniques, the known mineral deposits are used as training points for establishing spatial relationships with evidence layers. The spatial relationships between the input data and the training points are quantified and used to establish the importance of each evidence map and finally integrated into a single mineral prospectivity map (Nykänen and Salmirinne, 2007). These models predict known mineral occurrences well but predict undiscovered deposits poorly, because known mineral occurrences are used as training sites (Yousefi and Nykanen, 2016).

12. Weight of evidence

Bonham-Carter *et al.* (1989) and Bonham-Carter (1994) described the way in which the quantitative relationships between the data sets representing the deposit recognition criteria and known mineral occurrences are analysed using a statistical method based on Bayes' rule. Weight-of-evidence methodology are normally applied to explore situations in which there is an adequate number of mineral deposits or other location data that can be used as training points for calculating weights (Benomar *et al.*, 2006). The weight-of-evidence technique includes five steps (Bonham-Carter *et al.*, 1989; Lindsay *et al.*, 2014): 1) the estimation of prior probability (probability that a mineral occurrence exists in an area, given no additional information), 2) determination of weighting coefficients, 3) calculation of posterior probability (that is, the probability of the occurrence in an area, given weights and additional information), 4) testing for conditional independence, and 5) validation.

If a study region is divided into unit cells (or pixels) with a fixed size, S , and the total area is t , then $N(T) = t/S$ is the total number of unit cells in the study area. If a number of unit cells, $N(D)$,

containing an occurrence D , equal to the number of occurrences if S is small enough (i.e., one occurrence per cell), then the prior probability of an occurrence will be expressed as (Pazand and Hezarkhani, 2014):

$$P(D) = N(D) / N(T) \quad (6)$$

Now suppose that a binary predictor pattern B , occupying $N(B)$ unit cells occurs in the region and a number of known deposits occurs preferentially within the pattern, that is $N(D \cap B)$, clearly the probability of a deposit occurring within the predictor pattern is greater than the prior probability. Conversely, the probability of a deposit occurring outside the predictor pattern is lower than the prior probability. The favourability of locating an occurrence, exist of a predictor pattern, will be expressed by the conditional probability (Agterberg and Cheng, 2002; Pazand and Hezarkhani, 2014). It will be defined as follows:

$$p(D|B) = \frac{P(D \cap B)}{P(B)} = P(D) \frac{P(B|D)}{P(B)} \quad (7)$$

where $P(D|B)$ is the posterior probability of an occurrence given the predictor pattern, $P(B|D)$ is the posterior probability of being in the predictor pattern B , given an occurrence D , and $P(B)$ is the prior probability of the predictor pattern. Eq. 7 satisfies the Bayes' rule (Gongwen and Jianping, 2008). A pair of weights, W^+ and W^- , determined from the degree of overlap between the known prospects and the binary evidence map, calculates for each binary evidence map. The weights for the binary predictor pattern (factor or layer) are defined as (Agterberg and Cheng, 2002; Pazand and Hezarkhani, 2014):

$$W^+ = \ln \left\{ \frac{P(B|D)}{P(B)P(D)} \right\} \quad (8)$$

$$W^- = \ln \left\{ \frac{P(B|D)}{P(B)P(D)} \right\} \quad (9)$$

where W^+ and W^- are the weights of evidence when a binary predictor pattern is present and absent, respectively. The optimum cutoff distance was determined by calculating the weights (W^+ , W^-) for successive cumulative distance intervals away from the geological features, and examining the variation of the weights and contrast (C). The scientific basis for this is that if more points occur within a pattern than would be expected by chance, then W^+ is positive and W^- is negative. The magnitude of the contrast, C , determined as the difference of $W^+ - W^-$, provides a measure of spatial association between a set of points and a binary pattern. C is defined as (Agterberg and Cheng, 2002; Pazand and Hezarkhani, 2014):

$$C = W^+ - W^- \quad (10)$$

From 47 occurrences of porphyry copper deposits in the study area, 27 occurrences were put into the model as training points to obtain the weight of factors. The remaining 20 indices were used for model validation. The area of significant potential for porphyry copper mineralization [greater than the threshold value ($+\sigma$)] is equal to 2725.82 km². According to the analysis of the prediction results using weight-of-evidence modelling and GIS technology, the favorable area has

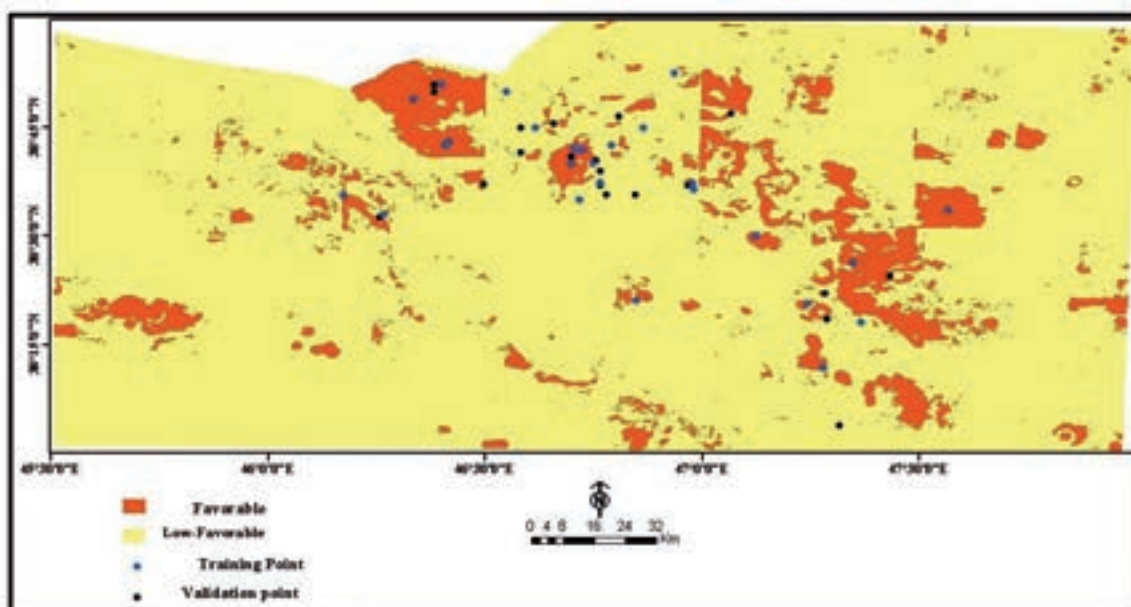


Fig. 14 - Potential mapping for Cu porphyry mineralization in Ahar-Arasbaran area according to weight of evidence method.

dropped to 11.78%, which is helpful for the next mineral exploration. This area contains 14 of the 20 known Cu porphyry deposits in the study area. Thus the model predicts 70% of the known Cu porphyry deposits (Fig. 14).

13. Artificial neural networks

Artificial neural networks have been used in many branches of science due to their versatile characteristics (Graupe, 2007). An artificial neural network operates by creating connections between many different processing elements, each analogous to a single neuron in a biological brain. Each neuron takes many input signals, then, based on an internal weighting system, it produces a single output signal that is typically sent as input to the other neurons (Hosseinali and Alesheikh, 2008). The ability of learning is one of the most important characteristics of artificial neural networks. The network weights are modified in the training process through a number of learning algorithms based on back propagation learning. A feed-forward multilayer network consists of three layers, namely input, output, and hidden layers. Each layer in a network contains an adequate number of neurons depending on specific applications. The number of neurons in the input layer is equal to the number of data sources and the number of neurons in the output layer is limited by the application and is represented by the number of outputs. The number of hidden layers and the number of neurons in each layer depend on the architecture of the network and usually are determined by trial and error (Hosseinali and Alesheikh, 2008). For a correct “learning,” the neural network needs to be supplied with a database of examples that are not deposits. Then by their opposition or contrast to deposits, networks enable the adaptation of an example’s weight to discriminate a deposit from a non-deposit (Bougrain *et al.*, 2003). For the

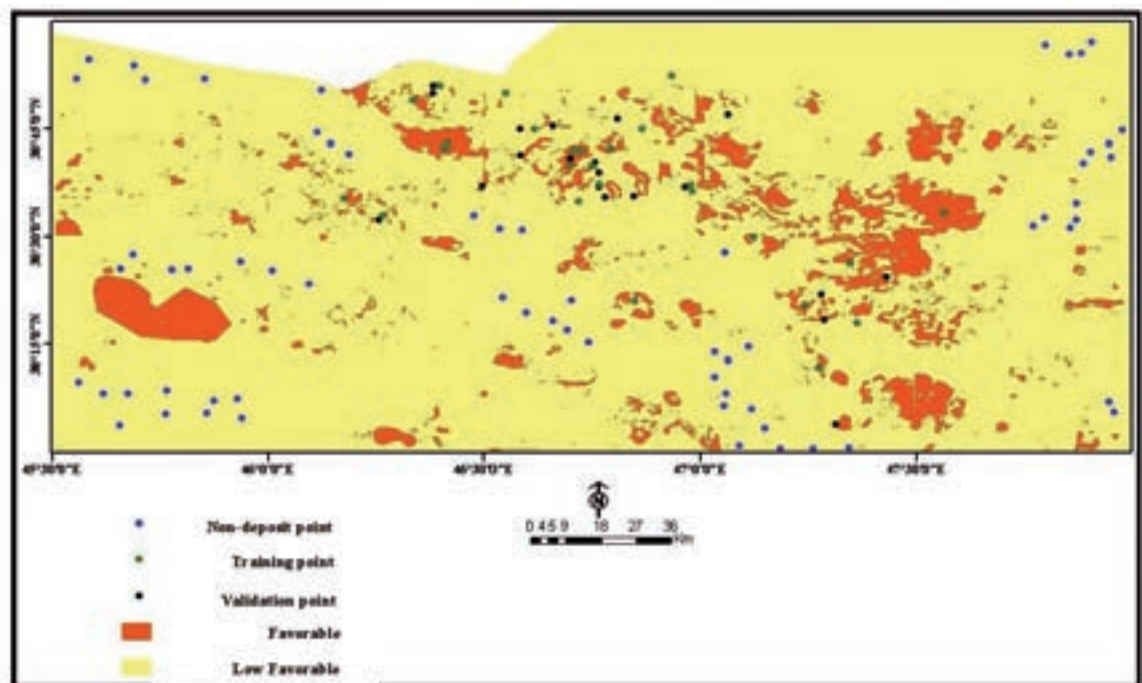


Fig. 15 - Potential mapping for Cu porphyry mineralization in Ahar-Arasbaran area by artificial neural networks method.

construction of the potential map using the artificial neural networks model as the weight-of-evidence method, 27 occurrences were put in as training points to obtain the weight of factors, and the remaining 20 indices were used for model validation. Along with the results of other models and geological conditions of the area, 64 points representing the non-deposit examples were selected and included in the model. Finally, an area of 2426.01 km² (about 10.48% of the study area) greater than threshold value ($+\sigma$) was identified as the potential area. This area contains 13 of the 20 known Cu porphyry deposits known in the study area. This model predicts 65% of the known Cu porphyry deposits (Fig. 15).

14. Discussion

Although different models and their applications for mineral potential mapping in different deposit types have been discussed in numerous papers and research works, a comprehensive study that used and compared different models for a study area and one mineralization type is rare. Such studies can show the advantages and disadvantages of different modelling techniques and make it possible to easily model for mineral potential mapping in other areas with similar geological conditions. The purpose of this study was, despite the satisfactory results of different methods alone, to assess the comparisons among the results of different methods. This will enable us to select ways to achieve the best possible results, and we can use these comparisons as a basis for assessing the possible savings in cost and time of exploration projects. It is also possible to combine the results to increase the likelihood of locating minerals. Using fuzzy logic, TOPSIS,

AHP, AHP-TOPSIS, fuzzy AHP, weight of evidence, and neural networks modelling techniques, the potential map for porphyry copper mineralizations in the Ahar-Arasbaran zone was obtained, and known deposits were validated. A suitable method for measuring the performance of a model for mineral potential maps consists of attempting to predict occurrences of deposits within the study area. The total number of known porphyry copper occurrences in the region, and the percentage coverage of them according to the method used, demonstrates the accuracy of the method. With regional-scale exploration activities, the aim is the reduction with maximum precision of the potential area; accordingly, the map with the lowest potential area and the highest point validation coverage is preferred. Therefore, by calculating the difference between the overall number of porphyry Cu occurrences in the study area and the percentage of those that occur in the potential areas, we can conclude that the best method to model porphyry copper mineralization in the Ahar-Arasbaran area is the AHP approach (Table 1). Then fuzzy and fuzzy AHP should be used in sequence, followed by the neural network modelling method to be used last (Table 1).

Table 1 - Validity of different modeling methods parameters.

Method	Potential area	Index coverage (%)	Area (%)	Index coverage (%) - Area (%)
Fuzzy	1437.7	76.5	6.2	70.3
AHP	2083.72	86.95	9	77.95
TOPSIS	3104.19	72.34	13.41	58.93
AHP-TOPSIS	2812.35	70.83	12.15	58.68
Fuzzy AHP	962.27	68.08	4.15	63.93
Weight of evidence	2725.85	70	11.78	58.22
Neural networks	2426.01	65	10.48	54.52

Final potential mapping of the study area, according to the advantages and disadvantages of each method and potential maps obtained by them, was prepared using overlapping maps obtained from different methods. Thus, with combining all the maps, areas that have been approved by the majority of the potential maps were chosen as the potential areas (Fig. 16). Finally, 1602.11 km² of the study area (about 6.92%) was identified as having the highest potential for porphyry copper mineralization.

Despite the validation of the results using actual porphyry copper mineralization occurrences in the region, to further validate our results, we used field surveys and results of new exploration activity. Ten potential areas were introduced, and then reviewed by field studies. In all of them, signs of copper mineralization and porphyry copper systems showed that more work is needed (Fig. 16).

15. Conclusions

Seven different approaches for potential mapping using fuzzy logic, TOPSIS, AHP, AHP-TOPSIS, fuzzy AHP, weight of evidence, and neural networks methods were tested and described. The following results were obtained:

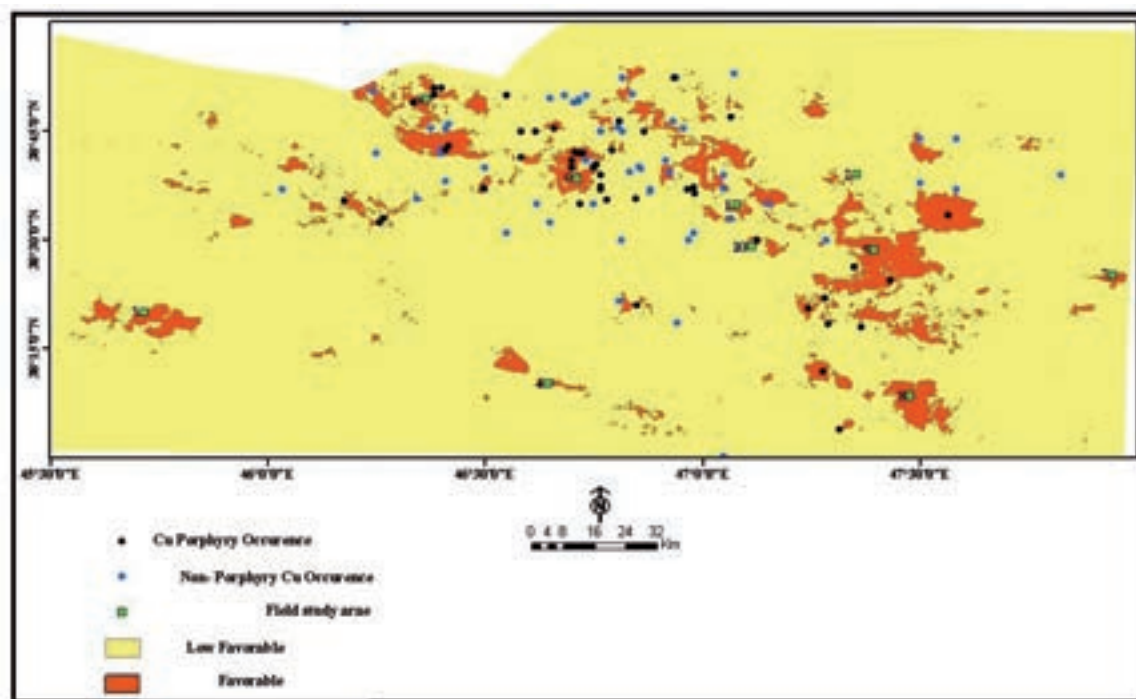


Fig. 16 - Final potential mapping for Cu porphyry mineralization in Ahar-Arasbaran area.

- both knowledge-driven and data-driven modelling approaches can be successfully used for porphyry copper mineral potential mapping in the study area;
- in regional-scale exploration with high-volume data, using GIS in the classification, communication, processing, and interpretation of data exploration is very effective;
- in comparison with data-driven methods, knowledge-based modelling methods are better at identifying potential porphyry copper deposits in this area because of past experience and expert knowledge. Also, in data-driven methods used for mineral prospectivity mapping, there is exploration bias resulting from accessibility factors and exploration criteria, because known mineral occurrences are used as training sites. Thus, data-driven models of mineral prospectivity, are affected by locations of known mineral occurrences (Carranza and Laborte, 2015; Yousefi and Nykanen, 2016);
- multivariate decisions methods (AHP, TOPSIS) with a strong mathematical basis have a strong ability to select areas of high potential. Results from different methods can be compared to identify the strengths and weaknesses of each;
- the AHP method, with its ability to compare paired variables and factors and to model incompatibility rate, showed the best results compared to other methods.

Finally, 1602.11 km² of the study area (about 6.92%) was identified as showing potential for porphyry copper mineralization. Initial results show that exploration operations in new areas are recommended.

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