Arab J Geosci (2016) 9: 364
DOI 10.1007/s12517-016-2384-z

ORIGINAL PAPER

Copper potential mapping in Kerman copper bearing belt by using ANFIS method and the input evidential layer analysis

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Received: 7 September 2015 / Accepted: 8 February 2016 / Published online: 26 April 2016

Abstract Earth science information used in mineral potential mapping has an empirical component comprising an exploration database and a conceptual component comprising an expert knowledge base. The hybrid neuro-fuzzy model combines conceptual and empirical components of available earth science information for predictive mineral potential mapping effectively. This paper describes a neuro-fuzzy model, which combines exploration data in the regional scale for copper potential mapping in Kerman copper bearing belt in south of Iran. Data layers or evidential maps are in six datasets namely lithology, tectonic, airborne geophysics, ferric alteration, hydroxide alteration, and geochemistry. The modeling result was 1044 pixels selected as favorable in order to continue the copper exploration in the study area; in other words, approximately 11.7 % of the area was selected. Fifty six known deposits out of 86 ones, equal to 65 % of all, were located in favorable zone. Other main goals of this study were to determine how each input affects favorable output. For this purpose, the histogram of each normalized input data with its favorable output was drawn. The histograms of each input dataset for favorable output showed that each information layer has a certain behavioral pattern. These behavioral patterns can be considered as regional copper exploration criteria.

Keywords Copper prospecting · Potential mapping · Hybrid neuro-fuzzy model · Evidential layer analysis · Behavioral pattern

Introduction

Mineral exploration, as Knox-Robinson (2000) puts it, is a multidisciplinary task requiring the simultaneous consideration of numerous disparate geophysical, geological, and geochemical datasets. Additionally, according to Brown et al. (2000), a variety of sources such as remote sensing, airborne geophysics, and large commercially available geological and geochemical data are increasing the size and complexity of regional exploration data.

Earth science information used in the mineral potential mapping has two components, empirical and conceptual. The empirical components are composed of a database that is derived from exploration activities. The relationships between data of exploration database are the base of the data-driven approaches. The conceptual components comprised expert's knowledge. They are the base of knowledge-driven approaches. The two approaches are generally considered dichotomous and therefore implemented in mutual exclusion. Consequently, a significant proportion of available information remains underutilized in both types of approaches to mineral potential mapping (Porwal et al. 2004).

Some of the spatial modeling techniques that have been proposed for mineral potential mapping are weights of evidence (Bonham-Carter et al. 1988, 1989; Agterberg et al. 1990; Xu et al. 1992; Rencz et al. 1994; Pan 1996; Raines 1999; Carranza and Hale 2000; Tangestani and Moore 2001; Carranza 2004; Agterberg and Bonham-Carter 2005; Jianping et al. 2005; Nykanen and Raines 2006; Porwal et al. 2006; Roy 2006; Nykänen and Ojala 2007; Raines et al. 2007; Oh

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and Lee 2008; Harris et al. 2008; Benomar et al. 2009), Bayesian network classifiers (Porwal et al. 2006), logistic regression (Chung and Agterberg 1980; Agterberg 1988; Oh and Lee 2008), fuzzy logic (An et al. 1991; Bonham-Carter 1994; Eddy et al. 1995; D'Ercole et al. 2000; Knox-Robinson 2000; Luo and Dimitrakopoulos 2003; De Quadros et al. 2006; Carranza et al. 2008; Nykänen et al. 2008), artificial neural networks (Singer and Kouda 1996; Harris and Pan 1999; Brown et al. 2000, 2003; Rigol-Sanchez et al. 2003; Behnia 2007; Skabar 2007; Oh and Lee 2008), and evidence theory model (Moon 1990, 1993; An and Moon 1993; Moon and So 1995; Porwal et al. 2003; Carranza et al. 2005).

The hybrid neuro-fuzzy model combines conceptual and empirical components of available earth science information for predictive mineral potential mapping effectively (Porwal et al. 2004). Most of mineral potential mapping studies were focused on modeling and evaluation of the model. These studies did not ponder on the effect of evidential layers on modeling output.

This paper describes a neuro-fuzzy model, which combines exploration data in the regional scale for copper potential mapping in Kerman copper bearing belt in south of Iran. Finally, the effect of each input parameter on the result (final map) will be discussed. The effects of the input parameters and their interpretation lead to a better understanding of copper mineralization mechanisms in the study area.

Study area

This paper studies a part of Urumieh–Dokhtar magmatic arc (Fig. 1), which is of the Alpine–Himalayan orogenic belt which resulted from the closure of the Neotethyan Ocean between Arabia and Eurasia (Sengor et al. 1988; Agard et al. 2005; Omrani et al. 2008). The protracted convergence history between Arabia and Eurasia comprised a long-lasting period of subduction followed by collision during the Tertiary (Omrani et al. 2008). Two magmatic belts dominated by calc-alkaline igneous rocks (Berberian and Berberian 1981) run parallel to the Main Zagros Thrust on the Eurasian upper plate and cut across the central Iran. Urumieh–Dokhtar magmatic arc, which is classified as an Andean magmatic arc (Alavi 1980; Berberian et al. 1982), forms an elongate volcanoplutonic belt running from eastern Turkey to south east Iran and has been interpreted as a subduction-related feature (Takin 1972; Berberian and Berberian 1981; Berberian et al. 1982). Magmatism in Urumieh–Dokhtar magmatic arc occurred mainly during the Eocene but resumed later, after a dormant period, during the Upper Miocene to Plio-Quaternary. According to geological and exploration studies (e.g., Tangestani and Moore 2002a, b; Hezarkhani 2006a, b; Atapour and Aftabi 2007; Boomeri et al. 2009), Urumieh–Dokhtar magmatic arc has great potential for porphyry-Cu deposits.

Some of the porphyry-Cu deposits in this magmatic arc that have been reported in the literature include the SarCheshmeh, Meiduk, Sungun, Chah-Firuzeh, and Reagan deposits (Hezarkhani 2006a, b, 2009; Boomeri et al. 2009; Afzal et al. 2011). Unpublished reports by National Iranian Copper Industries Company (NICICO) indicate that economically exploited porphyry-Cu deposits in Urumieh–Dokhtar magmatic arc contain copper grades ranging between 0.15 and 0.8 %. Associated igneous rocks vary in composition and are mainly granodiorites, quartzdiorites, diorites, diorite porphyry, granite-porphyry, monzonites, quartz-monzonites, and granites with ages of Cretaceous, Eocene, Oligocene–Miocene, and Neogene, which are spatially and genetically related to porphyry-Cu deposits in Urumieh–Dokhtar magmatic arc. In this magmatic arc, volcanic rocks consist of mainly pyroclastics, trachyandesites, trachybasalts, andesite-basalts, andesite lavas, tuffaceous sediments, dacites, rhyodacites, rhyolites, rhyolite tuffs, agglomerate tuffs, agglomerates, ignimbrites, basaltic rocks, and andesites where the age of Eocene and Neogene are spatially associated with porphyry-Cu deposits, and some deposits are hosted by these volcanic rocks (Yousefi and Carranza 2014).

The most significant features, related to mineralization, are the sedimentation, magmatic activity, and structural displacement that occurred during the Tertiary. The granodiorite and diorite are the most common intrusive rocks. The porphyry-Cu mineralization is related to regional scale faults, and the most important fault trends in the study area are N–S, NE–SW, E–W, and NW–SE, respectively (Jafari Rad and Busch 2011). The intrusive bodies are frequently hydrothermally altered where two fault systems intersect (Titley and Beane 1981). These locations have the best situation for porphyry mineralization. Hydrothermal alteration zoning follows the Lowell and Guilbert pattern (Lowell and Guilbert 1970).

Method: neuro-fuzzy hybrid model

Fuzzy logic (FL) and artificial neural network (ANN) are basically model-free and nonlinear estimators that mostly aim at achieving a stable and reliable model which can justify the noise and uncertainties in the complex data (Tahmasebi and Hezarkhani 2012).

A fuzzy inference system simulates humans' understanding of modeling concepts of informative components through applying fuzzy membership functions and if–then rule statements (Porwal et al. 2006; Jang et al. 1997). So far, various fuzzy inference systems have been introduced such as Mamdani (1974), Mamdani and Assilian (1975), Sugeno and Kang (1988), Sugeno and Tanaka (1991), Takagi and Sugeno (1985), Tsukamoto (1979), and Zadeh (1973). However, the Mamdani (Mamdani, 1974; Mamdani and Assilian 1975) and Takagi–Sugeno–Kang (Sugeno and

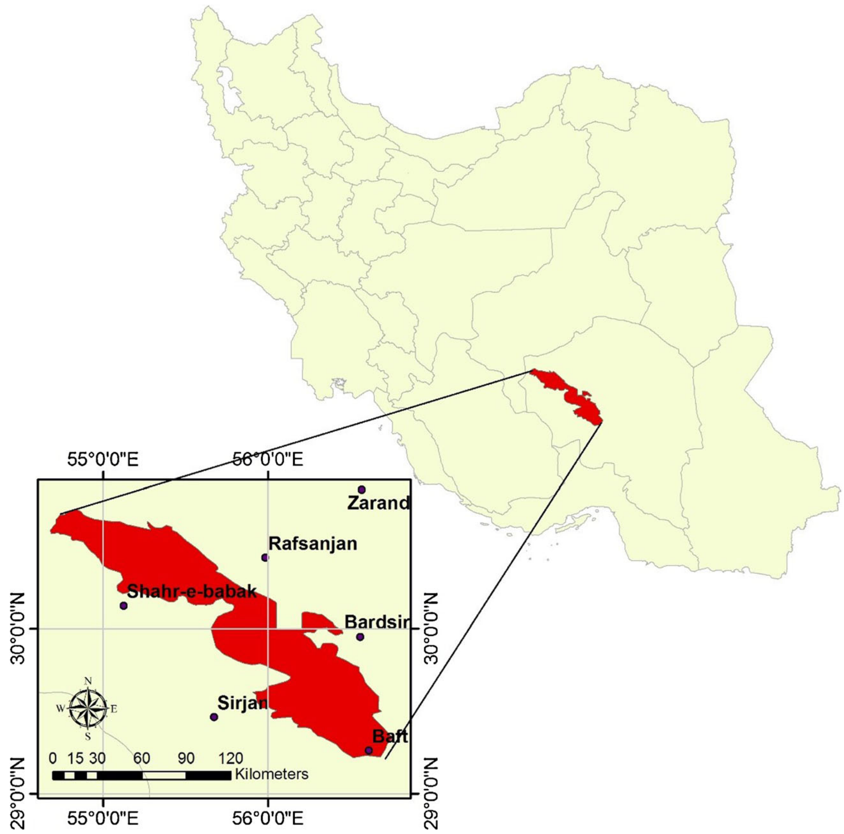


Fig. 1 Location of study area in Iran

Kang 1988; Sugeno and Tanaka 1991; Takagi and Sugeno 1985) methods are the most widely used ones. In the Mamdani method, both comparison (if) and result (then) statements have fuzzy rules, while in the Takagi-Sugno method, the comparison part uses fuzzy rules, whereas the result part is a mathematical function, commonly a first degree polynomial function (Jang et al. 1997; Buckley and Feuringb 1999). Fuzzy inference system (FIS) (Fig. 2) is composed of five functional blocks namely a rule base (containing a number of fuzzy if–then rules), a database (defines the MFs of the fuzzy sets used in the fuzzy rules), a decision-making unit (performs the inference operations on the rules), a fuzzification interface (to calculate fuzzy input), and a defuzzification interface (to calculate the actual output) (Jang 1993; Tahmasebi and Hezarkhani 2012). It is obvious that some problems such as determining the shape and the location of membership functions (MFs) for each fuzzy variable are involved with FL. The FL efficiency basically depends on the estimation of premise and the consequent parts (Tahmasebi and Hezarkhani 2012).

The ANN also has some advantages such as its capability of learning and high computational power. The problems like the number of hidden layers, the number of neurons in each hidden layer, learning rate, and momentum coefficient are also involved with ANN modeling (Tahmasebi and Hezarkhani 2012).

Jang (1992, 1993) combined both FL and ANN to produce a powerful processing tool, named adaptive neuro-fuzzy inference system (ANFIS) (Fig. 3). ANFIS uses an ANN learning algorithm to set fuzzy rule with the appropriate MFs from input and output data (Tahmasebi and Hezarkhani 2012). Actually, this technique is an appropriate solution for function

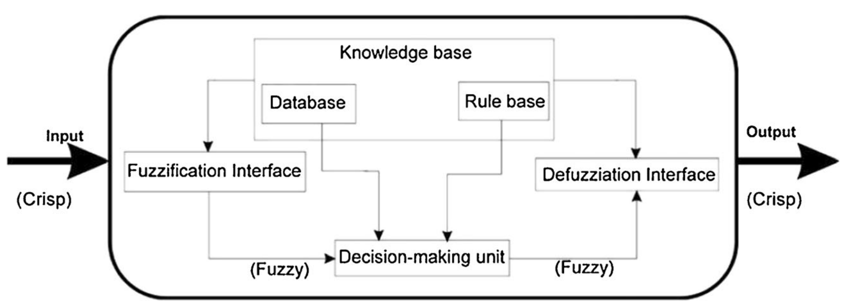


Fig. 2 Fuzzy inference system (FIS) (Jang 1993)

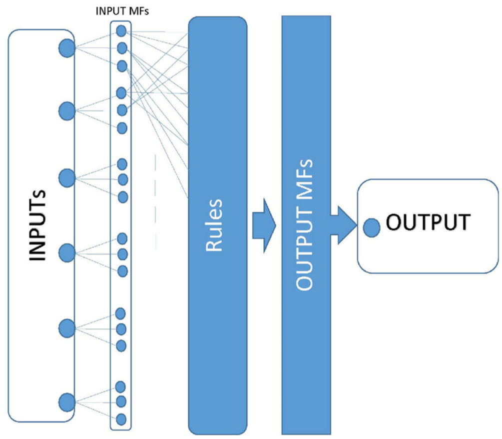


Fig. 3 Simplified ANFIS architecture used in hybrid neuro-fuzzy model for mineral potential mapping

approximation in which a hybrid learning algorithm is applied for the shape and the location of MFs (Buragohain and Mahanta 2008; Ying and Pan 2008; Tahmasebi and Hezarkhani 2012). This study applies ANFIS to map favorable copper mineralization areas.

Datasets and analysis

Data preparation

Data layers or evidential maps are in six datasets namely lithology, tectonic, airborne geophysics, ferric alteration, hydroxide alteration, and geochemistry (Fig. 5). The geological base map used for lithological layer was 1:250.000 geological map provided by Geological Survey of Iran (GSI). For a complete cover of the study area, Anar (Soheyli 1981), Rafsanjan (Zohrehbakhsh 1987), and Sirjan (Soheyli 1985) 1:250.000 geological maps were used. These maps were digitized and studied for lithology types; finally, nine groups were selected based on Singer diagram (2008) (Fig. 4). This diagram was proposed by Singer after studying host rocks of 407 known copper deposits. The lithological groups were selected based on frequency and availability of host rocks. Figure 5a shows the lithological map according to these groups.

Tectonic effect is another mineralization controller. Faults show a high rate of tectonic activity which means, if a large number of faults exist in a region, a high tectonic activity is expected. Therefore, at the first step, faults were extracted from geological map and modified considering Landsat 8 satellite image. Then, fault density was mapped according to extracted data. The results show the tectonically more or less crushed zones (Fig. 5b).

Airborne magnetic data is the third dataset used in this study. This data was extracted by Atomic Energy Organization of Iran (AEOI) during 1977 and 1978. The flight lines distance and the sensor altitude were about 500 and 120 m, respectively. According to Clark (1997), there is an axial conformity between magnetic anomaly and reduction to pole of magnetic data; RTP was used as an evidential map in data analysis. Figure 5c represents the RTP map of the study area.

Landsat 8 images are the fourth dataset used, which were processed after correction. Two evidential maps were derived from processed images as hydroxide and iron oxide alteration. Hydroxide alteration has a high reflection in band 6 and a strong absorption in band 7; therefore, by dividing band 6 into band 7, one can distinct the effect of the hydroxide alteration (Fig. 5d) (Chica-Olmo and Abarca 2002; Farrand 1997). It is similar about the iron oxide alterations. They have high reflection in band 4 and strong absorption in band 2. Therefore, band 4/band 2 ratio is used to distinguish iron oxide alteration (Fig. 5e) (Chica-Olmo and Abarca 2002; Farrand 1997). The results of these processes are demonstrated as grayscale images in which the white color represents the alteration zones.

Stream sediment geochemical data is the last dataset used in this study. This data is extracted from the eleven 1/100,000 sheets belonging to Dehaj, Robat, Anar, Shahr-e-Babak, Rafsanjan1, Rafsanjan2, Pariz, Chahar-Gonbad, Balvard, Bardsir, and Baft which were published by GSI. Outlier samples of copper grade were removed from the dataset and all the samples were attributed to their basin. The results were used as an evidential map (Fig. 5f).

All evidential layers with continuous amounts are encoded between 0 and 1 by using the flowing equation:

$$x_{norm} = (x - x_{min})/(x_{max} - x_{min})$$

where x is the data which should be normalized and x_{max} and x_{min} are the maximum and minimum of the original data, respectively. Moreover, x_{norm} is the normalized data that is transformed. Only for the lithology layer with discontinues amount 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 are assigned for the first to seventh lithology groups, respectively; however, 0.1 is assigned to any other host rocks.

Generation of feature vectors, training, and validation data

Most GIS-based approaches to mineral potential mapping use the concept of unique condition grids (Bonham-Carter and Agterberg 1990). In the context of hybrid neuro-fuzzy models, each unique condition is considered a feature vector, whose components are defined by the attributes of evidential maps comprising the unique condition. The number of dimensions of feature vectors is therefore equal to the number of input evidential maps (Porwal et al. 2004).

The six evidential maps encoded as class scores were digitally superposed. All evidential maps were combined to generate 8894 six dimensional feature vectors. Because the

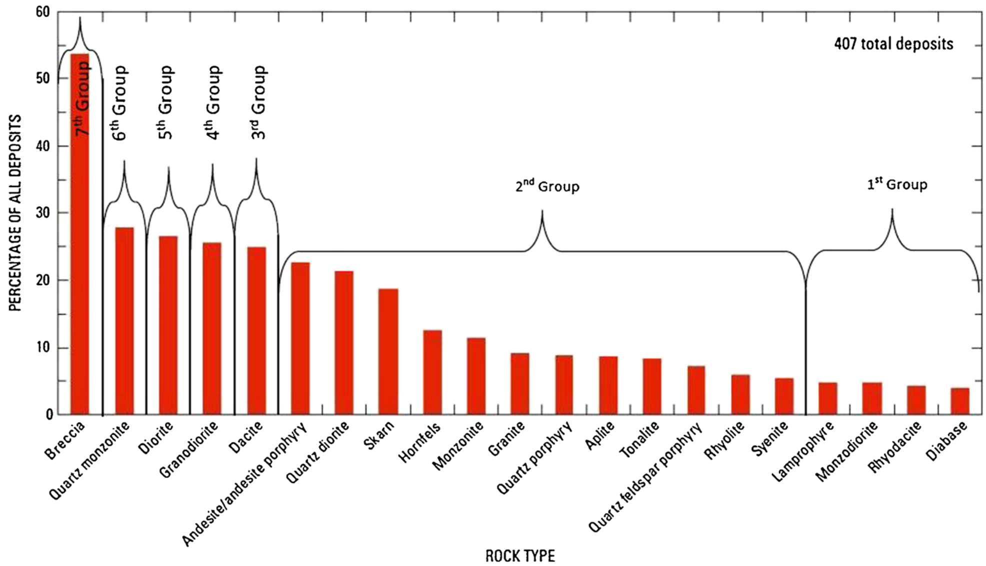


Fig. 4 Porphyry-Cu host rocks frequency diagram (Singer et al. 2008)

operation was carried out in a GIS environment, an associated database was automatically generated, which stored the components of the feature vectors.

Target vectors define output vectors to which input feature vectors are mapped by an adaptive neuro-fuzzy inference system. Input feature vectors with known target vectors constitute training vectors. Validation vectors, also known as target vectors, are used exclusively for validating the training of an adaptive neuro-fuzzy inference system.

Regarding mineral potential mapping, there is only one single-dimensional binary target vector encoded as 1 or 0, representing the presence or absence of a target mineral deposit, respectively. The feature vectors corresponding to presence or absence of a target mineral deposit constitute training/validation vectors. These vectors are referred to as deposit or non-deposit training/validation vectors, respectively.

In the methods like ANFIS which are based on trial and error, several parameters should be changed during the modeling; therefore, the dataset needs to be validated to control the ANFIS performance. The first subset is the training set by which the network finds an input–output spatial relationship by repetitive analysis of the training set (about 90 % of training/validation dataset). The second subset is the validation set (about 10 % of training/validation dataset).

As Brown et al. (2003) sets it, a well-explored region must be selected as the training/validation site. Accordingly, Sarcheshmeh and Meyduk were selected as two training sites. These sites contain 31 known copper indices and have been explored by National Iranian Copper Industries Company (NICICO) for many years and are among the most suitable sites for training/validation. In these two regions, 1568 pixels exist that used as training/validation data. 315 pixels show deposits and 1253 remaining pixels show non-deposits. Deposit pixels selected from known copper occurrences. Also, based on an expert knowledge of genetic models of the copper deposits, the feature vectors that are least likely to be associated with the target mineral deposit type can be selected as non-deposit pixels. Selected non-deposit locations have been previously studied by NICICO and considered as very low probability of hosting a copper mineralization.

Construction of ANFIS

Based on the prototypical ANFIS for mineral potential mapping, an adaptive neuro-fuzzy inference system was constructed with six inputs and an output. The fuzzy inference system of this network is Takagi–Sugeno type. Each input node contains three bell-typed fuzzy membership functions (MFs) that return the fuzzy membership value. Bell-shaped MFs are more flexible than other MFs, because they have three free parameters to get adjusted. Fuzzy inference system (FIS) is generated by grid partition method. This method divides the target space to maximum part. It means that all possible connections were used for generating of FIS. These connections are made by if–then rules. Used If–then rule layer was Takagi–Sugeno type and combines outputs by a first-degree polynomial function. Figure 3 shows a simplified ANFIS architecture used in modeling.

Network was learned by training data and training process was controlled by validation data. Using validation data in training process prevents overlearning error (Wang et al. 1994). Among 1568 used training/validation data, 1411 were for training and 157 for validation. Minimizing the sum square error (SSE) was the main training propose. Minimum SSE was achieved after 14 training epochs so the learning was stopped.

At the end of the 14th training epochs, the sum square error for validation vectors was converged to a minimum of

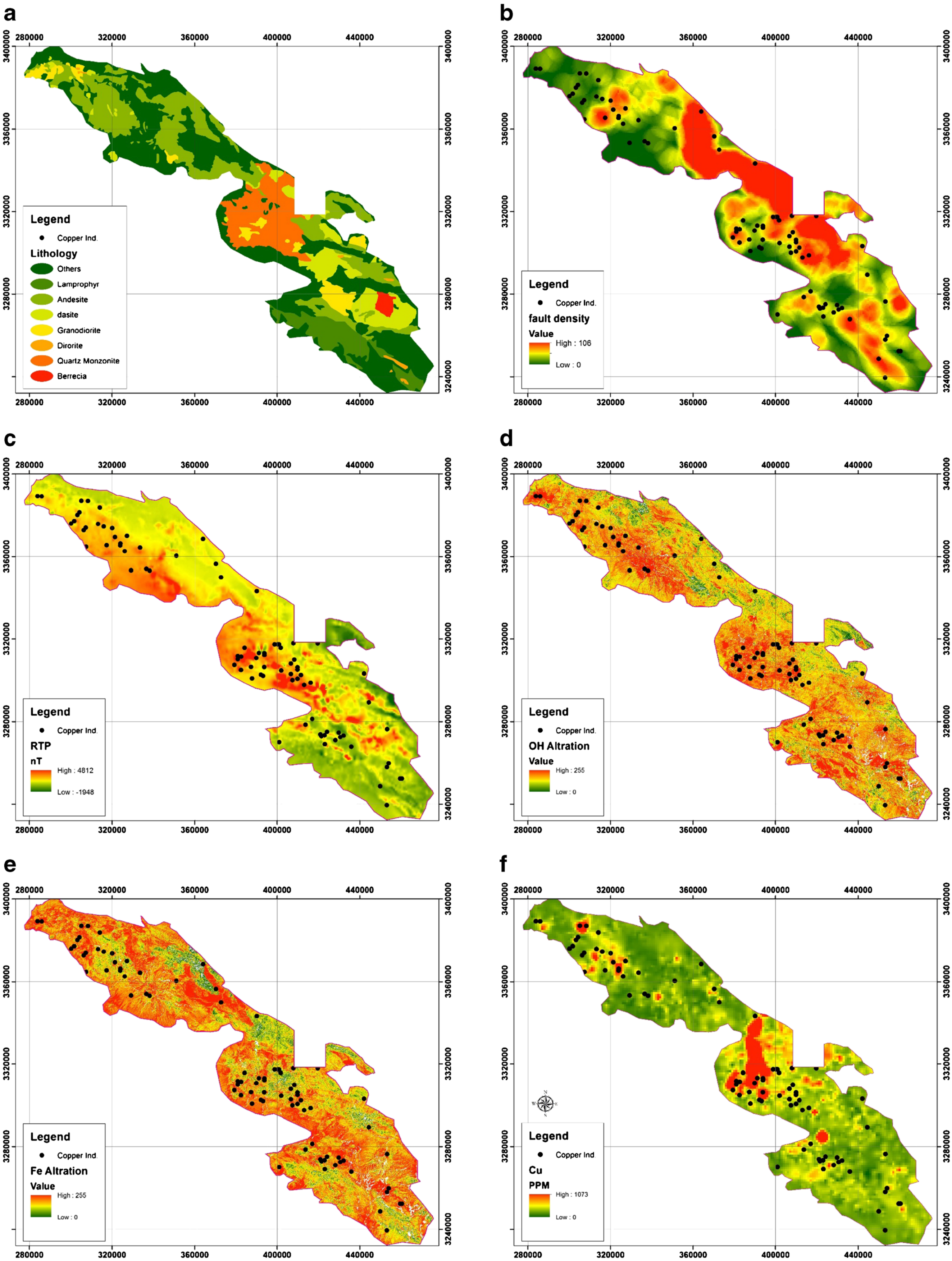

a
Legend
Copper Ind.
Lithology
Others
Lamprophyr
Andesite
dasite
Granodiorite
Diorite
Quartz Monzonite
Berrecia
b
Legend
Copper Ind.
fault density
Value
High : 106
Low : 0
c
Legend
Copper Ind.
RTP
nT
High : 4812
Low : -1948
d
Legend
Copper Ind.
OH Altration
Value
High : 255
Low : 0
e
Legend
Copper Ind.
Fe Altration
Value
High : 255
Low : 0
f
Legend
Copper Ind
Cu
PPM
High : 1073
Low : 0
280000
320000
360000
400000
440000
3400000
3360000
3320000
3280000
3240000

Fig. 5 Evidential layers after processing the exploration data (**a** lithological maps, **b** faults density, **c** magnetic RTP, **d** OH alteration, **e** Fe alteration, **f** geochemistry of copper)

0.120749 and then rises again (Fig. 6). Therefore, 14 epochs were selected for MPM process. The trained Takagi–Sugeno type fuzzy inference system was used for MPM of all the dataset available.

Results

All the study area feature vectors were classified by trained ANFIS. Each of the outputs represents the favorability of its related feature vector and indicates a pixel in final favorability map. All the outputs are rescaled to [0,1], then the results less than 0.68 are considered as unfavorable, and the results more than 0.68 are considered as favorable ones. This threshold value was selected according to inflection point in the predictive classification value versus cumulative percent area curve (Fig. 7). With this threshold, the high favorability zones occupy 11.7 % of the study area and contain all training deposit and about 84 % of validation deposits. The binary favorability map is shown in Fig. 8.

Having received the final modeling result, the effect of the input data on favorable areas was analyzed; therefore, the histogram of normalized input data resulting in favorable or high potential output was drawn. Each input effect on favorable area is represented in a diagram (Fig. 9). Analyzing the diagrams shows that the behavior of the input layers follows a special pattern, which means that most of the copper mineralization is correlated with a special range of the input data.

Discussion

Mineral exploration, nowadays, is infeasible with only one information layer. For this purpose, various data layers such as geology, geophysics, and geochemistry must be considered. Earth science information that is used in mineral potential mapping has an empirical component comprising an exploration database and a conceptual component comprising an expert knowledge base. The hybrid neuro-fuzzy model combines conceptual and empirical components for predictive mineral potential mapping effectively (Porwal et al. 2004).

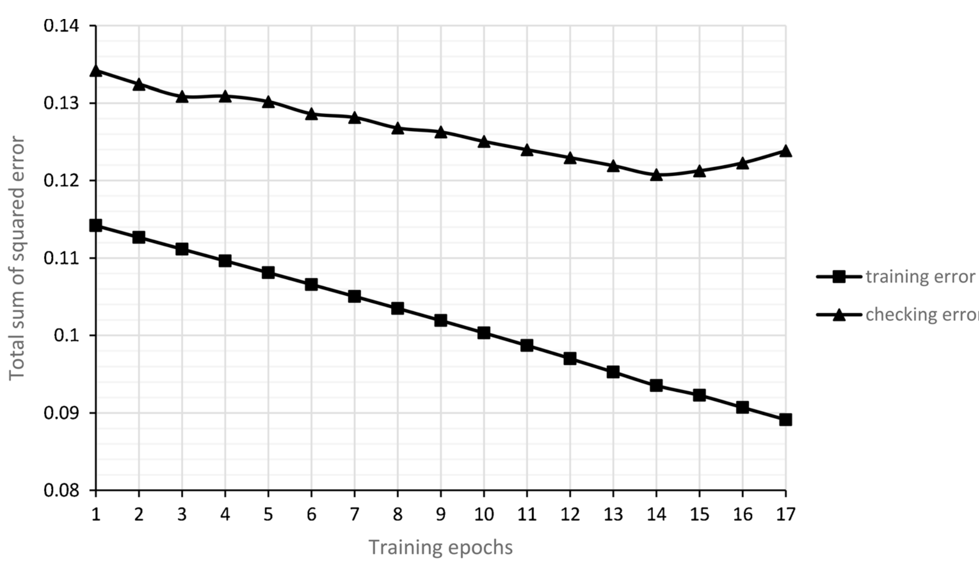
In this paper, ANFIS was used to combine exploration data in regional scale for copper potential mapping in the Kerman copper bearing belt which has great potential for porphyry-Cu deposits. Then, the effect of each input parameter on the result was discussed.

Data layers or evidential maps are in six datasets including lithology, tectonic, airborne geophysics, ferric alteration, hydroxide alteration, and geochemistry, and the study area is comprehensively covered by these datasets. The adaptive neuro-fuzzy inference system in the present application classifies an input feature vector as favorable or unfavorable with respect to copper deposits.

The modeling result was 1044 pixels selected as favorable in order to continue the copper exploration in the study area; in other words, approximately 11.7 % of the area was selected. Fifty six known deposits out of 86 ones, equal to 65 % of all, were located in favorable zone.

One of the main goals of this study was to determine how each input affects favorable output. For this purpose, the histogram of each normalized input data with its favorable output was drawn (Fig. 9). These histograms show the favorable pixel frequency for each input layers. The result

Fig. 6 Number of training epochs versus SSE for training and validation vectors



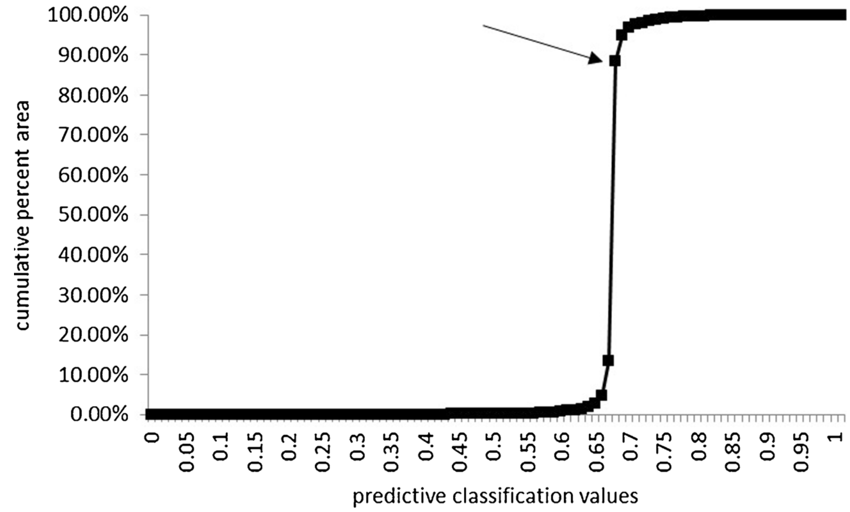


Fig. 7 Variation of cumulative percent area with predictive classification values. Inflection point marked by an *arrow*

was behavioral patterns extracted from each input information layer (evidential map) with the copper deposit potential viewpoint. These diagrams are discussed continuously.

- According to the histogram in Fig. 9a, copper mineralization events match four host rocks: quartz monzonite, andesite, dasite, and granodiorite; these findings match the host rocks of large mines such as Sarcheshmeh and Meyduk (Hezarkhani 2006c; Hassanzadeh 1993).
- Review of fault density diagram (Fig 9b) which reflects the intensity of tectonic activity indicates that the favorable zones are located in the lowest crunch ones. Therefore, it is assumed that intense tectonic activities reduce the probability of copper mineralization.

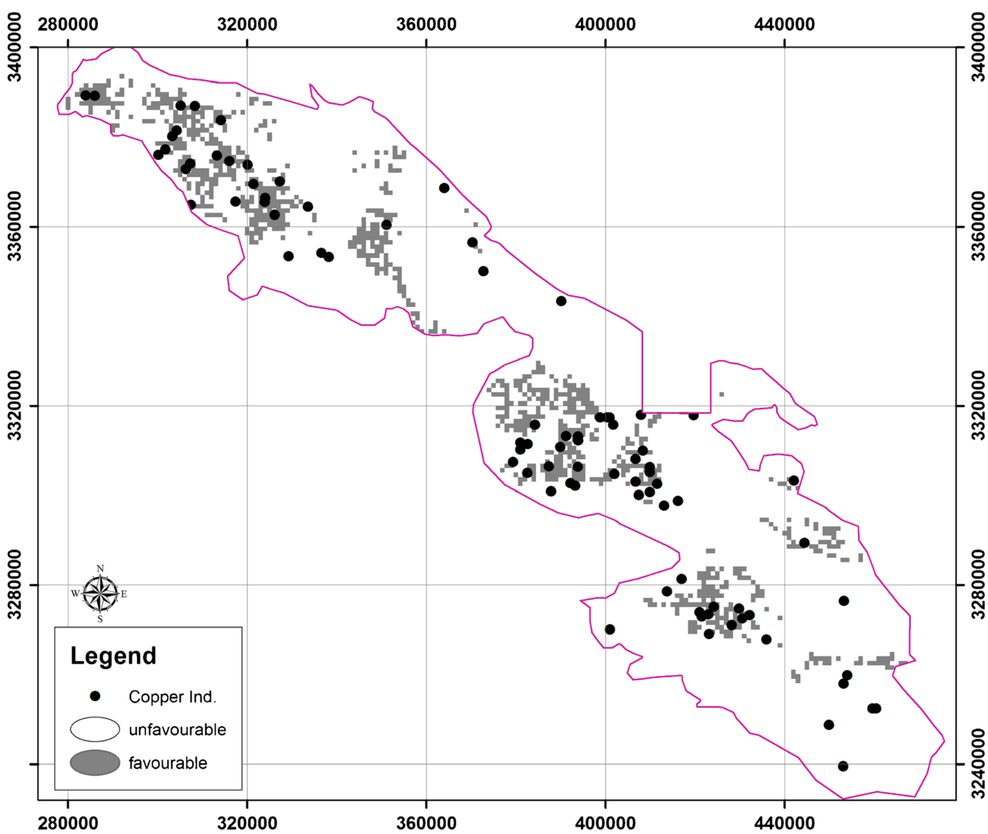
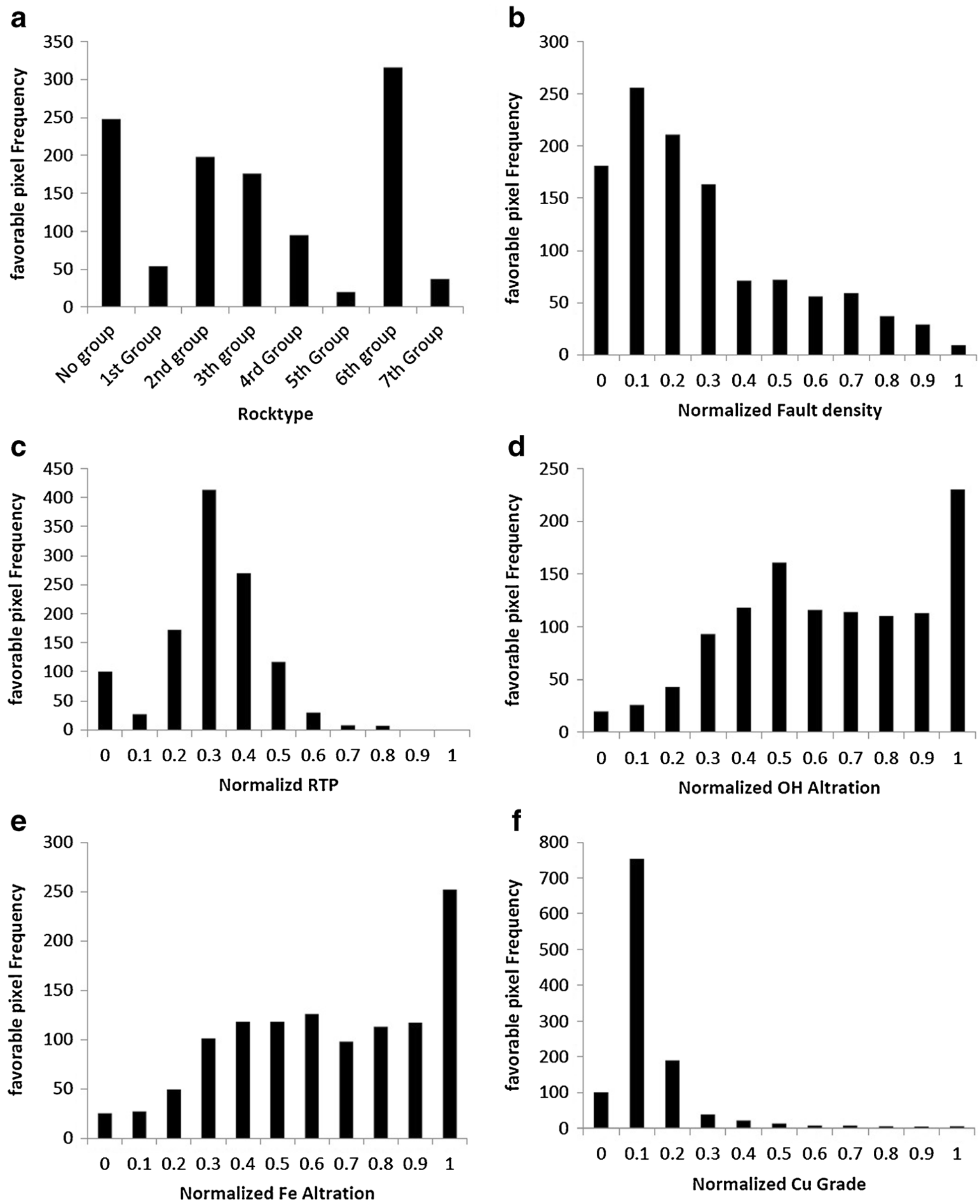


Fig. 8 Binary favorability map

Fig. 9 The histogram of the normalized input data related to the favorable pixels regarding copper potential (**a** lithological maps, **b** faults density, **c** magnetic RTP, **d** OH alteration, **e** Fe alteration, **f** geochemistry of copper)



- According to the magnetic RTP data from Fig. 9c, the probability of copper occurrences matches with non-magnetic anomalies. This reduction in magnetism or magnetic depletion is due to the destruction of magnetite by hydrothermal solutions (Thoman et al. 2000).
- Figure 9d, e expectedly demonstrates that high levels of alteration derived from Landsat 8 are correlated with favorable copper potential zones.
- Figure 9f indicates that areas with high favorability is merely not correlated with the very low grade copper values from stream sediment.

Finally, the results of Fig. 9 can be considered as regional copper exploration criteria.

Conclusion

An adaptive neuro-fuzzy inference system (ANFIS) was presented for modeling the copper potential in Kerman copper bearing belt. The results of the modeling were selecting 1044 pixels as favorable zones, meaning 11.7 % of the study area. Besides, 56 out of 86 copper indices (approximately 65 %) were located in favorable zones.

Most of the mineral potential mapping studies involve modeling and evaluation of the model. In this paper, in addition to these, the output of modeling in relationship with input layers was discussed. Therefore, the histograms of each input dataset for favorable modeling output showed that each information layer has a certain behavioral pattern.

Behavioral pattern of copper deposits is made from the distribution and types of rocks, mineralization, and alteration zones. Every evidential layer shows a part of this pattern. Therefore, these patterns can be considered as regional copper exploration criteria.

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