Predictive Cu porphyry potential mapping using fuzzy modelling in Ahar–Arasbaran zone, Iran

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**ABSTRACT**

Fuzzy set theory was successfully used to map areas of copper porphyry mineralization potential in the Ahar–Arasbaran district of Iran. Proximity to geological features is translated into fuzzy membership functions based upon qualitative and quantitative knowledge of spatial associations between known Cu porphyry occurrences and geological features in the area. Fuzzy sets of favourable lithology, geochemical anomaly, geophysical anomaly, structural feature, and alterations are combined using fuzzy logic as the inference engine. The fuzzy predictive maps delineate 84% of the known Cu porphyry occurrences. The results demonstrate the usefulness of a geologically constrained fuzzy set approach to map mineral potential and to redirect surficial exploration work in the search for yet undiscovered Cu porphyry mineralization in the mining district. The method described is applicable to other mining districts elsewhere.

**1. Introduction**

Geographical information systems (GIS) technology has shown growing application in many areas of knowledge, but especially in the mineral exploration. Mineral exploration involves the collection, analysis, and integration of data from different surveys. Mineral exploration generally starts on a small-scale (large areas) and, then, progresses to a larger scale (small areas) in order to define targets for more detailed investigations (Quadros, Koppe, Strieder, & Costa, 2006). Before the construction of a predictive model, which can be defined as representing the favourability or probability of occurrence of a mineral deposit of the type/style sought, a schematic subdivision has to be drawn depending on the type of inference mechanism considered. There are two general types of predictive modelling strategies: (1) knowledge-driven; and (2) data-driven (Feltrin, 2008).

A third method is also used, which in fact combines the two main methods (Pazand & Hezarkhani, 2016). The former means that evidential weights are estimated subjectively based on one’s expert opinion about spatial association of target deposits with certain geological features and is based on genetic (ore genesis) associations, whereas the latter means that evidential weights are quantified objectively with respect to locations of known target deposits (Bonham-Carter, 1994; Carranza & Hale, 2001; Carranza, van Ruitenbeek, Hecker, van der Meijde, & van der Meer, 2008; Cheng & Agterberg, 1999; Moon, 1998; Porwal, Carranza, & Hale, 2004). Knowledge-driven approaches rely on the geologist’s input to weight the importance of each data layer (evidence map) 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 the geologist in the modelling process (Harris et al., 2001). Examples of knowledge-driven approaches include Boolean logic, index overlays (Harris, 1989), analytical hierarchy process (Wilkinson, Harris, & Grunsky, 1999), and fuzzy logic (An, Moon, & Bonham-Carter, 1992).

In this paper, we report the results of mapping Copper porphyry potential in the Ahar–Arasbaran district by employing the theory of fuzzy sets. The Ahar–Arasbaran metallogenic zone has been studied for decades because of its mineral potential for metallic ores, especially skarn copper (skarn and porphyry) and gold sulphides of which many occurrences are known in the area (Hezarkhani, 2006; Hezarkhani & Williams-Jones, 1996; Hezarkhani, Williams-Jones, & Gammons, 1997, 1999; Mollai, Dave, & Sharma, 2004; Mollai, Sharma, & Pe-Piper, 2009). The aim here is to demonstrate methods for processing the data and producing a Cu porphyry prospectivity map. This is important as each modelling method has advantages and disadvantages and one or the other may be more appropriate given certain geologic environments and exploration scenarios. However, the Cu prospectivity maps are compared in a general sense by evaluating how each map has predicted the known Cu prospects.
The purpose of this work was to use the GIS techniques to perform the analysis and to provide maps for a better understanding of mineral potentials in the study area which evaluate fuzzy method for mineral potential mapping in order to define areas for detailed investigation.

2. Study area

Ahar–Arasbara area measures about 23,132 km² and is located in the Azerbaijan province of north-western Iran. Iran can be divided into two marginal, active, fold belts located in the NE (Kopeh Dagh), resting on Eurasian Hercynian basement and in the SW (Zagros), overlying the Precambrian Arabian plate (Nabavi, 1976) (Figure 1). The Iranian plateau is located between these marginal fold belts. Intrusive rocks of Iran are of Precambrian, Mesozoic and Tertiary age (Stockline & Nabavi, 1973). The Tertiary plutonic bodies were mainly intruded during the Late Eocene–Oligocene, Oligo-Miocene and Pliocene epochs and host important mineralization. In the Alborz unit, Precambrian basement rocks are of Gondwanan affinity. Tectonic movements in the Late Precambrian caused significant uplift in Azerbaijan and locally formed angular unconformities (Efekharnezhad, 1975). Vertical movements during the Cambrian are inferred from stratigraphic gaps between the Cambrian and younger rock units. Silurian and Early Devonian sedimentary sequences, as well as Upper Carboniferous sedimentary rocks, are absent in Azerbaijan (Nabavi, 1976). A thick Triassic to Upper Cretaceous sedimentary-volcanic sequence was subsequently folded during Late Cretaceous–Early Tertiary orogenic movement (Efekharnezhad, 1975).

During the Late Eocene–Oligocene, the Alborz and central Iran units were cut by several intrusive bodies. Late Eocene–Oligocene (mainly Oligocene) plutonic activity was reported by Khain (1975) from the Lesser Caucasus to northern Azerbaijan (Pourhosseini, 1981; Stockline & Efekharnezhad, 1969). Urumieh–Dokhtar volcanic belt, which was first identified by Stocklin and Setudenia (1972), consists of alkaline and calc-alkaline volcanic rocks (Figure 1) and related intrusive (I-type) and was formed by subduction of the Arabian plate beneath central Iran during the Alpine orogeny (Berberian, 1976, 1983; Berberian & King, 1981; Pourhosseini, 1982; Stocklin & Setudenia, 1972). A belt of skarn–porphyry Cu deposits of late Tertiary age extends from Urumieh–Dokhtar in the NW Iran region (Figure 1) and includes the well-known Sungun porphyry skarn deposit (Hezarkhani & Williams-Jones, 1997). Important Cu skarn deposits are found in and around the Oligocene–Miocene volcanic rocks in the area (Hezarkhani, 2006; Mollai et al., 2004, 2009) (Figure 1).

3. Conceptual model

Porphyry copper deposits due to the large and important reserves have been well-studied. Also, these types of deposit have a special pattern that is important for regional exploration they are very good (Abedi, Mostafavi Kashani, Norouzi, & Yousefi, 2017; Yousefi & Carranza, 2017). Most of the porphyry copper deposits
have been intensively studied in the Mesozoic-Cenozoic orogenic belts of the American Cordillera and East Pacific Rim (e.g., Ahmad & Rose, 1980; Dilles & Einaudi, 1992; Sillitoe, 1973) and their properties is relatively well understood. Several conceptual models have been proposed to explain the different styles of Cu Porphyry mineralization (Bliss, 1992; Gruen, Heinrich, & Schroeder, 2010; Sillitoe, 1999, 2010; Sillitoe & Gappe, 1984; Volkov et al., 2006; Xu et al., 2009). In Iran, all known porphyry copper mineralization occurs in the Cenozoic Urumieh–Dokhtar orogenic belt (Figure 1). This belt was formed by subduction of the Arabian plate beneath central Iran during the Alpine orogeny (Berberian & King, 1981; Pourhosseini, 1981) and hosts two major porphyry Cu deposits (Zarasvandi et al., 2015). The Sarcheshmeh deposit is the only one of these being mined, and contains 450 million tonnes of sulphide ore with an average grade of 1.13% Cu and 0.03% Mo (Waterman & Hamilton, 1975). The Sungun deposit, which contains 500 million tons of sulphide reserves grading 0.76% Cu and 0.01% Mo (Hezarkhani & Williams-Jones, 1999), is currently being developed. A number of subeconomic porphyry copper deposits are all associated with mid- to late-Miocene diorite/granodiorite to quartz-monzonite stocks. Classic patterns of hydrothermal alteration (Hezarkhani, 2006, 2007) exist in most of these deposits. Based on the available spatial data-sets, we indentified following regional-scale recognition criteria for porphyry copper deposit occurrence in the Ahar–Arasbaran area:

(1) Host rock lithology
(2) Geophysics anomaly
(3) Geochemical anomaly
(4) Structural feature
(5) Alteration map

A general framework of this modelling can be seen in Figure 2.

### 4. Fuzzy sets

In classical set theory, the membership of a set is defined as true (=1) or false (=0). In fuzzy set theory, a fuzzy set is defined as a subset from a large set whose membership in the subset may not be complete. Fuzzy sets are represented by membership functions. Membership function, \( \mu_A(x) \), is a mapping of the fuzzy membership of \( x \) from the universe of discourse \( X \) into the unit interval \([0, 1]\), thus:

\[
\mu_A(x) : X \rightarrow [0, 1]
\]

The grade of membership is large (traditionally 1) for objects which fully belong to the fuzzy set; it is small (traditionally 0) for objects which do not belong to the fuzzy set (Zimmermann, 1991). In a fuzzy set, with increasing degrees of certainty, the membership of a class is closer to 1. Thus, individual classes of maps can be evaluated regarding their membership in a fuzzy set, based on a subjective judgement. Grade of membership usually is represented by a membership function which need not be linear or even continuous; indeed, many interesting fuzzy sets have extremely non-linear membership functions (Carranza & Hale, 2001). The membership always relates to a certain proposition. In our example, the proposition is “favorable location for Cu porphyry mineralization.”

For combining fuzzy sets, Zadeh (1965) and Zimmermann (1991) define a number of set operators based on fuzzy mathematics. The most widely used operators in fuzzy modelling are the fuzzy AND, fuzzy OR, the fuzzy complement, the fuzzy algebraic sum, the fuzzy

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**Figure 2.** General framework applied for data integration.
algebraic product, and the gamma operator. The fuzzy AND operation is equivalent to a Boolean AND (logical intersection) operation on classical set values of 1 and 0. It is defined as:

\[ \mu_{\text{combination}} = \text{MIN}\left(\mu_A, \mu_B, \mu_C, \ldots\right) \]  

(2)

where \( \mu_A \) is the fuzzy membership value for map \( A \) at a particular location, \( \mu_B \) is the fuzzy membership value for map \( B \), and so on. The effect of this operation is to make the output map be controlled by the smallest (minimum) fuzzy membership value occurring at each location. The fuzzy AND operation is appropriate where two or more pieces of evidence for a hypothesis must be present together for the hypothesis to be true.

The fuzzy OR is similar to the Boolean OR (logical union) whereby the output fuzzy membership values are controlled by the maximum values of any of the input maps, for any particular location. The fuzzy OR is defined as:

\[ \mu_{\text{combination}} = \text{MAX}\left(\mu_A, \mu_B, \mu_C, \ldots\right) \]  

(3)

This operator, in some circumstances, can be reasonable for mineral-potential mapping where favourable evidences for the occurrence of mineralization are rare and the presence of any evidence may be sufficient to suggest favourability.

The fuzzy algebraic product is defined as:

\[ \mu_{\text{combination}} = \prod_{i=1}^{n} \mu_i \]  

(4)

The combined fuzzy membership values tend to be small with this operator, because of the effect of multiplying several numbers less than 1. The output is always smaller than, or equal to, the smallest contributing fuzzy membership value, and is thus "decrease.

The fuzzy algebraic sum operator is complementary to the fuzzy algebraic product, and is defined as:

\[ \mu_{\text{combination}} = 1 - \prod_{i=1}^{n} (1 - \mu_i) \]  

(5)

The result of this operation is always larger than, or equal to, the largest contributing fuzzy membership value. The effect thus is "increase.

The fuzzy "\( y \)-operator" (Zimmermann & Zysno, 1980) is defined as:

\[ \mu_{\text{combination}} = \left( \prod_{i=1}^{n} \mu_i \right)^{1-y} \left( 1 - \prod_{i=1}^{n} (1 - \mu_i) \right)^y \]  

(6)

This "\( y \)-operator" is obviously a combination of the fuzzy algebraic product and the fuzzy algebraic sum, where \( y \) is a parameter between the range 0 and 1. When \( y \) is 1, the combination is the same as the fuzzy algebraic sum; when \( y \) is 0, the combination equals the fuzzy algebraic product. The parameter indicates where the actual operator is located between the logical "and" and "or." The fuzzy method enables evidence maps to be combined in a series of steps regarded as an inference net (flowchart), instead of combining them in a single operation. The inference net is, in fact, a simulation of the logical process defined by a specialist.

5. Methods and result

5.1. Criteria description

The data used in this study were selected based on the relevance with respect to Cu porphyry exploration criteria as discussed previously. Airborne magnetic data (total field and vertical gradient) were used to identify linear magnetic anomalies representing geological features such as magnetite-bearing lithologies, ductile high-strain zones, shallow intrusive body, and faults. A number of geologic maps of differing scales (100,000 and 250,000) were used to prepare host rock evidence map. Total of 7000 stream sediment geochemical data were processed and determined anomaly and threshold (Hongjin, Daoming, Yanxiang, Yangang, & Xisheng, 2007; Rubio, Nombela, & Vilas, 2000; Woodsworth, 1972) of Cu, Mo, Pb, Zn, As, Au, Sb as pathfinder of Cu porphyry mineralization and prepare geochemical evidence map. Structural layer (faults), extracted from the geological maps and magnetic data. The area was divided into 100 \times 100 m network and fault density per each cell was calculated and prepare fault concentration map as structural evidence map. Remote sensing data (Aster data) were used for extraction of advance argillic, argillic, phyllic, and iron oxide alteration layers (Azizi, Tarverdi, & Akbarpour, 2010) and to prepare an alteration evidence map. These evidence maps for creating proximity zones (buffering) around different features were buffered (Table 1) and ready for data integration. The score of class is calculated using following equation:

\[ X_{ij} = W_i \times W_j \]  

(7)

where \( W_i \) is the weight of the \( i \)-th evidential map and \( W \) is the weight of the \( j \)-th evidential class. Based on their subjectively assessed favourability, all classes of an evidential map are ranked in the scale of 1–10 in a reverse direction that is the most favourable class is ranked 10, and the least favourable class is ranked 1. Values of 10 are not assigned for evidential map because we can never be certain completely that a given distance is completely essential for the occurrence of copper mineralization. We used linear membership function for fuzzification of multiclass evidential maps in a knowledge-driven approach. Fuzzy membership values for evidential maps are given in Table 1.
Table 1. Fuzzy membership values for evidential maps.

| Evidential class | Map weight | Class weight | Class score | Fuzzy membership | Evidential class | Map weight | Class weight | Class score | Fuzzy membership |
|------------------|------------|--------------|-------------|------------------|------------------|------------|--------------|-------------|------------------|
| Geology          | 9          | 10           | 90          | 0.90             | Geophysics       | 6          | 6            | 36          | 0.36             |
| Intrusive        | 9          | 8            | 72          | 0.72             | Magnetic intensity 1 | 6          | 5            | 30          | 0.30             |
| Buffer 1000 m    | 9          | 7            | 63          | 0.63             | Magnetic intensity 2 | 6          | 2            | 12          | 0.12             |
| Buffer 2000 m    | 9          | 6            | 54          | 0.54             | Magnetic intensity 3 | 6          | 0            | 0           | 0.00             |
| Volcanic         | 8          | 8            | 64          | 0.64             | Anomaly < Cu     | 9          | 9            | 81          | 0.81             |
| Buffer 1000 m    | 8          | 6            | 48          | 0.48             | Threshold < Cu   | 9          | 7            | 63          | 0.63             |
| Buffer 2000 m    | 8          | 5            | 40          | 0.40             | Background       | 9          | 4            | 36          | 0.36             |
| Buffer 3000 m    | 8          | 4            | 32          | 0.32             | Background       | 9          | 0            | 0           | 0.00             |
| Buffer 1000 m    | 8          | 3            | 24          | 0.24             | Anomaly < Mo     | 9          | 9            | 81          | 0.81             |
| Buffer 2000 m    | 8          | 2            | 16          | 0.16             | Threshold < Mo   | 9          | 7            | 63          | 0.63             |
| Buffer 3000 m    | 8          | 1            | 8           | 0.08             | Background       | 9          | 4            | 36          | 0.36             |
| Fault            |            |              |             |                  | Density1         | 7          | 10           | 70          | 0.70             |
| Density2         | 7          | 9            | 63          | 0.63             | Background       | 9          | 0            | 0           | 0.00             |
| Density3         | 7          | 8            | 56          | 0.56             | Background       | 9          | 3            | 27          | 0.27             |
| Density4         | 7          | 7            | 49          | 0.49             | Background       | 9          | 0            | 0           | 0.00             |
| Density5         | 7          | 6            | 42          | 0.42             | Background       | 9          | 7            | 63          | 0.63             |
| Density6         | 7          | 5            | 35          | 0.35             | Background       | 9          | 5            | 45          | 0.45             |
| Density7         | 7          | 4            | 28          | 0.28             | Background       | 9          | 3            | 27          | 0.27             |
| Density8         | 7          | 3            | 21          | 0.21             | Background       | 9          | 0            | 0           | 0.00             |
| Density9         | 7          | 2            | 14          | 0.14             | Background       | 9          | 7            | 63          | 0.63             |
| Density10        | 7          | 1            | 7           | 0.07             | Background       | 9          | 5            | 45          | 0.45             |
| Phyllitic        | 9          | 9            | 81          | 0.81             | Background       | 9          | 0            | 0           | 0.00             |
| Buffer 500 m     | 9          | 8            | 72          | 0.72             | Anomaly < As     | 9          | 7            | 63          | 0.63             |
| Buffer 750 m     | 9          | 7            | 63          | 0.63             | Threshold < As   | 9          | 5            | 45          | 0.45             |
| Buffer 1000 m    | 9          | 6            | 54          | 0.54             | Background       | 9          | 3            | 27          | 0.27             |
| Argillitic       | 9          | 9            | 81          | 0.81             | Background       | 9          | 0            | 0           | 0.00             |
| Buffer 500 m     | 9          | 8            | 72          | 0.72             | Anomaly < Au     | 9          | 7            | 63          | 0.63             |
| Buffer 750 m     | 9          | 7            | 63          | 0.63             | Threshold < Au   | 9          | 5            | 45          | 0.45             |
| Buffer 1000 m    | 9          | 6            | 54          | 0.54             | Background       | 9          | 3            | 27          | 0.27             |
| Advanced argillitic | 9          | 9            | 81          | 0.81             | Background       | 9          | 0            | 0           | 0.00             |
| Buffer 500 m     | 9          | 8            | 72          | 0.72             |                    |             |              |             |                  |
| Buffer 750 m     | 9          | 7            | 63          | 0.63             |                    |             |              |             |                  |
| Buffer 1000 m    | 9          | 6            | 54          | 0.54             |                    |             |              |             |                  |

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5.2. Integration of fuzzy sets

Fuzzy sets can be combined altogether using one fuzzy operator or a variety of different fuzzy operators. The two-stage inference engine used here (Figure 2) comprises four parallel networks that sequentially combine collateral fuzzy evidential maps transmitted by the fuzzifier through the fuzzy OR operator to yield intermediate fuzzy evidential maps in the first stage (Figure 3),

![Figure 3](image.png)

Figure 3. Maps of fuzzy membership values of (A) favourable host environment; (B) favourable structure feature; (C) favourable alteration feature.
Table 2 gives the combined fuzzy favourability values and their respective area coverage in the synthesized fuzzy favourability maps. The plots of the cumulative fuzzy favourability and the cumulative areas are shown in the Figure 5. It can be seen from the plots and Table 2 that the threshold combined favourability value is less than 0.5 for the three maps obtained using $\gamma$ values of 0.75, 0.80, and 0.90, whereas it is 0.5 for the map

which are combined in the second stage using the fuzzy $\gamma$ operator to generate the synthesized fuzzy favourability map.

The intermediate fuzzy evidential maps were combined in the second stage of the inference engine using the fuzzy $\gamma$ operator with $\gamma = 0.75, 0.80, 0.85$, and $0.90$, to produce the fuzzy favourability maps shown in Figure 4.
Validation of the results

The results were validated by overlaying the known mineral deposits on the binary favourability map (Figure 6). It can be seen that the favourable areas, which occupy 1338 km$^2$, contain 16 of the 19 known Cu Porphyry deposits in the

5.3. Validation of the results

The results were validated by overlaying the known mineral deposits on the binary favourability map (Figure 6). It can be seen that the favourable areas, which occupy 1338 km$^2$, contain 16 of the 19 known Cu Porphyry deposits in the
study area. Thus, the model predicts 84.2% of the known Cu porphyry deposits; while at the same time reduce the search area to less than 5.7% of the total area.

6. Conclusions

The characteristics of a certain type of mineral deposits can be different in different areas, which are a function of the relative importance of individual factors of mineralization in different areas, are related to geological features associated to mineralization. In this research, data layers have been integrated according to their favourability in porphyry copper mineralization using fuzzy logic methods that the following results were obtained:

1. The application of fuzzy set theory to predictive mineral potential mapping provides a strong theoretical framework for handling the complexity of modelling multiclass evidential maps in a flexible and consistent way.

2. A qualitative and quantitative knowledge of the spatial association between known mineral occurrences and geological features in an area is important for mineral potential mapping.

3. The qualitative and quantitative knowledge of spatial association between known mineral occurrences and geological features are together useful in the subjective decision on the appropriate fuzzy membership functions or scores. A qualitative knowledge alone may have proven inadequate to produce a fuzzy predictive map of Cu porphyry potential for the area.

4. The design of the fuzzy inference network to combine the evidences for mapping mineral potential must be based upon the knowledge of the genesis or mode of formation of known mineralization in a particular area.

5. The knowledge-driven fuzzy models reported in here result in demarcation of potential zones occupying less than 6% of the study area. This is a significant result in terms of reduction in search area.

6. The best predictive maps produced by this study are comparable with the results of previous geological work. These maps predict 84% of the known occurrences. These maps can be used to direct exploration work to search for undiscovered occurrences in the area.

7. This method is useful for exploration of Cu porphyry deposits because of its very significant pathfinder feature such as alteration pattern, geochemical pattern, and geological environment.

Disclosure statement

No potential conflict of interest was reported by the authors.

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