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Combining AHP with GIS for Predictive Cu Porphyry Potential Mapping: A Case Study in Ahar Area (NW, Iran)

Kaveh Pazand,[1,4] Ardeshir Hezarkhani,[2] Mohammad Ataei,[3] and Yousef Ghanbari[1]

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Using the analytic hierarchy process (AHP) method for multi-index evaluation has special advantages, while the use of geographic information systems (GIS) is suitable for spatial analysis. Combining AHP with GIS provides an effective approach for studies of mineral potential mapping evaluation. Selection of potential areas for exploration is a complex process in which many diverse criteria are to be considered. In this article, AHP and GIS are used for providing potential maps for Cu porphyry mineralization on the basis of criteria derived from geologic, geochemical, and geophysical, and remote sensing data including alteration and faults. Each criterion was evaluated with the aid of AHP and the result mapped by GIS. This approach allows the use of a mixture of quantitative and qualitative information for decision-making. The results of application in this article provide acceptable outcomes for copper porphyry exploration.

KEY WORDS: Mineral potential mapping, AHP, Cu porphyry, Ahar.

INTRODUCTION

Geographic 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) to define targets for more detailed investigations (Quadros et al. 2006). Before the construction of a predictive model, which can be defined as representing the favorability 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. 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's expert opinion about 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; Carranza and Hale 2001; Cheng and Agterberg 1999; Porwal et al. 2004; Carranza et al. 2008). 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 modeling process (Harris et al. 2001). Examples of knowledge-driven approaches include Boolean logic, index overlays (Harris 1989), analytic hierarchy process (AHP) (Hosseinali and Alesheikh 2008), and fuzzy logic (An et al. 1992). The integration of GIS and AHP is a powerful tool to solve

[1]Department of Mining Engineering, Science and Research Branch, Islamic Azad University, Ponak Avenue, Tehran, Iran.
[2]Department of Mining, Metallurgy and Petroleum Engineering, Amirkabir University, Hafez Avenue No. 424, Tehran, Iran.
[3]Department of Mining, Geophysics and Petroleum Engineering, Shahrood University of Technology, 7th tir Sq., PO Box 36155-316, Shahrood, Iran.
[4]To whom correspondence should be addressed; e-mail: kaveh.pazand@gmail.com

the site selection and potential mapping problem (Kontos et al. 2003; Hosseinali and Alesheikh 2008; Sener et al. 2010). AHP is a systematic decision approach first developed by Saaty (1980). AHP is a decision analysis method that considers both qualitative and quantitative information and combines them by decomposing ill-structured problems into systematic hierarchies to rank alternatives based on a number of criteria (Chen et al. 2008). As a result, the AHP has the special advantage in multi-indexes evaluation (Ying et al. 2007).

In this article, we report the results of mapping Copper porphyry potential in the Ahar district by combining GIS with AHP. The Ahar zone has been studied for decades because of its mineral potential for metallic ores, especially copper (Skarn and porphyry) and gold sulfides many occurrences of which are known in the area (Mollai et al. 2004, 2009; Hezarkhani 2006, 2008; Hezarkhani et al. 1997, 1999; Hezarkhani and Williams-Jones 1996). The aim here is to demonstrate the method for processing the data and producing Cu porphyry prospectively map. However, the Cu prospectively maps are compared in a general sense by evaluating how the map has predicted the known Cu prospects.

ANALYTIC HIERARCHY PROCESS (AHP)

The AHP is an approach for facilitating decision-making by organizing perceptions, feelings, judgments, and memories into a multi-level hierarchic structure that exhibits the forces that influence a decision (Saaty 1994). The AHP method breaks down a complex multi-criteria decision problem into a hierarchy and is based on a pairwise comparison of the importance of different criteria and sub criteria (Saaty 2005; Forman and Selly 2001). The AHP process is developed into three principal steps. The first step establishes a hierarchic structure. The first hierarchy of a structure is the goal. The final hierarchy involves identifying alternatives, while the middle hierarchy levels appraise certain factors or conditions (Saaty 1996; Jung 2011). The second step computes the element weights of various hierarchies by means of three sub-steps. The first sub-step establishes the pairwise comparison matrix. In particular, a pairwise comparison is conducted for each element based on an element of the upper hierarchy that is an evaluation standard. The second sub-step computes the eigenvalue and eigenvector of the pairwise comparison matrix. The third sub-step performs the consistency test (De Feo and De Gisi 2010). Let $C_1, \ldots, C_m$ be m performance factors and $W = (w_1, \ldots, w_m)$ be their normalized relative importance weight vector which is to be determined by using pairwise comparisons and satisfies the normalization condition (Dambatta et al. 2009):

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

The pairwise comparisons between the m decision factors can be conducted by asking questions to 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 (Joshi et al. 2011):

$$A = (a_{ij})_{m\times m} = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mm} \end{bmatrix}, \tag{2}$$

where a_{ij} represents a quantified judgment on w_i/w_j with $a_{ii} = 1$ and $a_{ij} = 1/a_{ji}$ for $i, j = 1, \ldots, m$.

If the pairwise comparison matrix $A = (a_{ij})_{m\times m}$ satisfies $a_{ij} = a_{ik}a_{kj}$ for any $i, j, k = 1, \ldots, m$, then A is said to be perfectly consistent; otherwise, it is said to be inconsistent. Form the pairwise comparison matrix A, the weight vector W can be determined by solving the following characteristic equation:

$$AW = \lambda_{\max} W, \tag{3}$$

where $\lambda_{\max}$ 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):

$$\mathrm{CR} = \frac{(\lambda_{\max} - n)/(n-1)}{\mathrm{RI}} \tag{4}$$

where RI is the average of the resulting consistency index depending on the order of the matrix (Ying et al. 2007). 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; Karamouz et al. 2007; Hsu et al. 2008; De Feo and De Gisi 2010).

STUDY AREA

The Ahar area (one of 1:100,000 sheets in Iran) is located in East Azarbayejan province, NW Iran in the northern part of the Urumieh–Dokhtar magmatic arc (Fig. 1) and covers an area of about 2500 km^2.

Continental collision between the Afro-Arabian continent and the Iranian microcontinent during closure of the Tethys ocean in the Late Cretaceous resulted in the development of a volcanic arc in NW Iran (Mohajjel and Fergusson 2000; Babaie et al. 2001; Karimzadeh Somarin 2005). In Iran, the entire known porphyry copper mineralization occurs in the Cenozoic 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 Cu deposits. The Sarcheshmeh deposit is the only one of these being mined, and contains 450 million tones of sulfide ore with an average grade of 1.13% Cu and 0.03% Mo (Waterman and Hamilton 1975). The Sungun deposit, which contains 500 million tones of sulfide reserves grading 0.76% Cu and 0.01% Mo (Hezarkhani and Williams-Jones 1998), is currently being developed. A number of economic and subeconomic porphyry copper deposits are all associated with mid- to late-Miocene diorite/granodiorite to quartz-monzonite stocks in Ahar area in this belt (Hezarkhani 2008). The composition of volcanic rocks in Ahar area varies from calc-alkaline to alkaline during Eocene to Quaternary. Regionally, the oldest country rocks are Cretaceous sedimentary, and sub-volcanic rocks include conglomerate, marl, shale, andesite, tuff, and pyroclastic rock, followed by Eocene latite and ignimbrite. The Oligocene–Miocene intrusive rocks include granodiorite, diorite, gabbro, and alkali syenite (Mahdavi and Amini Fazl 1988). The youngest rocks of the region are Quaternary volcanic (Fig. 1).

METHODOLOGY

The flowchart of the methodology is shown in Fig. 2. The research procedures are as follows:

- Determining Cu porphyry exploration criteria.
- Preparing map layers in a GIS environment as raster layer.
- Using pairwise comparison to obtain relative weights.
- Using the AHP to specify the most preferred alternative.

In this article, a primary screening was not performed, and the whole region was evaluated for Cu porphyry potential.

CRITERIA DESCRIPTION AND APPLICATION

The data used in this study were selected based on the relevance with respect to Cu porphyry exploration criteria. The five main criteria as input map layers including airborne magnetic, stream sediment geochemical data, geology, structural data, and alteration zone were used. At the regional and local scales, airborne magnetic surveys, which are rapid and economic, have been a part of porphyry deposits' explorations. Both intrusions and related alteration systems may have characteristic magnetic signature, which in the ideal case, form distinctive anomalies in regional surveys. These patterns 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 used for identifying magnetic lineation, faults, and intrusive body. Geologic data inputs to the GIS are derived and compiled from geologic map of 1:100,000 scale, and lithologic units were hand-digitized into vector (segment) format. Each polygon was labeled according to the name of each litho-stratigraphic formation, and the host rock evidence map including intrusive and volcanic rock as the two sub-criteria was prepared. There are 620 stream sediment geochemical samples of the −80-mesh (0.18 mm) fraction, which were analyzed by the AAS (atomic absorption spectrophotometry) method. After normalization, data were assigned to four classes: values that are equal to or less than the mean are considered low background; values between the mean and mean plus one standard deviation ($\bar{x}$ + SD) are threshold; values between ($\bar{x}$ + SD) and ($\bar{x}$ + 2SD)

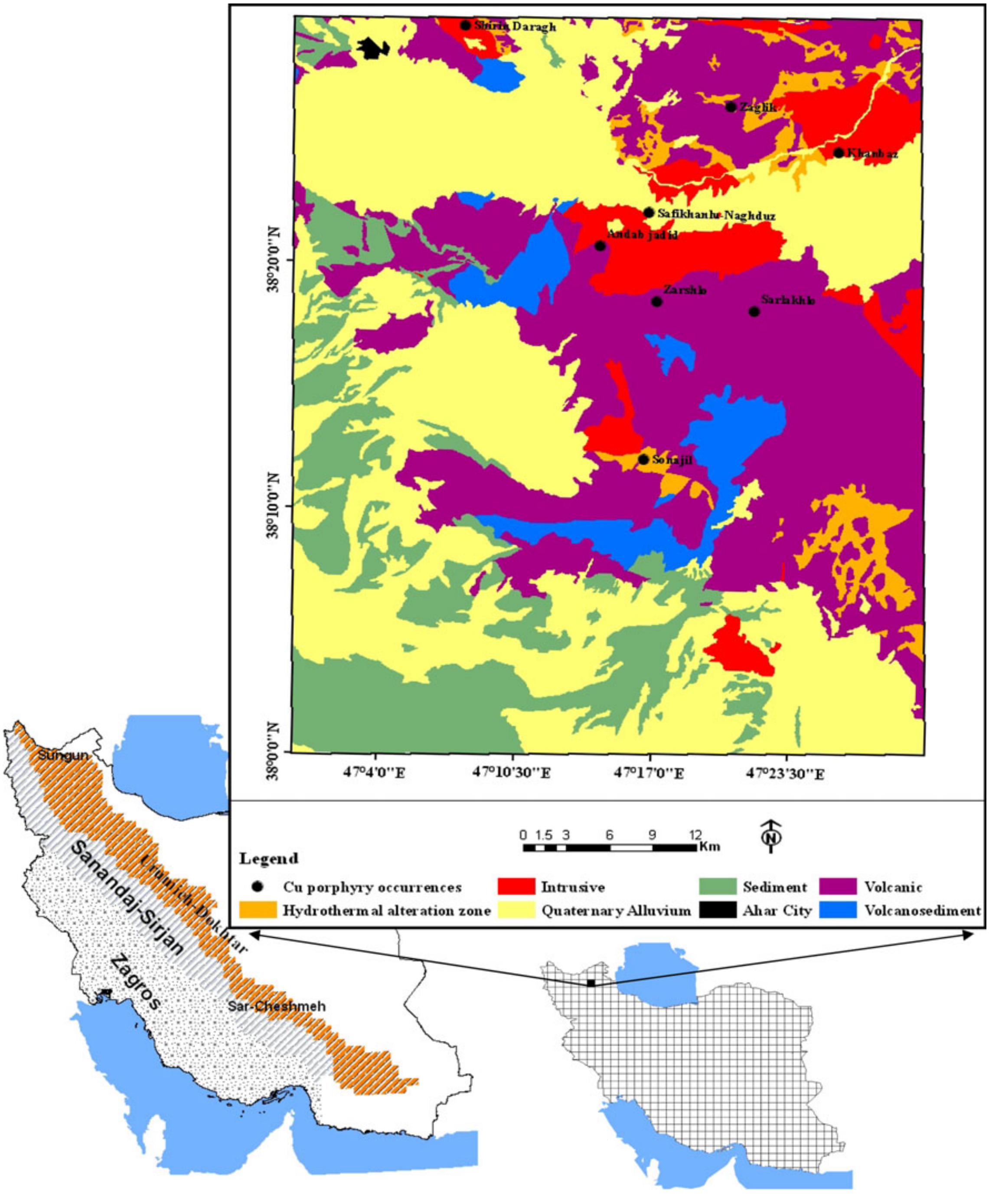

Figure 1. Major structural zones of Iran (after Nabavi 1976) and the locations of these zones in the Ahar area with its modified and simplified geologic map (after Mahdavi and Amini Fazl 1988).

are slightly anomalous; and values greater than ($\bar{x}$ + 2SD) are highly anomalous (Woodsworth 1972; Rubio et al. 2000; Hongjin et al. 2007). These processes for Cu, Mo, Pb, Zn, As, Au, Sb, and Ba as eight pathfinders of Cu porphyry mineralization were performed, and their geochemical evidence maps as geochemical sub-criteria were prepared. Linear structural features interpreted from aeromagnetic data and remotely sensed data were combined with faults available in geologic maps to

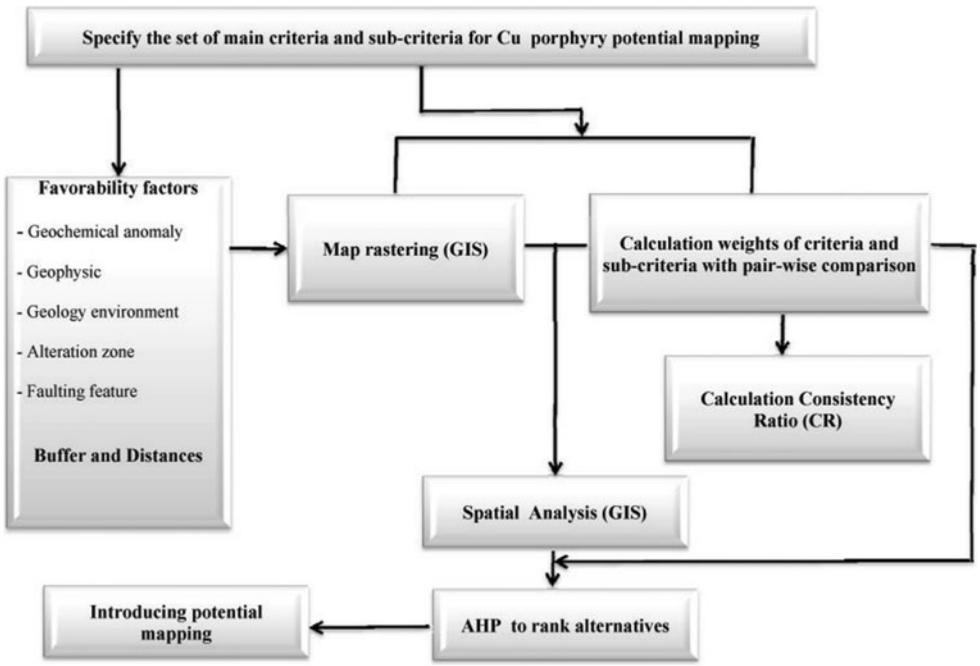

Figure 2. Flowchart of model for Cu potential mapping.

generate a structural evidence map. The map provided in this layer was classified and coded into 10 main classes according to their respective density per unit area. Remote sensing data (Aster data) were used for the extractions of argillic, phyllic, and iron oxide alteration layer (Azizi et al. 2010) as three alteration sub-criteria, and the alteration evidence map was prepared.

These evidence maps were buffered with values according to Table 1 and converted to raster with cell size 100×100 m using ArcGis software (Figs. 3, 4).

THE AHP SOLUTION

The evaluation system was divided into the following steps. At first, the criteria for Cu porphyry potential were determined and placed in a hierarchic structure (Fig. 5); then, relative importance weights for criteria were computed with a pairwise comparison method (Saaty 1980) and was used in a GIS environment to obtain potential map. Each layer in this hierarchic structure was compared in pairwise comparisons related to each of the elements at the level directly above. The level of the structure was established by analyzing the relationship of each index.

The pairwise comparison matrix (PCM) is used for determining weights. PCM is formed by the decision makers who allocated their opinions about criteria, sub-criteria, and alternatives by using Table 2, and it must comply with the following attributes: $a_{ii} = 1$ and $a_{ij} = 1/a_{ji}$.

Relative importance of the criteria was analyzed by Delphi method, also called Expert Judgment System. In this research, we invited experts with Cu porphyry backgrounds to give the corresponding relative importance of each factor, then analyzed all the opinions, and finally, gained the rank of relative importance for each factor as shown in Table 2. Pairwise comparisons of all the related attribute values were used for establishing the relative importance of hierarchic elements. Decision makers evaluated the importance of pairs of grouped elements in terms of their contribution to the higher hierarchy. Finally, all the values for a given attribute were pairwise compared. The weight (W) of each factor in each hierarchy was calculated by their structural models (Fig. 5). Criteria weight (W_i) was calculated by normalizing the weight (W) of each factor. W_i is the criteria weight, i.e., The CR values of all the comparisons were lower than 0.10, which indicated that the use of the weights was suitable (Saaty 1996). Pairwise comparison matrix

Table 1. Map Layer Buffering and Values

Evident	Class Values	Evident	Class Values
Geology		Geochemistry	
Intrusive	10	Anomaly < Cu	10
Buffer 1000 m	8	Threshold < Cu < Anomaly	6
Buffer 2000 m	6	Background < Cu < Threshold	3
Buffer 3000 m	4	Background	1
Volcanic	10	Anomaly < Mo	10
Buffer 1000 m	8	Threshold < Mo < Anomaly	6
Buffer 2000 m	6	Background < Mo < Threshold	3
Buffer 3000 m	4	Background	1
Fault		Anomaly < Zn	10
Density	10	Threshold < Zn < Anomaly	6
Density	9	Background < Zn < Threshold	3
Density	8	Background	1
Density	7	Anomaly < Pb	10
Density	6	Threshold < Pb < Anomaly	6
Density	5	Background < Pb < Threshold	3
Density	4	Background	1
Density	3	Anomaly < Sb	10
Density	2	Threshold < Sb < Anomaly	6
Density	1	Background < Sb < Threshold	3
Alteration		Background	1
Phyllic	10	Anomaly < As	10
Buffer 500 m	8	Threshold < As < Anomaly	6
Buffer 750 m	6	Background < As < Threshold	3
Buffer 1000 m	4	Background	1
Argillic	10	Anomaly < Au	10
Buffer 500 m	8	Threshold < Au < Anomaly	6
Buffer 750 m	6	Background < Au < Threshold	3
Buffer 1000 m	4	Background	1
Iron oxide	10	Anomaly < Ba	10
Buffer 500 m	8	Threshold < Ba < Anomaly	6
Buffer 750 m	6	Background < Ba < Threshold	3
Buffer 1000 m	4	Background	1
Geophysic			
Magnetic intensity 1	10		
Magnetic intensity 2	7		
Magnetic intensity 3	4		
Magnetic intensity 4	2		

for geochemical criteria is shown in Table 3, and the importance of each factor as weight (W) of factor is calculated.

It is apparent that the Cu anomaly is the most important factor (weight = 0.4038), followed by Mo being the next most important factor with $w = 0.2242$. CR = 0.001 for the pairwise comparison of the criteria, which is considered reasonable (CR < 0.1). The calculations for the sub-criteria of alteration and geologic were performed and their weights obtained (Tables 4, 5).

Based on the results of Tables 3–5, the main criteria, including geochemistry, geology, alteration, magnetism, and faults to calculate the final matrix, were used. In this comparison matrix, criteria importance coefficients were calculated (Table 6).

In Table 6, it is shown that the alteration is the most important factor (weight = 0.384), followed by geology being the next most important factor with $w = 0.2533$. Geochemistry's weight is equal to 0.2468, and those for the two magnetic and faults layers with equal weights, respectively, are 0.0346 and 0.0814. The consistency ratio is CR = 0.0658, which for the pairwise comparison of the criteria is reasonable (CR < 0.1). To determine the final score, Saaty (1980) uses the hierarchic composition principle (Eq. 5); this results in the production of the vector regarding all the decisions at every level of the hierarchic structure:

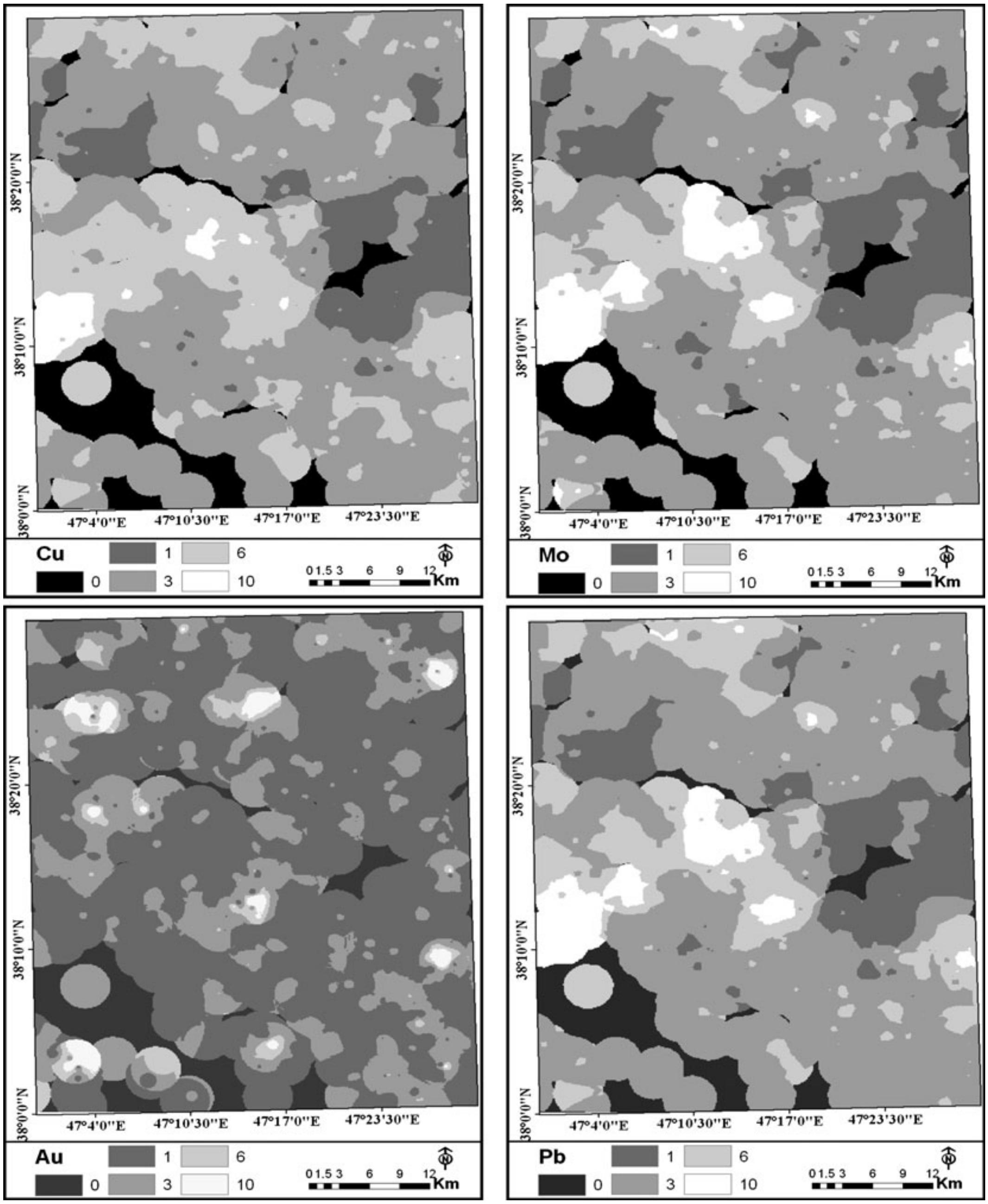

Figure 3. Geochemical index layers of Cu, Mo, Au, and Pb.

$$\text{Result} = \sum_{j=1}^{n} \sum_{i=1}^{m} W_j W_i, \quad (5)$$

where W_j is the importance weight of the *j*th criteria, and W_i is the preferred weight of the *i*th alternatives. Final potential map for Cu porphyry using the obtained score and ArcGis software are provided (Fig. 6).

Regarding the final map layer, the appropriate areas were identified for Cu porphyry mineralization (Fig. 6). Certainly, there are different methods for analyzing model sensitivity. In this study, we use the amount of covering the known Cu porphyry index with the introduced areas. As seen in the maps of the total number of the eight known porphyry copper indexes in the region, six occurrences were located

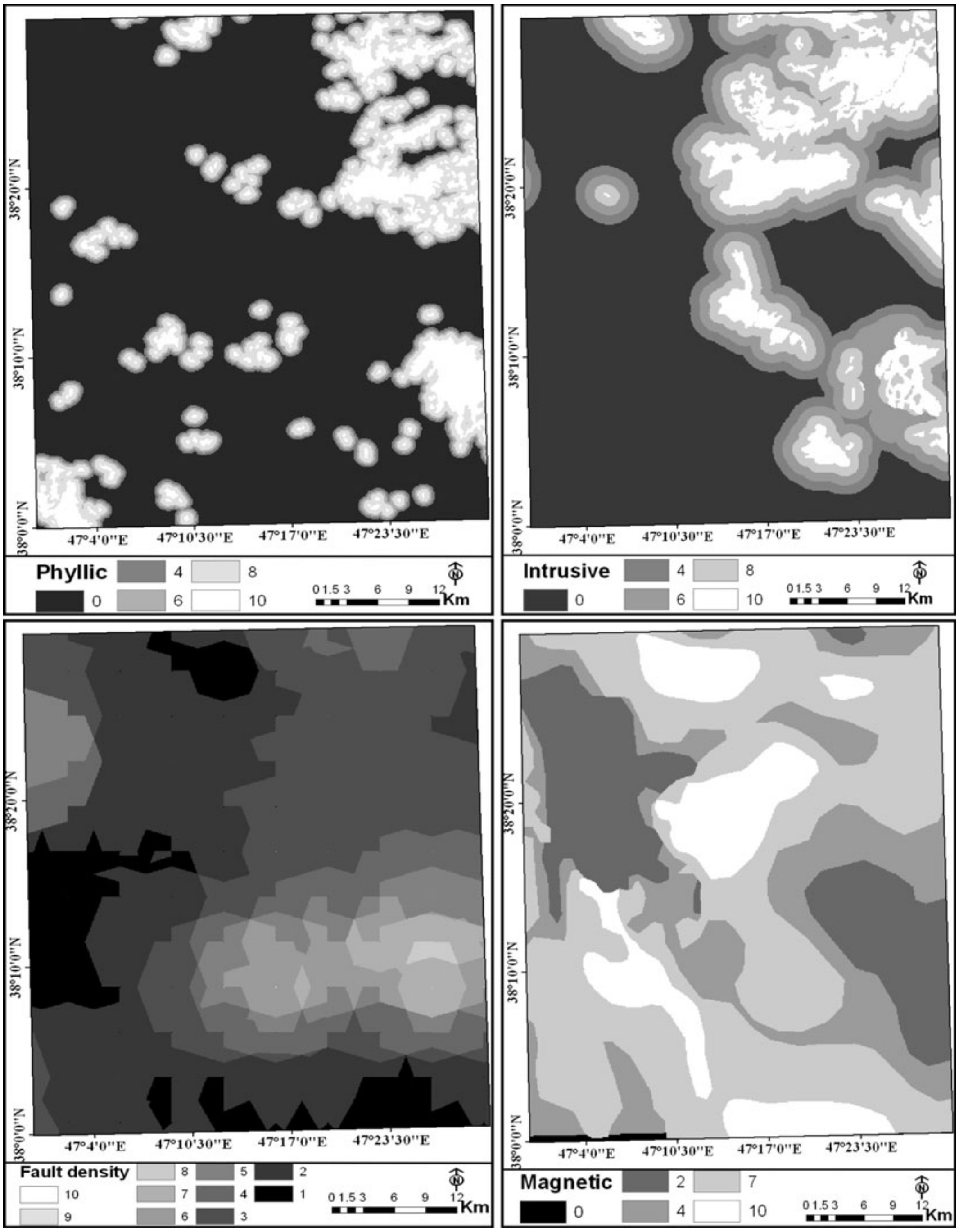

Figure 4. Phyllic alteration, intrusive rock, fault density, and magnetic index layers.

in areas with high potential, and the other two located in areas with a potential average; this means that model predicts 75% of the known Cu porphyry deposits, and ability and the accuracy of the method are confirmed.

CONCLUSIONS

Exploration strategies for non-renewable resources have been changing rapidly along with the accelerating innovations in computer hardware and

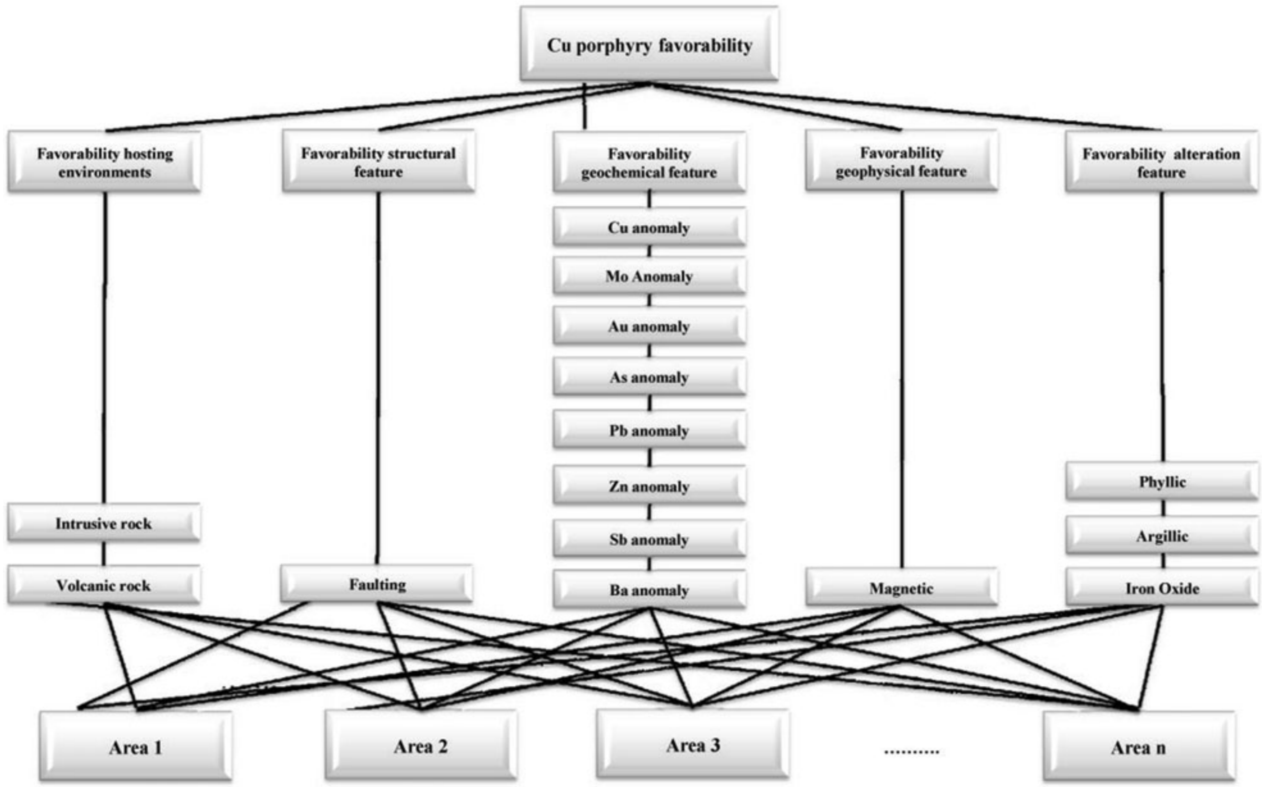

Figure 5. The hierarchic structure of the AHP framework.

Table 2. Various States for Pairwise Comparison and Their Numerical Rates (Saaty 1980)

Intensity of Importance	Definition
1	Equal importance or preference
2	Equal to moderate importance or preference
3	Moderate importance or preference
4	Moderate to strong importance or preference
5	Strong importance or preference
6	Strong to very strong importance or preference
7	Very strong importance or preference
8	Very to extremely strong importance or preference
9	Extreme importance or preference

information processing technology. The results demonstrated the following

(1) This methodology allowed us to have a deeper understanding of the problem and helped us follow a systematic approach to evaluate the potential alternatives.
(2) It allowed for combining both the quantitative and qualitative information.

Table 3. Pairwise Comparison Among Geochemical Sub-Criteria

	Zn	Sb	Pb	Mo	Cu	Ba	Au	As	*W*
Zn	1	1	1	0.2	0.1429	1	0.3333	0.5	0.0438
Sb	1	1	1	0.2	0.1429	1	0.3333	0.5	0.0438
Pb	1	1	1	0.2	0.1429	1	0.3333	0.5	0.0438
Mo	5	5	5	1	0.3333	5	3	3	0.2242
Cu	7	7	7	3	1	7	5	5	0.4038
Ba	1	1	1	0.2	0.1429	1	0.3333	0.5	0.0438
Au	3	3	3	0.3333	0.2	3	1	2	0.1176
As	2	2	2	0.3333	0.2	2	0.5	1	0.0791

CR = 0.001.

Table 4. Pairwise Comparison Among Alteration Sub-Criteria

	Phyllic	Iron Oxide	Argillic	*W*
Phyllic	1	2	1	0.4
Iron oxide	0.5	1	0.5	0.2
Argillic	1	2	1	0.4

CR = 0.023.

(3) The model developed enables decision makers to compare different scenarios with respect to appropriate criteria, and thus

provides a real time, interactive, and graphical display of the overall properties.

(4) This methodology combining the AHP with GIS provided an improved method for potential mapping, which enhanced the capability of spatial analysis by the GIS and the capability of multi layers' analysis by the AHP.

(5) The application of the AHP method for the predictive mineral potential mapping provides a strong theoretical framework for handling the complexity of modeling multiclass evidential maps in a flexible and consistent way.

(6) A qualitative and quantitative knowledge of the spatial association between known mineral occurrences and geologic features in an area is important for mineral potential mapping.

(7) The design of the AHP procedure to obtain the evidences for mapping mineral potential must be based upon the knowledge of the genesis or the mode of formation of known mineralization in a particular area.

(8) This method is useful for exploration of Cu porphyry deposits because of its very significant pathfinder features, such as alteration and geochemical patterns, and geologic environment.

(9) This combination of the methods can also be used in any similar study regions of other metals.

Table 5. Pairwise Comparison Among Geology Sub-Criteria

	Intrusive	Volcanic
Intrusive	1	3
Volcanic	0.3333	1

CR = 0.002.

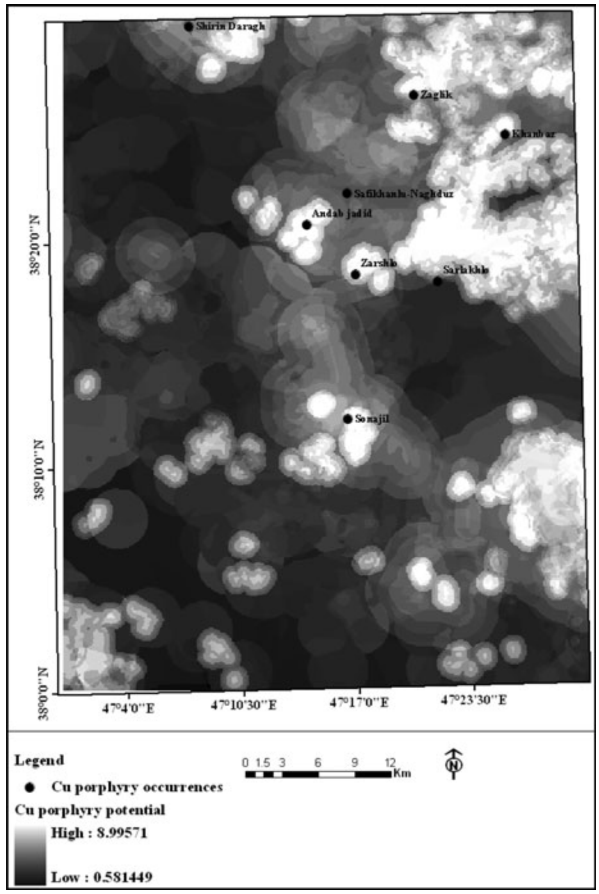

Figure 6. Potential mapping for Cu porphyry mineralization in Ahar area.

Table 6. Pairwise Comparison Among Main Criteria

	Fault	Geochemical	Geology	Alteration	Magnetic	*W*
Fault	1	0.2	0.2	0.2	5	0.0814
Geochemical	5	1	1	0.5	6	0.2468
Geology	5	1	1	0.5	7	0.2533
Alteration	5	2	2	1	7	0.384
Magnetic	0.2	0.1667	0.1429	0.1429	1	0.0346

CR = 0.0658.

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