Detection of Copper Mineralization Potential Zones Using Analytic Hierarchy Process: Case Study of Zarrin Area in Center of Iran

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Abstract

Due to costly and time consuming Basic and detailed exploration stage mineral exploration operations and high risk, so Mineral Potential Mapping and modeling using data crucial step in reducing the risks and costs of exploration. Various methods for mapping and finding potential of promising areas already developed. One of the most effective given the nature of geological phenomena is hierarchical. The Analytic Hierarchy Process (AHP) method extensively used for studying, comparing and combining various information layers in spatial analysis. Combination of Hierarchical method with GIS, provides a highly efficient method to studying of promising areas of mineralization. In this hierarchical method and with the help of GIS, data in the form of Zarrin Area were analyzed and presented promising areas.

Keywords: AHP; GIS; Mineral Potential Mapping; Integration; Mineral Exploration; Zarrin Area.

1- Introduction

Mineral exploration aims to discover new mineral deposits in a region of interest. One of the main steps in mineral exploration is to distinguish prospective areas within the region of interest (Carranza *et al*., 1999; Kontos *et al*., 2003). On the other hand, since the exploration operations in the high-risk public and detailed and high cost, so the potential mineral mapping modeling and using the available data step in controlling risk mitigation and exploration costs. Two crucial step in the production and marketing potential plans include: Recognize factors affecting the reconciliation and the selection of an appropriate integration (porwal, 2006; Kontos *et al*., 2003). Mineral prospectivity mapping (MPM) aims to delineate target areas that are most likely to contain mineral deposits of a certain type in the region of interest (Quadros *et al*., 2006).

In order to conduct, MPM is a multi-step process of generating evidential maps (i.e., extracting and weighting of features indicating the presence of the mineral deposit-type sought), combining evidential maps, and finally ranking promising target areas for further exploration (Carranza *et al*., 2001; Carranza, 2008; Yousefi *et al*., 2012; Abedi *et al*., 2013). Various MPM approaches have been developed in the last two decades which can be categorized generally into data- and knowledge driven ones (Carranza, 2008; Carranza *et al*., 2008). In data driven techniques, the information acquired from the known mineral deposits are used as ‘training points’ to establish spatial relationships between the known deposits and particular geological, geochemical and geophysical features based upon numerous statistical/mathematical algorithms (Carranza 2008). Examples of the data driven methods are weights of evidence, logistic regression, neural networks and evidential belief functions (Carranza and Hale, 2002; Porwal *et al*., 2003;

Quadros *et al*., 2006; Carranza, 2008). In these MPM approaches geoscientist's expert judgment is applied to weight evidential features. Boolean logic, index overlay, evidential belief functions, and fuzzy logic (Chung and Moon, 1990; Moon, 1990; An *et al*., 1991; Nykänen and Salmirinne, 2007; Carranza, 2008; Jung, 2011) are examples of knowledge-driven methods.

The knowledge and data-driven MPM methods each have their weaknesses in application. In terms of data-driven methods, enough known mineral deposits are needed as 'training points' to ensure well performance. For the knowledge-driven methods, the assignment of meaningful weights to each evidential layer is a highly subjective exercise that usually involves trial and error, even in cases where 'real-expert' knowledge is available, and particularly when a number of different experts are involved (Feltrin, 2008; Ishizaka *et al*., 2013; Du *et al*., 2016; Asadi *et al*., 2016). Nevertheless, the analytical hierarchy process (AHP) proposed by Saaty (1980, 1994, 1996) can resolve this difficulty in evaluating the relative importance of each evidential layer, aided by making pairwise comparisons (Carranza 2008). In addition, this method is straightforward for decision-makers (DMs) to use to structure a complex problem into a systematic hierarchy using the AHP technique (Forman *et al*. 2001).

How to measure intangibles is the main concern of the mathematics of the AHP. The AHP has been mostly applied to multi-objective, multi-criteria and multiparty decisions because decision-making has this diversity (Figueira *et al*., 2005; Hosseinali *et al*., 2008). In this paper, the modeling and integrate geophysical data and geology and satellite images with analytical methodology Analytical Hierarchy Process (hierarchical) or briefly in AHP GIS environments for exploration of mineral angiogenesis copper at 1:100,000 sheet of Zarrin has been used.

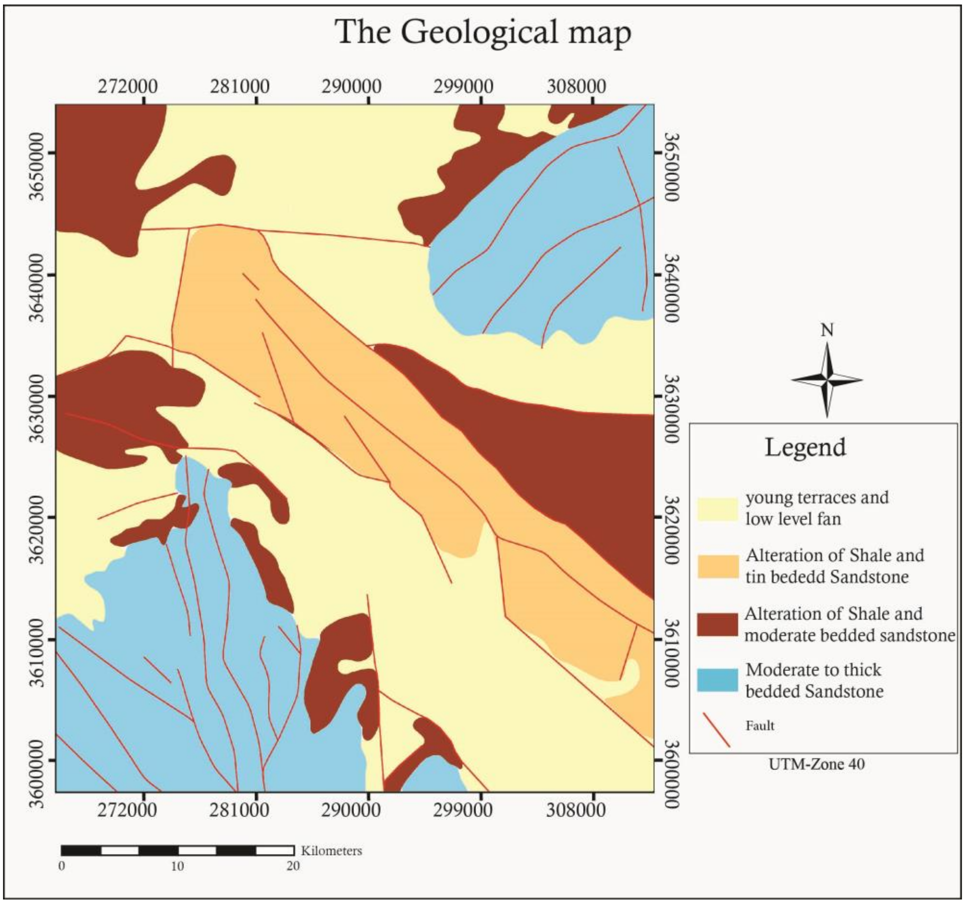

Figure 1) Geological map of study area, Modified after (Emami) and (Karimpour)

2- Methodology

AHP approach the issue to systematically smaller constituent parts and then guided the decision - makers through a series of pairwise comparisons about the importance of each of the elements in a hierarchical model to judge (Ho *et al*., 2010; Pazand *et al*., 2011; Bernascon *et al*., 2011; Pazand *et al*., 2014). In order to conducting comparisons and hierarchy of classification criteria and sub - criterion , after the sort of sub-criteria and indicators of the top - down of the geometric mean to determine the relative value of each of these is using pairwise comparisons (Sener, 2004; Jung, 2011).

In this way to determine the relative importance of each parameter compared to other parameters of their effectiveness in used it to locate the weight of the most important parameter (Saaty ,1980; Ying *et al*., 2007; Chen *et al*., 2008; Dambatta *et al*. 2009; Sener *et al*., 2010). Finally, all of the main parameters weight with the help of the AHP method to each of them given with the help of the relationship with integrated and zoning map obtained (Cheng *et al*., 2007).

$$S = \sum_{i}^{n} W_i \times S_{ij} / \sum_i^n W_i \tag{1}$$

S weight of each pixel in output map and W_i of ith parameter weight and S_{ij} normalized weight class pixel (i. e. the map of the jth class i).

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×m pairwise comparison matrix as follows (Joshi *et al*. 2011):

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

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, …, 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, …, 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 λ_{max} is the maximum eigenvalue of A (Wang *et al*. 2008; Bernasconi *et al*. 2011; Lee *et al*. 2013). The pairwise comparison matrix A should have an acceptable consistency, which can be checked by the following consistency ratio (CR):

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

If CR≤0.1, the pairwise comparison matrix is considered to have an acceptable consistency; otherwise, it is required to be revised (Saaty, 2005; 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 (Karamouz *et al*., 2007; Hsu *et al*., 2008; De Feo *et al*., 2010; Houshyar *et al*., 2014; Kubler *et al*., 2014).

3- Geology and Data

The studied area within the range between 45°30´ to 55°00´ the eastern and 32°30´ to 33°00´ north latitude. That metal potential mineral containing copper, which is a major part of the mineral copper in the region, has been focused on the face veil brigade. In order to access the potential of copper Exploration research in the area of the geological map 1:100000, perceptions of the magnetic geophysical airborne method and satellite images ETM^+ related to Landsat satellite.

Geophysical data, geology and satellite images as a GIS layer of information on the environment, and with the AHP approach to determine the best potential areas of reconciliation.

Geological factors controlling factors in the study area can be structural, lithological and climatic outlined. Paleozoic formations of stones, rocks and Cretaceous granitic rocks, highlands region have created. Orogenic activity and thereby create faults, thrust, thrusts and folding, a significant impact on the structure and consequently much of the geological formation of the topography of the region (Aghanabati, A, 2004).

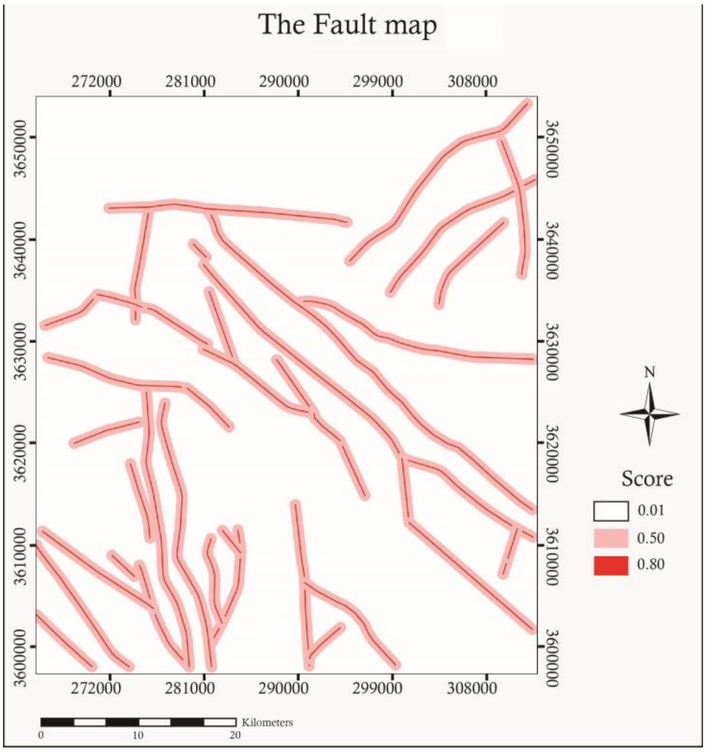

Figure 2) Faulted areas of study area, Modified after (Emami) and (Karimpour).

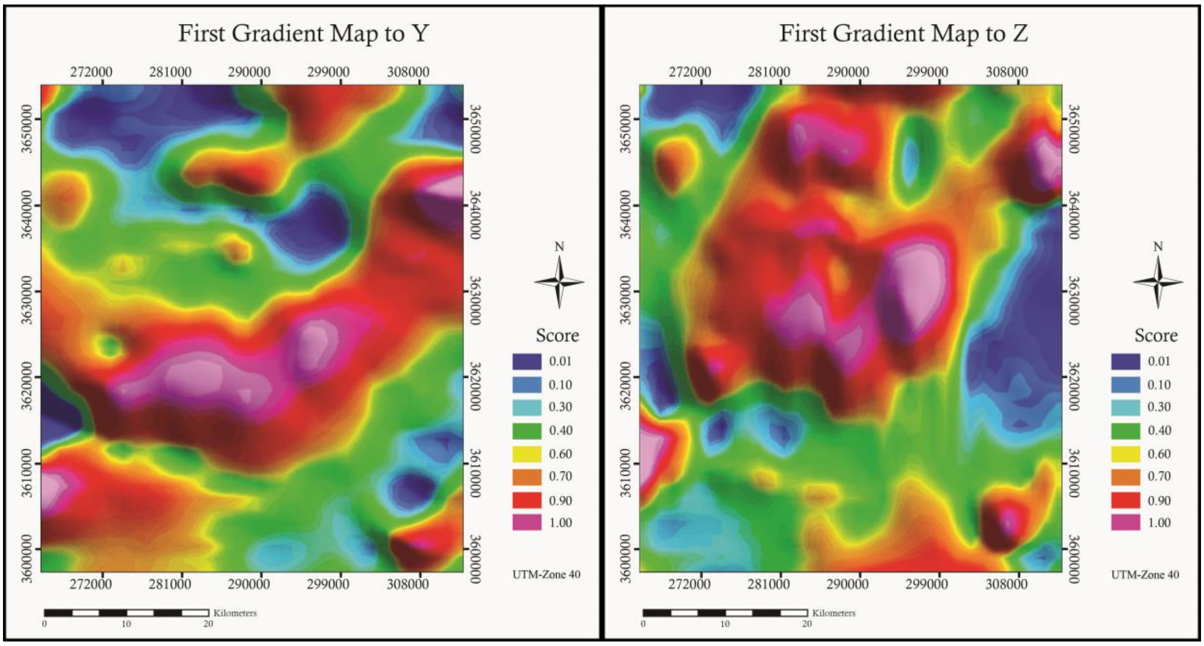

Figure 3) Airborne geophysical map study area, right: first gradient map to Z , Left: first gradient map to Y.

Paleozoic formations dezo, Tashak, Padha and shotori containing hard rock such as dolomite and sandstone-quartzite have made more mountains and peaks or Neogene units due to being erodible loose, low hills have formed (Fig. 1). Also wind erosion caused formation of sandy hills in the center of plain (Wilmsen, M, 2010). Rock units related to Mineralization, fractures and mineral traces were obtained from geological map of 1: 100,000 Zarrin Area and database were formed (Figs. 1, 2).

3.1- Airborne geophysical layer

Airborne geophysical data used by the Geological Survey were collected in 1978. Flight lines distance is 7.5 km with a sensitivity of 0.5 nT were collected by Proton magnetometer. After using reduce to pole filter, vertical derivative filter using gradients, the areas with positive anomalies in the northern parts of eastern, central and south-eastern and steadily with total field anomaly displayed on the screen. The anomalies in shallower areas with an in-depth overview map due to the impact of the stronger anomalies did not show themselves. With this filter to remove anomalies have been stronger and weaker anomalies appeared (Fig. 3, Aghdam, 2007).

3.2- Remote sensing layer

Using ETM+ satellite data of Landsat Satellite and processing and interpretation of visual and spectral methods to identify geological structures and Copper Mineralization related to hydrothermal alterations and the preparation of new maps. The visual method was considered more spatial resolution images and thus creates multispectral images Landsat ETM+ PC Sharpen combining the pixels with a resolution of 15 meters provides space was done (Mahdizadeh Tehrani, 1391). Spectral processing was used to identify hydrothermal alteration (Figs. 4 and 5).

Spectral angle mapper and Least Square Fit methods were applied to ETM+ satellite imagery data to map hydrothermal alterations and iron oxides. Hydroxyl clay minerals such as kaolinite (argillic alteration, phyllic, propylitic) and iron oxides were mapped from Landsat ETM+ data using the LS-Fit method.

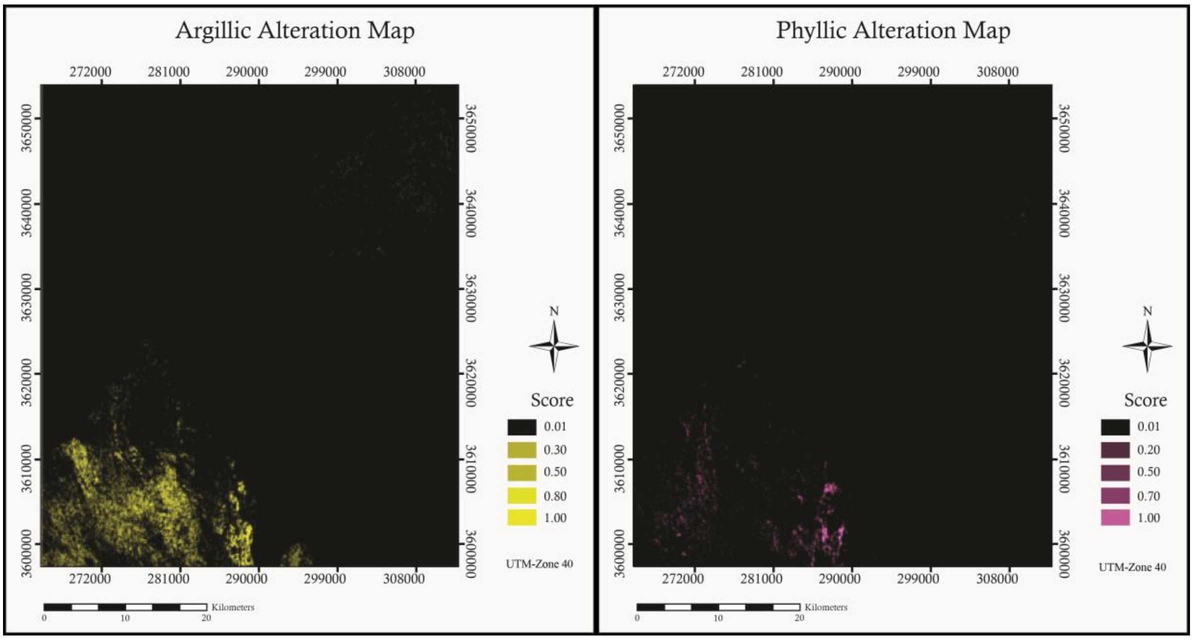

Figure 4) The provided spectral processing map argillic alteration (right) and phyllic alteration (left).

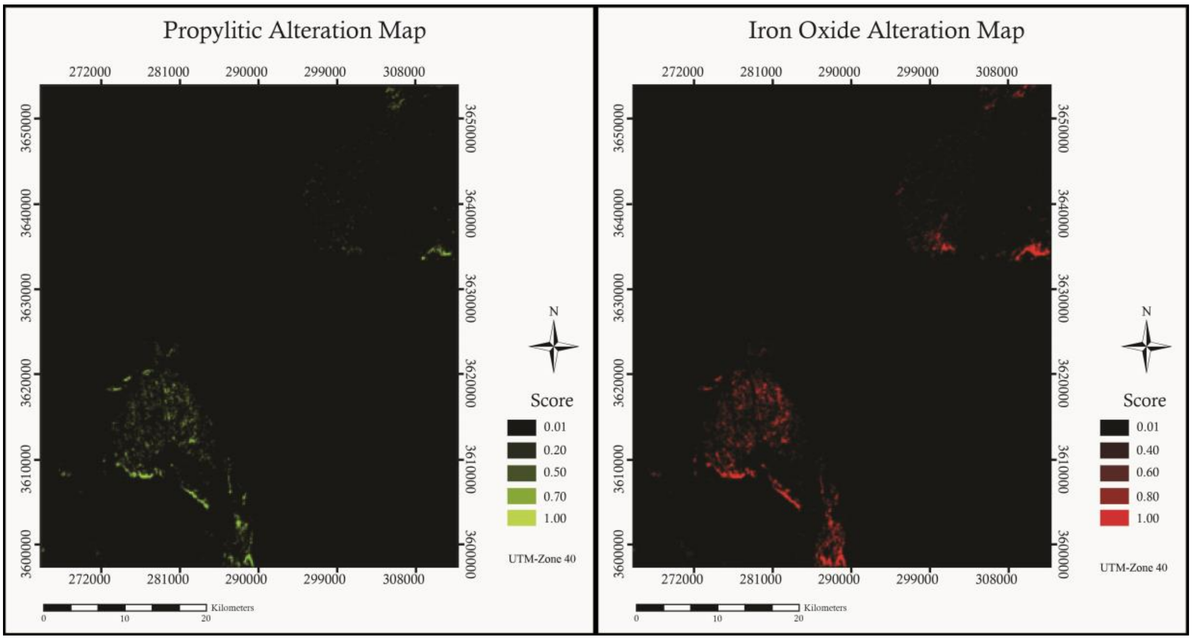

Figure 5) The provided spectral processing map propylitic alteration (right) and iron oxide alteration (left).

After processing the ETM+ data, argillic, phyllic, propylitic, and iron oxide alteration were identified. Techniques for determining and delineating regions of alteration were obtained using Spectral Angle Mapper – SAM (Kruse *et al*., 2003). The spectrum related to each pixel of ETM+ imagery is compared with a specific size called end-member which is related to maximum absorption by the mineral in question. In this research, end-members of USGS spectral library were used (Clark *et al*., 2007). Considering spectral specifications of other altered minerals in ETM+ imagery, it is possible to identify hydrothermal alteration regions using minerals which are specific to that type of alteration. Muscovite is an indicator of phyllic zone and kaolinite points to argillic zones. Images obtained from SAM method are black and white, whose shadow intensity is inversely dependent on similarity between end-member numbers and spectra related to each specific pixel (Gabr *et al*., 2010; Azizi *et al*., 2010).

3.3- Geochemical layer

Using stream sediment geochemical data in the study area to generate geochemical anomalies associated with copper mineralization. One hundred fifty stream sediment samples were collected and analyzed for 9 elements by the Geological Survey of Iran. we only used the Cu analytical results for mapping stream sediment geochemical anomalies for data integration modeling. To obtain a raster map of Cu anomaly, catchment basins were prepared using the locations of stream sediment samples and digital elevation model of the area. Then, the Cu concentration of each sample is assigned to its related catchment basin. Dalli and Zavarian and their surrounding areas show strong catchment basin Cu anomalies.

4- Discussion

At this level recall layers of information obtained in the previous step to incorporation them and determined metal promising areas in the study area. New layers of information at this level require the accuracy of raw data used for the processing and preparation of this layer. The incorporation raster data layers for spatial information management system were put into. Entrance information layers at this level require the accuracy of raw data used for the processing and preparation of this layer. At incorporation level, information layers as raster were imported to spatial information management systems.

Prediction of targets when several layers are integrated, the areas with greatest value of weights are the more important with respect to mineral exploration potential for a discovery. For each layer some alternatives were defined and based on importance of each layer in copper exploration the weights were given. Export choice software was used for calculating the value of each class of a layer concerning value of the layer in comparison to other layers with AHP method.

Table 1) Pairwise comparisons of criteria with respect to the Copper.

	Fault	Geochemical	Alteration	Lithology
Fault	1	2	4	6
Geochemical	0.5	1	3	5
Alteration	0.25	0.33	1	4
Lithology	0.16	0.2	0.25	1

The resulting relationships are indicated below and summarized in Table 1. Faults are slightly better than geochemical anomalies (2:1); faults are moderately better than alterations (4:1); faults are quite better than lithology (6:1); geochemical anomalies are little better than alterations (3:1); geochemical anomalies are better than lithology (5:1); alterations are moderately better than lithology (4:1). The weight factors are determined in three ways: using experts' knowledge, using knowledge data, and using experts' knowledge and knowledge data combined (Table 1). The fourth stage combines the important coefficient of choices, or combination of weights. Computing final weights: the final weight of each choice in a hierarchical process is achieved through the sum of the importance of criteria multiplied by the weight of choices. Fifth stage is eigenvalue method, which is one method to obtain ultimate weights of criteria. The result is a potential map for exploration of targets that has an excellent correlation with discovered mines and indicators of ore (Fig. 6).

Table 2) Borehole classification and AHP results.

No.	Quantitative class	Qualitative class	Estimated class
1	1	Week	1
2	3	Good	3
3	1	week	3
4	2	Moderate	2
5	3	Good	4
6	2	Moderate	2
7	4	Very Good	3
8	3	Good	3
9	4	Very Good	4
10	2	Moderate	3
11	4	Very Good	4
12	2	Moderate	1
13	2	Moderate	3
14	3	Good	2
15	4	Very Good	3
16	2	Moderate	2
17	1	week	1
18	2	Moderate	1
19	2	Moderate	2
20	4	Very Good	4
21	4	Very Good	3
22	1	week	1
23	4	Very Good	3
24	2	Moderate	2
25	4	Very Good	4
26	3	Good	2
27	2	Moderate	3

Figure 6 shows the classification of the mineral prospectivity area using the AHP for Copper Ore Deposit. By considering the other non-drilled areas, additional borehole drilling will not be suggested. The areas belonging to classes 3 and 4 have potential for further drilling. The classifications of mineral prospectivity areas can be used to prioritize high-potential zones for additional exploratory drilling. In the case study, 27 boreholes were classified after analyzing the concentration of economically viable Cu along them. As shown in Table 2, the areas that belong to classes 3 and 4 can be considered suitable candidate zones for detailed study, and the remaining areas are excluded from further study because they do not have a sufficient value to justify the drilling of additional boreholes. The weight of the misclassification error for each borehole is highly dependent on the corresponding misclassified classes. For example, the amount of error will be higher if a borehole has a class of 4 when the actual class is 1, and the error will be lower if a borehole is classified as class 2 when the actual class is 1. If an area is classified as class 2, the experts of a prospecting project will likely refuse to perform additional drilling, but they might continue the project and suggest additional borehole drilling in the same zone if it is designated as class 4.

Table 3) Confusion matrix for total boreholes.

Estimated class	1	2	3	4
Real class				
1	3	0	1	0
2	2	5	3	0
3	0	2	2	1
4	0	0	4	4

The correct classification rate (CCR) was calculated by varying the degree of the polynomial. The CCR as a criterion was obtained from the confusion matrix by dividing the summation of diagonal elements by the total boreholes. This matrix function allowed the comparison of the four borehole classes. The estimated classes and real classes of boreholes comprise Table 3, in which the entries are the number of classified boreholes. Table 3 shows the confusion matrix for the 27 boreholes, in which the CCR is 0.575.

5- Conclusion

Mapping and modeling promising areas using existing data crucial step in reducing exploration risk and costs for exploration operations in general and detailed process is costly and time-consuming. Various methods for potential detection and the introduction of promising areas already developed. One of the most effective given the nature of geological phenomena is hierarchical. The Hierarchical method extensively used for studying, comparing and combining various information layers in spatial analysis. Combination of Hierarchical method with GIS, provides a highly efficient method to studying of promising areas of mineralization. In this hierarchical method and with the help of GIS, data in the form of Zarrin Area were analyzed and presented promising areas.

The results of this study indicated that the correct classification rate of the mineral prospectivity map based on 27 boreholes drilled in the study area is 0.575. The method applied classifies the area under study into several classes, in which exploration zones are prioritized for drillings. The main reason to use the analytic hierarchy process is to increase the resolution of decision-making related to binary classification, which identifies only prospective and non-prospective areas.

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