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RECONNAISSANCE OF COPPER AND GOLD MINERALIZATION USING ANALYTICAL HIERARCHY PROCESS (AHP) IN THE RUDBAR 1:100,000 MAP SHEET, NORTHWEST IRAN

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Abstract

Generally during the preliminary exploration stages, the mineralization and exploration targets will be evaluated using mineral potential modeling. Mineral potential mapping includes recognizable mineralization determination criteria, data preparation, generating factor maps, and combining of factor maps into the appropriate inference networks. The Rudbar 1:100,000 map sheet is a part of western Alborz zone in NW Iran, and exploration layers including stream sediment geochemical anomalies, tectonics, alteration and lithology were processed with the purpose of determination of copper and gold targets in the Rudbar sheet. Finally, the data were integrated using the Analytical Hierarchy Process (AHP). Target areas were delineated as having high mineral potential for recognition the location of undiscovered copper and gold deposits in the investigated area, especially in central and southern parts of the area.

Key words: *analytical hierarchy process; mineral potential modeling; Rudbar; Iran.*

1. Introduction

Target generation is a multi-stage mapping activity from regional-scale to local-scale. Every scale of target generation involves collection, analysis and integration of various thematic geoscience data sets in order to extract fragments of spatial geo-information such as geological details, geochemical and geophysical anomalies associated with mineral deposits of the type sought and prospective areas defined by correlation of this information. The process of analyzing and integrating such pieces of spatial geoinformation is known as predictive modeling. To understand the concepts of predictive modeling of geochemical anomalies and prospective areas using Geographical Information System (GIS), it is imperative to define and understand what the model means [1-3]. The main purpose of GIS is to make evaluations or predictions with different specific data integration models, and to combine spatial and attribute data from various sources in order to provide support for knowledge-driven models and approaches. An example of a knowledge-driven approach is the Analytic Hierarchy Process (AHP). The application of the AHP method, developed by references [4], has been applied by many authors worldwide [5-18]. AHP is a decision analysis method that considers both

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qualitative and quantitative information and combines them by decomposing ill-structured problems into systematic hierarchies to rank alternatives based on a number of criteria [17, 19]. As a result, the AHP has the special advantage in multi-indexes evaluation [12, 17]. The aim of this paper is to discuss prediction of gold and copper exploration targets in the Rudbar 1:100,000 map sheet (NW Iran) by use of AHP method in GIS.

2. Geological setting

The Rudbar 1:100,000 geological map sheet is located in Gilan province which is part of the western Alborz zone, NW Iran., Based on physiographic-tectonic zoning map of Iran's sedimentary basins [20], dominant structural trend in West- Central Alborz and lesser Caucasus province (No. 9) is NW-SE (Fig. 1).

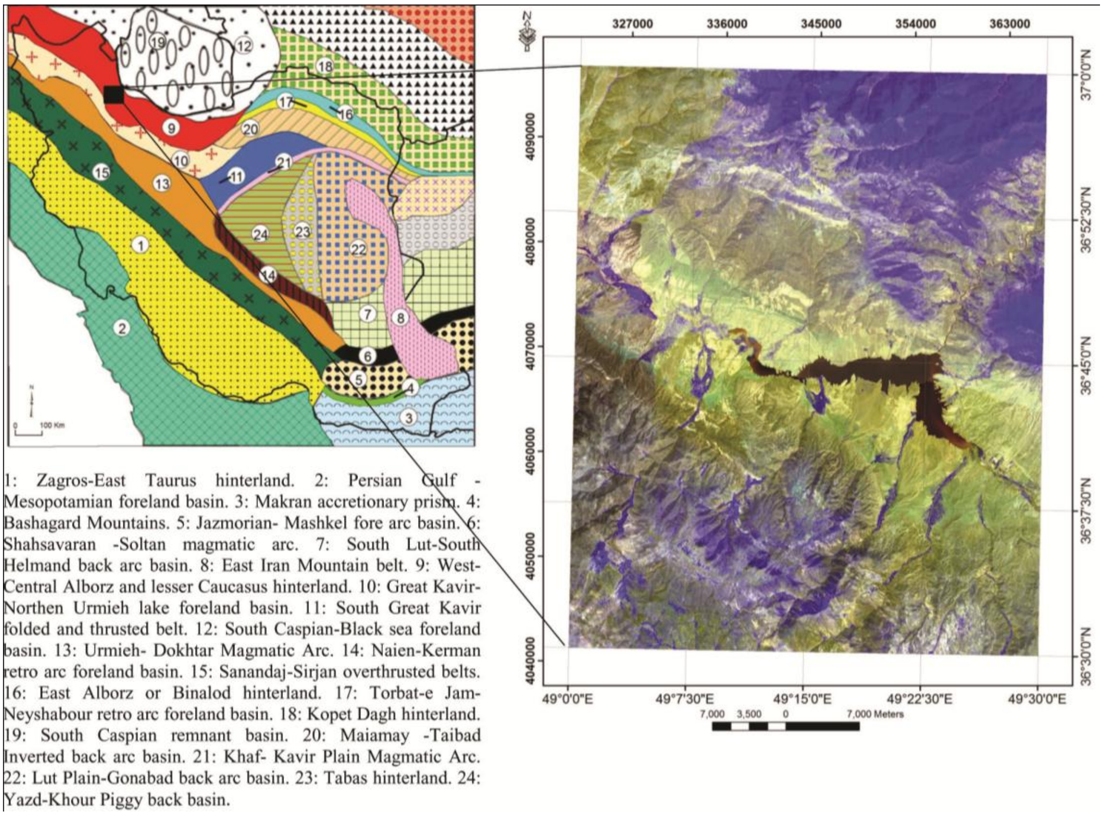

Figure 1. Generalized tectonic map of Iran [32] the study area is shown in the square box and satellite images of the Rudbar 1:100,000 map sheet.

From tectonics view, it contains deformed zone (fold and thrust belt) of Cimmerian miniplate that formed in northern active margin until late Triassic. Then it has rifted by tension in a back arc basin of Neotethyian subduction zone in the south margin of Cimmerian miniplate. Development of that rift stopped in the late Cretaceous and then, renewed in the Eocene by spreading in submarine arc basin of Neotethyian subduction zone. In the other word, this hinterland is result of a magmatic arc system spreading in the evolutional back arc basin. After that, West- Central Alborz and lesser Caucasus hinterland has formed by deformation and regional uplift from SW part of Caspian Sea to Black sea. Recently, Damavand and Sebalan cones have formed by late volcanism that related to final subduction of oceanic slab in south Caspian basin toward south and southwest. Five dominant orogenic phases and four deformational events in Alborz Mountain building processes have suggested by [21]. The first deformational event is one from the Syn-collision type between Cimmerian–Eurasian plates (late Triassic) and the other ones are from post-collision deformational events and in with the deformational of sedimentary cover which is result of shortening and increasing the thickness of passive continental crust in north of Cimmerian miniplate. ([20, 22, 23]: Fig. 1). One of the noticeable features of magmatic highlands in the study area is the presence of large granitic and granodioritic bodies, which have intruded into the Eocene pyroclastic rocks (Karaj formation). These represent post-Eocene intrusive bodies of the Pyrenean orogenic phase intruding in the direction of very deep fundamental NW-SE faulted zones in the Tarom mountain ranges (Fig. 2).

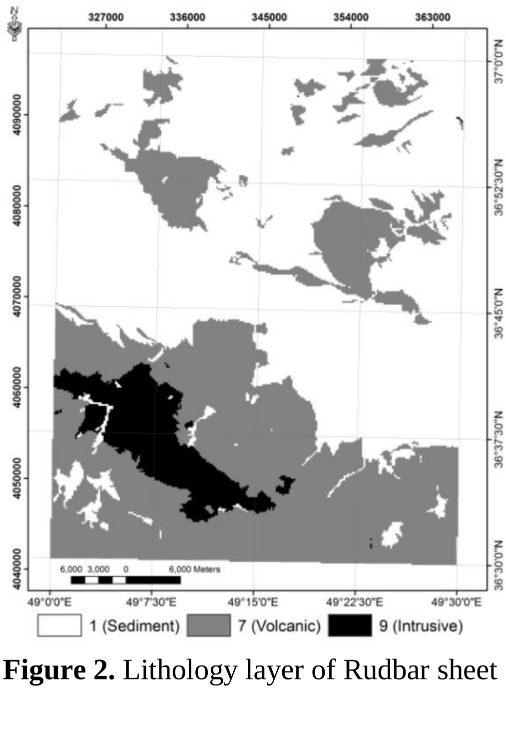

Figure 2. Lithology layer of Rudbar sheet

Alteration halos in Eocene volcano-clastic rocks are one of the characteristic consequences of these intrusive events. There are sub-volcanic intrusions with silicic, argillic, propylitic and sericitic alterations. Similar plutons and intrusions are common in the Alborz–Azerbaijan structural zone of Iran, and it is likely that there are concealed plutons related to this extensive Cenozoic magmatism [24]. The intrusions contain ore minerals of Cu, Pb, Zn, Au, Ag and Fe such as chalcopyrite, chalcocite, malachite, magnetite, galena and sphalerite. Mineralized Cu veins including malachite, chalcocite, bornite and azurite were occurred in Eocene ignimbrites and tuffs which have similar trends with major faults in the area, especially NNW-SSE. Mineralization of gold, copper, lead-zinc and kaolinite are associated with these hydrothermal alteration halos [25].

3. Material and methods

AHP is a multi-objective, multi-criteria decision-making model that enables the user to arrive at a scale of preference drawn from a set of alternatives [26]. It helps decision makers to evaluate their strategy and understanding of the problem. This mathematical method is widely utilized in different branches of geosciences including the reconnaissance of new exploration targets and mineralization. The process consists of several steps: (1) break a complex unstructured problem down into its component factors that are the parameters chosen in this study; (2) arrange these factors in a hierarchic order; (3) assign numerical values according to their subjective relevance in order to determine the relative importance of each factor; and (4) synthesize the rating to determine the priorities to be assigned to these factors [14, 15, 17, 18, 27].

4. Discussion and results

It is now possible to undertake digital and statistical modeling of the mineral potential of areas [13, 16, 18, 28, 29]. In GIS the exploration layers were processed. In the first step, all data layers are digitized from hardcopy maps and georeferenced. After that, maps were reclassified and proximity maps were produced. Due to its simplicity and efficiency in overlying, factor maps are converted to raster. The layers are then weighted and integrated. Pairwise comparisons are performed on nine standard statements of AHP and the digits from 1 to 9 are assigned to statements where the higher the number is, the stronger the preference is.

4.1. Lithology layer

The most important components of this layer are the intrusive rocks (i.e. granite – monzonite and aplite) with NW-SE trend, and volcanics including. Basic to intermediate and slightly metamorphosed volcanic rocks. The sandstone, epiclastic sandstone and younger geological units, such as the older and younger terraces, have been assigned the least value (Fig. 2).

4.2. Structural layer

Linear structural features interpreted from remote sensing data and checked in field geological studies were combined with faults shown on geologic maps to generate a structural evidence map. Two major linear trends, NW-SE and NE-SW, have been recognized. In addition, a N-S trend has been identified (Fig. 3).

4.3. Alteration layer

Iron oxide, argillic, phyllic, propylitic and silica alteration zones were identified by processing Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images, as well as field investigations were extracted [30] for the alteration evidence map (Fig. 4).

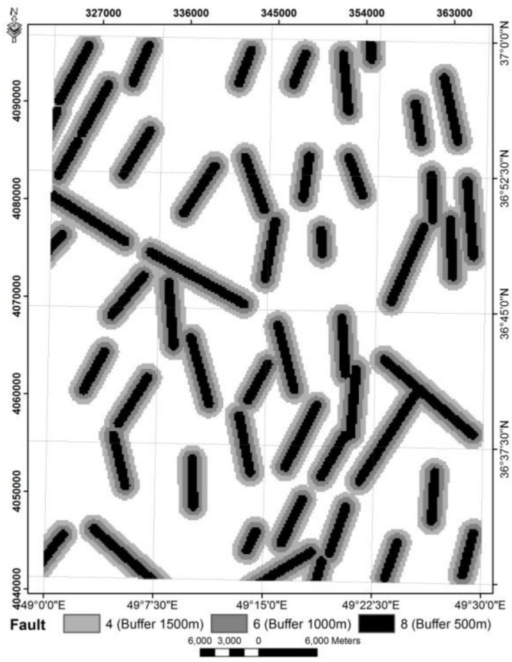

Figure 3. Structural layer of the Rudbar map sheet.

4.4. Geochemical layer

Stream sediment geochemistry data play a key role in the reconnaissance of mineralization and exploration targets. The identification of the background and anomaly values is a fundamental issue in geochemical exploration [15, 31, 32].

837 stream sediment geochemical samples were analyzed by the ICP-MS method for 44 elements, including copper and gold. The number-size (N-S) fractal method, established by reference [33], was used for delineation of high intensive Cu and Au anomalies (Fig. 5). These layers were buffered with values according to Table 1.

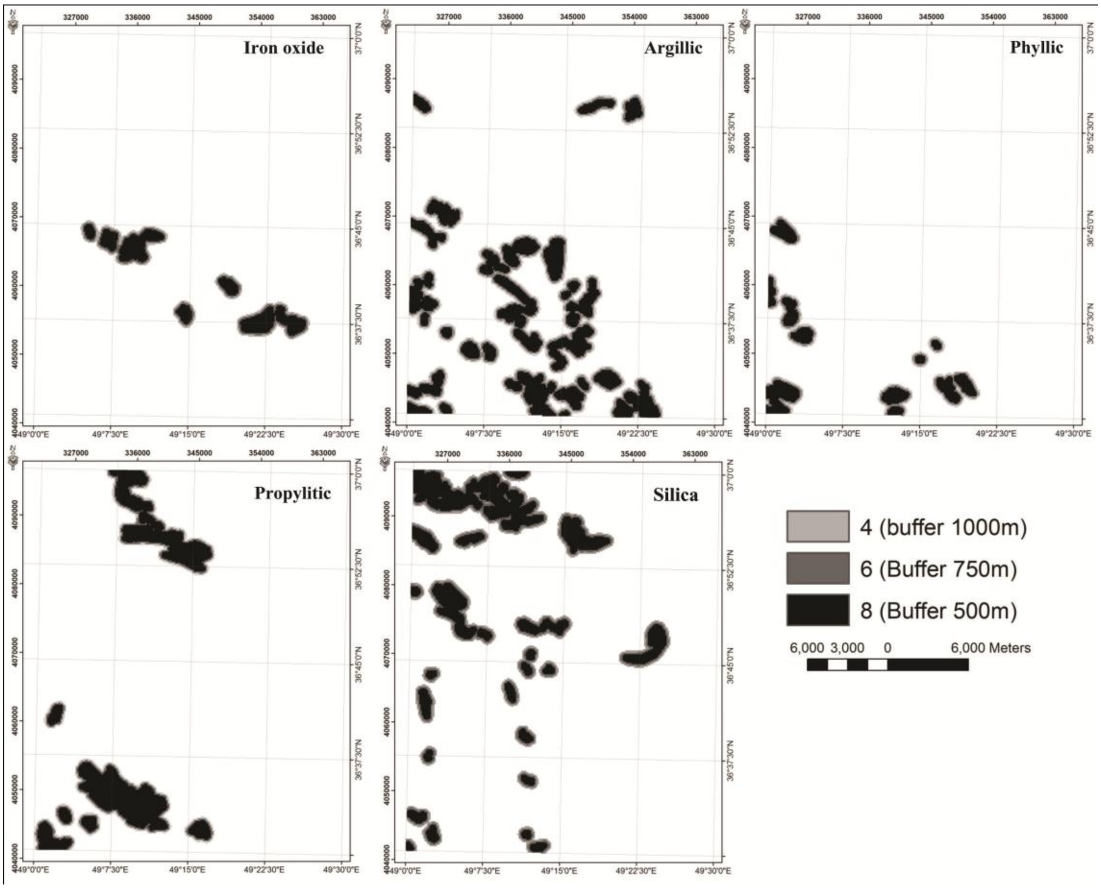

Figure 4. Alteration layer of the Rudbar map sheet

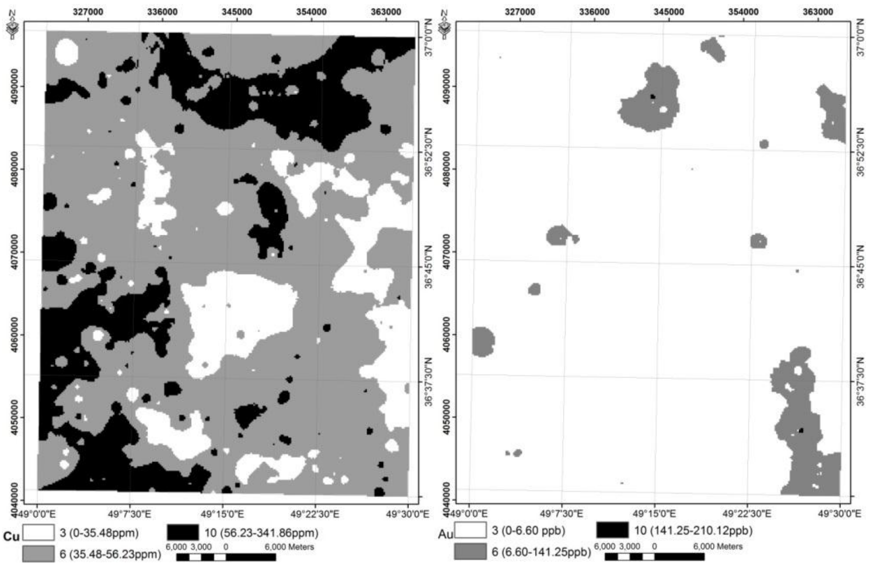

Figure 5. Cu and Au geochemical layers of the Rudbar map sheet

Table 1. Map Layer Buffering and Values

Evident	Class values	Evident	Class values
Alteration		**Fault**	
(Iron oxide) Buffer 500m	8	Buffer 500m	8
(Iron oxide) Buffer 750m	6	Buffer 1000m	6
(Iron oxide) Buffer 1000m	4	Buffer 1500m	4
(Argillic) Buffer 500m	8		
(Argillic) Buffer 750m	6	**Geochemical**	
(Argillic) Buffer 1000m	4	Anomaly<Cu	10
(Phyllic) Buffer 500m	8	Threshold<Cu<Anomaly	6
(Phyllic)Buffer 750m	6	Background<Cu<Threshold	3
(Phyllic) Buffer 1000m	4	Anomaly<Au	10
(Propylitic) Buffer 500m	8	Threshold<Au<Anomaly	6
(Propylitic) Buffer 750m	6	Background<Au<Threshold	3
(Propylitic) Buffer 1000m	4		
(Silica) Buffer 500m	8	**Lithology**	
(Silica) Buffer 750m	6	Intrusive	9
(Silica) Buffer 1000m	4	Volcanic	7

4.5. Prediction of copper and gold targets

When several themes are combined, the areas with the greatest coincidence of weights display the greatest probability for the occurrence of undiscovered mineralization [34-35]. The factor map of this area is produced using the analytical hierarchy process (AHP) by aid of ArcMap GIS software. AHP relies on three fundamental assumptions:

• Preferences for different alternatives depend on separate criteria that can be reasoned about independently and given numerical scores.

• The score for a given criteria can be estimated from sub-criteria. That is, the criteria can be arranged in a hierarchy and the score at each level of the hierarchy can be calculated as a weighted sum of the lower level scores.

• At a given level, suitable scores can be calculated from only pair-wise comparisons [13].

In this process each layer, has different classes to according values of their units. The first stage is to draw the hierarchical tree. The hierarchical tree has three main levels, these are purpose, criteria, and choices, and its level of criteria is divided into various sub-criteria [15, 36]. The hierarchy tree is presented in Fig. 6.

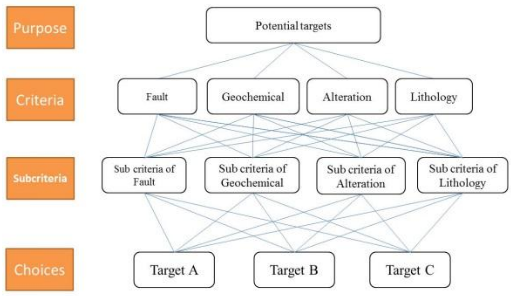

Figure 6. Decision hierarchy for determination of target areas

The purpose, which is to reconnaissance of copper and gold mineralization according to the criteria and subcriteria of the following levels, is given at the top level (level 1). There are four main criteria presented in level two of the hierarchy, those are fault, geochemical anomaly, alteration and lithology. These are further divided into several subcriteria. For instance, the criterion of alteration is divided in five subcriteria as iron oxide, argillic, phyllic, propylitic and silica zones. The criterion of geochemical anomaly is divided in copper and gold subcriteria. From the second and third levels, the best targets are selected. In the second stage the criteria are put into a matrix and then the significance (weight) of criteria and sub-criteria is determined. They are compared in pairs, and then all the criteria are weighted by using the normalization method. A value of relationship, from a nine level graduated scale (equal, slightly better, little better, moderately better, better, quite better, much better, critically better, utterly better), was attributed to these pairings [37] (Table 2). The third stage is to prepare the scale of comparison of pairs. The weight of each factor demonstrates the importance and value of the factor relative to the other factors in the operations to determine locations, thus the wise and correct selection of weights is a great aid in determining the intended purpose.

Table 2. Results of the comparison of layers and the weight of each layer

Results of comparison	Weight or value
Equal	1
Lightly better	2
Little better	3
Moderately better	4
Better	5
Quite better	6
Much better	7
Critically better	8
Utterly better	9

The resulting relationships are indicated below and summarized in Table 3.

Table 3. Pairwise comparisons of criteria with respect to the goal

	Fault	Geo-chemical	Altera-tion	Litho-logy
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**

Consistency ratio: 0.0506

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 (Fig. 7).

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.

In order to measure the degree of consistency of decision making, the consistency index (CI) is estimated through:

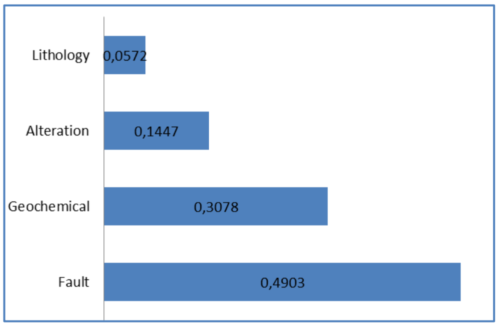

Figure 7. Priorities for criteria with respect to goal

$$CI = (\lambda max - p)/ (p - 1) \quad (1)$$

Where λmax is the biggest eigenvalue of comparison matrix and p is the number of criteria or dimension of matrix. The consistency ratio (CR) can be calculated as:

$$CR = CI/RI \quad (2)$$

In eq (2) RI is the random index (the consistency index of a randomly generated pairwise comparison matrix). It can be shown that RI depends on the number of elements being compared. The consistency ratio (CR) is designed in such a way that if $CR < 0.10$ then the ratio specify a logical level of consistency in the pairwise comparison; if $CR >= 0.10$, then the values of the ratio are incoherent [15, 38]. In this study, $CR = 0.0506$ and in is acceptable for this AHP. Finally, potential map of studied area were prepared by AHP method (Fig. 8) and show on geological map (Fig. 9). Certainly, there are different methods for analyzing model sensitivity. In this study, we use the amount of covering the known Copper and gold hydrothermal occurrences with the introduced areas. As seen in the maps of the total number of the 24 known hydrothermal copper occurrences in the region, 14 occurrences were located in areas with high potential, and the other 5 located in areas with a potential average; this means that model predicts 79.1% of the known copper and gold hydrothermal deposits, and ability and the accuracy of the method are confirmed.

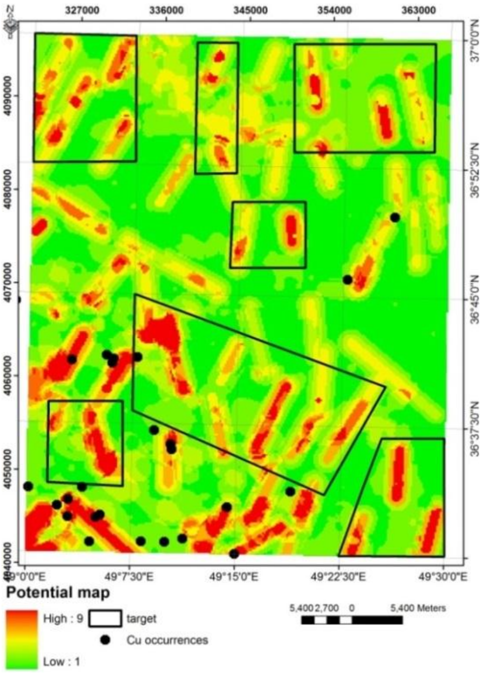

Figure 8. Rudbar potential map prepared by GIS & AHP method

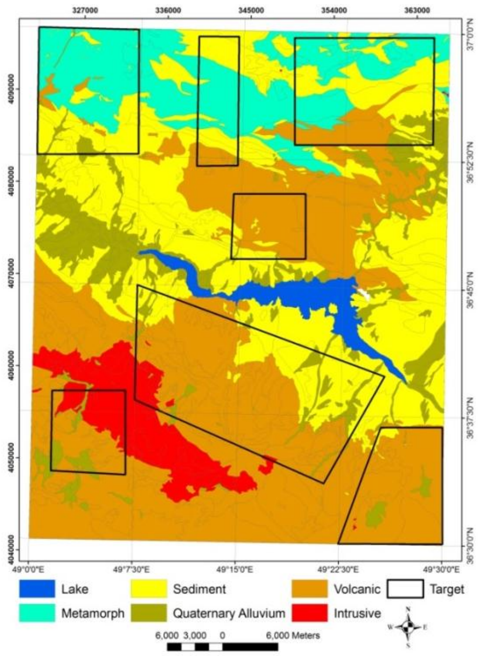

Figure 9. Potential target of Rudbar sheet

5. Conclusion

The Rudbar 1:100000 map sheet is a part of western Alborz zone that includes intrusive rocks such as granite – monzonite and aplite, which extend NW to SE through the investigated area. Mineral potential modeling was applied to the prediction of copper and gold targets. Stream sediment anomalies, structural, alteration and lithology data were processed as exploration layers, and the data combined by using the analytical hierarchy process. The potential map was compared with known copper and gold occurrences in the studied area which is show a strong correlation of classified target areas from AHP with corresponding hydrothermal copper and gold occurrences. Target areas were identified in a preliminary model to predict the location of undiscovered copper and gold deposits especially in central and southern parts of the Rudbar map sheet.

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