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Mineral Prospectivity Modeling with Airborne Geophysics and Geochemistry Data: a Case Study of Shahr-e-Babak Studied Area, Southern Iran

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Abstract

The present paper gives out data-driven method with airborne magnetic data, airborne radiometric data, and geochemistry data. The purpose of this study is to create a mineral potential model of the Shahr-e-Babak studied area. The studied area is located in the south-eastern of Iran. The various evidential layers include airborne magnetic data, airborne radiometric data (potassium and thorium), lineament density map, cu geochemistry signature, and multi-variate geochemistry signature (PC1). High magnetic anomalies, lineament structures, and alteration zones (K/Th) were derived from airborne geophysics data. Geochemistry signatures (Cu and PC1) were derived from stream sediment data. The principal Component Analysis (PCA) as an unsupervised machine learning method and five evidential layers were used to produce a porphyry prospectivity model. As a result of this combination, mineral prospectivity model was produced. Then a plot of cumulative percent of the studied area versus pca prospectivity value was used to discrete high potential areas. Then to evaluate the ability of this MPM, the location of known cu indications was used. The results confirm an acceptable outcome for porphyry prospectivity modeling. Based on this model high-potential areas are located in south southwestern and eastern parts of the studied area.

1. Introduction

Mineral prospectivity modeling (MPM) or mineral prospectivity mapping helps to prioritize exploration areas based on a particular type of mineralization [1]. MPM helps to discover deposits that are located beneath covered rocks. The MPM method is a branch of computer science that is based on geospatial data, especially geophysics and geochemistry data [2]. The combination of geo-physical and geochemical data can facilitate mineral exploration. Recently, geological structures consisting of porphyry intrusion, lineaments structure, and alteration zones have been discovered by airborne geophysics data. The magnetic method is a significant tool in detecting geological formations (such as contact, lineaments, and bodies) [3]. Igneous rocks especially sub-volcanic rocks like granodiorite and diorite have been shown a basic role in mineralization. A high magnetic anomaly can be related to these bodies. On the other hand, lineament structures like faults are suitable conduits for conducting hydrothermal solutions and mineralization. Lineament structure can be extracted by airborne magnetic data and directional derivative. The tilt angle method is a basic tool for extracting lineament structures [4]. Similarly, airborne radiometric data can detect radioelements (potassium, thorium, and uranium) in surface structures. The radiometric signature of different geological units and alteration zones change due to variations in radioelement concentration [5]. Potassium-thorium ratio (K/Th) concentration can identify alteration zones because K radioelemet is more mobile than thorium, especially in alteration zones, so increase in K concentration can distinguish these zones [6].

Interpretation of stream sediment samples can reveal the signature of mineralization. The signature of multi-element anomalous is an

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essential problem in interpreting geochemistry data. Multi-variate analysis is a useful tool for this aim because multi-element anomalous should be evaluated [7].

PCA is an unsupervised machine learning method that transforms multivariate data into nondependent components. The ranking of these components is based on their variances. This method is widely used in geosciences [8, 9, 10, 11].

The aim of this paper is to mineral prospectivity area related to cu porphyry mineralization in the Shahr-e-Babak studied area in southern Iran. To achieve this purpose, geospatial data and an unsupervised machine learning method are used. Thus linement structures, bodies, and alteration were extracted by airborne radiometric and magnetic data. Geochemistry data is used to reveal anomalous related to porphyry mineralization. These evidential layers are combined with an unsupervised machine learning method to prioritize the high potential area of cu porphyry mineralization.

2. Geological Setting and Mineralization

The studied area lies between latitude 55 to 55 30 N and 30 to 30 30 E, and is located in the Kerman Province. Figure 1 shows the location of the studied area. The major part of the studied area is covered with Eocene andesitic rocks and Eocene volcano-sedimentary units. In the central, eastern, and northern western parts of the studied area, cretaceous stocks of meta-volcanic rocks are outcropped [12].The existence of huge Eocence volcanic rocks, especially andesite rocks, is a clear property of the studied area. These volcanic rocks are hosted mineralization and alteration in the studied area. Middle Eocene to Miocene stocks with diorite to granodiorite composition were intruded in the studied area. These stocks caused porphyry mineralization in the Shahr-e-Babak studied area. Widespread alteration zones were created around these stocks. The plutonium complex of the studied area was completed in the Upper Miocene. The northern eastern part of the studied area is covered with young alluvial. Flysch unit covers the studied area in the north. Old alluvium covers south western part of the studied area. Volcanic rocks with andesite to basalt composition outcrop in the studied area in north northwest. Also volcanic rocks with sandstone and limestone are covered east. The pyroclastic unit is widespread in the central part of the Shahr-e-Babak studied area.

Shar-e-Babak has of high potential for porphyry mineralization in the copper metallogenic belt in the Kerman Province. The studied area is a part of the Urumieh-Dokhtar magmatic zone. The Urumieh-Dokhtar magmatic zone has the richest potential for porphyry mineralization in Iran. More, the 200 indeces of cu outcrops were discovered in this zone. The geology map of Shahr-e-Babak studied area is shown in Figure 2.

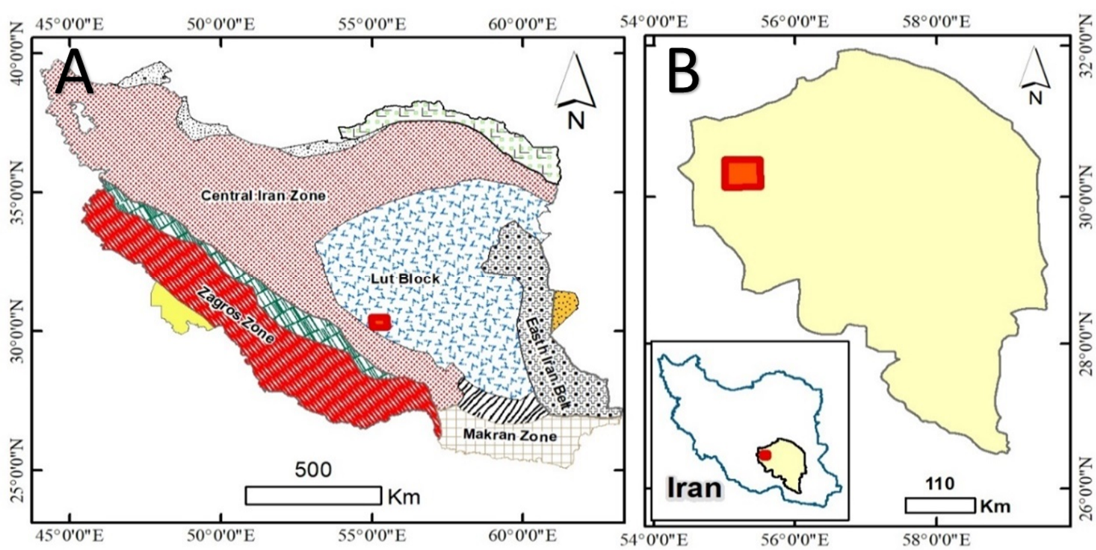

Figure 1. A: Geographical location of the Shahrbabak area. B: The location of the range in the structural zones of Iran.

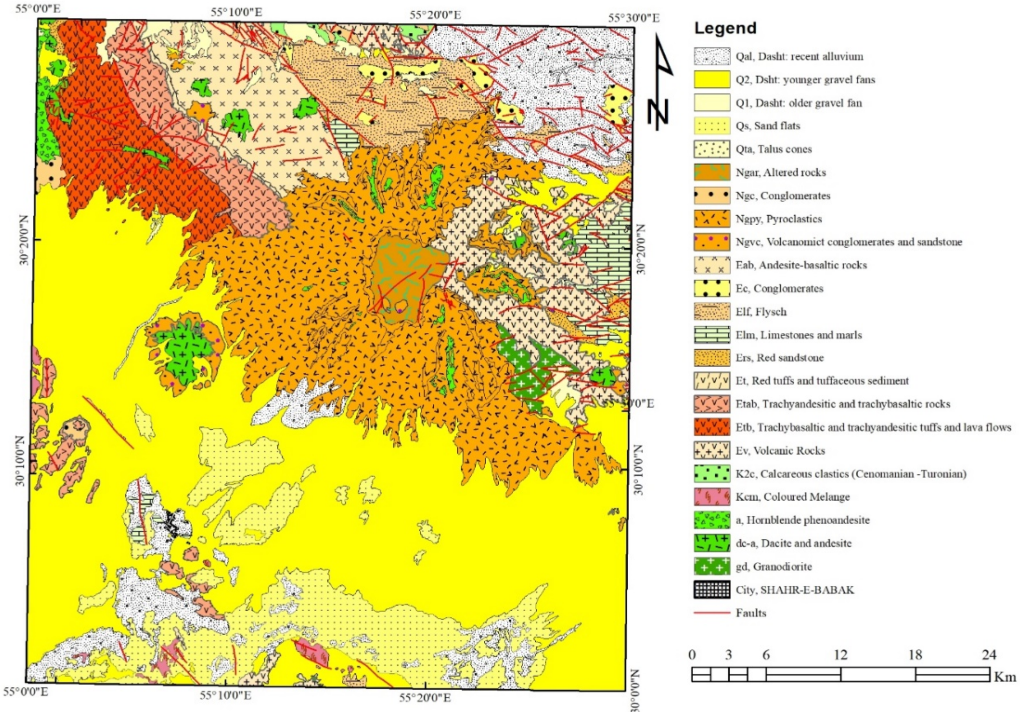

Figure 2. Geological map of Shahrbabak area taken from Shahrbabak 1:100000 geological map.

3. Materials and Method

3.1. Geochemistry data

Porphyry mineralization can be identified by the stream sediments method. In several areas, the stream sediments method has led to identifying high potential areas for porphyry mineralization [13, 14, 15]. The appropriate geochemical assemblage consists of Cu-Au – Mo – Ag – Sb – As – Pb, and Zn. Stream sediment samples were surveyed by the Geological Society of Iran (GSI). A dataset of 604 samples was surveyed. These samples were analyzed for Cu, Pb, Zn, Sb, Ni, Co, Cr, and B. The QQ plot and histogram were drawn to survey normalized condition and outlier data. The outlier data were replaced by the Dorfell method. Then the logarithmic method was used to normalize data. Cu anomaly map was drawn out as an evidential layer in porphyry prospectivity. A typical method in pattern recognition in geochemistry data consists of discriminant analysis, cluster analysis (kmeans, cmeans, hierarchical cluster analysis…), and factor analysis. In this paper, factor analysis was used to extract the element assemblage of porphyry mineralization in the Shahr-e-Babak studied area. Based on the result from factor analysis, the mineral assemblage in Shahr-e-Babak studied area consists of Cu – Pb - Zn in PC 1. Thus the resulting map was used as an evidential layer in porphyry prospectivity in the studied area.

3.2. Geophysics data

The airborne geophysics data in the Shahr-e-Babak studied area consists of aeromagnetic data and radiometric data. The radiometric data include uranium, thorium, and potassium. This data was surveyed by the Atomic Energy Organization of Iran. This data was obtained at a flight spacing of about 500 m and an altitude of about 120 m. To pre-process data, the reduction to pole filter (RTP) was applied to the total magnetic intensity map. The RTP filter aligns better magnetic anomalies with geological structures [16]. The high magnetic anomaly (porphyry intrusion) was extracted visually (Figure 3a). Then the proximity to the layer was created from high magnetic anomalies.

To extract magnetic lineaments, different methods can be used. Most of these methods are based on directional derivatives. The tilt angle method [17] was used to extract magnetic lineaments. The initial concept of this method is based on horizontal and vertical derivatives of total magnetic intensity [18]. Then the heat map of lineaments was created. Figure 3e shows high-magnetic anomaly and heatmap of magnetic lineaments.

The aeroradiometric data can be applied to geological interpretation and detection of alteration areas [5, 19]. To extract the alteration zone, the ratio of K/Th was applied because the increase in potassium and decrease in thorium is an indication of ore deposits [5, 6]. High K/Th areas were extracted from the K/Th anomaly map based on mean plus standard deviation (3d). In the next step, the proximity to the layer was created from high K/Th areas.

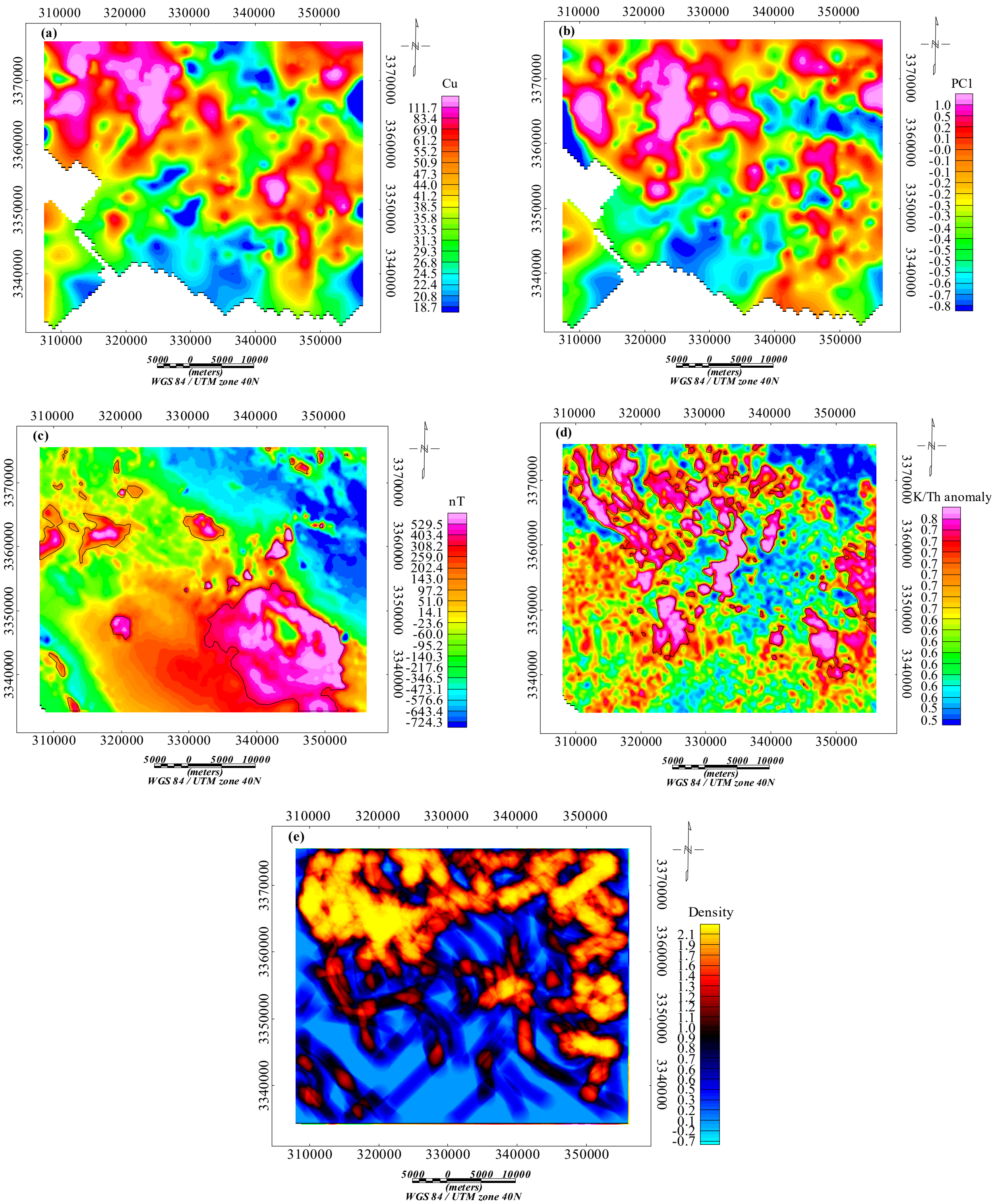

Figure 3. Evidential layer of Shahr-e-Babak studied area (a) Cu geochemical signature (b) PC1 geochemical signature (c) High magnetic anomalies (d) High K/Th anomalies (e) Line density.

3.3. Methods

In this section, we describe methods for mineral prospectivity with airborne geophysics and geochemistry data. In the first step, all data was transformed to the raster file. Then this raster file should be standardized to input to the machine learning method. To standardize geospatial data, logistic transformation was used. In the next step, the PCA method was used to predict porphyry mineralization modeling with airborne geophysics and geochemistry data. Figure 4 describes the main step of this research work.

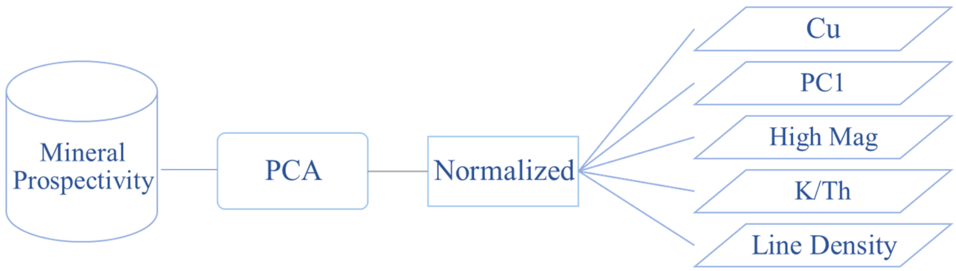

Figure 4. The flow chart of methodology shows different steps to produce MPM for cu porphyry mineralization.

3.3.1. Logestic transformation

The values of different layers of evidence vary significantly in magnitude. As a result, they cannot be compared or overlayed to create a mineral potential map. In this paper, the logistic function was employed to transform discrete data of various magnitudes into continuous values ranging from 0 to 1. Yousefi, M. and Carranza, E. [20] introduced an improved approach utilizing logical functions to optimize the method. Through a data-driven approach, the parameters can be computed, ensuring that the resulting value consistently falls within the range of 0 to 1.

To produce evidential layer five geospatial data (high magnetic anomaly, linear structures, high ratio of K/Th, cu signature, and pc1 multivariate signature) in the Shahr-e-Babak studied area. We used geochemical and airborne geophysics data Because these data originated from different sources; maximum and minimum all of these data are different. Logistic transformation can be used to transform these data in the same space([0 1]). To apply this transformation, the following Equation was used [21]:

$$F_E = \frac{1}{1+e^{-s(x-i)}} \tag{1}$$

X is the original value of geospatial data, and F_E is the logistic transformation of these data. s and i are the slope and inflection points of this transformation. In this step, all evidential layers were fuzzified with this transformation.

According to the proposed method [20], the appropriate values for the slope (s) and turning point (i) of the logistic function are obtained from the solution of two equations and two unknowns presented below. In these formulas, EV and F_{EV} are evidential layer values and fuzzy scores of evidential layers. The results in I and S are presented in Table 1. The fuzzified maps with logistic function are presented in Figure 5.

$$\mathrm{F_{Evmax}} = \frac{1}{1+\mathrm{e}^{-\mathrm{s}(\mathrm{EVmax}-\mathrm{i})}} \tag{2}$$

$$\mathrm{F_{Evmin}} = \frac{1}{1+\mathrm{e}^{-\mathrm{s}(\mathrm{EVmin}-\mathrm{i})}} \tag{3}$$

$$\mathrm{s} = \frac{9.2}{\mathrm{F_{Evmax}} - \mathrm{F_{Evmin}}} \tag{4}$$

$$\mathrm{i} = \frac{\mathrm{F_{Evmax}} + \mathrm{F_{Evmin}}}{2} \tag{5}$$

Table 1. Calculated logistic function parameters for evidential layers.

Evidential layer	s	i
Cu	0.245	198.7950
PC1	0.76	6.03
High mag	0.0075	6087.5
K/Th	0.0058	7930.5
Line density	2.23	2.055

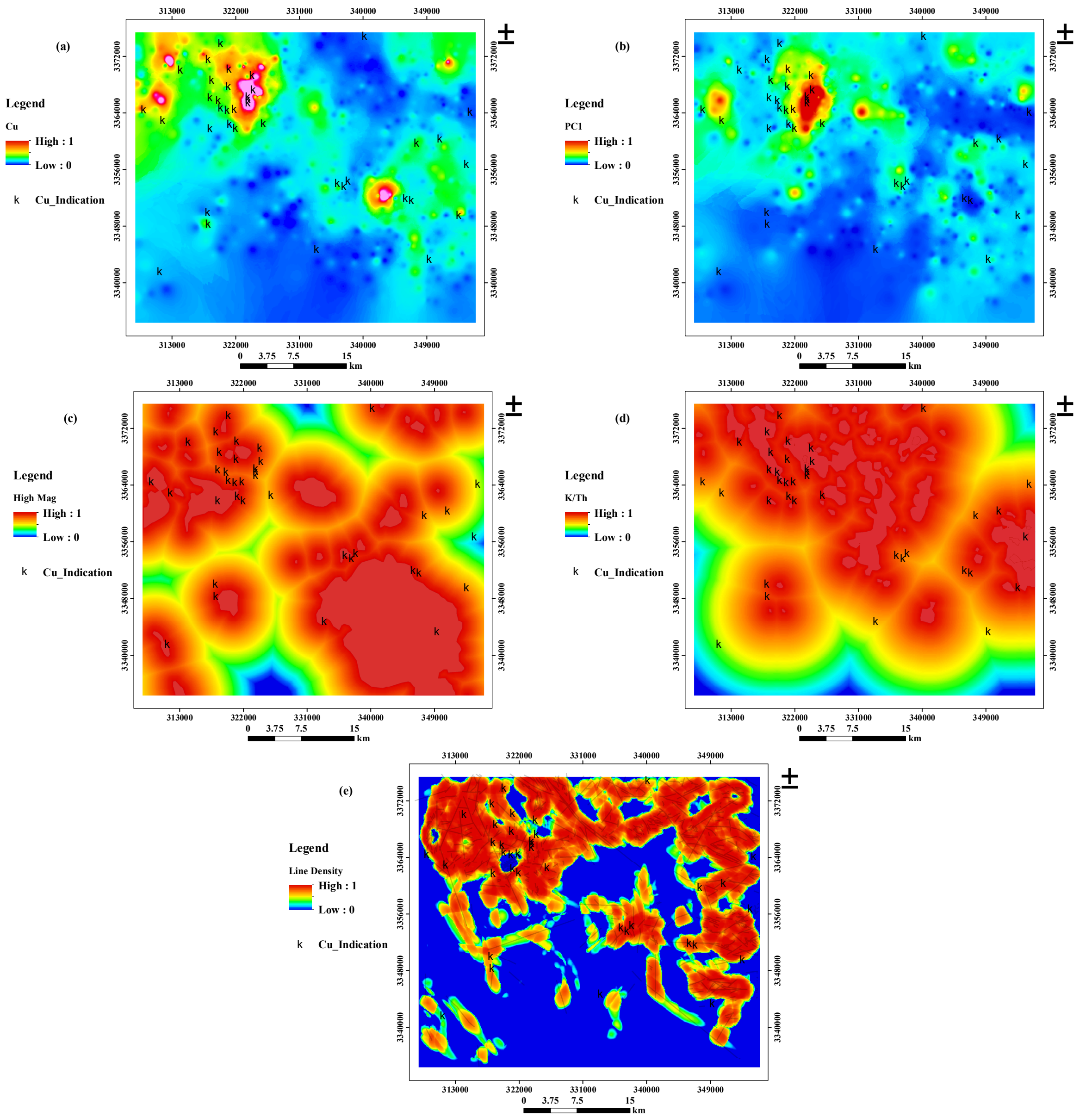

Figure 5. Logistic transformation of evidential layers (a) cu geochemical signature (b) PC1 geochemical signature (c) High magnetic anomalies (d) High K/Th anomalies (e) Line density.

3.3.2. Principal component analysis

Principal component analysis (PCA) is an unsupervised machine learning method. PCA can assumed as fitting a p-dimensional ellipsoid to the data. Each axis of p dimensional is considered a principal component. If the axis of this ellipsoid is small, then the variance of this axis is small too. To calculate the dimensions of this ellipse, its center of all datasets must be found. This center is calculated from subtracting of mean of the variable's observed values from each of those values. Principal component analysis (PCA) is one of the best multivariate data analyses. PCA is a general multivariate technique that applies sophisticated mathematical principles to reduce correlated variables to a small size which is called principal components (PC_S). The PCA method was multivariate data analysis originally, but it was applied in a wide range of other applications [21]. The total variance of variables is calculated in PCA and PCS as the optimal amount is calculated for a major part of the variance [22].

The major purpose of PCA consists of six parts

1. Calculate the most important feature of the dataset
2. Reduce the size of the dataset by retaining these features

3. Simplify the description of this dataset.
4. Interpretation and analyzing the structure of variables
5. Reducing the dimension of data without any missing information
6. This method is applied in data compression.

It was seen that already variables can be normalized within statistical transformation with different methods. In the PCA method, dataset should be normalized or standardized [23].

The fuzzified transformation was used to standardize input data. The flowchart of this study is shown in Figure 4.

4. Results and Discussion

4.1. Model prediction and mineral mapping

Principal component analysis is an unsupervised machine learning method. This mathematical method uncovered a relationship between exploratory data and a reduced amount of data. PCA is a statistical process that transforms correlated features into linear uncorrelated features with orthogonal transformation with decreased variation. The linear transformation assumes the component will explain all of the variance in each variable [24] have noted that an advantage of using PCs over a prior or user-defined group of elements as variables for investigation is that they represent linear combinations of elements that are likely controlled by mineral stoichiometry. This linear transformation may present a more logical representation of the geological evidential layer and mineralization (Table 1). The pc1 was calculated more than 66% over data variability. Principal component analysis is a technique for feature extraction. So it combines input variables in a certain way. We can then remove the least important variables, while still keeping the most valuable parts of all variables. Each of the new variables after PCA are all independent from each other. This is an advantage because the assumptions of the linear model require that our independent variables remain independent of each other. This event shows the high impact of geochemistry signatures in mineral prospectivity modelling in Shahr-e-Babak studied area. The low impact of magnetic anomalies is due to alteration and demagnetization in the mineralization host rock.

The method surveys the interrelation between datasets. The main goal of PCA is to decrease the dimension of the dataset, while preserving the pattern of these data. This process is done without any knowledge of these data. Available exploratory data related to cu mineralization consist of geochemical data: cu and pc1; geophysics data: high magnetic anomalies, K/Th anomaly, and line structure resulting from magnetic data. All of these data were transformed into a raster file with a 100 × 100 pixel size. For pre-processing of these data, Arcgis 10.8.1 and Oasis montaj 8.4 were used, and MATLAB software was used for data integration. The geophysics data interpretations were done in the Geosoft software consisting reduction to pole of total magnetic intensity map, extracting of magnetic lineament structures, and airborne radiometric process. The proximity to and continuous dataset of evidential layers were produced in ARCGIS software and data integriation (PCA method) was done in the MATLAB environment. The component matrix of this data integration is shown in Table 2. The pc1 and cu geochemistry anomaly shows the greatest impact in the prospective model. The lowest impact belongs to the high magnetic anomaly. Mineralization in the studied area caused demagnetization in the host rock of porphyry mineralization in the Shahr-e-Babak studied area. Mafic volcanic rocks consisting andesite and andesite basalt reflect high magnetic anomaly in total magnetic intensity map. But in Shahr-e-Babak studied area, especially in north west of this area, these rock units reflect low to moderate magnetic anomaly because cu occurences are located around high magnetic anomaly, this evidential layer reflect positive role in mineral prospectivity modelling. The MPM model is shown in Figure 6. All selected evidential layers are useful tool in dentification of mineralization potential area. Therefore, their integration provides good results in identifying these areas.

Table 2. Total variance explained.

Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of variance	Cumulative, %	Total	% of variance	Cumulative %
1	2.220	44.400	44.400	2.220	44.400	44.400
2	0.992	19.841	64.241			
3	0.903	18.070	82.311			
4	0.611	12.216	94.527			
5	0.274	5.473	100.000			

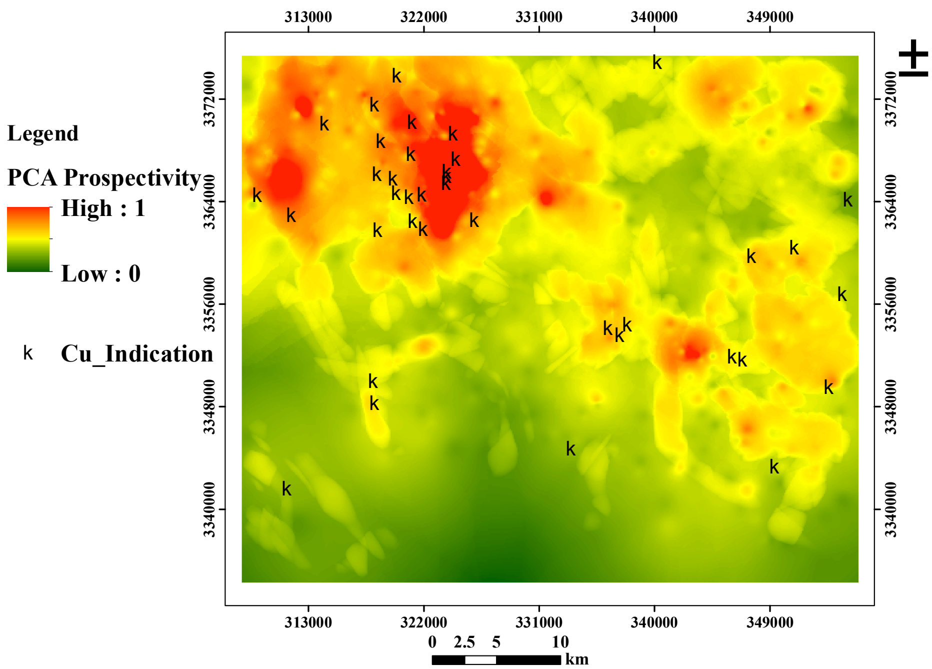

Figure 6. Favorability/Predictive map for cu porphyry mineralization over the Shahr-e-Babak studied area.

Table 2. Component matrix.

	Component 1
PC1	0.811
Cu	0.849
K/Th	0.597
High_Mag	0.297
Line_Density	0.631

4.2. Model evaluation

For evaluation resulting from the PCA prospectivity model, a variation classified of prospectivity value versus cumulative percent area was drawn out [25, 26] (Figure 7). Using this plot, the breaking point to the discrete high potential area was distinguished. Based on the resulting map, most of the cu indications are located in high-potential areas. The resulting map shows high-potential areas located in the northwestern and eastern parts of the studied area. Low potential areas occupy the southern and northeastern parts of the studied area. Based on this map, high-potential areas are appropriate for further exploration (Figure 8). The mineral potential model with PCA method was compared with fuzzy-gamma method (Figure 9). The operation of PCA method is better than fuzzy-gamma method.

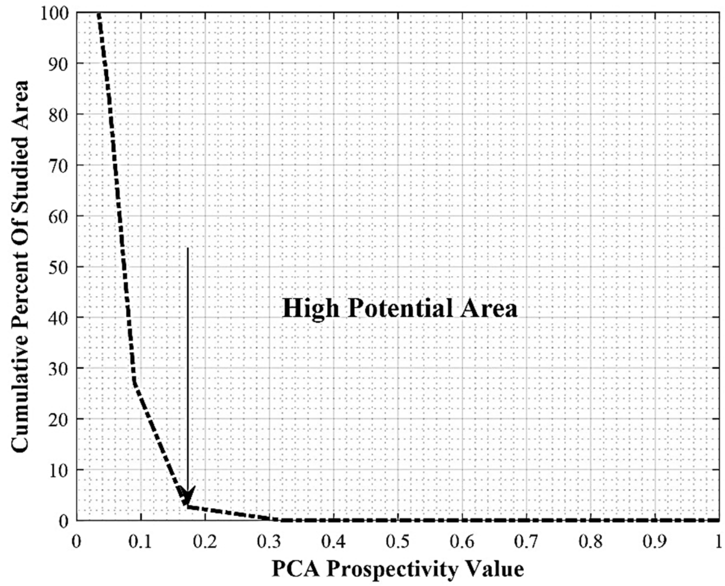

Figure 7. The plot of cumulative percent of studied area versus fuzzy AHP prospectivity value.

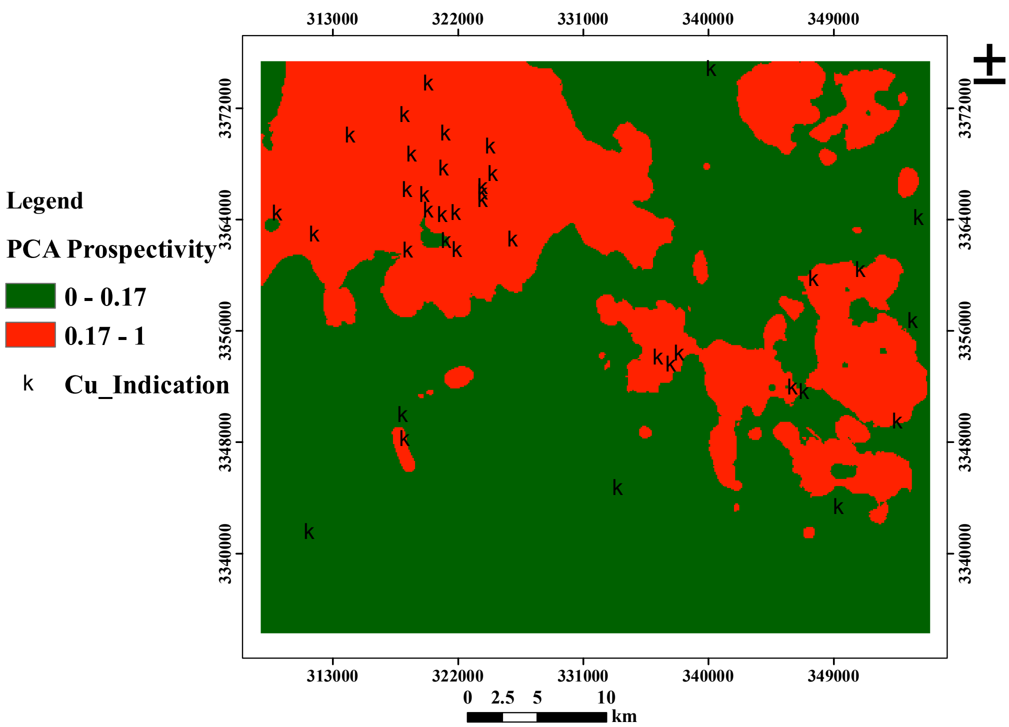

Figure 8. The prospectivity map model shows different potential areas were distinguished by the plot in Figure 7.

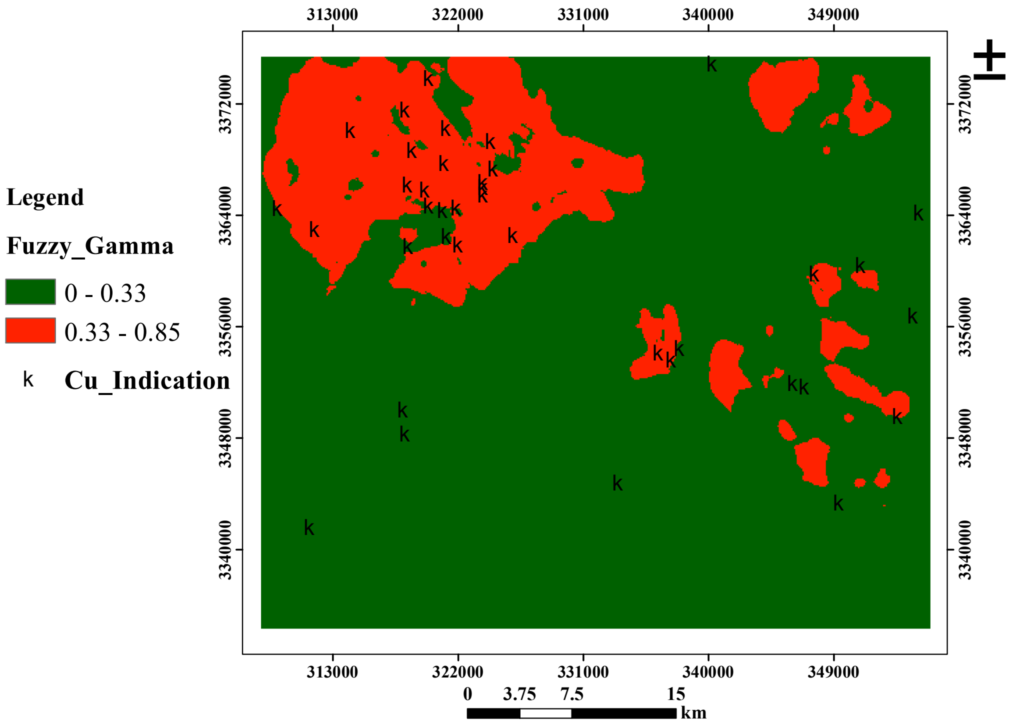

Figure 9. The prospectivity map model with fuzzy-gamma method.

5. Conclusions

In this paper, airborne geophysics including aeromagnetic data and aeroraiometric data were used to extract geological structures. The high magnetic anomaly was extracted from airborne magnetic data and it was related to geological body formation. Lineament structures were extracted from airborne magnetic data and with the tilt angle method. Linear structures conduct mineralizing solutions to the surface. These solutions create alteration zones and mineralization in the host rocks. In this study, alteration zones were extracted with airborne radiometric data. The ratio of K/Th was used to extract the alteration zone. Potassium radioelement is more mobile than thorium. Thus K/Th shows concentration in the alteration zone. Geo-chemistry data was used as porphyry mineralization signatures. Multi-variate geochemistry data was used to reveal these signatures. Five evidential layers consisting of high magnetic anomaly, density map of linear structures, alteration zone, cu geo-chemistry signature, and multivariate geochemistry signature were produced. These evidential layers can govern the mineral prospectivity of porphyry mineralization in the Shahr-e-Babak studied area. PCA method was used for data integration in this study. The following conclusions were obtained:

1. All of the evidential layers are located in PC1 because of all of these evidential layers are effective in porphyry mineralization prospectivity in the Shahr-e-Babak studied area.
2. Cu signature and multi-element geochemistry signature show the greatest effect in MPM in the Shahr-e-Babak studied area.
3. High magnetic anomalies reflect the lowest effect in porphyry mineralization prospectivity because of alteratimon zones caused demagnetization in the host rock of cu mineralization.
4. High-potential areas are located in the northwestern and eastern parts of the studied area. These areas can be appropriate for further exploration in the future.
5. Airborne geophysics and geochemistry data can play an essential role in MPM.

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مدل‌سازی پتانسیل معدنی معدنی با استفاده از داده‌های ژئوفیزیک هوابرد و ژئوشیمی: مطالعه موردی منطقه مورد مطالعه شهربابک، جنوب ایران

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چکیده:

مقاله حاضر روش مبتنی بر داده را با داده های مغناطیسی هوابرد، داده های رادیومتری هوابرد و داده های ژئوشیمی ارائه می دهد. هدف از این مطالعه ایجاد مدل پتانسیل معدنی منطقه مورد مطالعه شهربابک است. منطقه مورد مطالعه در جنوب شرقی ایران واقع شده است. لایه‌های شواهد مختلف شامل داده‌های مغناطیسی هوا، داده‌های رادیومتری هوابرد (پتاسیم و توریم)، نقشه چگالی خطواره‌ها، آنومالی ژئوشیمی مس و آنومالی ژئوشیمی چند متغیره (PC1) است. ناهنجاری های مغناطیسی بالا، ساختارهای خطی، و مناطق دگرسانی (K/Th) از داده های ژئوفیزیک هوابرد به دست آمدند. آنوملالی ژئوشیمی از داده‌های رسوب آبراهه‌ای جریان استخراج شد. تجزیه و تحلیل مؤلفه اصلی به عنوان یک روش یادگیری ماشینی بدون نظارت و پنج لایه شاهد برای تولید یک مدل پتانسیل پورفیری استفاده شد. در نتیجه این ترکیب، مدل پتانسیل معدنی تولید شد. سپس نموداری از درصد تجمعی منطقه مورد مطالعه در مقابل مقادیر مدل تولید شده به روش PCA تولید شد. این نمودار برای ارزیابی توانایی مدل در تشخیص نواحی پرپتانسیل استفاده گردید. که نتایج قابل قبولب را برای توانایی مدل در پیش‌بینی نواحی امیدبخش مس پورفیری ایجاد می کند. . بر اساس این مدل، مناطق با پتانسیل بالا در بخش‌های جنوب ،جنوب غربی و شرقی منطقه مورد مطالعه قرار دارند.

کلمات کلیدی: تجزیه و تحلیل مؤلفه های اصلی، مغناطیسی هوابرد، رادیومتری هوابرد، شهربابک، پورفیری.