ORIGINAL PAPER

Ranking potentially favorable mineralization zones using fuzzy VIKOR vs. Dempster-Shafer-fuzzy AHP methods, a case study: southeast of the Sarcheshmeh copper mine, Kerman, Iran

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Abstract

In this study, a different ranking method has been proposed to prioritize the mineral potential areas and select the best potential area to decrease potential risks of mineral exploration. In this regard, at first, the area located in the east-southeast of the Sarcheshmeh copper mine was selected as mineral targets due to their high potential of porphyry copper occurrences. Then, the favorable porphyry copper areas were determined through collecting and integrating multiple exploratory evidential layers derived from remotely sensed imagery, geochemical, geophysical, lithological, and structural maps and images using the fuzzy logic approach in the GIS environment. Next, through building the decision matrix, the fuzzy VIKOR and Dempster-Shafer-fuzzy AHP methods were applied to estimate the favorability for copper porphyry deposits from information data layers, and the selected prospects were ranked and prioritized based on their scores obtained by each method. A comparison of the results obtained from each method with the previously discovered porphyry copper deposits and indications in the study area revealed a great match between the predicted and known deposits. The validation of results proved the ability of the proposed approach in detecting the highly favorable areas, particularly in the areas embedding known porphyry copper mineralizations. Finally, by applying the fuzzy VIKOR method to the potential areas located in the study area, the Darreh-Zar porphyry mine, as well as a region in the southeast of the Saecheshmeh mine, and a region in the south of Kouhpanj with the minimum values of Q parameter in fuzzy VOKOR method, i.e., 0.021, 0.046, and 0.166, were chosen as the best areas. The results of ranking through the Dempster-Shafer-fuzzy AHP method showed that a region in the southeast of the Sarcheshmeh mine with a priority value of 0.742, a region in the south of Kouhpanj with a priority value of 0.727, and the Dareh zar porphyry mine with a priority value of 0.653, are the best potential areas. The results of the fuzzy VIKOR and Dempster-Shafer-fuzzy AHP methods for ranking the potential areas are consistent with each other, which are validated by previously known areas as well.

Keywords Ranking method · Mineral prospectivity mapping · GIS · Copper porphyry · Fuzzy VIKOR · Fuzzy AHP · Dempster-Shafer

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Introduction

Minerals are the basic human needs and their usage is expanding every day. As the discovery of new deposits is becoming increasingly difficult, the new and advanced policies must be deployed not only to reduce the high costs of discovering a large mineral deposit but also to decrease its potential risks. To this end, it requires a systematic exploration. The first stage in a systematic exploration project is to prospect a new mineralization in a region of interest, known as mineral prospectivity mapping (MPM). The MPM is the process of creating a map that illustrates the favorability of a mineralization occurrence in a specified area by combining

the geological, geophysical, geochemical maps in a regional-scale exploration. Identifying high potential areas within a promising region is one of the fundamental objectives in mineral exploration projects. Besides, many researchers applied satellite data and remote sensing methods appropriately to find mineralization areas and produce the MPM (Pour et al. 2018; Ahmadirouhani et al. 2018; Askari et al. 2018; Sheikhrahimi et al. 2019; Noori et al. 2019). Several steps should be taken before creating the MPM. In the first step, the exploratory data should be validated by correcting possible outliers, enhancement processing, and interpretation. Next, the input exploratory data should be factored to different independent evidential layers as the predictor of an unknown mineralization. Finally, these evidential layers should be integrated to highlight the mineralization characteristics using data, knowledge, or any combination of these approaches in the GIS environment. The GIS-based MPM models in general are classified into knowledge-driven, data-driven, and hybrid models. The knowledge-driven models are distinguished by integrating evidential maps and computing model parameters based on expert knowledge. The data-driven models are those using locations of known mineral occurrence as training points (Joly et al. 2015; Yousefi and Carranza 2015), and the hybrid models contain both existing data and expert knowledge (Cheng and Agterberg 1999; Porwal et al. 2003; Zuo et al. 2009). Since the MPM method is a multicriteria decision-making (MCDM) task that its purpose is detecting and prioritizing prospective areas for exploring undiscovered mineral deposits (Carranza and Laborte 2015; Carranza 2011; Porwal and Carranza 2015), applying it with other multi-criteria decision-making methods can have acceptable results in identifying the best mineralization areas. Moreover, using geographic information alone to determine areas of mineralization may not work well in this respect. Therefore, if multi-criteria decision-making policies are applied in ranking and selecting the appropriate options in order to perform exploration operations, a considerable amount of money, time, and energy could be saved, which will provide much better results. Creating a mathematical exploratory algorithm according to the mineralization type is a complex task. Nowadays, various approaches have been recommended for data analysis in order to produce mineral prospectivity mapping (Panahi et al. 2017; Yazdi et al. 2019). Zhang et al. (2017) used the fuzzy logic and fuzzy AHP methods for producing the MPM of porphyry and detecting hydrothermal vein copper deposits in the Dananhu-Tousuquan island arc, Xinjiang, NW China. Khajehmiri et al. (2016) used the fuzzy AHP and GIS for detecting prospective Cu–Au porphyry in the Mokhtarn 1:100000 geological sheet, in Southern Khorasan, east of Iran. Abedi et al. (2017) applied evidential belief functions (EBFs) as a knowledge-driven MPM method by the Dempster-Shafer's rule of combination. They used this method to weigh and combine large scale exploration datasets to localize the prospects. Abedi et al. (2016) used the regular and the generalized version of the VIKOR method to produce two mineral potential maps in the central Iranian volcanic-sedimentary belt in Kerman province, in the Urumieh-Dokhtar magmatic arc zone. In another study, Ghezelbash and Maghsoudi (2018) applied hybrid AHP-VIKOR, as a developed knowledge-driven method for producing MPM and integrating the various exploration evidence layers. In their study, the AHP method has been used to calculate and assign the weights and importance of spatial criteria and the VIKOR has been applied to produce the final prospectivity model. In the recent study, the new attitude in applying the AHP-fuzzy TOPSIS method was used in mineral potential mapping, in which proper weights were assigned to each information layer using the AHP method based on knowledgeable information and field studies (Rahimi et al. 2020). In the other study, the Fuzzy AHP approach and GIS have been applied to delineate prospective zones of gold mineralization areas and generation of a MPM. In this study, a knowledge-driven fuzzy AHP method has been applied to extract knowledge on the comparative importance (weights) of the sub-criteria layers (Forson et al. 2019).

So far, the fuzzy Logic, VIKOR, fuzzy VIKOR, AHP, fuzzy AHP, and Dempster-Shafer methods have been used separately in mineral exploration and other studies. For instance, Alipour et al. (2017) developed a new hybrid MCDM method by combining the fuzzy AHP and cumulative belief degree model to correctly evaluate energy alternatives for investment in Iran. Moreover, in Arabameri et al. (2019), a comparison of statistical methods and MCDM has been accomplished using four methods, including evidential belief function (EBF), frequency ratio (FR), TOPSIS, and VIKOR, to obtain the map of flood hazard susceptibility (Arabameri et al. 2019).

However, until now, the combination of the fuzzy AHP and Dempster-Shafer methods has not been used to rank and prioritize exploration areas and to compare the results of ranking the fuzzy VIKOR and Dempster-Shafer-fuzzy AHP methods in mineral exploration studies. According to the mentioned studies that have been used as variable methods of MPM, the method used in this study, in terms of having appropriate conditions for weighing the criteria and considering the existing uncertainties, is an appropriate method in finding the mineralization areas and prioritizing them. Hence, in the current study, the exploration datasets were obtained from different sources, including geology, remotely sensed imagery, geophysics, and geochemistry. These datasets were fed into the favorability mapping model using the proposed MCDM approaches, which will be explained in the following sections. Results obtained for each method were compared, and finally, the best regions for further field exploration surveys were proposed.

Study area

The study area is located on the Vulcano-Plutonic zone of Urmia-Dokhtar in the southeast of the Sarcheshmeh copper mine in Kerman Province, Iran. This zone is the largest known copper belt in Iran in which important copper deposits such as Sungun, Sarcheshmeh, Midok, and Darrehzar are located there. The formation of this zone is the result of magmatic activity in the Cenozoic and especially in the Neogene-Pleistocene (Jafari Rad and Busch 2011; Abbaszadeh and Hezarkhani 2013; Zarasvandi et al. 2005). The Urumieh-Dokhtar magmatic belt (UDMB) is one of the main Cu-Mo metallogenic belts extended from NW to SE of Iran. This zone is a part of the Alpine-Himalayan orogenic belt. The direction of this belt is NW–SE and is parallel to the Zagros orogenic belt. Also, this belt is one of the main demonstrations of convergence between Eurasia and Gondwana. The Dehaj-Sarduieh volcano-plutonic belt is a part of the Urumiyeh-Dokhtar magmatic arc and especially in the Kerman Cenozoic magmatic arc (KCMA). This belt plays a vital role in the formation of copper deposits that are associated with Miocene intrusive formations, which have been intruded and emplaced in the Eocene sedimentary-volcanic sequence (Daneshvar Saein and Afzal 2017; Noorizadeh et al. 2018). The study area includes parts of two 1:100,000 scale Pariz and Chahargonbad quadrangle lithological maps. According to the position of the study area in the southeast part of the Sarcheshmeh copper mine, the considerations of EIA regulations are noticed in this area. The simplified lithology map of the study area is shown in Fig. 1.There are many faults and fractures in the study area. Important faults and fractures have a northeastern-southwestern trend that these tectonic movements along with the region's magmatism belonged to the Quaternary (Khan Nazer 1995).

Due to the location of the study area, which is located in the Central Iranian Volcanic Belt (CIVB), the predominant formation of the region consists of igneous rocks and has fewer sediments and streams (Shahabpour and Doorandish 2008). This region is located in the areas where there are porphyry copper mineralization like other porphyry copper mines, e.g., Sarcheshmeh, Midok, and Songun. In the study area, information from 11 main Cu-Mo porphyry deposits was collected, as depicted in Table 1. The rocks in the areas where the mineralization took place consist of volcanic-sedimentary complexes, oligomycin penetrating masses, and Quaternary dacite lavas. The Eocene complex is made up of pyroclasts created by andesitic tracheal lava and tracheal-tracheal lavas, and most of these complexes are deformed. Intrusive bodies are porphyritic granodiorites in which numerous dykes have been injected. The origin of this granodiorite is probably the hybrid magma (Khoi et al. 1999).

According to the studies about the porphyry copper deposit model, porphyry copper deposits consist of copper, molybdenum, and gold minerals, disseminated or in a stockwork of small veinlets inside a large mass of altered rock (Singer and Mosier 1981). The host rock is generally a pyrite-rich porphyry arranging in combination from granodiorite to tonalite, but alkaline porphyries are locally significant. Some existing important evidence in porphyry copper deposits such as alterations, commonly argillic, phyllic, and propylitic, iron oxide, lineaments, associated with large faults and structures, and clusters of intrusions that may host porphyry copper deposits (Raines 1978; Turner et al. 1982; Abrams et al. 1983) help us to produce geological, geophysical, and geochemical evidential layers.

Proposed methodology

The steps of applying the proposed method are shown in Fig. 2. For ranking and choosing the best area, first, the exploration information layers were created as the criteria for decision-making. Then, the layers were overlaid through the fuzzy logic to obtain the potential areas. In the next step, the attributes were ranked, and the best of which was selected by applying the fuzzy VIKOR method. Afterwards, the best attributes were selected again by weighting the criteria using the fuzzy AHP method and ranking the attributes using the Dempster-Shafer-fuzzy AHP method. In the end, the results of ranked attributes obtained by the two methods were compared and validated using the known mines and mineral prospects in the study area. Therefore, in all steps, fuzzy MCDM approaches were applied to obtain results and produce an accurate MPM in which potential areas are appropriately ranked. Applying this methodology in the mineral exploration field accompanied by many uncertainties is an appropriate and reliable approach to obtain more accurate results and can be used in further studies.

Fuzzy VIKOR method

In this study, an extended version of VUKOR has been utilized in a way this method has been applied for subjective and objective weights (Shemshadi et al. 2011). The trapezoidal fuzzy function is used to apply the fuzzy VIKOR method here. The steps to perform this method is explained in the following (Shemshadi et al. 2011; Opricovic and Tzeng 2004; Zadeh 1996):

Step 1: Producing the decision matrix and fuzzy weighting vector based on Table 2, used to convert linguistic variables to numbers:

Step 2: Creating a decision matrix according to the profit criteria or cost type (positive or negative aspects). In this regard, the fuzzy rating for the ith alternative regarding the jth criterion of the kth decision maker would be shown as (Shemshadi et al. 2011):
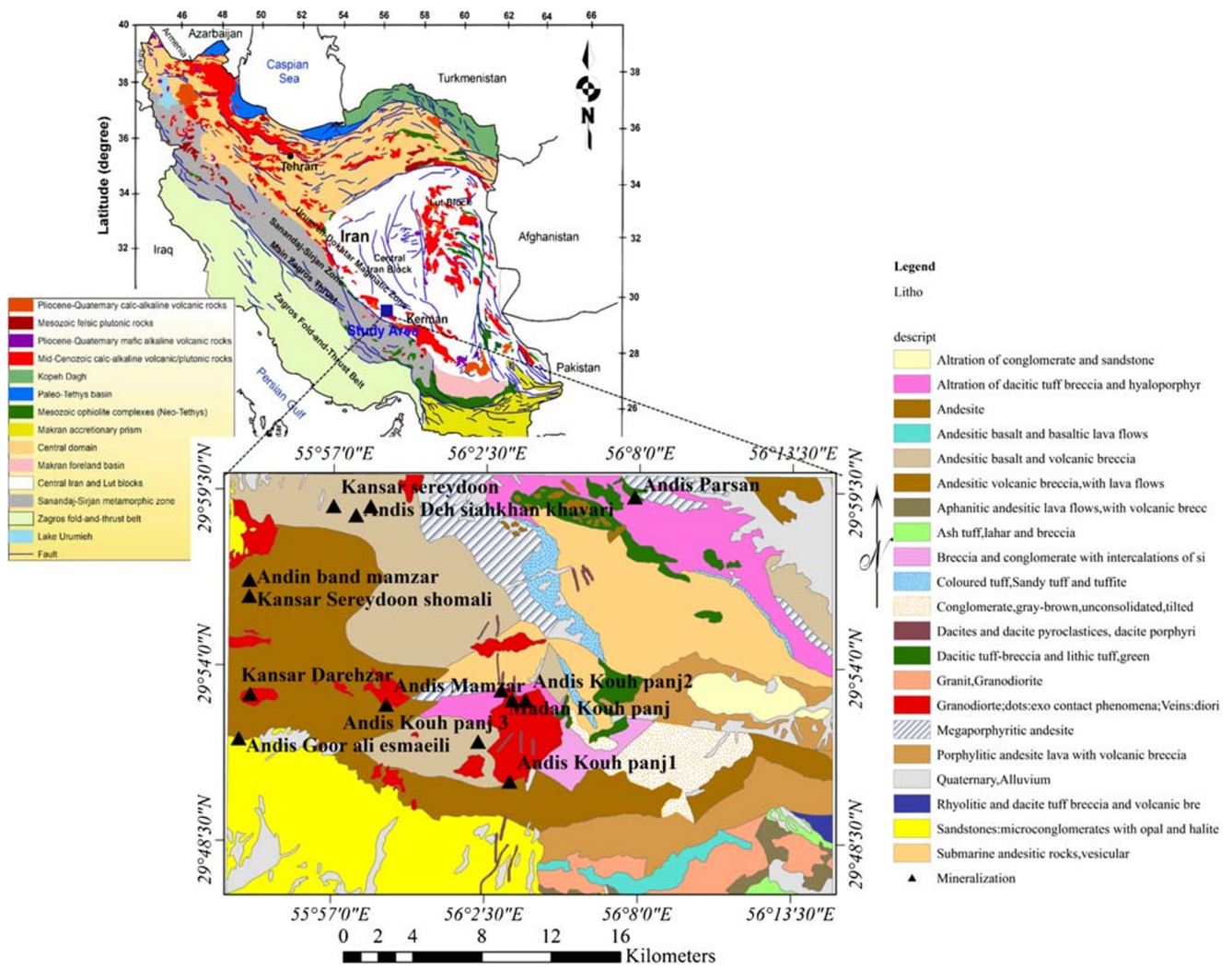
Fig. 1 Geological map of the eastern areas of the Sarcheshmeh deposit (source: Geological Survey of Iran)

$$\widetilde{u}ij = \left\{ \left(\frac{a_{ij}}{c_{ij}^*}, \frac{b_{ij}}{c_{ij}^*}, \frac{c_{ij}}{c_{ij}^*}, \frac{d_{ij}}{d_{ij}^*} \right), \widehat{jIB} \right\} \quad (1)$$

$$\widetilde{u}ij = \left\{ \left(\frac{a_{ij}^-}{a_{ij}}, \frac{a_{ij}^-}{b_{ij}}, \frac{a_{ij}^-}{c_{ij}}, \frac{a_{ij}^-}{d_{ij}} \right), \widehat{jIC} \right\} \quad (2)$$

Table 1 Characteristics of Cu-Mo porphyry deposits in the KMB (Daneshvar Saein and Afzal 2017; UTM projection in zone 40)

| Name	y_in_utm	x_in_utm	Cu (%)	Mo (ppm)
Andis Mamzar	3,304,752	401,948.3	0.3	17
Andis Band Mamzar	3,312,215	393,836.4	0.11	13
Andis Parsan	3,317,846	419,616.5	0.36	21
Kansar Darehzar	3,306,366	393,780.4	0.43	50
Andis Deh Siahkhan Khavari	3,317,388	400,318	0.16	11
Kansar Sereydoon	3,317,402	398,710.2	0.2	23
Andis Goor Ali Esmaeili	3,302,062	393,202.5	0.24	30
Madan Kouh Panj	3,308,125	403,453.3	0.21	45
Andis Kouh Panj1	3,297,702	413,027.5	0.23	40
Andis Kouh Panj2	3,306,224	409,875	0.3	37
Andis Kouh Panj3	3,303,018	406,629	0.2	45
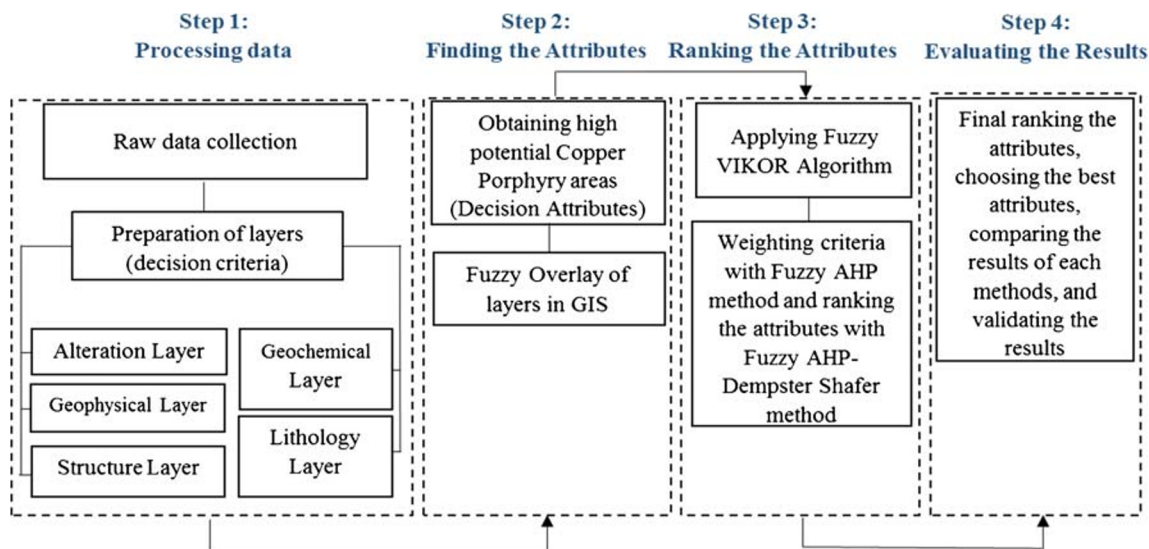
Fig. 2 Schematic representation of the ranking method model proposed for prioritization of porphyry copper areas

Step 3: Defuzzifying the fuzzy weights of each criterion in the decision matrix for obtaining the crisp values.

Step 4: Weighting the normal decision matrix.

Step 5: Calculating the overall performance evaluation as follows (Shemshadi et al. 2011):

$$F = \left[f_{ij} \right]_{m \times n}, f_{ij} = \text{defuzz}\left(u_{ij} \otimes w_j^s \right) \tag{3}$$

Step 6: Determining the worst f_j^- and the best f_j^* values of all criterion ratings as follows (Shemshadi et al. 2011):

$$f_j^* = \max_i \left\{ f_{ij} \right\} \tag{4}$$

$$f_j^- = \max_i \left\{ f_{ij} \right\} \tag{5}$$

Step 7: Computing the values of S_i and R_i as follows (Shemshadi et al. 2011):

$$S_i = \sum_{j=1}^n \frac{w_j^0 \left(f_i^* - f_{ij} \right)}{\left(f_i^* - f_i^- \right)} \tag{6}$$

$$R_i = \max_i \left(\frac{w_j^0 \left(f_i^* - f_{ij} \right)}{\left(f_i^* - f_i^- \right)} \right) \tag{7}$$

Step 8: Computing the values Q_i as follows (Shemshadi et al. 2011):

$$S^- = \max_i \{ S_i \} \tag{8}$$

$$S^* = \min_i \{ S_i \} \tag{9}$$

$$R^- = \max_i \{ R_i \} \tag{10}$$

$$R^* = \min_i \{ R_i \} \tag{11}$$

$$Q_i = \frac{\upsilon \left(S_i - S^* \right)}{S^- - S^*} + \frac{(1 - \upsilon)\left(R_i - R^* \right)}{R^- - R^*} \tag{12}$$

where υ is introduced as a weight for the policy of maximum group utility, whereas $1-\upsilon$ isthe individual-regret weight.

Step 9: Ranking the alternatives by sorting the values S, R, and Q in an ascending order.

Step 10: Proposing the alternative ($A^{(1)}$) as the best rank solution by the measure Q (i.e., minimum).

Fuzzy AHP method

After the introduction of the fuzzy AHP method by Saaty in the 1970s, many models of fuzzy AHP have been proposed by various researchers. In these methods, the concept of fuzzy and AHP have been used in combination (Saaty 1977).

Table 2 Fuzzy linguistic variables and fuzzy numbers corresponding to each of the attributes

Performance	Abbreviation	Fuzzy number
Very poor	VP	(0, 0, 0.1, 0.2)
Poor	P	(0,0.2, 0.2, 0.3)
Medium poor	MP	(0.2, 0.3, 0.4, 0.5)
Fair	F	(0.4, 0.5,0.5, 0.6)
Medium good	MG	(0.5, 0.6, 0.7, 0.8)
Good	G	(0.7, 0.8, 0.8, 0.9)
Very good	VG	(0.9, 0.9, 1, 1)

Table 3 Pairwise comparison by Saaty's crips and fuzzified scales (Saaty 1980)

Saaty's Crips Scale	Judgment definition	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
1	Equal importance (E)	(1, 1, 2)	(1/2, 1, 1)
2	Least important (L)	(1, 2, 3)	(1/3, 1/2, 1)
3	Weak importance (W)	(2, 3, 4)	(1/4, 1/3, 1/2)
4	Less strong importance (LS)	(3, 4, 5)	(1/5, 1/4, 1/3)
5	Strong importance (S)	(4, 5, 6)	(1/6, 1/5, 1/4)
6	More strong importance (MS)	(5, 6, 7)	(1/7, 1/6, 1/5)
7	Very strong importance (VS)	(6, 7, 8)	(1/8, 1/7, 1/6)
8	Extremely important (Ex)	(7, 8, 9)	(1/9, 1/8, 1/7)
9	Very extremely important (VE)	(8, 9, 9)	(1/9, 1/9, 1/8)

Considering this matter that it is easier for decision makers to make linguistic judgments than that to give a definite answer, the use of fuzzy concepts in decision-making has become very important. Van Laarhoven and Pedrycz (1983) proposed a method for the fuzzy analysis hierarchical process based on the least logarithmic method. The large number of calculations and the complexity of the steps of this method made it not welcomed. Another method called "developmental analysis" was proposed by Chang (1996). The numbers used in this method are the triangular fuzzy numbers. Table 3 shows these fuzzy numbers.

The essential steps of the procedure conducted in this study are shown as follows:

Step 1: Defining the decision-making problem.
Step 2: Decomposing the complex problem in a hierarchical structure with decision elements.
Step 3: Establishing a pairwise comparison matrix of the criteria by triangular fuzzy numbers and calculating the weight of criteria.

As shown in Table 3, a 9-point scale was applied to explain the relative importance of criteria (Tsaur et al. 2002). The weights of criteria are calculated using the geometric mean method (Buckley 1985).

Step 4: Converting to crisp value.

Suppose the fuzzy evaluation for criterion i would be (l_i, m_i, u_i), where l, m, and u represent the lower, the middle, and the upper values. For every criterion, each fuzzy evaluation must be converted into the crisp value.

The relative weight of triangular fuzzy numbers of all criteria needs to be defuzzified using the Centroid of Area method (Chou and Chang 2008).

$$W_i = \frac{(u_i - l_i) + (m_i - l_i)}{3} + l_i \tag{13}$$

Finally, the defuzzified values are normalized by Chou and Chang (2008):

$$NW_i = \frac{W_i}{\sum_{i}^{n} W_i} \tag{14}$$

Step 5: Consistency ratio checking.

Consistency ratio (CR) is needed for checking the weight assigned by the decision maker in a way if CR < 0.1, judgment in pairwise comparisons is consistent. CR is achieved using Eqs. (15) and (16), and Table 4 (Chou and Chang 2008).

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{15}$$

$$CR = \frac{CI}{RI} \tag{16}$$

Step 6: Suppliers' ranking.

The overall performance of each supplier was achieved by the weighted sum method and based on the achieved final score of the suppliers, ranking will be carried out.

Dempster-Shafer-fuzzy AHP method

The Dempster-Shafer theory is one of the popular theories used for modeling and reasoning inaccuracies in intelligent systems. This theory—known as the theory of belief functions—is an extension of the Bayesian theory of

Table 4 Consistency index (CI) (Chou and Chang 2008)

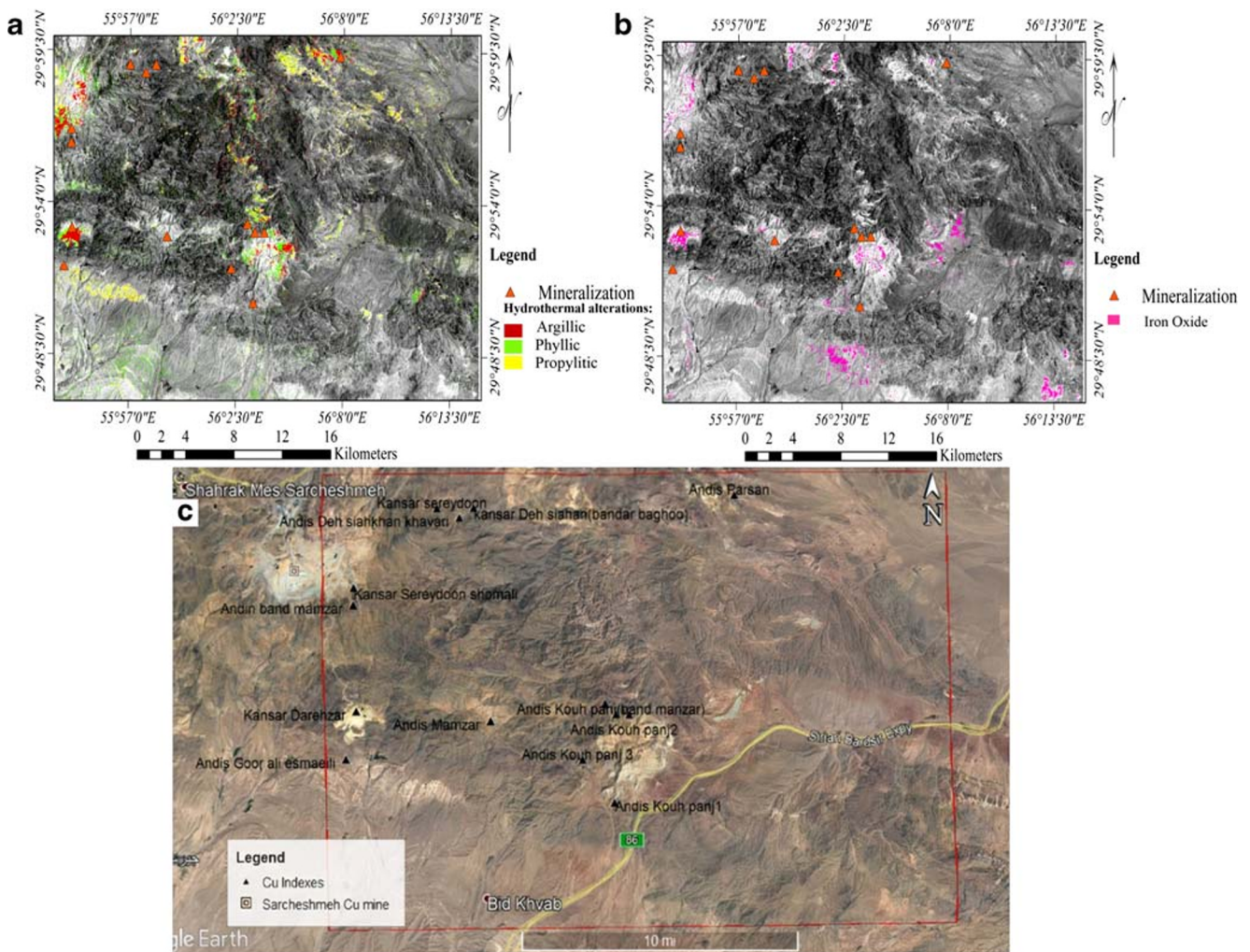| n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Fig. 3 Images of processing the satellite data related to the east of the Sarcheshmeh area on the pixel size of 30 m. Alteration areas are shown in the colors indicated in the legend in the images. (A) Hydrothermal alteration in the study area. (B) Iron oxide outcrops in the study area. (C) The Google Earth image of the study area displays some existing field evidence

subjective probability. The name of the Dempster-Shafer theory is made because of the efforts of two researchers Dempster (1968) and Shafer (1976). This theory came to the attention of all researchers in the early 1980s. Belief functions have been proposed for modeling someone's degrees of belief.

Beynon et al. (2000) first used and proposed the method Dempster-Shafer-AHP. This method is a hybrid method that consists of two different theories: the Dempster-Shafer theory, as a mathematical foundation, and the AHP, as a structure of the method. The AHP method is one of the MCDM methods that is widely used in various studies.

Another aspect of the AHP model was highlighted by Beynon et al. (2000) which represented that ignorance does not take into account. The essential idea of the Dempster-Shafer theory is that numerical measures of uncertainty may be assigned to overlapping sets, subsets of hypotheses, events, or propositions, as well as the individual hypothesis. In the Dempster-Shafer theory, the measures of uncertainty are

known as basic probability assignments (BPAs). The vital components of the Dempster-Shafer theory are as follows (Altieri et al. 2017):

- a finite set of hypotheses $= \{h_1, h_2, \ldots h_n\}$ is called as Frame of Discernment,
- the BPA is a function m: $2 \rightarrow [0,1]$ that satisfies the following hypotheses: (i) $m(\emptyset) = 0$, ii) $\sum_{B \subset A} m(x) = 1$,
- the belief measure is a function Bel: $2 \rightarrow [0,1]$, in a way Bel $(A) = \sum_{B \subset A} m(B) = 1$, for all $A \subseteq \theta$.
- The plausibility measure is a function Pls: $2 \rightarrow [0,1]$, in a way Pls $(A) = \sum_{B \cap A \neq \phi} m(B)$, for all $A \subseteq \theta$.
- The Dempster-Shafer rule's combination allows combining the BPAs. The denominator $1 - \sum_{B \cap A = \phi} m_1(A) m_2(B)$ is the normalization factor, and $\sum_{B \cap A = \phi} m_1(A) m_2(B)$ is the

degree of conflict between the pieces of evidence (Kohlas and Monney 2013):

$$[m_1 \oplus m_2] = \begin{cases} 0, C = \phi \\ \dfrac{\sum\limits_{B \cap A = C} m_1(A)m_2(B)}{1 - \sum\limits_{B \cap A = \phi} m_1(A)m_2(B)} \end{cases} \quad (17)$$

In Dempster-Shafer, the relation between the belief (Bel) and plausibility (Pls) measures is as follows (Kohlas and Monney 2013):

$$\text{Bel}(A) = 1 - \text{Pls}(-A) \text{ and } \text{Pls}(A) = 1 - \text{Bel}(A) \quad (18)$$

According to the ability of the Dempster-Shafer theory to express uncertain information, this theory has been widely used in many fields such as obscure data, decision-making analysis, modeling, and risk assessment.

The Dempster-Shafer-AHP method should be utilized in presence of ignorance in an MCDM problem. Ignorance is a set of imprecision, incompleteness, and uncertainty categories. Smets (1991) makes a difference between these three categories, based on the subjective and objective components. The uncertainty as the subjective component is linked to the observer without certainty about the available information. This information only persuades some form of deficient knowledge or belief in the observer. In the current study, the Dempster-Shafer-fuzzy AHP method has been applied for the first time for the mineral exploration problems and mineral prospectivity mapping. In this regard, it could be able to demonstrate the uncertainty embedded in the users' judgment related to the quality parameters, because in this

case, each of the exploration criteria is treated as an evidence (Altieri et al. 2017). Therefore, it is possible to combine them according to the Dempster-Shafer theory using the weights of criteria obtained from the fuzzy AHP method. In this case, by using the weights obtained from the fuzzy AHP method and applying the Dempster-Shafer theory, the attributes can be prioritized and the best attribute selected. In order to prioritize the attributes by this hybrid method, a mass function, as presented in Eq. (19), has been used (Beynon et al. 2006).

$$m(s_i) = \frac{a_i \times P}{\sum\limits_{j=1}^{d} a_j}, i = 1, 2, \ldots, d \quad (19)$$

where P is the weights of each criterion obtained by the fuzzy AHP method, $a_1, a_2, \ldots, a_d$ are the values of each criterion in each zone, and $S_1, S_2, \ldots, S_d$ are the indicators of attribute groups.

Processing exploration data

The essential step of MPM is processing exploration data correctly and producing accurate information layers as evidential maps for mineralization type sought. This is because ultimate prospectivity models are affected by various detailed specifications of a certain deposit type sought in different areas and consequently by the diversity of individual geo-evidential layers, each of which is affected by the geological features of the study area. Therefore, all available exploratory data in the study area for porphyry copper mineralization were carefully processed, and information layers related to them were obtained.
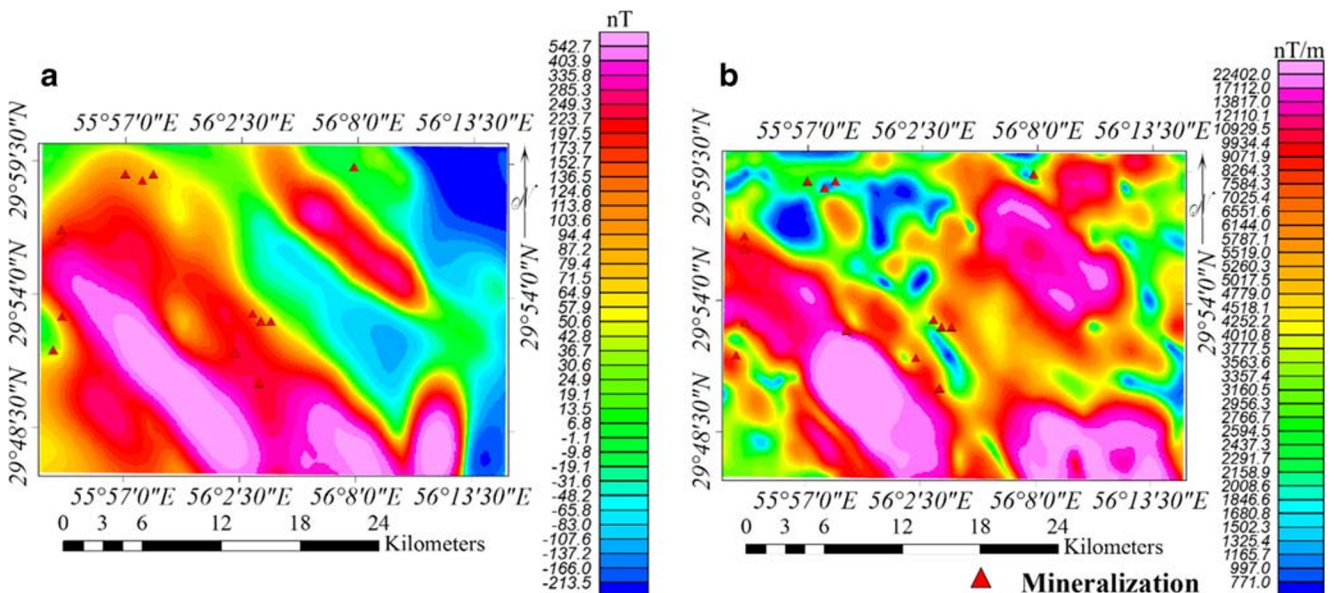

Fig. 4 Images from magnetic data processing related to the east of the Sarcheshmeh area on pixel size 30 m. Magnetic property reduces from pink color areas to blue color areas. (A) Image from the analytical signal in the study area. (B) Image of reduced to pole filter

Table 5 The results of the ordinary PCA to categorize the selected elements into the following six groups based on the significant loadings in each component

	PC1	PC2	PC3	PC4	PC5	PC6
Pb	0.542	0.67	− 0.263	− 0.217	− 0.368	0.076
Ni	0.76	− 0.447	0.009	− 0.191	0.062	0.427
Cu	0.748	− 0.012	− 0.108	0.648	− 0.089	0.02
Co	0.699	− 0.54	0.05	− 0.186	− 0.246	− 0.35
Mo	0.482	0.342	0.805	− 0.009	0.045	− 0.013
Zn	0.765	0.285	− 0.27	− 0.115	0.483	− 0.171
Eigenvalue	2.737	1.124	0.804	0.552	0.443	0.340
Var	45.609	18.728	13.407	9.198	7.384	5.673
Cum. var.	45.609	64.337	77.745	86.943	94.327	99.86

Preparation of exploration information layers

The associated geological, geochemical, geophysical, and remotely sensed data covering the study area were processed, and the required evidential layers were prepared. In this section, the preparation procedures of deriving the main evidential layers from primary raw data are described.

Satellite imagery layer

It is well known that the dominant alterations in the altered areas are argillic, phyllic, and propylitic types. Therefore, in order to prepare these layers, satellite data processing of the

three relevant imagery datasets including ETM$^+$, ASTER, and ALI was used to map different minerals based on their unique spectral characteristics (absorbance wavelengths). For this purpose, cloud-free Landsat ETM$^+$ data in the reflectance format (path/row160/39; attainment date: July 21, 2002) were orthorectified and reprojected applying the digital elevation model. Also, a cloud-free level B1 ASTER data recorded on May 25, 2007, and two cloud-free level 1B ALI data on August 18, 2004, that covered the study area were collected. These data were obtained by the US Geological Survey Earth Resources Observation and Science Center. The images were pre-georeferenced to UTM zone 40 North projection WGS–84 datum and processing methods such as band rationing, LS-Fit, PCA (principal component analysis), and SAM (spectral angle mapper) were applied to them. The results of processing the satellite imagery data are shown in Fig. 3.

Geophysical layer

The geophysical data (aeromagnetometry) used for producing geophysical layer were prepared in 1977 for the Atomic Energy Organization of Iran. A survey was done on an airplane with flight line spacing selected at 500 m and height at 150 m. The data were in the form of a 1:50,000 scale geophysical contour map. The geophysical data were converted into digital form. Accordingly, a set of 832 data points were selected to stably downward continue the reduced-to-pole (RTP) map of the aeromagnetic data at a height of 150 m. The RTP technique is applied to remove the dipolar nature of magnetic anomalies and transform

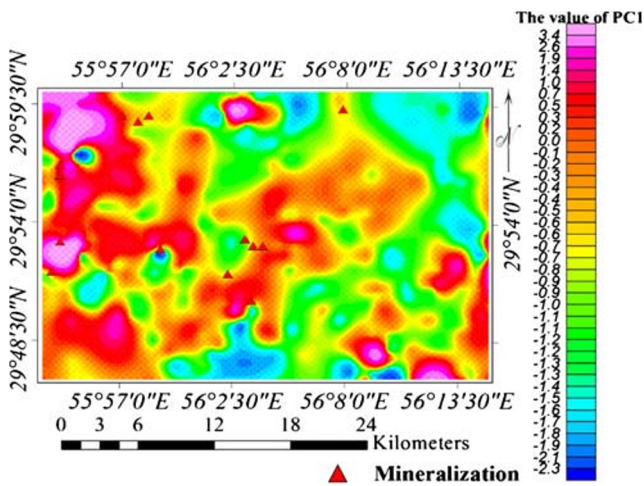**Fig. 5** Location of stream sediment samples within the study area
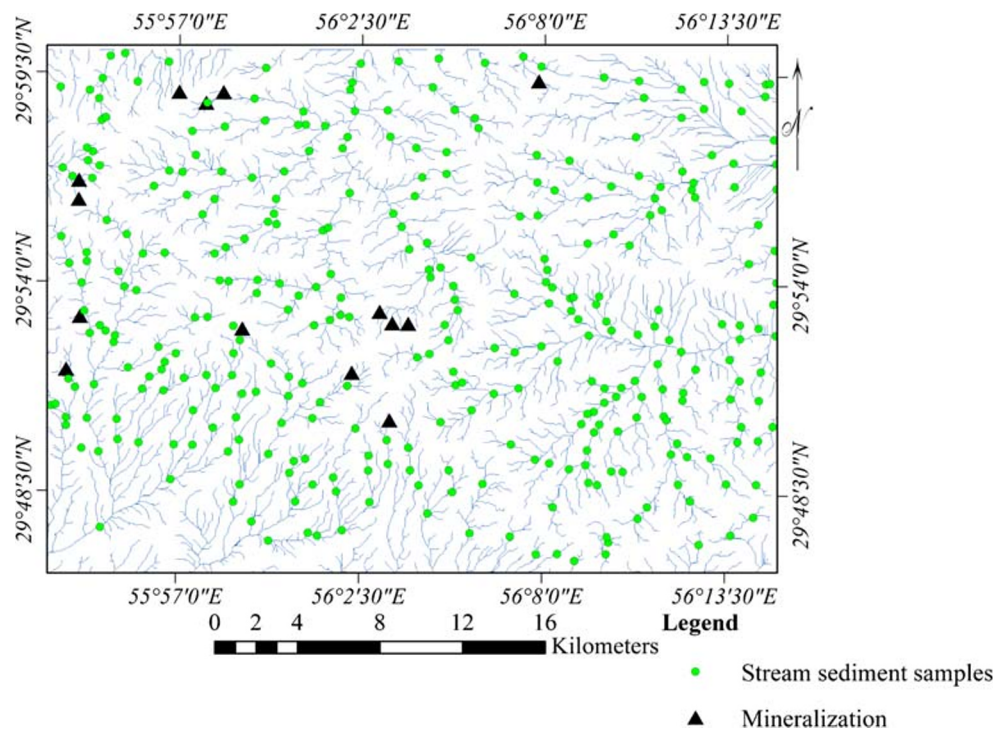
Fig. 6 Raster image of PC1 on geochemical data of the east of the Saecheshmeh area. The existence probability of Cu porphyry increases from pink color areas to blue color areas

sediment samples has been collected by the Geological Survey of Iran in the study for a sampling density of one sample per 3 km^2, and the drainage network and the spatial distribution of stream sediment samples on this network are shown in Fig. 5. At first, sample catchment basins (SCB) were computed. In order to identify stream sediment anomalies, local background for elements required to be calculated for each SCBs (Carranza 2009, 2010; Yousefi et al. 2013). Six components were deduced by the PCA, and the values of loadings and scores were calculated. PC1, PC2, PC3, PC4, PC5, and PC6 were obtained 45.609, 18.728, 13.407, 9.198, 7.384, and 5.673 of the total variance in multi-variate data, respectively. As shown in Table 5, the PC1 as the PC component with a high positive correlation coefficient for Mo and Cu concentrations and a low correlation coefficient for Zn and Pb concentrations was selected as the geochemical predictor of favorable porphyry copper mineralization as shown in Fig. 6.

their asymmetric shape to a symmetric shape (Ansari and Alamdar 2009). After that, the analytic signal filter is applied to enhance the exhibition of the shape of magnetic bodies (Kheyrollahi et al. 2018) (Fig. 4).

Geochemical layer

The geochemical evidential layer was prepared based on the analytic results of Zn, Pb, Cu, Mo, Sb, Co, Sn, Ba, W, and B since these elements have been presented in former studies as the indicators of porphyry copper mineralization (e.g., Sillitoe 2010; Yousefi et al. 2012; Carranza 2015; Asadi et al. 2016). For this purpose, the number of 336 geochemical stream

Structural layer

The structural evidential layer in the region was prepared from three other layers that are indicative of faults and lineaments as the main structural elements. In this regard, the final structural layers are the faults plotted in the geological map, lineaments derived from remotely sensed images through the application of directional filters, and the main regional structures obtained through applying the tilt angle and the horizontal derivative on aeromagnetic data. Figure 7 shows the final structural map compiled by all the above-mentioned structural indicators.

Finally, the geological data layer was prepared using the digitized 1:100,000 geological map of the study area.

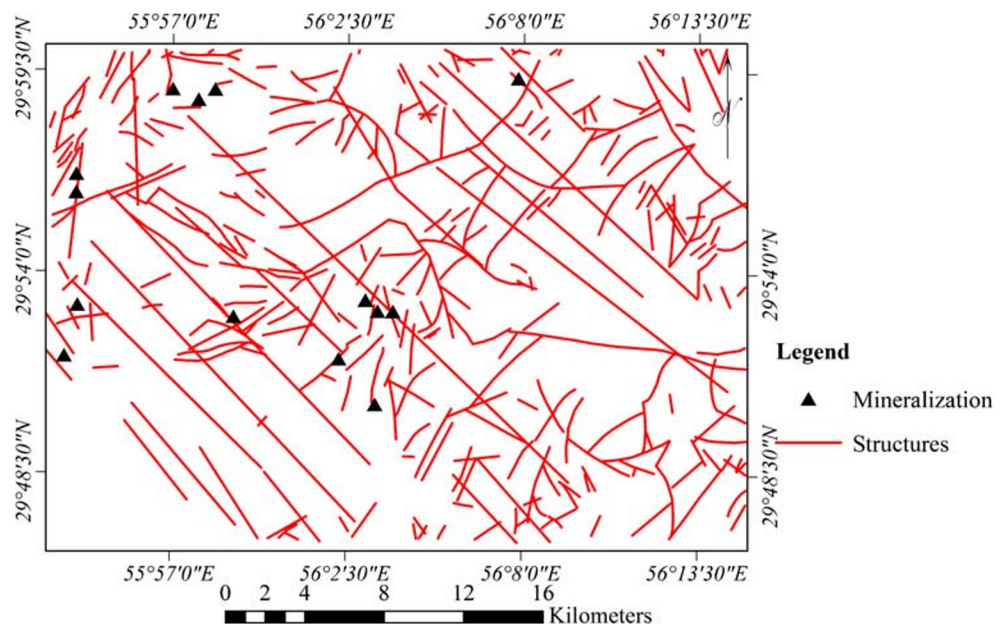**Fig. 7** Structural map of the east of the Sarcheshmeh area

Table 6 Geological units in the east of the Sarchshmeh area and the scores given to each unit according to their importance

Description	Value	Normalized value
Granodiorte;dots: exo contact phenomena;veins: diorite	10	0.09434
Sandstones:micro-conglomerates with opal and halite	1	0.009434
Granite, granodiorite	10	0.09434
Dacites and dacite pyroclastics, dacite porphyry	8	0.075472
Andesitic volcanic breccia with lava flows	7	0.066038
Andesitic basalt and volcanic breccia	6	0.056604
Colored tuff, sandy tuff, and tuffite	4	0.037736
Megaporphyritic andesite	8	0.075472
Alteration of dacitic tuff breccia and hyalo-porphyritic dacite	7	0.066038
Submarine andesitic rocks, vesicular	5	0.04717
Dacitic tuff-breccia and lithic tuff, green	5	0.04717
Andesite	7	0.066038
Porpylitic andesite lava with volcanic breccia	7	0.066038
Alteration of conglomerate and sandstone	4	0.037736
Conglomerate,gray-brown,unconsolidated,tilted	4	0.037736
Breccia and conglomerate with intercalations of siltstone	4	0.037736
Aphanitic andesitic lava flows, with volcanic breccia	4	0.037736
Ash tuff, lahar, and breccia	1	0.009434
Rhyolitic and dacite tuff breccia and volcanic breccia	4	0.037736
Quaternary, alluvium	0	0

Preparing the evidential maps

The procedure used to obtain the final evidential factor layers is discussed and presented in this section.

1. Geological factor layer: the surface geological map of the area was used to separate all different rock types covering the surface area followed by specifying the association of each rock unit with porphyry copper mineralization according to the experts' opinions and after that, the weights were normalized. Table 6 shows these values (Yazdi et al. 2014).

2. Geochemical factor layer: this layer was directly obtained after processing and eliminating the background effects and applying the PCA method on stream sediment samples covering the study area. The separation of geochemical anomaly classes is based on stream sediment data and catchment-based model by applying PCA factors related to the Cu porphyry mineralization. For the interpolation of geochemical data, many algorithms have been proposed in studies that multifractal moving interpolation methods, e.g., MIDW, IDW, and multifractal Kriging, are the most common and useful methods among them. These approaches make the discernment of geochemical populations easier by increasing geochemical anomalies and separation from geochemical background values. Therefore, the kriging method was used for the interpolation of values of geochemical signatures (Afzal et al. 2013; Yuan et al. 2015; Parsa et al. 2017).

3. Geophysical factor layer: for preparing this layer at first, the filter reduced to the magnetic pole (RTP) was applied to place the anomalies above their causative bodies (Baranov 1957), based on the local inclination and declination values of IGRF model-1975, using Oasis Montaj Software (Geosoft Inc.). After applying the RTP filter, the analytic signal filter was applied for detecting magnetic bodies and their edges obviously and this map efficaciously places magnetic anomalies on top of their creator bodies (Kheyrollahi et al. 2018). Figure 8 shows this procedure.

4. Alteration factor layer: the alteration images of argillic, phyllic, propylitic, and iron oxide were used for preparing the combined alteration factor. As mentioned in the previous section, this classification for alteration areas was done according to the known mineralization occurrences and the available expert information from the study area. Each alteration image was given a weighting coefficient
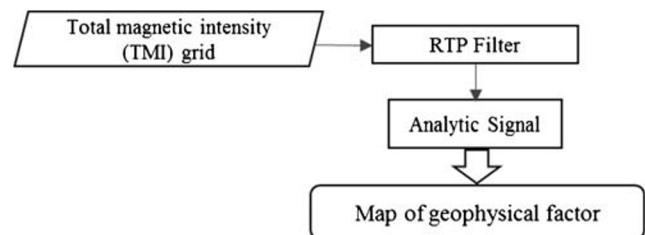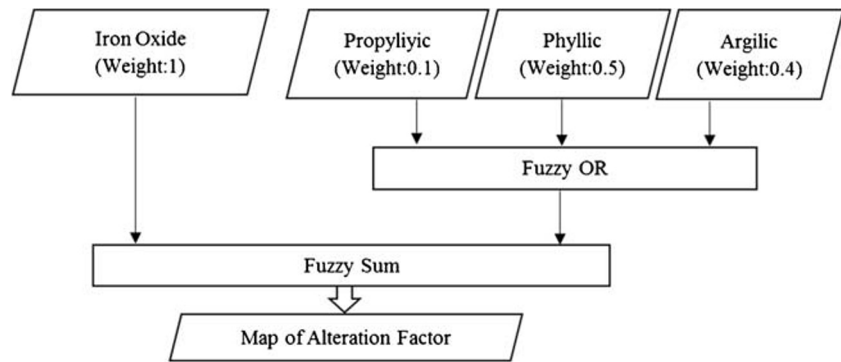
Fig. 8 Fuzzy overlay layers from geophysics data to obtain information geophysics layer from the east of the Sarcheshmrh area

based on their degree of association with porphyry copper mineralization by asking expert opinions and normalizing the numbers of weighting coefficients. The procedure of producing the final alteration factor indicating favorable mineralization areas in the region is depicted in Fig. 9.

5. Structural factor layer: this layer was produced through combining maps that are indicative of faults, such as geological fault map, the structures derived from remotely sensed imagery, as well as the structures extracted from horizontal derivative and tilt angle of residual magnetic maps. Based on the correlation of each derived structural evidence with the known porphyry copper mineralization in the area, a weighting coefficient was normalized and allocated to each of them based on experts' knowledge and then combined in the GIS environment according to the procedure shown in Fig. 10.

## Results of integration of evidence maps and ranking the potential areas

Evidential maps should be integrated to produce target areas for further exploration of the mineral deposit type sought (Bonham-Carter 1994; Carranza 2008). Also, the

prioritization of mineralization areas in MPM should be specified. In this section, the process of combining evidential maps to generate MPM for Cu porphyry mineralization and ranking the potential areas is illustrated.

Combining evidential factors using a fuzzy logic approach

After obtaining all evidential factors in a GIS environment, it is necessary to transform their values into 0 to 1 range. In order to obtain the final favorable areas, the obtained evidential factor layers were combined using the fuzzy gamma operator. The reason for using the fuzzy gamma operator for integrating the weighted evidential maps and obtaining the final prospectivity map (Fig. 11) is that this operator consists of a fuzzy algebraic product and fuzzy algebraic sum. The fuzzy algebraic product has a decreasing effect and if it is used alone in integrating evidential layers, there is very little favorable area in the final mineral prospectivity map. But fuzzy algebraic sum has an enhancing effect and in the final prospectivity map, there are more favorable areas. Therefore, by determining the proper value of gamma, it could be possible to obtain an accurate final prospectivity map. Considering the available data of known porphyry copper mineralization areas and the amount of association of the final potential map with different gamma values with them,
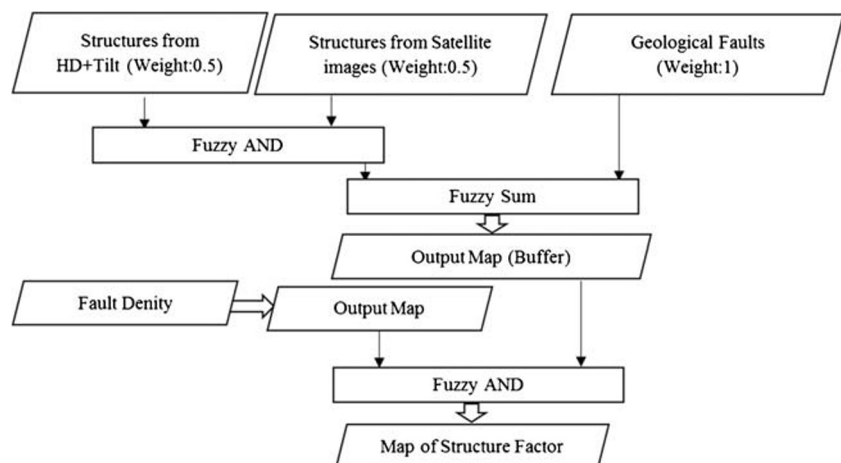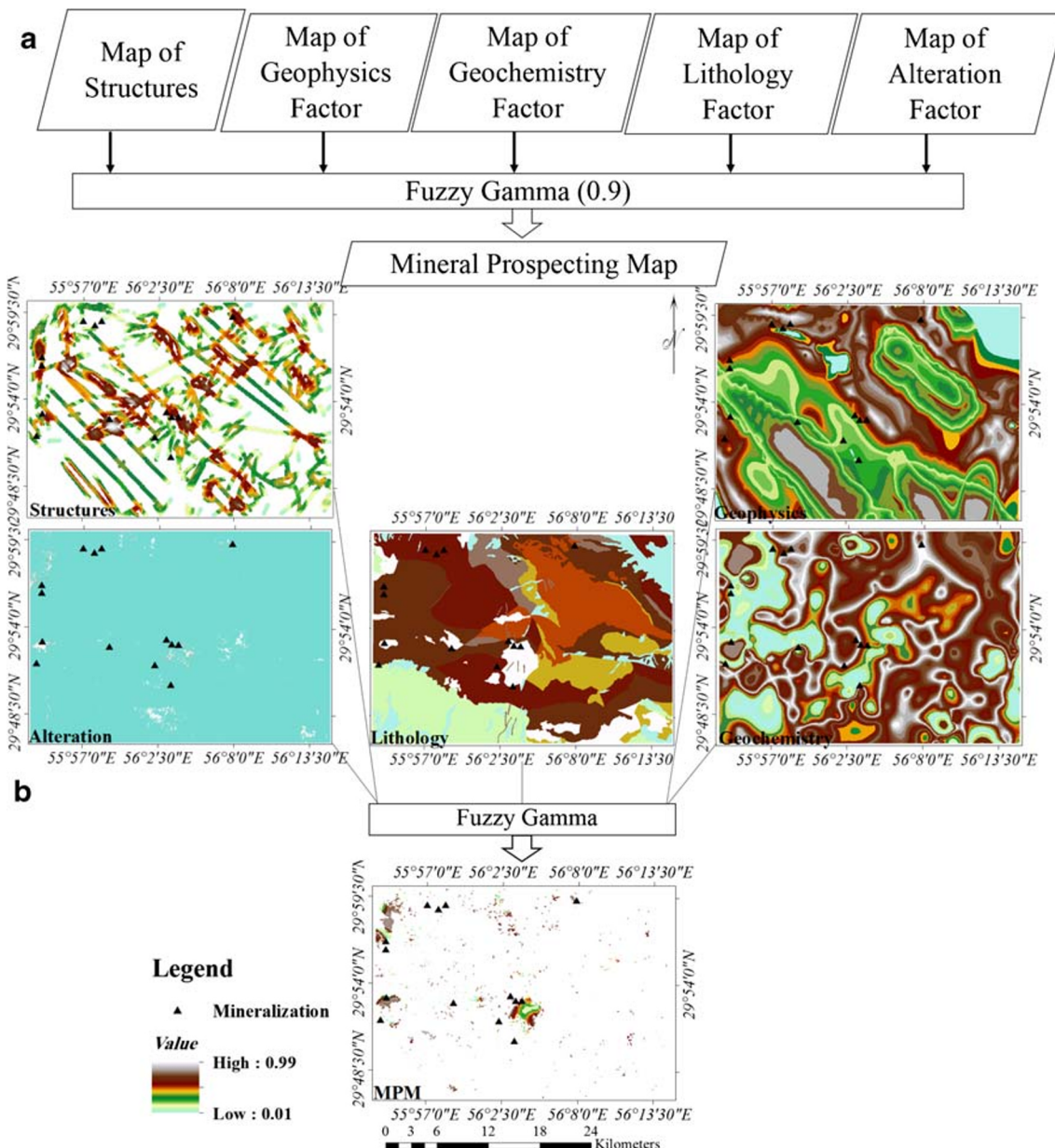
Fig. 11 (A) Fuzzy overlay exploration information layer to obtain the final mineral prospecting map of the east of the Sarcheshmeh area. (B) The indicator maps and the MPM result of the integration of them

we chose the best gamma value and we used the fuzzy gamma operator (0.9) (Yousefi and Carranza 2015). Moreover, by testing other values for gamma operator, it specified that using gamma with 0.9 value would create a better mineral potential map and cover more known copper porphyry mineralization.

Favorable areas are then obtained from the prospectivity fuzzy logic map through applying a statistical threshold value resulting in several polygons of highly favorable areas in the GIS (Fig. 12). The threshold cut-off value was determined based on trial and error, and the constraint of each polygon should cover the area with a minimum of 2 km^2 and also being located in the vicinity of known copper indicators scattered throughout the study area.

Results of fuzzy VIKOR

The data used in the previous step of the fuzzy VIKOR algorithm were analyzed using the above-mentioned decision-making method. The fuzzy VIKOR method results were obtained using two modes, one using all six criteria and one without using criteria. Tables 7, 8, and 9 explain all modes regarding the 20 attributes (Fig. 12), and also the related results.

Attributes were ranked according to the results obtained by applying the fuzzy VIKOR method. According to step 9 of applying the fuzzy VIKOR algorithm, Table 9 shows the ranked attributes and the Q value obtained for each attribute

Fig. 12 Favorable porphyry copper mineralization zones derived from fuzzy integration approach introduced as the targets (alternatives) to the fuzzy VIKOR and Dempster-Shafer-fuzzy AHP methods
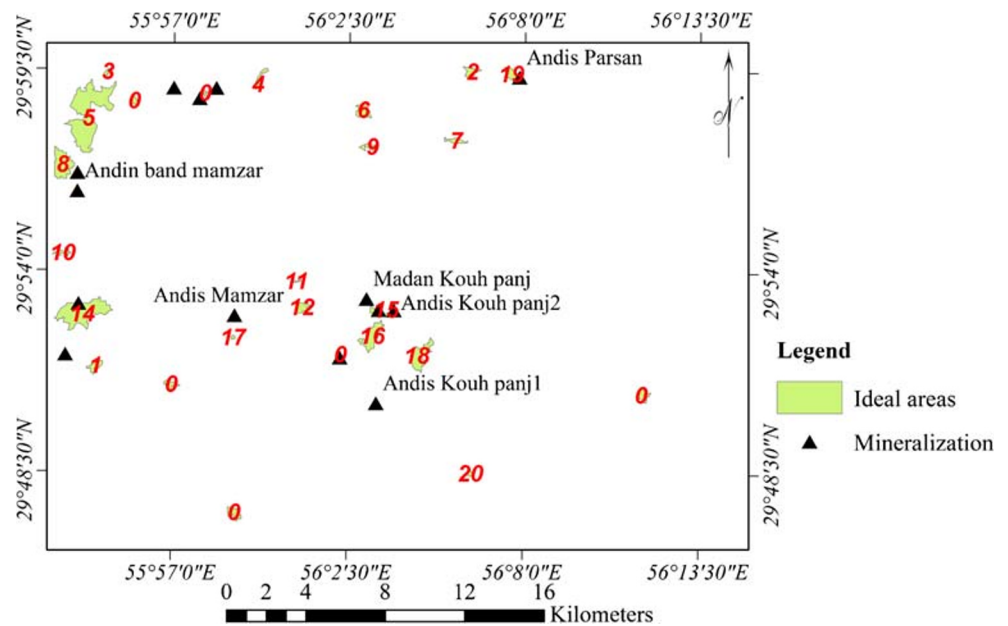
in a way the Crisp S_i was obtained by Eq. (9), Crisp R_i was obtained by Eq. (11), and Crisp Q_i was obtained by Eq. (12).

Results of Dempster-Shafer-fuzzy AHP for ranking

By computing the correlation matrix and calculating the amount of correlation coefficient between information exploration layers obtained in the previous section, it was found out that the correlation coefficient between exploration layers is under 0.6 value (Table 10) and this means we can use the AHP and fuzzy AHP methods for obtaining the weights of each layer or criteria. The procedure for computing triangular fuzzy function in the fuzzy AHP method is outlined as follows:

The fuzzy weighting vectors were formed based on Table 11 and used for converting linguistic variables to numbers.

Thirty experts were requested to express their pairwise comparisons for the criteria using the scale provided in Table 3, and the following weights were obtained using the fuzzy AHP method (Table 12).

According to the favorable porphyry copper mineralization zones in Fig. 12, the average values of each criterion in each zone for applying the Dempster-Shafer-fuzzy AHP method were obtained as shown in Table 13.

In the next step, the grouping of options is performed based on each criterion. According to the reached values for each criterion in each zone, the decision tree was formed as shown in Table 14:

Because the area criterion was used to consider the desirability of the zones and according to the number of criteria, the area criterion was omitted in the nest stages, the weights obtained by the fuzzy AHP method for lithology, alteration, structures, geochemistry, and geophysics criteria were 0.5039, 0.2915, 0.1359, 0.0343, and 0.0343, respectively. The values of mass function were obtained using Eq. (19) (Beynon et al. 2006).

After calculating the mass function for each group of attributes, the criteria were sorted in order of their importance and were checked for their values of subscription and non-subscription and then combined using the Dempster-Shafer algorithm. Since in the Dempster-Shafer algorithm one uses the weights obtained from the fuzzy AHP method, in the denominator, where we put the result of subtracting the non-subscription value from the number one, both results of multiplying the values of two criteria were used instead of one. In this way, at the last stage of the bifurcation combination, a value is obtained for each attribute, and if this value is higher than the other attributes, it will show the priority of copper porphyry potential in the southeast of Sarcheshmeh. Thus, depending on the values of each of the attribute, we can rank the attributes. The values obtained from the Dempster-Shafer-fuzzy AHP method for each attribute are shown in Table 15.

Table 7 Values for each of the linguistic variables allocated to each of the six criteria

Area VL	Lithology VH	Alteration VH	Geochemistry VH	Geophysics M	Structures MH
0	0.8	0.8	0.8	0.4	0.5
0	0.9	0.9	0.9	0.5	0.6
0.1	1	1	1	0.5	0.7
0.2	1	1	1	0.6	0.8

Table 8 Linguistic variables allocated to each of the six criteria for different 20 attributes

Zone ID	Area	Lithology	Alteration	Geochemistry	Geophysics	Structures
1	P	P	MP	VG	VG	F
2	P	VP	MP	MG	G	VG
3	P	P	VP	VP	VG	P
4	VP	MG	F	VG	VG	MP
5	VG	MG	MG	G	VG	MG
6	MP	MG	P	G	VG	MG
7	VP	VP	VP	G	VP	MG
8	VG	F	F	G	G	F
9	VP	MG	P	F	VG	MG
10	P	P	F	VG	VP	VP
11	P	MP	VP	G	P	VG
12	P	F	MP	G	P	G
13	VP	VG	VP	VG	P	MP
14	VG	MG	VG	G	P	MP
15	VP	VG	P	F	F	G
16	VG	VG	MP	G	VP	MP
17	VP	MP	VP	G	MG	VG
18	VG	VG	MP	G	MG	F
19	P	P	P	F	VP	MG
20	VP	MP	VP	VG	P	G

Discussion

Producing an excellent evidential map in terms of predicting mineralization areas has always been a challenging issue for geologists in MPM (Yousefi et al. 2019; Montsion et al. 2019; Sun et al. 2020). MPM is a beneficial tool to highlight areas of interest in challenging exploration settings and identifying new mineralization areas. MPM is efficient when applied in

Table 9 Favorable porphyry copper mineralization zones derived by fuzzy integration approach introduced as the targets (alternatives) to the fuzzy VIKOR

Alternatives	Crisp S_i	Crisp R_i	Crisp Q_i	Ranking order based on min Q_i
1	2.516	1.103	0.352	5
2	1.858	1.033	0.290	8
3	2.596	1.106	0.378	14
4	1.775	0.857	0.333	18
5	0.858	0.747	0.021	19
6	2.075	1.149	0.321	16
7	2.090	1.091	0.323	2
8	2.346	1.139	0.046	15
9	2.317	1.086	0.317	13
10	2.115	1.046	0.355	20
11	2.458	1.146	0.360	9
12	2.625	1.092	0.340	6
13	1.944	1.116	0.304	7
14	0.989	0.797	0.166	17
15	1.905	1.140	0.296	4
16	1.678	0.847	0.288	12
17	2.175	1.091	0.331	1
18	2.345	0.937	0.181	10
19	2.672	1.088	0.245	11
20	2.129	1.080	0.315	3

Table 10 Matrix of correlation coefficients between Layers

Layers	Alteration	Lithology	Geochemistry	Geophysics	Structures
Alteration	1.00000	0.00632	0.00805	0.02367	0.04040
Lithology	0.00632	1.00000	0.00186	− 0.00564	− 0.01528
Geochemistry	0.00805	0.00186	1.00000	0.02612	0.01740
Geophysics	0.02367	− 0.00564	0.02612	1.00000	0.01115
Structures	0.04040	− 0.01528	0.01740	0.01115	1.00000

a team setting, with experts from different geoscientific fields providing their expertise to assign suitable weights to model inputs. Due to the complication of the geological procedure, prospectivity modeling of specific mineralization in the region of interest requires the simultaneous attention of various geodatasets. Identifying potential areas in mineral prospectivity map and choosing the best area are the other challenging issues that in many mineral exploration studies discussed about the various methods for ranking and prioritizing attributes (Abedi et al. 2015; Pazand and Hezarkhani 2015; Feizi et al. 2017; Arabameri et al. 2020).

In this study, the data integration methods have been applied to the satellite imagery, the airborne geophysics, geochemical layer, structural layer, and geological map with 1:100,000 scale in order to produce MPM and to find high potential zones of Cu porphyry mineralization that should be considered for further investigations. A vital problem after determining the potential zones is to propose a ranking method to prioritize these zones and finding the best area for further exploration operation. Hence, using a suitable and trustworthy method is necessary. For this purpose, in this study, we used two hybrid methods of fuzzy MCDM that include the fuzzy VIKOR method and fuzzy AHP method combined with a proposed Dempster-Shafer method. The advantages and disadvantages of each MPM method were demonstrated by Abedi et al. (2012). In this paper, another technique for generating a prospectivity mineral map was applied. Establishing the geological databases using the Dempster-Shafer-fuzzy AHP and fuzzy VIKOR methods is achievable for the representation of evidence of prospectivity mapping related to Cu porphyry deposits. Because of the specifications and capabilities of the fuzzy MCDM methods, the fuzzy VIKOR and fuzzy AHP methods have been widely applied in mineral prospectivity mapping in recent years (Panahi et al. 2017;

Ghezelbash and Maghsoudi 2018; Mami Khalifani et al. 2019). The fuzzy VIKOR method focuses on ranking and selecting a set of alternatives in a fuzzy environment. This method is based on the aggregating fuzzy measure Q that computes the distance of an alternative to the ideal solution (Alguliyev et al. 2015). The fuzzy AHP method takes into cognisance the uncertainties by applying fuzzy numbers to compare the relation among criteria or alternatives (Forson et al. 2019). Here, this method was engaged to make a decision on the priority weights of evidential layers based on triangular fuzzy numbers. Moreover, the Dempster-Shafer theory is often used to combine data and information, but this method can be used in decision-making problems and prioritization of different attributes using different criteria. Due to the effectiveness of the fuzzy AHP and Dempster-Shafer methods, a combination of these two methods would present acceptable results.

Analyzing the results obtained by the fuzzy VIKOR method and comparing them with the results of implementing the Dempster-Shafer-fuzzy AHP method show that in mineral exploration studies, these methods can be used for ranking the favorable mineralization zones and these methods can help geologists to choose top targets for focusing and further studies in the future. As in the previous studies related to the preparation of the potential map, these methods have been used efficiently, and good results have been obtained (Seraj and Delavar 2018; Riahi et al. 2020; Mokhtari et al. 2020). Comparing the results obtained in this study with other studies that have used similar methods to obtain mineral prospectivity maps and ranking attributes, it is clear that applying these methods in the field of mineral potential mapping is useful and feasible too. The proposed innovative knowledge-driven approach is based on expert knowledge and features of the known Cu occurrences in the study area to produce a predictive model for porphyry Cu mineralization. In this

Table 11 Fuzzy weights for our criteria in the fuzzy AHP method

	Lithology	Alteration	Geochemistry	Geophysics	Structures
Lithology	E	MS	E	VS	MS
Alteration	1/MS	E	VS	VS	MS
Geochemistry	1/A	1/VS	E	L	L
Geophysics	1/VS	1/VS	1/L	E	L
Structures	1/MS	1/MS	1/L	1/L	E

Table 12 The weights obtained for each of the criteria using the fuzzy A

Criteria	Weight
Alteration	0.2915
Geochemistry	0.0343
Geophysics	0.0345
Lithology	0.5039
Structure	0.1359

method, mineral potential mapping problems, such as weighting and scoring evidential layers, producing an accurate mineral prospectivity map, and ranking the potential areas are considered. Therefore, this applied method is applicable in other mineral exploration studies to produce MPM and choose the best mineralization area. In potential mapping studies and ranking potential areas, as discussed in the "Introduction" section, some common MCDM and fuzzy MCDM methods were applied (e.g., Abedi et al. 2016; Asadi et al. 2016; Duan et al. 2016); this paper is an effort to apply the Dempster-Shafer-fuzzy AHP and fuzzy VIKOR methods for solving the MCDM problem under uncertainty and fuzziness, in mineral prospectivity mapping to predict the Cu porphyry potential zones with the five relating factors.

The top three targets covering the well-known Darehzar porphyry copper deposit, the areas close to the Sereydoon deposit and its northern areas, are the best three priorities. Therefore, it can be concluded that the ultimate common choice through the application of the Dempster-Shafer-fuzzy AHP and fuzzy VIKOR MCDM methods would be the Darehzar area with the highest value in the Dempster-Shafer-fuzzy AHP and fuzzy VIKOR methods.

Through comparing the properties of existing porphyry copper deposits in the region with the targets obtained as the best top priorities out of the Dempster-Shafer-fuzzy AHP and fuzzy VIKOR methods, it is concluded that the methodology used in the current study could provide valid results consistent with the governing geological settings of the studied area. This could be achieved through the sequential application of the Dempster-Shafer-fuzzy AHP and fuzzy VIKOR methods in the course of solving an MCDM problem. Thus, such application could be used in the prioritization of the target sites, and the selection of the best favorable areas for further ground follow-up exploratory works. fuzzy logic with extreme adaptability in examining natural language meanings can model and explain the human mind's ambiguities and the environment and the uncertainty in human judgment. Therefore, the results of this study have beneficial implications for decision-making, managers' policymaking, and planning. The procedure's appropriate performance relies on experts working together in an open forum, within a standard model. Progress of integrative methods, such as the one proposed here, is key to unfastening the untapped mineral potential of non-traditional exploration settings.

Table 13 The average value for each criterion in each zone

Criteria attribute	Area (km^2)	Lithology	Alteration (normalized)	Geochemistry (normalized)	Geophysics (normalized)	Structures (normalized)
1	0.3	0.6	0.3	0.9	0.7	0.5
2	0.3	0.5	0.2	0.8	0.7	0.9
3	0.3	0.6	0.1	0.5	0.8	0.3
4	0.2	0.8	0.4	0.9	0.7	0.4
5	1	0.8	0.6	0.9	0.8	0.6
6	0.5	0.8	0.2	0.8	0.8	0.7
7	0.2	0.5	0.1	0.8	0.3	0.6
8	1	0.8	0.4	0.8	0.7	0.6
9	0.2	0.8	0.2	0.7	0.7	0.7
10	0.3	0.6	0.4	0.9	0.2	0.2
11	0.3	0.7	0.1	0.8	0.3	0.8
12	0.4	0.7	0.3	0.8	0.3	0.8
13	0.2	1	0.1	0.9	0.4	0.5
14	0.9	0.9	0.7	0.9	0.3	0.5
15	0.2	1	0.2	0.7	0.5	0.8
16	0.9	0.9	0.3	0.8	0.2	0.5
17	0.1	0.7	0.1	0.7	0.6	0.9
18	0.9	1	0.3	0.8	0.5	0.6
19	0.3	0.6	0.2	0.7	0.2	0.7
20	0.1	0.7	0.1	0.9	0.3	0.7

Table 14 The decision tree for the DS-fuzzy AHP method

	Area		Lithology		Alteration	
	Attributes	**Value**	**Attributes**	**Value**	**Attributes**	**Value**
S_1	1, 2, 3, 10, 11, 19	0.3	1, 3, 10, 19	0.6	1, 12, 16, 18	0.3
S_2	4, 7, 9, 13, 15	0.2	2, 7	0.5	2, 6, 9, 15, 19	0.2
S_3	5, 8	1	4, 5, 6, 8, 9	0.8	3, 7, 11, 13, 17, 20	0.1
S_4	6	0.5	11, 12, 17, 20	0.7	4, 8, 10	0.4
S_5	12	0.4	13, 15, 18	1	5	0.6
S_6	14, 16, 18	0.4	14, 16	0.9	14	0.7
S_7	17, 20	0.1				
	Structures		**Geophysics**		**Geochemistry**	
	Attributes	**Value**	**Attributes**	**Value**	**Attributes**	**Value**
S_1	1, 13, 14, 15	0.5	1, 2, 4, 8, 9	0.7	1, 4, 5, 10, 13, 14, 20	0.9
S_2	2, 17	0.9	3, 5, 6	0.8	2, 6, 7, 8, 11, 12, 16, 18	0.8
S_3	3	0.3	7, 11, 12, 14, 20	0.3	3	0.5
S_4	4	0.4	10, 16, 19	0.2	9, 15, 17, 19	0.7
S_5	5, 7, 8, 18	0.6	13	0.4		
S_6	6, 9, 19, 20	0.7	15, 18	0.5		
S_7	10	0.2	17	0.6		
S_8	11, 12, 15	0.8				

Conclusion

The current study aimed to investigate the possibility of employing a sequential application of the Dempster-Shafer-fuzzy AHP and fuzzy VIKOR methodologies to make a method for ranking the best favorable targets in the area covering the eastern to southeastern regions of the well-known Sarcheshmeh copper deposit. In this regard, five different spatial evidence layers, which were known to be an indicator or having a meaningful association with porphyry copper mineralization, were identified. The fuzzy logic approach was then applied to recognize the favorable porphyry copper mineralization areas and produce MPM, and a fuzzy prospectivity modeling was obtained based on the expert opinion and attributes of already known mineral deposits. Moreover, the weights were assigned to each class of layers according to the fuzzy logic and AHP method. Investigating and comparing the favorable areas obtained through the fuzzy method in the preliminary stage of favorability mapping with known porphyry copper mineralization throughout the studied area guaranteed the integration of all favorable prospects to be introduced to the next stages and prevent missing potentially essential areas. Using the Dempster-Shafer-fuzzy AHP and fuzzy AHP methods with different conditions resulted in ranking the well-known Dareh-Zar area, as the top priority with a score of 0.8477 for the Dempster-Shafer-fuzzy AHP method and Q value 0.166 for the fuzzy VIKOR methods. This area was followed by target areas tagged as 5 and 8 in Tables 9 and 15, which are close to the well-known deposits like Sereydoon and Northern Sereydoon as the second and third priorities with a Q value of 0.021 and 0.046 for the fuzzy VIKOR method and 0.748 and 0.528 for the Dempster-Shafer-fuzzy AHP method, respectively. Also, the target area tagged as 18 with a score of 0.181, which is near the KouhPanj prospect, was identified using the fuzzy VIKOR method. Therefore, the known Cu porphyry mineralization occurrences were used

Table 15 Ranked favorable porphyry copper mineralization zones derived from the Dempster-Shafer-fuzzy AHP method

Attributes	Value	Ranking order
14	0.847726	1
5	0.748244	2
8	0.528792	3
4	0.514821	4
18	0.505964	5
16	0.457511	6
15	0.438697	7
10	0.410578	8
12	0.38169	9
13	0.371982	10
6	0.335677	11
9	0.334663	12
1	0.312219	13
17	0.251919	14
2	0.238083	15
11	0.235719	16
19	0.224486	17
20	0.221803	18
7	0.116201	19
3	0.110799	20

to compare and evaluate the capability of the fuzzy VIKOR and Dempster-Shafer-fuzzy AHP methods in ranking the potential areas and selecting the best area for the development of further exploration operations. Other areas were ranked and prioritized by applying the fuzzy VIKOR and Dempster-Shafer-fuzzy AHP methods on the areas proposed by preliminary fuzzy integration outputs, resulting in new prospects to be focused for further field exploration surveys. The predicted and ranked regions of the two methods are highly similar. There has been no proven deposit in some high favorability zones, which requires to be prospected and verified in the future, and it can be said that this study's prediction results provide a prospecting direction for this area.

Compliance with ethical standards

Conflict of interest   The authors declare that they have no conflicts of interest.

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