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Improving hybrid outranking methods for porphyry Cu potential mapping, a case study in Chahargonbad region

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Abstract

In this study, evidential layers for porphyry copper mineralization, including geology, lineaments, geophysics, and geochemistry of Geological map at 1: 100,000 scale of Chahargonbad district, were weighted and integrated using new and innovative hybrid methods to produce a mineral potential map. To this purpose, firstly, all exploration data were preprocessed and processed using valid and proper methods, and accurate evidential layers were produced. Then, each layer was evaluated, and finally, all evidential layers were integrated to obtain a mineral prospectively map for porphyry Cu mineralization of the study area. To weigh, evaluate and validate each of the evidential layers and the obtained mineral prospectively maps plots of concentration–area (C–A) fractal model and prediction–area (P–A) and normalized density (Nd) as approved methods were conducted. Also, two-hybrid methods of fuzzy gamma and a multi-criteria decision-making outranking method "MOORA" have been applied to mineralization potential mapping. The fuzzy gamma and MOORA results show ore prediction rates of 71% and 76%, which identifies 29% and 24%, respectively, of the area as potential zones. Accordingly, the MOORA method can be used efficiently for mineral prospectively mapping for further exploration studies.

Introduction

One of the main steps in mineral exploration studies to find new economic mineral deposits is to identify potential mineralization areas in the study area. Since mineral exploration projects are costly, time-consuming, and energy-intensive, it is essential to limit the study area to focus on exploration operations and conduct detailed explorations. It is possible by preparing a reliable mineral prospectivity mapping (MPM) (Bonham-Carter, 1994; Hronsky and Groves, 2008; Porwal and Carranza, 2015). In preparing MPM, an exploratory key, various earth science data such as geology, geochemistry, remote sensing, and geochemistry are integrated (Agterberg et al., 1990; Bonham-Carter, 1994). The vital goal of MPM is to determine new mineralization in the study area by expanding potential areas of mineralization that have already been explored (Abedi and Norouzi, 2015). MPM simultaneously maximizes the profitability of a mining exploration project while reducing costs (Chen and Wu, 2015). MPM is usually performed in three primary and essential stages (Bonham-Carter, 1994; Carranza, 2008; Najafi et al., 2014; Yousefi and Carranza, 2015b; Fatehi and Asadi, 2016; Parsa et al., 2017a, b), 1) Identification and collection of exploratory criteria based on the target mineralization, 2) Preparation of evidential layers by weighing and extracting required features indicating the existence of the mineralization, 3) Integration of evidential layers and ranking of desirable mineral areas. Numerous functions are used to integrate data correctly, modifying ordinary arithmetic or logic operators to use complex mathematical functions to map target areas and thus map mineralization (Porwal and Carranza, 2015).

Today, Geographic Information System (GIS) tools provide a framework for expert users to use spatial data analysis methods to determine prospect areas by integrating mineralization evidential layers (An et al., 1991; Agterberg, 1992; Carranza, 2004; Haldar, 2012; Porwal and Carranza, 2015). For GIS-based MPM, outranking multi-criteria decision-making procedures have been widely used and improved from the past to the present based on data-driven, knowledge-driven, or hybrid (a combination of data-driven and knowledge-driven methods) classifications (Pan and Harris, 2000; Nykänen et al., 2008; Yousefi et al., 2012; Porwal and Carranza, 2015). The present paper aims to propose a new hybrid method to map the porphyry copper mineralization potential and compare the results with the gamma fuzzy hybrid method. The method used is multi-objective optimization by ratio analysis (MOORA), which is part of the outranking multi-criteria decision method and is used in combination in this study. Assigning weights to the criteria in the combination and integration of evidential layers has been done using known mineral occurrences in the study area. There are 28 known porphyry Cu mineralization indices in the study area, and it is essential to use the location of their occurrence in performing hybrid methods to achieve reliable results. Therefore, the study presented here attempts to map the potential areas of porphyry copper for further studies in the Chahargonbad sheet in Kerman province, SE of Iran. In this regard, two methods of fuzzy gamma and multi-criteria decision-making MOORA have been used (Bahrami et al., 2019a, b). The reason for using these two methods is to use effective and tested methods to obtain a potential map in the study area, compare the obtained results, and evaluate them. Finally, the MPMs related to mineralization potential areas were validated using the parameters obtained from the data-driven prediction-area (P-A) plot.

Study area

The study area is located in Central Iran's southern part of the volcanic-sedimentary belt (Urmia-Dokhtar zone). The geographical position of the 1:100000 scale Chahargonbad quadrangle sheet is in latitude 29°30′ to 30 ° and longitude 56 ° to 56 ° 30′. Chahargonbad copper deposit is located in the mountainous areas of eastern Sirjan. The lowest altitude is 2077 meters, and the highest is 3017 meters above sea level. The region's topography is high, and its altitude is 2400 meters above sea level (Saffar Heydari, 2016). Most of Iran's copper deposits are located in the Urmia-Dokhtar magmatic belt. As part of this belt, the study area is the source of essential deposits such as Sarcheshmeh, Darehezar, Meyduk, and Chahargonbad. Due to its similar tectonic position to other copper belts in the world, such as the Andean volcanic belt, this belt has the potential for copper mineralization, which is the reason of particular attention for exploration studies, and this area is a part of the Zagros orogenic belt. Geologically, the areas around the Chahargonbad copper deposit are composed of the Eocene pyroclastic complex and two limestones narrow zones of Oligocene-Miocene and Quartz intrusive formed after the Miocene, probably. Quartz diorite porphyries are the only intrusive rocks that are outcrop in the Chahargonbad region and form irregular lens-like masses that are stretched in an east-west direction and are probably geologically related to the post-Miocene period. The only effect of these intrusions on adjacent rocks is hydrothermal alteration, apparently without the phenomenon of contact with the formation of hornfels (Saffar Heidari, 2016). As mentioned, the study area is covered by Chahargonbad 1: 100000 quadrangle map, and its area is about 2600 square kilometers, which has been prepared by the Geological Survey and Mineral Exploration of Iran (GSI) (Khan-Nazer et al., 1995). Figure 1 shows a simplified geological map of the study area and its location in the Urmia Dokhtar magmatic belt.

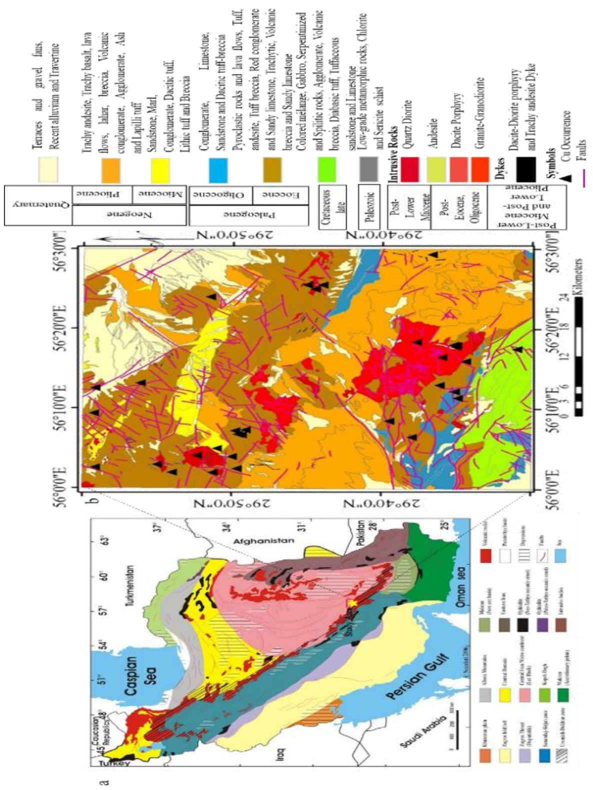

Fig. 1. (a) Location of the study area in the Urmia-Dokhtar magmatic belt, (b) Simplified geological map of sheet 1: 100000 Chahargonbad (reproduction using a map prepared by the Geological Survey of Iran, (Khan-Nazer et al., 1995).

Evidential layer preparation

At first, all available exploratory data from the study area related to the target mineralization were collected and analyzed. In the present study, as mentioned, the data were evaluated and analyzed theoretically and computationally based on availability due to the spatial relationship with porphyry Cu mineralization. Then, five evidential layers were obtained as individual mineralization prospectivity maps to identify the potential areas of porphyry Cu mineralization, including lithological information layer, lineaments, geochemical, geophysical, and remote sensing as follows.

- Geological evidential layer: For this purpose, the information in the geological map prepared from the study area was processed. Layers derived from the Chahargonbad geological map include lithological units and faults, each individually converted to vector format using ArcGIS software. Based on the relationship of porphyry Cu mineralization with rock formations, rock units such as granodiorite, dacite, andesite, and other formations were quantified in the range of 0-1 based on importance. The quantified units were extracted from the geological map of the study area to prepare an evidential layer for MPM. Faults are another effective parameter in the formation of ore deposits, the close relationship of which with mineralization has been widely confirmed by various studies (Sibson, 1987; Cox, 1999; Robert and Poulsen, 2001). Fault zones in the geological map were hand-digitized using ArcGIS software in vector formatting to show the characteristics of fault zones as an evidential layer.

- Geochemical evidential layer: Determining an anomaly in the multi-elemental geochemical characteristics of the target mineralization is a critical step in mineral exploration (Carranza and Hale, 1997). For geochemical explorations in the Chahargonbad area, we preprocessed and processed 846 samples of 80 mesh of stream sediments analyzed for nine elements of Cu, Mo, Zn, Pb, Ag, Co, Ni, Cr, and Ba by the GSI. After processing geochemical data, methods such as multivariate statistical methods that can help classify and rank anomalies in geochemical data and define the spatial distribution of sample elements and are identified by host anomaly segregation anomalies and then factor analysis (FA) as a proper multivariate method that leads to the production of fewer uncorrelated components, were used to plot the main geochemical component of copper mineralization and subsequently to create a geochemical evidential map.

- Remote sensing evidential layer: One of the most critical advantages of remote sensing images is detecting areas of hydrothermal alterations (Sabins, 1999), which has attracted considerable attention over the past decades due to its acceptable and economically viable results (Abrams et al., 1983; Kruse et al., 1993). To date, various types of remote sensing data have been used to identify areas with hydrothermal alterations, the potential capabilities of each of which have been expressed through various studies. Many image processing methods and remote sensing data are used to show alteration areas. The most common alterations in the predominant mineralization of copper are the alterations of potassium, argillic, phyllite, propylitic, and iron oxide (Pour et al., 2018). For the present study area, the hydrothermal alterations of argillic, phyllite, propylitic, and iron oxide are associated with porphyry Cu mineralization. ASTER, ETM +, and Landsat 8 (OLI) satellite data and spectral processing methods such as band ratio (BR), principal component analysis (PCA), spectral angle mapper (SAM), and least-squares fitting (LS-Fit) methods were applied to obtain remote sensing evidential layer.

- Geophysical evidential layer: In geology and mineral exploration studies, airborne geophysical data is used as one of the most important sources of information to study the geological characteristics and subsurface structures such as faults, intrusion bodies and latent plutonic, weathering and alteration, and geological changes (Holden et al., 2008, Kheyrollahi et al., 2018). The use of aeromagnetic and airborne radiometric data in obtaining magnetic information layers, structures and edges, and areas related to potassic alteration as a guide for identifying porphyry Cu mineralization is fully described in our previous works (Riahi et al., 2019, Riahi et al., 2021).

- Lineaments evidential layer: In porphyry copper mineralization, there are many areas with lineaments and faults, which are a passage for magmatic fluids and the formation of ore deposits, and act as a guide in identifying areas of this mineralization (Farahbakhsh et al., 2019). Three types of lineaments can be identified using the available data. The first type, as described, are faults obtained from the geological map, the second type are the lineaments obtained by applying directional filters on satellite image data, and the third type are structures and edges obtained from applying filters on aeromagnetic data. Combining these three types of lineaments in one layer, the evidential layer related to porphyry Cu mineralization in the study area is obtained.

Evidential layers weighting

It was mentioned that using the P-A model and determining the prediction rate according to the intersection point can determine the relative importance of the evidential layers as criteria related to the target mineralization in the study area. In addition, using values in both the right and left axes of the P-A plot can be used to weight the evidential layers as a data-driven method. Since the primary purpose of the present study is to obtain a potential mapping to identify porphyry Cu mineralization, it is necessary to obtain quantitative weights for each layer. We can obtain a normalized density quantity by calculating the ratio of the prediction rate to the corresponding occupied area. In the following equations, the use of P-A plot parameters is explained (Yousefi and Carranza, 2015 a, b):

$$N_d = \frac{P_r}{O_a} \tag{1}$$

Where Nd is the normalized density, Pr is the prediction rate, and Oa is the occupied area by the mineralization, extracted from the intersection point of the P-A plot. The normalized density is used to calculate the weight of each map according to the following equation (Yousefi and Carranza, 2015 a, b):

$$W_E = \ln N_d \tag{2}$$

Where WE is the final weight of each evidential layer calculated using the P-A plot and its intersection point.

Evidential layers integration

A) Fuzzy Logic

Fuzzy set theory and fuzzy logic (Zadeh, 1965) are used in knowledge-driven assigning weights to the evidential layers that require the opinion of experts in geosciences based on the degree to which each evidence corresponds to the occurrence characteristics of the deposit (Bonham-Carter, 1994; Carranza and Hale, 2001; Nykänen et al., 2008). One of the critical steps in fuzzy logic MPM is assigning fuzzy membership scores to evidential layers in the range [0,1], also called fuzzification spatial evidence (Carranza, 2008). Several fuzzy operators are used after determining the weights of the fuzzy evidence to integrate the evidential maps to create a mineral potential map and determine the target areas of the target mineralization for further exploration. The most common fuzzy operators used for MPM are the fuzzy algebraic operators AND, OR, SUM, PRODUCT, and the fuzzy gamma operator (Bonham-Carter, 1994). In the present study, the fuzzy gamma operator (γ) was used to produce MPM as follows:

Fuzzy Product: $\mu_{\text{Product}}(x) = \prod_{i=1}^{n} \mu_i(x)$

Fuzzy Sum: $\mu_{Sum}(x) = 1 - \prod_{i=1}^{n} \mu_i(x)$

Fuzzy Gamma:

$$\mu_{\gamma}(x) = \left[\mu_{Sum}(x)\right]^{\gamma} \times \left[\mu_{\text{Product}}(x)\right]^{1-\gamma}$$

(3)

3.3.2. MOORA method

The MOORA method, first introduced by Brauers (2004), is a multi-objective optimization technique that can be successfully used to solve various complex decision-making problems. This method simultaneously uses the favorable and unfavorable criteria for ranking and selecting one or more alternatives from all the alternatives. This method is based on relative analysis and reference point method, which, of course, in the development path, a multiplicative form was added to it and led to the production of the multi-MOORA method as a powerful method in multi-objective optimization. The main features of the MOORA method are simplicity and ease of implementation, low mathematical calculations, and fast. The steps to solve the problem by this method are as follows:

1) Creation of decision matrix: Similar to all multi-criteria decision-making methods, we must first form the decision matrix. The decision matrix is called the number of alternatives evaluation matrix based on several criteria.

$$x = \left[x_{ij}\right]_{m \times n} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{4}$$

2) Decision matrix normalization: Vector normalization method is used for normalization in MOORA method.

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \tag{5}$$

Where nij is the dimensionless value of the i-th alternative of the j-th criterion and is always in the range of [0,1].

3) Creation of a weighted decision matrix: The criteria weights must also be known in advance, which were obtained in this study using the P-A plot as described. Here we multiply the weight of each criterion in the normal decision matrix and form the weighted normal decision matrix. Also, the desirability and non-desirability of normalized values based on the ratio system approach should be determined, which is calculated with Eq. 6.

$$\gamma_i = \sum_{i=1}^{g} W_j \times n_{ij} - \sum_{j=g+1}^{n} W_j \times n_{ij}, (j = 1, \ldots, n) \tag{6}$$

g represents the number of desirable criteria that should be maximized and g+1 represents the number of undesirable criteria that should be minimized.

4) Ranking of alternatives based on the reference point approach: In this step, a reference point should be obtained for each criterion, which is equal to the largest value of criteria for desirable criteria (positive) and equal to the smallest value of criteria for undesirable (negative) criteria.

For objectives to be maximized ri = max wj.nij

For objectives to be minimized ri = min wj.nij

To select the optimal alternative using Eq. 6 can be calculated as follows (Bahrami et al., 2019a).

$$Min\left\{\max\left|W_j \times r_j - W_j \times n_{ij}\right|\right\} \tag{7}$$

4. Results and Discussion

After obtaining all the evidential layers as exploratory criteria for porphyry Cu mineralization, each layer was rasterized in a pixel size of 100×100 m and transferred using a logistic function from the limitless values to the range of [0,1]. Each map was classified using the fractal analysis method of concentration-area (C-A) to identify the appropriate threshold for classifying each continuous layer. Then the P-A plots for each were obtained, and the parameters required to evaluate and weight each layer were extracted. Figures 2 to 6 show each evidential layer along with the corresponding plots. Table 1 also describes the parameters extracted from the P-A plots for each layer.

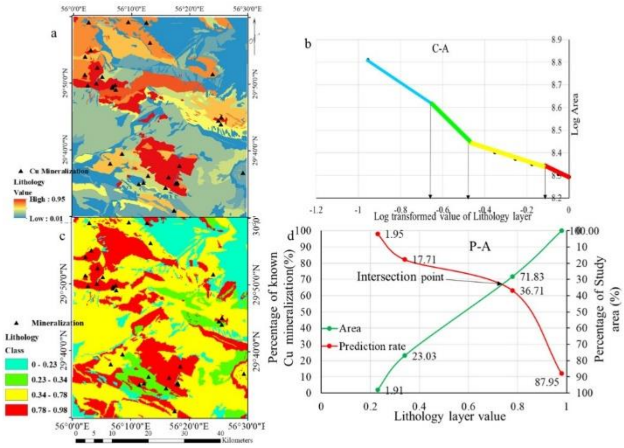

Fig. 2. (a) Fuzzified lithological evidential layer using a sigmoidal logistic function, (b) Full logarithmic plot obtained from C-A method for lithological layer, (c) Classified lithological layer obtained from C-A fractal method related to (a), (d) P-A plot of the lithological layer.

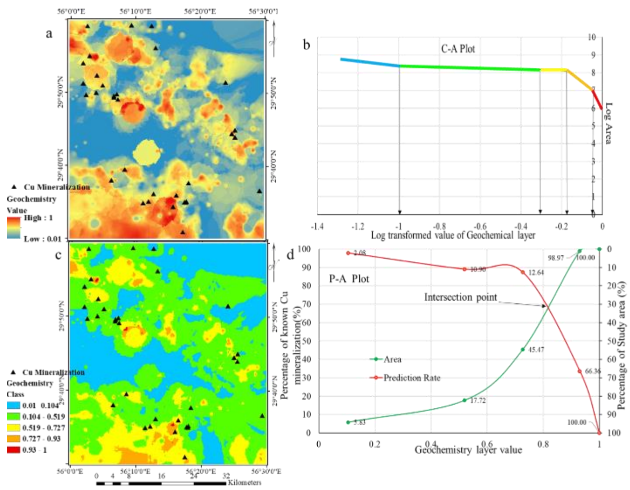

Fig. 3. (a) Fuzzified geochemical evidential layer using a sigmoidal logistic function, (b) Full logarithmic plot obtained from C-A method for geochemical layer, (c) Classified geochemical layer obtained from C-A fractal method related to (a), (d) P-A plot of the geochemical layer.

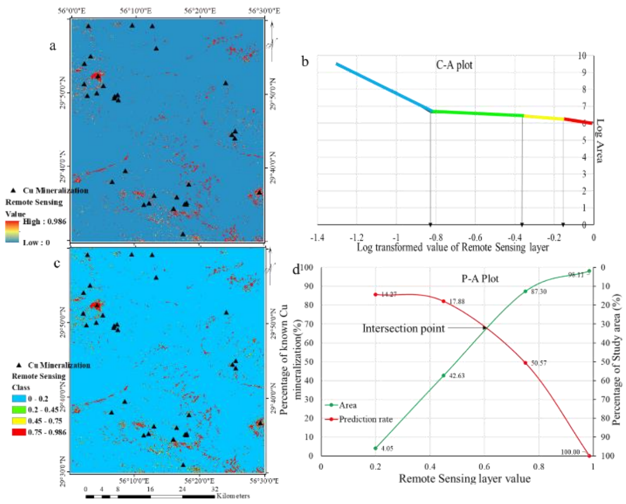

Fig. 4. (a) Fuzzified remote sensing evidential layer using a sigmoidal logistic function, (b) Full logarithmic plot obtained from C-A method for remote sensing layer, (c) Classified remote sensing layer obtained from C-A fractal method related to (a), (d) P-A plot of the remote sensing layer.

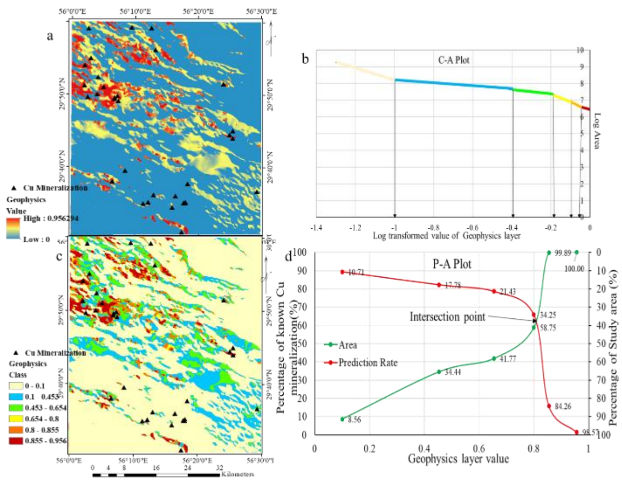

Fig. 5. (a) Fuzzified geophysical evidential layer using a sigmoidal logistic function, (b) Full logarithmic plot obtained from C-A method for geophysical layer, (c) Classified geophysical layer obtained from C-A fractal method related to (a), (d) P-A plot of the geophysical layer.

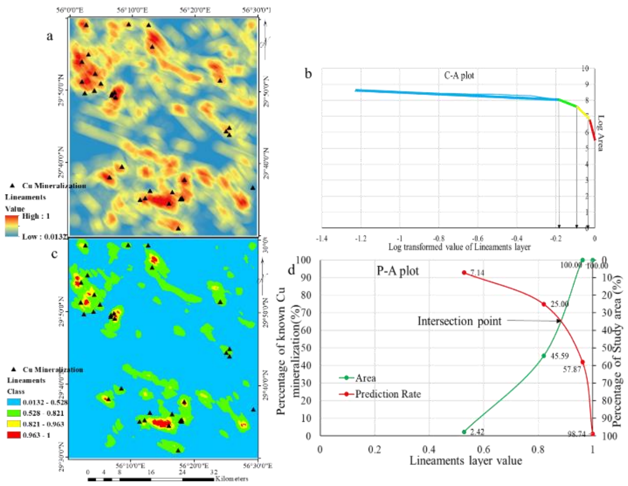

Fig. 6. (a) Fuzzified lineaments evidential layer using a sigmoidal logistic function, (b) Full logarithmic plot obtained from C-A method for lineaments layer, (c) Classified lineaments layer obtained from C-A fractal method related to (a), (d) P-A plot of the lineaments layer.

Table 1. Parameters derived from P-A plots for different evidential layers in the study

Evidential layer	Prediction Rate%	Occupied area%	Normalized density (Nd)	Weight
Lithology	67	32	2.03	0.708
Geochemistry	68	32	2.13	0.754
Remote Sensing	68	32	2.13	0.754
Geophysics	63	27	1.7	0. 532
Lineaments	65	35	1.86	0.619

As mentioned, due to the knowing the position of 28 known porphyry Cu mineralization occurrences in the study area, to weigh and evaluate evidential layers, we can use them. Therefore, according to the weights obtained for each layer using the available data, MPMs obtained from fuzzy gamma and MOORA methods identify mineralization potential areas more accurately. Also, P-A plots for validation and performance evaluation of each method can reasonably evaluate the efficiency of the applied methods in producing MPM. The results of integrating the evidential layers using the fuzzy gamma method and the MOORA outranking multi-criteria decision-making method and evaluating them are shown in Figures 7 and 8, respectively.

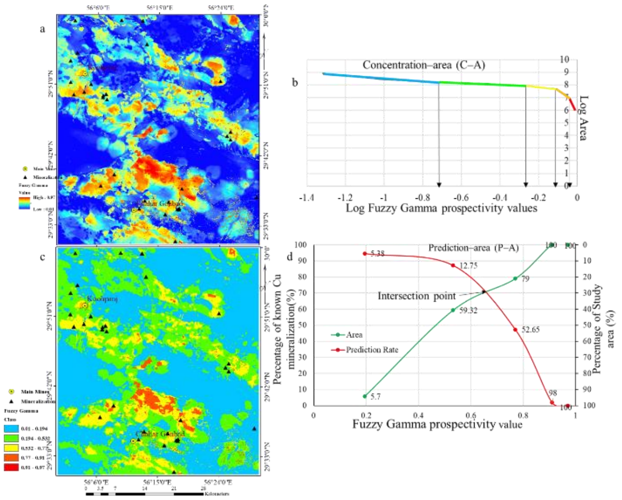

Fig. 7. (a) Final model of porphyry Cu MPM by gamma fuzzy method (b) Full logarithmic plot obtained from C-A fractal model of fuzzy gamma model, (c) Classified fuzzy gamma model obtained from C-A plot related to (a), (d) P-A plot of fuzzy gamma model.

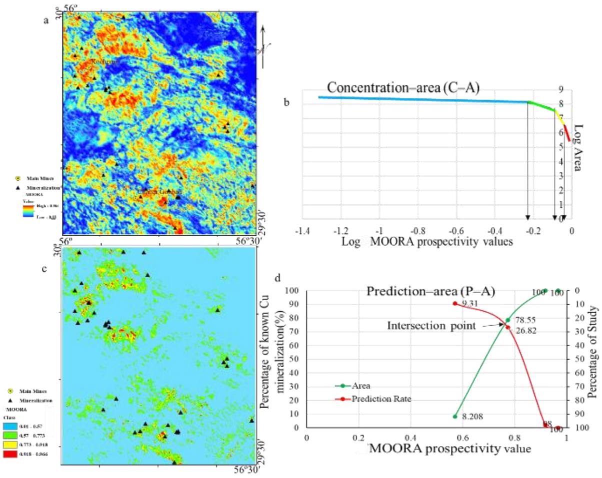

Fig. 8. (a) Final model of porphyry Cu MPM by MOORA method (b) Full logarithmic plot obtained from C-A fractal model of MOORA model, (c) Classified MOORA model obtained from C-A plot related to (a), (d) P-A plot of MOORA model.

By evaluating the final models obtained from the fuzzy gamma and MOORA methods by their P-A plots, it is discovered that the MOORA method can predict up to 77% of the known mineralization occurrences in 23% of the area and the normalized density for this MPM model is 3.35, which is obtained from the ratio of the percentage of known mineralization occurrences to the occupied area from the intersection point of the P-A plot. These values for the MPM model obtained from the fuzzy gamma method are 71%, 29%, and 2.45, respectively. Given that the value of the normalized density for the MPMs obtained from both methods is greater than one, it can be inferred that the methods used act as efficient methods in integrating exploratory evidential layers to identify target mineralization areas. Furthermore, the MOORA outranking multi-criteria decision-making method has been more successful and better than the fuzzy gamma method in this case.

Conclusion

This study aims to show the successful application of the hybrid fuzzy gamma and MOORA outranking multi-criteria decision-making methods in producing the porphyry Cu mineral potential maps in the Chahargonbad area. The MOORA method alone has no possibility of the use of expert judgments in determining the weight of criteria, so it will not have adequate accuracy in introducing potential mineralization areas, but in the case of obtaining the weight of evidential layers as criteria based on existing known mineralization occurrences as specified this method can work satisfactorily. Using this method in the hybrid form will ultimately reduce potential regions' area and increase the predict accuracy. For producing MPM, five main criteria as evidential layers including lithological layer related to porphyry Cu mineralization, geochemical anomaly, lineaments density map of faults in the region and lines and edges obtained from satellite and aeromagnetic data, geophysical evidential layer, and remote sensing layer of hydrothermal alterations in the study area were considered. In order to prepare the mentioned evidential layers for integration and thus to produce an MPM, the evidential layers were firstly transformed by sigmoid logistic function in the range [0,1] and then classified using C-A fractal analysis method to determine different communities. In the next step, the criteria were weighted, and finally, using fuzzy gamma and MOORA methods, all porphyry Cu mineralization potential areas were obtained from the integration of evidential layers, ranked, and maps representing potential porphyry Cu regions were created. The P-A plot evaluated the validity of these MPMs. According to this plot, the intersection point of the prediction rate curves and the corresponding occupied area showed 71% for the fuzzy gamma model and 77% for the MOORA model. Therefore, the mentioned models can be used in selecting and prioritizing the target mineralization areas for the next exploration operation. Also, it can be concluded that the MOORA model in this study has been more effective in obtaining the porphyry Cu mineralization potential map in the study area.

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