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Evidential data integration to produce porphyry Cu prospectivity map, using a combination of knowledge and data-driven methods

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ABSTRACT

Producing an accurate and valid mineral prospectivity map is one of the most significant parts of mineral exploration studies. For this purpose, it is needed to obtain valid evidential layers and integrate them with an accurate methodology. Knowledge and data-driven methods are two primary techniques applied to combine various evidential layers for mineral prospectivity mapping, of which each of them includes a variety of analytical techniques. In this study, in the first step, satellite data, aeromagnetic and airborne radiometric data, stream sediment geochemical data and geological data were applied to create valid remote sensing, geophysical, geochemical, lineaments and lithological evidential layers of the study area that are an essential factor in recognition porphyry copper mineralization, then in the second step, based on the known mineralization occurrences data, the evidential layers were weighted. Finally, these layers were integrated using fuzzy logic and index overlay methods in a combination of knowledge and data-driven way. Validation of each layer was done using available data in the second step. The final mineral prospectivity map was evaluated, and the confirmation of this layer detected that the final mineral prospectivity map obtained from data-driven multi-index overlay method has a higher ore prediction rate of 76%, which identifies 24% of the area as potential zones for further exploration.

Mineral prospectivity mapping (MPM) is one of the topics of spatial multi-criteria decision-making, and mineral exploration experts use different criteria for this purpose according to the scale of the study (Bonham-Carter, 1994; Carranza, 2008; Abedi & Norouzi, 2016; Ferrier *et al*., 2019). The main steps in preparing an MPM consist of determining the factors of mineralization type sought, qualifying information, preparing factors maps, combining maps and evaluating the results (Karimi *et al*., 2008; Brandmeier *et al*., 2020). Depending on the type of mineralization and the study area characteristics, the number and type of exploration criteria are determined to produce an accurate and reliable final MPM.

Porphyry copper deposits are the most important source of copper and molybdenum in the world (John *et al*., 2010; Sillitoe, 2010; Chiaradia, 2020). These deposits may also contain significant amounts of gold, silver, tungsten and tin. The diversity of natural conditions governing complex geological systems and mineralization control processes has led to the exploration of porphyry copper ores or any other type of mineral in a situation of uncertainty. Waste of time, money and energy results from exploration operations in a condition of uncertainty and risk (Carranza, 2008). MPM is used as a critical method in mineral exploration, and its primary purpose is to reduce the cost, time and energy of exploration operations, while making an exploration program profitable (Chen & Wu, 2016; Sun *et al*., 2019). Weighting evidential patterns and integration of predictive maps to model mineral potential and thus identify exploration targets are made in several ways.

Data-driven methods, also called monitored methods, are suitable in areas where previous exploration and studies have been done in considerable detail (brown fields areas). In these areas, known mineralization locations are used as teaching and learning points, and MPM is created by examining the relationship between the location of these known places and spatial control patterns (Bonham-Carter *et al*., 1989; Carranza, 2008; Ma *et al*., 2020). Methods of weighted evidence, the extended weight of evidence, Logistic regression, evidential estimation functions, Bayesian network classification and artificial neural networks are different types of data-driven methods (Abedi *et al*., 2012; Ma *et al*., 2020). Using the location of known deposits as training points causes an error and a random tendency in these methods (Coolbaugh *et al*., 2007; Sun *et al*., 2019).

Producing MPM using knowledge-based methods performs when the number of known deposit types sought in the study area is low or there is no known deposits (green areas) (Bonham-Carter, 1994; Carranza, 2008; Juliani & Ellefmo, 2019). Therefore, in these methods, assigning weight to the evidential patterns and maps, and finally, the combination of evidential maps to introduce potential areas based on comparison and expert judgment is done, which causes a systematic error and is considered a limitation of such methods (Yousefi & Carranza, 2015a). Essential knowledge-driven methods are Boolean logic, index overlay, fuzzy logic, wildcat modelling and multi-criteria decision-making methods (Carranza, 2010; Hamzeh & Karimpour, 2020).

The third group of producing MPM methods is a combination of the two categories of the above methods. Fuzzy weights-of-evidence and neuro-fuzzy inference systems are examples of this category. Combined or hybrid methods in weighting and integration exploratory layers have the limitations of knowledge-based and data-driven methods (Yousefi & Nykänen, 2017; Ma *et al*., 2020). In recent years, another class of MPM methods has been used to weight spatial evidential values (Nykänen *et al*., 2008; Montsion *et al*., 2019). These methods use an appropriate logistics function to model the mineral potential instead of using known deposits and discretizing the continuous data to the desired classes through expert opinion. MPM is a key to process merges multiple geoscience datasets applied across various scales. For geographic information systems-based MPM as multi-criteria decision-making method, assigning weight to spatial evidential values and combining different types of exploratory evidential layers to produce a single individual data set and the existence of uncertainty is a significant challenge. Moreover, integration of the evidential layers using various methods based on GIS overcome the problems caused by uncertainty and thus identify meaningful exploration goals (Yousefi & Carranza, 2015b; Sun *et al*., 2019). In this study, an appropriate sigmoidal logistic function was used to weigh the exploratory evidential layers and finally produce the MPM so that the results would not be affected by any random or systematic errors resulting from data-driven and knowledge-based modelling (Harris *et al*., 2015; Parsa *et al*., 2016; Yousefi and Carranz, 2016). In this work, based on applying various processing methods on available spatial datasets in the study area, the maps of each exploration data group were generated as five individual layers of evidence of prospectivity for porphyry Cu deposits, namely remote sensing, lithology, lineaments, geochemistry and geophysics. After that, by applying Concentration–Area (C–A) fractal model (Cheng *et al*., 1994; Yousefi & Carranza, 2015b) and a Prediction–Area (P–A) plot according to the known mineralization occurrence data, each different prospectivity layer was classified and evaluated, and by normalized density (Mihalasky & Bonham-Carter, 2001; Yousefi & Carranza, 2015c) the layers were weighted. Finally, to identify the target areas for the exploration of porphyry Cu deposits, two methods of fuzzy logic and data-driven multi-index overlay (DMIO) were applied to integrate weighted evidential layers and obtain MPM. For this purpose, 1: 100,000 sheet of Chahargonbad area of Kerman province, Iran, as the study area has been selected due to its location on the Urmia–Dokhtar magmatic belt (most of the known porphyry copper deposits in Iran are located within this belt) and the lack of an accurate MPM in this region. Therefore, the research presented here endeavours to outline Cu potential zones in subsequent investigations appertaining the Chahargonbad area of SE Iran, using two of the noted integration methods that DMIO method was more accurate and produced more successful results.

CONCEPTUAL MODEL OF PORPHYRY CU DEPOSITS AND THE STUDY AREA

Porphyry copper deposits are usually located in linear parallel orogenic belts. They have a stock work to large-scale deposit of low grade (quality 0.4–1.0%) and high tonnage (up to 1000 million tons). These orogenic belts can be tens to hundreds or even thousands of kilometres long. One of the porphyry copper deposits is a composite, cylindrical and stock-like intrusive mass with an elongated or irregular outcrop with dimensions of about 2.0 × 1.5 km and is often surrounded by medium-grained rocks with a uniform grainsize texture. In the pre-orogenic stages, massive sulphide deposits of magmatic origin were formed from basaltic volcanoes, and at the end of this stage, copper and iron skarns and the first porphyry coppers formed from plagioclase phyric subvolcanic granitoid magmatism. Geological experts have not found significant copper deposits formed within the middle of the orogenic period, but rather most of the world's porphyry copper deposits have formed in the final stages of the associated orogeny. Porphyry copper mineralization results from the cooling of large igneous bodies of the granite family with combinations of subvolcanic granite to granodiorite to tonalite, quartz monzodiorite and diorite (Karimi et al., 2009; Aghazadeh *et al*., 2015). Among the proposed models for hydrothermal alteration, Lowell and Gilbert (1975) describe the pattern of hydrothermal alteration zoning of the San Manuel-Calamazo (Arizona) mineralization mass and compare their findings with 27 other porphyry copper deposits (Sillitoe, 2010). According to their claim, porphyry Cu deposits typically exist in connection with four hydrothermal alteration zoning patterns that, in common, contain potassic, phyllic, argillic, and propylitic from the centre to the outer parts, significantly extending recognizable spatial characteristics (John *et al*., 2010).

The quadrangle map of Chahargonbad district, with about 2500 km^2, is located in the southern part of the Urmia–Dokhtar volcanic belt and is part of Kerman province, Iran (Fig. 1a). Due to the fact that the Urmia–Dokhtar belt is vital in terms of porphyry copper mineralization, the fabric of the study area also has the essential potential to search for these deposits due to its location within this belt. Geologically, the region is covered by Eocene sedimentary and volcanic complexes and, in two narrow regions, Oligo-Miocene limestones and quartz diorite intrusions are exposed. The lithology of the complexes is mostly andesitic tuff, tuffite, limestone and conglomerate, and andesite. Tuffs have a crystal-clastic texture. Oligo-Miocene limestones are discontinuous within the complex and have a set of coral fossils. The quartz diorite body was emplaced as a long, continuous intrusion that extends in an east–west direction. The effect of this intrusion has appeared as diverse alteration and earlier hornfels of the surrounding host rocks. The complex collections have several faults and folds that provide conditions for the infiltration of hydrothermal fluids that facilitated derivative hydrothermal alteration. Supergene minerals on the surface include chalcocite, covellite, malachite, azurite and limonite, whereas

narcasite, galena, sphalerite and

hematite (Dimitrijevic, 1973; Shahabpour, 1994; Hosseini *et al*., 2017). Each lithologic unit was identified to determine the better relationship between geological formations and porphyry copper mineralization, as shown in Fig. 1(b).

Figure 1

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(a) Position of the study area in Urumieh-Dokhtar magmatic belt (UDMB) in Iran, southeast of Kerman. (b) Geological map of Chahargonbad district (Source: Geological Survey of Iran).

PROPOSED METHODOLOGY

The steps of applying the proposed method are shown in Fig. 2. The evidential layers were first created by processing geology, satellite images, geophysics, and geochemistrical data to obtain the final Mineral prospectivity mapping (MPM) and potential areas of porphyry Cu mineralization. Then, by C-A and P-A plots, the layers were evaluated, and the prediction rate of each layer was obtained. Also, by applying normalized density, the evidential layers were weighted. In the next step, all indicator layers should be overlaid through suitable integration methods. Two-hybrid methods of Fuzzy Logic and data-driven multi-index overlay were selected and used to obtain the high potential areas. In the final step, the mineral prospectivity mapping (MPM) from the mentioned integration methods were evaluated, and according to the prediction rate of each potential map, the final MPM was obtained.

Figure 2

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Schematic representation of the MPM producing for identifying porphyry copper mineralized areas.

Generation of continuous evidential maps with sigmoidal logistics transformation function

MPM is produced to identify exploration target areas for a particular type of deposit, and therefore, based on a conceptual model of the sought deposit, the required spatial data set should be collected and used to produce evidential maps. Since spatial data sets do not have the same maximum and minimum values, they do not have the same unit and dimension. Therefore, it is valuable to transfer the evidential values to the same space to better interpret

r, a sigmoid logistic function

(Equation 1), whose parameters are defined as data-driven (Yousefi & Carranza, 2015a, b), can be used to transfer values of evidential layers to the same space. In this study, in order to transfer the spatial values of evidential layers to the same space [0,1] and to weight the values in each evidential map, which show the relative importance of each evidential value, the following logistics function has been used:

μ x = 1 1 + e − s x − i ,

$$\mu_x = \frac{1}{1 + e^{-s(x-i)}} , \quad (1)$$

where μ_x is the transfer value, *i* and *s* are the inflexion point and slope of the logistic function, respectively, and *x* is a map value to be transformed in the [0,1] range.

Fractal analysis discretization and prediction-area plot of evidential maps

Identifying anomaly populations from background values is essential for exploration studies (Bai et al., 2010). Therefore, selecting a proper method for anomaly-background separation is vital in Mineral prospectivity mapping. C-A fractal model, which was initially suggested by Cheng *et al*. (1994) for separation of geochemical anomalies to determine thresholds, in a data-driven approach instead of using an arbitrary way, for the discretization of spatially continuous values in evidential layers (e.g., Parsa *et al*., 2016; Yousefi & Carranza, 2016; Ghezelbash & Maghsoudi, 2018; Daviran *et al*., 2020; Ghezelbash *et al*., 2021) is successfully used in various fields of geosciences.

The prediction–area (P-A) plot is a method to obtain prediction rate-occupied area of each map, which can be applied to analyse and evaluate the efficacy of various prospectivity maps in identifying types of mineralization and assign weights to evidential maps (Yousefi and Carranza 2014, 2015a, 2015c; Parsa *et al*., 2016; Ghezelbash & Maghsoudi, 2018; Daviran *et al*., 2020; Ghezelbash *et al*., 2021). The P-A plot has two curves, that is, the curve of the percentage (prediction rate) of known mineralization places based on the classes of the evidential layer or prospectivity map obtained from the C-A plot and the curve of the percentage of occupied areas based on the map classes examined. In the P-A plot, a higher amount in the intersection point of the two curves describes a small area containing many mineral deposits. Moreover, it determines a more suitable model to prioritize mineralization areas (Yousefi and Carranza, 2013, 2014, 2015a, 2015c; Daviran *et al*., 2020; Ghezelbash *et al*., 2021).

Normalized density

Normalized density is calculated by the prediction rate of each class divided by its corresponding occupied area, based on the total study area that assigns quantitative weights to classes of indicator layers. Here, to weigh the whole evidence layer and weight quantitatively to indicator layers, the prediction rate to the corresponding occupied area ratio was applied to calculate the normalized density using the intersection point in the prediction–area (P-A) plot. The parameters required to calculate the normalized density were obtained from the intersection point of the P-A plot. Normalized density was applied for ranking evidential layers as follows (see Yousefi & Carranza, 2015a, 2015b, 2015c):

N d = P r O a ,

$$N_d = \frac{P_r}{O_a} , \tag{2}$$

where N_d is normalized density, and P_r and O_a are prediction rate and occupied area from the P-A plot of each map.

The weight of each evidential layer can be obtained using the normalized density values obtained for each of them, according to the following equation (Yousefi & Carranza, 2015a, 2015b, 2015c):

W E = ln N d ,

$$W_E = \ln N_d, \tag{3}$$

where W_E is an objective weight of each evidential layer assigned to each map computed using the P-A model and its interception point.

Fuzzy logic prospectivity model

Since values of each evidential layer in this study have been given weights applying a logistic function and their weights are in the [0,1] range, they can be counted as fuzzy evidential layers. So the evidential layers can be combined with fuzzy operators (Bonham-Carter, 1994; Torppa *et al*., 2019). Therefore, each fuzzy operator included Fuzzy AND, OR, Product, Sum, and Gamma, can be employed considering the type of target mineralization and the purpose of the mineral prospectivity mapping (MPM). We used the fuzzy gamma operator, Equation (4), with a high gamma value (0.95), to combine the weighted evidential layers because, for MPM studies, a value of gamma more than 0.9 makes more accurate results (e.g. Bonham-Carter, 1994; Knox-Robinson, 2000; Yousefi & Carranza, 2015a; Sanusi & Amigun, 2020). The output map of applying this method is a logistic-based fuzzy MPM, that continuous evidential layers were utilized for combination.

$$\mu_c = \left[1 - \prod_{i=1}^{n}(1-\mu_i)\right]^{\gamma} \times \left[\prod_{i=1}^{n}\mu_i\right]^{1-\gamma}, \tag{4}$$

where μ_c for each unit cell is the final prospectivity score, μ_i is the fuzzy score for the cell of the *i*th input layer and ($1 \leq \gamma \leq 0$) (Yousefi & Carranza, 2016). The gamma operator accurately represents decision-making with the help of the γ parameter, which indicates the degree of compensation and is set between 0 and 1, implying no compensation at all or whole compensation. In most efficient implementations (Von Altrock, 1997), γ takes values between 0.1 and 0.9. The parameter γ identifies where the operator is located between the logical ‘AND’ and `OR’ (Peneva & Popchev, 1999).

Data-driven multi-index overlay

One of the most common methods to integrate the evidential layers is a knowledge-driven method to produce mineral prospectivity mapping named the multiclass index overlay method (Bonham-Carter, 1994; Nykänen, 2008; Moradi et al., 2015). By applying this method, indicator layers are discretized within several random classes, and then the weighted indicator layers can be integrated subjectively. However, in this study, the weights of continuous values of each indicator layer were calculated neither using precisely the locations of known mineralization occurrences nor applying the expert's opinions (Yousefi & Carranza, 2015a; Parsa *et al*., 2016). According to the percentage of known mineralization areas and the study area's percentage from the prediction–area (P-A) model, the weights of indicator layers were calculated by Equation (3) and assigned to layers base on their potential in identifying mineralization occurrences. Thus, the index-overlay can be applied as a new function named data-driven multi-index overlay (DMIO) that is presented as follows:

$$\mathrm{DM}_{\mathrm{IO}} = \frac{\sum_i^n T_{vi} w_i}{\sum_i^n W_i}. \tag{5}$$

For each pixel of a layer in this study, DMIO is the score of the applied method; W_i shows the weight of each indicator layer *i*, indicated using intersection point of P–A plot and normalized density method, Equations (2) and (3). The T_{vi} is the pixel value in each indicator layer *i* transformed using a logistic function (Equation 1) (Yousefi & Carranza, 2015a, 2015b).

PREPARING AND EVALUATION THE EVIDENTIAL MAPS

The associated geological, geochemical, geophysical, and remotely sensed data covering the study area were processed, and the required evidential layers were prepared. This section describes the preparation procedures for deriving the main evidential layers from primary raw data. After producing each evidential layer from exploration data, firstly, they were divided into a pixel size of 100 m × 100 m network, and secondly, their values were transformed using the logistic function into the [0,1] range (Equation 1) (Yousefi and Carranza, 2014, 2015; Yousefi *et al*., 2014;). After that, all of them were evaluated and weighted using C-A and prediction–area plots.

Remote sensing layer

There are four types of alteration in porphyry Cu mineralization areas: argillic, phyllic, propylitic and potassic, and also iron oxides/hydroxide minerals such as limonite, jarosite and hematite and gossan are common in these mineralization types. Three satellite data of ETM^+ (LE07_L1TP_160040_20190321_20190322_01_RT; path/row 160/40), two cloud-free ASTER (levels L1T), and two Landsat 8 OLI, cloud-free images level 1T, (LC81600392013199LGN00; path/row160/39, and LC81600402013199LGN00; path/row160/40) cover the target study area that were georeferenced to UTM zone 40 North projection WGS−84 datum.

For obtaining hydrothermal alteration layers, which include Argillic, Phyllic, and Propylitic and iron oxide layers from ETM^+ satellite data, three methods were applied: Band Ratio, Principal Component Analysis and Least-Squares Fitting (LS-Fit).

For ASTER satellite data, processing procedures such as a BR named Relative Absorption Band Depth (Wu *et al*., 2019), Spectral Angle Mapper, Matched Filtering (MF) and PCA were utilized to find hydrothermal iron oxide alteration.

Finally, BR, PCA and Mixture Tuned MF methods were adopted (Pour & Hashim, 2015; Pour *et al*., 2018; Routh *et al*., 2018) to obtain hydrothermal alteration and iron oxide from Landsat 8 satellite data.

The base of the selection of the alteration areas was the amount of conformity between the alteration areas and lithological units of the study area. Potassic alteration areas were detected using geophysical radiometric data and lithological features (Markandeluyu *et al*., 2014; Mosusu *et al*., 2016; Riahi *et al*., 2021). The high K/eTh ratio indicates an elevated potassic alteration in the radiometric map, which occurs during porphyry Cu mineralization (Shives *et al*., 1995; John *et al*., 2010).

Each alteration layer was evaluated and weighted by C-A and P-A plots and integrated using the Fuzzy OR operator (Equation 6). The fuzzy OR is comparable with the Boolean OR (logical union), whereby the result fuzzy membership values represent the highest values of each input layer for each particular location. This operator, in different circumstances, can be appropriate

Loading [MathJax]/jax/output/HTML-CSS/fonts/STIX-Web/Symbols/Regular/Main.js for the occurrence of target mineralization is limited, and the existence of each evidence may be adequate to propose favourability (Fig. 3a).

$$\mu_{\text{Combination}} = \max\,[\mu_A,\ \mu_B,\ \mu_C,\ \ldots], \tag{6}$$

where μ_A is the fuzzy membership value for map A at a particular location, μ_B is the fuzzy membership value for map B, and so on.

Figure 3

Open in figure viewer | PowerPoint

(a) Map of the remote sensing layer that shows the hydrothermal alteration and iron oxide in the study area. (b) Concentration–area model (C–A), log–log plots for the values of the remote sensing map (a). (c) Discretized values of the remote sensing map. (d) Prediction–area (P–A) plot for the discretized remote sensing layer in (c).

Geophysical layer

All airborne geophysical data were collected in 1976–77 by Prakal Company for the Iran's Atomic Energy Organization. For data gathering across Iran, flight altitude was such that the nominal terrain clearance was nearly 120 m. The distance between flight lines was 7.5 km, and tie lines with 40 km spacing and direction of azimuth flight lines were 045° and 225°. The aeromagnetic data over Chahargonbad district (target study area) with a flight distance of nearly 500 m were provided after applying basic magnetic data corrections such as daily correction and elimination of the magnetic effect of the core field of the earth by the International Geomagnetic Reference Field model of 1975 and alignment. Reduction to the magnetic pole, which move residual magnetic data to positive portions of the signal over the causative sources of the anomaly, was applied to the data to facilitate the geological interpretation and discover the intimate links between magmatic bodies and magnetic signals (Baranov, 1957). In addition, analytic signal (Equation 7) and total horizontal derivative (Equation 8), respectively, were applied to eliminate the magnetic complexity of the geological environment, enhance the boundaries and extend magnetic blocks deeper than 1 km (Arisoy & Dikmen, 2013; Kheyrollahi *et al*., 2018). The C-A and P-A plots for each geophysical map from mentioned filters were obtained to weigh the geophysical indicator layers. Weighted geophysical layers were merged using fuzzy AND operation (Equation 9) to produce the signature of magnetic complication of the geological environment in a single indicator map

the product map be controlled

by the minimum fuzzy membership value present at each location of the study area. The fuzzy AND operator are proper where two or more pieces of evidence for a hypothesis are required to be existing simultaneously for the hypothesis to be valid.

$$|AS(x,y)| = \left(\frac{\partial T}{\partial x}\right)^2 + \left(\frac{\partial T}{\partial y}\right)^2 + \left(\frac{\partial T}{\partial z}\right)^2, \tag{7}$$

$$TDX = \left(\frac{\partial T}{\partial x}\right)^2 + \left(\frac{\partial T}{\partial y}\right)^2, \tag{8}$$

where T is the magnetic field, $\partial T/\partial x$ and $\partial T/\partial y$ are the two orthogonal horizontal derivatives of the magnetic field and $\partial T/\partial z$ is the vertical derivative of the magnetic field.

$$\mu_{Combination} = \min[\mu_A, \mu_B, \mu_C, \dots] \tag{9}$$

Figure 4

Open in figure viewer | PowerPoint

(a) Map of the geophysical layer that shows the magnetic bodies and potassic alteration areas in the study area. (b) Concentration–area model (C–A), log–log plots for the values of the geophysical layer (a). (c) Discretized values of the geophysical layer. (d) Prediction–area (P–A) plot for the discretized geophysical layer in (c).

Geochemical layer

After applying the catchment basins method on stream sediment geochemical data containing Cu, Mo, Zn, Pb, Ag, Co, Ni, Cr and Ba to reduce background lithological environment, univariate and multivariate analyses methods were applied to geochemical data to identify porphyry Cu mineralization areas. The two elements of copper and molybdenum showed the highest correlation in the Pearson Product correlation table and have a linear relation in the dendrogram of the region, and also according to the fact that these two elements are in the same paragenetic group; therefore, the geochemical map of these elements increase the possibility of identifying the porphyry Cu mineralization areas. Factor Analysis (FA), one of the beneficial methods for processing geochemical data, was applied on geochemical data, and the best factor map for Cu was selected as a geochemical indicator map (Reimann *et al*., 2002; Carranza, 2011; Yousefi *et al*., 2012, 2013; Gysi *et al*., 2020). Finally, to obtain a final geochemical layer, three maps of Cu and Mo and FA was weighted by C-A and P-A plots and combined the fuzzy OR (Equation 6) operator (Fig. 5a).

Figure 5

Open in figure viewer | PowerPoint

(a) Map of the geochemical layer that shows the related areas with porphyry Cu mineralization. (b) Concentration–area model (C–A), log–log plots for the values of the geochemical layer (a). (c) Discretized values of the geochemical layer. (d) Prediction–area (P–A) plot for the discretized geochemical layer in (c).

Lineaments layer

Due to the significant importance of linear structures, fractures and especially faults in the passage of magmas and derivative fluids and focusing mineralization to form valuable deposits, such as porphyry Cu deposits, the areas where there is a high density of lineaments are considered as a reliable indicator for mineralization. In this study, the final layer of lines was obtained by combining these three maps:

1. lineaments resulting from the application of directional filters on satellite data;
2. linear structures and edges of formations, obtained from the application of directional derivatives filters on aeromagnetic data;
3. the final principal group of lineaments related to the target mineralization used to create the final lineaments evidential layer is the faults layer obtained from the geological map of the study area. The fault density was obtained for creating this layer, and the prepared fault concentration map was applied as a structural evidence map.

$$\mathrm{THDR} = \partial\, \mathrm{Tilt}\, \partial\, x\, 2 + \partial\, \mathrm{Tilt}\, \partial\, y\, 2\, ,\ \mathrm{Tilt} = \tan\, -\, 1\, (\, \partial\, T\, /\, \partial\, z\, \partial\, T\, \partial\, x\, 2 + \partial\, T\, \partial\, y\, 2\,)\, , \tag{10}$$

$$\cos\theta = \partial\, T\, \partial\, x\, 2 + \partial\, T\, \partial\, y\, 2\, \mathrm{AS}\, . \tag{11}$$

As for the point (2) above, it is worth noting that there are various edge detection filters to extract lineaments from aeromagnetic data. Filtering procedures, such as vertical and tilt derivatives, are generally applied to identify high amplitude, that here in addition two method approaches were also used to recognize lineaments more accurately. The total horizontal derivative of the tilt angle approach (Verduzco *et al.*, 2004), based on the total horizontal derivatives of tilt angle, is sensitive to noise impact and could not adequately exhibit deep-level geologic boundaries (Equation 10). The theta angle method (Wijns *et al*., 2005) (Equation 11), which adjusts the total horizontal derivatives via investigating the signal amplitudes (Roest *et al*., 1992), has produced satisfying results, yet the boundaries delineated are diffused to some extent. Therefore, these methods are a composition of vertical and horizontal derivatives and enhance the boundary of the shallow and deep magnetic sources simultaneously (Arisoy & Dikmen, 2013; Zhang *et al*., 2015)

Figure 6(a) shows the final lineaments density layer compiled by all the above-mentioned structural indicators. Like other evidential layers, C-A and P-A plots were applied to calculate each map's weight, and after that, the Fuzzy AND operator (Equation 9) also were applied to combine them.

Figure 6

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(a) Map of lineaments layer that shows all the lineaments and structures in the study area. (b) Concentration–area model (C–A), log–log plots for the values of the lineaments layer (a). (c) Discretized values of the lineaments layer. (d) Prediction–area (P–A) plot for the discretized lineaments layer in (c).

Lithological layer

In order to prepare the lithological factor map of the region, first, the 1: 100,000 geological map of the region was digitized, then the same rock units were placed in a group due to having the same degree of importance. As a result, the number of rock sets was reduced to a small number, and a lithological factor map was obtained. Then, a specific value was assigned to each lithological category based on their importance and potential as hosts of porphyry Cu mineralization. In this way, the final lithological evidential layer for porphyry Cu mineralization was produced, as shown in Fig. 7(a).

Figure 7

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(a) Map of lithological layer of the study area. (b) Concentration–area model (C–A), log–log plots for the values of the lithological layer (a). (c) Discretized values of the lithological layer. (d) Prediction–area (P–A) plot for the discretized lithological layer in (c).

Evaluation and weighting the evidential layers

Considering the preceding discussion, features of obtained evidential layers (e.g. alteration, geophysical anomalies, geochemical anomalies, lineaments distribution and lithological features) have fractal dimensions. In this paper, as mentioned, the C–A fractal model (Figs 3, 4, 5, 6 and 7b) proposed by Cheng *et al*. (1994, 1999) was used to determine data-driven thresholds, for classification of spatially continuous values in evidential layers to get discretized weighted evidential layers (Figs 3, 4, 5, 6 and 7c). After that, the prediction–area plot was used to evaluate and weigh evidence maps (Figs 3, 4, 5, 6 and 7d).

INTEGRATION OF EVIDENTIAL LAYERS

Aiming to model the mineralization prospectivity of porphyry Cu in the Chahargonbad geological sheet, weighted evidential layers were combined to generate target areas. In this study, two combination functions, namely (1) fuzzy logic prospectivity model and (2) Data-driven multi-index overlay were used.

Integration using fuzzy logic

As mentioned, the fuzzy gamma operator with a high value of $\gamma = 0.95$ was used to ensure that the operator neither dominantly increased nor decreased. The output map (Fig. 8a) is a logistic-based fuzzy mineral prospectivity map produced using integrating the weighted evidential layers.

Figure 8

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(a) MPM of fuzzy logic operation generated by combining continuous maps of transformed values of evidential layers using Equation (4). (b) Concentration–area model (C–A), log–log plots for MPM values in (a). (c) Discretized MPM. (d) Prediction–area (P–A) plot for the discretized MPM in (c).

Integration using data-driven multi-index overlay

As mentioned previously, the data-driven multi-index overlay (DMIO) method is a kind of index overlay applied in a data-driven way. Here, continuous values in evidential layers are weighted without directly applying known mineral occurrences and without expert judgment (Yousefi & Carranza, 2015a, 2015b). The weights of evidence maps are indicated regarding their ability to predict mineralization occurrence areas based on the prediction–area (P–A) plot. Therefore, Equation (5) of DMIO can be adapted based on obtained evidential layers as follows:

$$DM\ IO = TV\ RS\ W\ RS + TV\ Gph\ W\ Gph + TV\ Gch\ W\ Gch + TV\ LD\ W\ LD + TV\ Lith\ W\ Lith\ W\ RS + W\ Gph + W\ Gch + W\ LD + W\ Lith\ , \quad (12)$$

where W_{RS}, W_{Gph}, $W_{Gch,}$ W_{LD}, and W_{Lith} are weights of indicator layers, namely remote sensing (RS), geophysical layer (Gph), geochemical layer (Gch), line density (LD), and lithology (Lith), that are weighted according to their respective P–A model (Figs 3, 4, 5, 6 and 7d). In Equation (12), TV_{RS}, TV_{Gph}, TV_{Gch}, TV_{LD} and TV_{Lith} are the transformed pixel values in their indicator layers (Yousefi & Carranza, 2015a, 2015b). The MPM for porphyry Cu mineralization in the study area by the DMIO method created applying Equation (12) is displayed in Fig. 9(a).

Figure 9

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(a) MPM of data-driven multi-index overlay function generated by combining continuous maps of transformed values of evidential layers using Equation (11). (b) Concentration–area model (C–A), log–log plots for MPM values in (a). (c) Discretized MPM. (d) Prediction–area (P–A) plot for the discretized MPM in (c).

Evaluation the results

In the study area, there is 28 known porphyry Cu mineralization areas. This known porphyry Cu mineralization was plotted utilizing their prediction–area (P–A) attributes to evaluate the fuzzy logic, and data-driven multi-index overlay (DMIO) models were produced in this study. Hence, the relation of known Cu deposits with various classes of an mineral prospectivity mapping (MPM) is evaluated by overlaying the places of known Cu deposits on a discretized model (e.g. Carranza *et al*., 2005; Yousefi and Carranza, 2012, 2013; Parsa *et al*., 2016). We used the C–A fractal model (Figs 8b and 9b) introduced by Cheng *et al*. (1994, 1999) to define threshold prospectivity values for the discretization of the fuzzy logic and DMIO models (Figs 8a and 9a) (Yousefi & Carranza, 2015a, 2015b, 2015c). According to Figs 8(b) and 9(b), we discretized the fuzzy logic and DMIO MPMs (Figs 8c and 9c), and then the P–A plots (Figs 8d and 9d) for these models created.

According to the intersection point in Figs 8(d) and 9(d), the fuzzy logic (Fig. 8a) predicts 29% of the study area as prospective in which 71% of the known porphyry Cu occurrences are delineated (Fig. 8b), and the DMIO (Fig. 9a) predicts 24% of the study area as prospective in which 76% of the known porphyry Cu occurrences are delineated (Fig. 9b). Accordingly, their normalized densities are 2.448 (71/29) and 3.167 (76/24); also, their weights are 0.895 (ln 2.448) and 1.153 (ln 3.167), respectively, showing meaningful association with mineral localities.

These results (Table 1) determine that areas with high prospectivity values, based on these applied models, can be used as exploration guidelines for further studies; according to Mihalasky and Bonham-Carter (2001), who suggested classes of evidential layers or, in this paper, prospectivity models that have the normalized density more than one are dependable preospective maps for types of mineralization. But as it is obvious, the values of prediction rate, normalized density, and weight of the DMIO model are higher than other layers, and it can be selected as the final MPM for porphyry Cu in this study. Also, Fig. 10 illustrates the advantages of combining evidential layers using the DMIO method compared to the fuzzy Logic method.

Table 1. Results of evaluation final layers for porphyry Cu prospectivity mapping

Layers	Prediction Rate (Pr)	Occupied area (Oa)	Normalized density (Nd)	Weight
Remote Sensing	67	33	2.0303	0.708
Lithology	68	32	2.125	0.753
Geophysics	62	38	1.631	0.489
Geochemistry	69	31	2.225	0.8
Lineaments	65	35	1.857	0.619
Fuzzy logic MPM	71	29	2.448	0.895
Data-Driven Index Overlay MPM	76	24	3.167	1.153

Figure 10

Open in figure viewer | PowerPoint

Comparing the performance of the two applied methods, as displayed in the diagram, the difference between the percentage of known mineralization and the percentage of the study area in the DMIO method is higher, showing its superiority to the fuzzy Logic method.

DISCUSSION

To investigate a specific type of mineralization, the data-driven method cannot be used in mineral prospectivity mapping (MPM) if there are no known mineralization occurrences in the study area, or the number of known mineralization occurrences is low. Also, if the knowledge-based method is used in these cases, the weight assigned to a single evidential layer by two or more experts may be different. Here, this problem is solved to produce the evidential layers by using C-A and prediction–area plots with the locations of known mineral occurrences and overlaying the locations of known mineralization deposits on the evidential maps.

The integration of evidential layers is done using the fuzzy logic method through several operators. These operators include OR, AND, fuzzy sum, fuzzy product and finally fuzzy gamma. Fuzzy operators involve a type of uncertainty since output obtained through these operators is only affected mainly by the amount of input, which are the pixel values of each layer, or the disadvantages of both types of operators are included simultaneously. Due to the mentioned reasons and the fact that the final MPM obtained from this method had a lower prediction rate, and it can be said that the DMIO method is more reliable than fuzzy logic, therefore the final MPM obtained from this method is dependable.

CONCLUSIONS

According to the studies conducted here, the obtained results can be summarized as follows:

- The data-driven multi-index overlay (DMIO) method can overcome the limitations of the fuzzy logic method and improve the uncertainties related to the mineral potential mapping.
- In addition to being statistically accurate, this method is also valid for both types of brown field areas (areas with good exploratory surveys or areas where there are sufficiently known occurrences of the deposit being sought) and green field areas (areas with much fewer and or less significant known mineralization occurrences).
- The combination of data-driven and knowledge-driven methods introduced in this paper will produce a mineral prospectivity mapping (MPM) in which the produced target mineralization areas are reasonably compliant with known mineralization occurrences (evaluation and validation points).
- The combined method introduced in this paper, which uses data-driven and knowledge-driven methods simultaneously, solves the problem of directional weight allocation to evidential layers, improves the model output and produces more reliable porphyry Cu potential areas that can be used for further exploration studies. Indeed, if the focus of subsequent exploration activities as ground-based and large-scale exploration was on these areas, it will avoid spending time and money in areas with lower mineralization potential.
- In this study, fuzzy logic and DMIO were used to integrate evidential layers, and a data-driven prediction-area method was used to evaluate the results of the final MPM. The results show that for the prospective (potential) DMIO model, 76% of the known deposits in

24% of the study area are predicted. Therefore, this method can be used to model mineral potential and identify target areas in exploration studies of a particular type of deposit.

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DATA AVAILABILITY STATEMENT

Data are available on reasonable request to the corresponding author via email address maysamabedi@ut.ac.ir.

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