A Hybrid Fuzzy Ordered Weighted Averaging Method in Mineral Prospectivity Mapping: a case for Porphyry Cu Exploration in Chahargonbad District, Iran

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Abstract

This research case study presents a fuzzy ordered weighted averaging (FOWA) method for mineral prospectivity/potential mapping (MPM) at Chahargonbad district in SE Iran, a system whereby new areas of high prospectivity for porphyry Cu mineralization are identified. The ultimate goal of this research is to find the complex and hidden relationships between the evidence layers and known ore occurrences using a comprehensive consideration of a multi-disciplinary geospatial data set. Hence, thirteen evidences are accurately derived from available databases, including geological, geochemical, geophysical, and remote sensing, and integrated through a FOWA multi-criteria decision-making approach to delineate favorable Cu-bearing zones. FOWA methodology uses a wide range of decision strategies to synthesize input geospatial evidences utilizing multiple values for an alpha parameter as the cornerstone of the algorithm that controls the experts' attitude toward the MPM risk. It is reflected through the generation of seven mineral potential maps to search the most suitable one(s). Considering a prediction-area plot for data-driven weight assignment of each evidence map, the hybrid FOWA outputs are searched for the most appropriate map in targeting notable Cu occurrences. The desired synthesized evidence map could indicate an ore prediction rate of 77%, where known Cu deposits were distributed at favorable zones occupying 23% of the whole district area.

Keywords: Fuzzy ordered weighted averaging, Mineral potential/prospectivity mapping, Evidence layers, Porphyry Copper, Chahargonbad

1. Introduction

Mineral potential/prospectivity mapping (MPM), as an essential tool for exploration, investigates all geological processes responsible for the distribution of mineral deposits, then uses them to map areas with potential mineralization [1, 2, 3]. Increasing the number of geospatial databases and decreasing the areas prone to ore mineralization have motivated exploration groups to employ diverse geospatial data sets and state-of-art statistical techniques to evaluate them systematically; subsequently they are employed to help identify blind spatial trends in the data associated with mineralization processes. Nevertheless, utilizing, developing, and proposing novel and valid methods have been of focused interest in MPM [4].

In MPM, geospatial databases are mostly comprised of geology, geochemistry, remote sensing, and geophysics attributes by which key indicators are integrated in a single favorability map for the desired target sought [5, 6]. The principal objective of MPM is to determine the main regions favorable to ore formation (fluid reaction and trapping) in the prospect areas and (or) to expand and (or) discover new ore occurrences [7, 8]. MPM simultaneously maximizes the profitability achieved during a mineral exploration task, while minimizing cost and risk of those preliminary exploration activities [9].

Nowadays, contrary to popular and conventional categories of MPM (i.e. the knowledge- and data-driven techniques), two modern variants of MPM have attracted considerable attention [10, 11]: 1) a hybrid approach derived from the integration of knowledge- and data-driven methods that simultaneously considers the opinions of experts and the spatial features of known mineral deposits [12, 13, 14], and 2) assigning weights to continuous spatial evidence layers regardless of the opinions of experts, in other words applying a data-driven way for calculating the weights, rather than using expert judgment [15, 16]. However, combining two data- or knowledge-driven methods or two modern variants can be introduced as a hybrid approach. For example, in numerous studies decision-makers “DMs” have used a combination of two or more different multi-criteria decision making “MCDM” methods to formulate better decisions by combining advantages of at least two of these conventional methods to make up for the shortcomings of single methods [17, 18, 19]. Considering all the above-mentioned aspects successful implementation of MPM requires simultaneously careful selection of the appropriate target area and precise preparation of input geospatial evidences/criteria (i.e. geological, geochemical, remote sensing, and geophysical layers) related to the type of deposit sought. Accordingly, the MPM can be considered as an MCDM problem.

In this study the fuzzy ordered weighted averaging (FOWA), as a well-developed and well-known methods in MPM [20], is utilized to integrate thirteen evidence layers (i.e., decision criteria in MCDM), and produce the mineral potential map of porphyry-related Cu occurrences at the Chahargobad district in Kerman province of Iran. We have discussed the application of the FOWA method to an exploratory geospatial database, designed and extracted from airborne geophysical data, geological layers (i.e. fault and host rock zones), various extracted alteration layers from remote sensing images and stream sediment geochemical data. FOWA is one of the most practical MCDM methods [21], rarely applied in MPM, which has power of modelling uncertainty and risk in criteria aggregating [20]. In this research to benefit from this exclusive feature, the concentration–area (C–A) fractal model [22], prediction–area (P–A) plot, and normalized density method [23, 24], are applied to classify, evaluate, and assign data-driven weights to evidence layers and consequently in evaluation and validation of the Cu favorability map. The hybrid FOWA method is examined with various values of input parameters, which control experts' attitude toward risk-taking or -averse on synthesized geospatial layers. It provides reliable insights about the mineralized areas, and can be used in future studies and other regions of interest as a powerful approach with capability of producing different outputs according to the opinion of experts.

2. Geological features of the study area

Chahargonbad district is located within the southern part of the Urumieh–Dokhtar volcanic belt, an Andean-like magmatic arc, north of the city of Sirjan in Kerman Province, Iran. This portion of the Urumieh–Dokhtar magmatic belt (UDMB) is known for some well-known porphyry Cu deposits, such as Sarcheshme, Darehazar, Meidok, and Chahargonbad [25, 26], which were the result of subducting the Neotethys oceanic plate beneath the Iranian plate. The studied region is ~2,600 square kilometers, and outlined by the quadrangle map of Chahargonbad at a scale of 1:100,000 (Fig. 1a) by the Geological Survey of Iran (GSI) [27]. Due to its tectonic and geological characteristics, a part of the Zagros orogenic belt, which are similar to other copper belts in the world, the UDMB is highly favorable for copper mineralization. From a geological point of view, the study area mainly consists of the Eocene pyroclastic complex and two narrow zones of Oligocene-Miocene limestone and intrusive quartz diorite, which were probably emplaced after the Miocene. The host pyroclastic complex is mainly composed of andesitic tuffs, tuffite with limestone, conglomerate, and andesitic flows. Porphyritic quartz diorites are the only intrusive rocks that outcrop in the Chahargombd area, forming several irregularities that are stretched in the east-west direction, and are most likely post-Miocene in age. The main manifestation of these fertile intrusions on the nearby rocks is extensive and locally intense hydrothermal alteration of various types [27, 28]. Most rock outcrops in the Chahargonbad district are Eocene volcano-sedimentary rocks. Southwest of the study area, the oldest geological unit is exposed as a tiny outcrop of a metamorphic sequence. Quaternary alluviums are the youngest geological units in the target area, with greater distribution in the northeastern part (Fig. 1b) [27]. The notable tectonic activity of late Miocene age caused folding then faulting of most rocks in this area with a dominant NW-SE trend. The late brittle activity gave rise to differential dilatancy in the older rocks facilitating the high-level emplacement of quartz dioritic magmas and locally co-eruptive products, as well as infiltration and then circulation of hydrothermal-magmatic fluids. The Cu-bearing occurrences are typically closely related to these coincident geological features, with intrusions spatially and temporally linked to several types of alteration.

Fig. 1.

3. Methodology

3.1. Evidence mapping

Evidence layers were created through processing all geological, geophysical, geochemical data, and satellite images, while a geospatial database is designed for porphyry Cu MPM. Thirteen evidence layers were discussed in detail by revisiting a multi-disciplinary geospatial database produced by authors (see [19, 29, 30, 31]). Figure 2 presents a succinct outline and schematic flowchart of geospatial data management in this region, which concisely explains all steps required for the final stage of data integration key to accomplishing a hybrid FOWA method.

For producing the various remote sensing evidences, satellite imagery data were processed by a sequence of techniques, such as False color composition, band ratio, Ls-Fit, principal component analysis, and spectral base methods (spectral angle mapper and mixture tuned matched filtering) on ASTER and OLI data. They could produce hydrothermal alteration layers for argillic, phyllic, propylitic, and iron oxide mapping. In addition to the various alteration types, lineaments mapping from applying directional filters was applied to highlight these structural features.

By comparing the results of different filters applied to the aeromagnetic geophysical data, analytic signal (AS), and total horizontal derivative (TDX) layers were merged in a single map, and the magmatic intrusive units responsible for magnetic signatures and ore-forming process were mapped as a geophysical layer. In addition, deep-seated hidden faults and magnetic lineaments were extracted from directional derivative-based filters, which are the total horizontal derivative of the tilt angle (THDR) and the theta angle on the aeromagnetic data. A ratio of K/eTh from airborne radiometric data (see Mohebi et al. 2015) [38], was computed to map areas in association with the potassic alteration frequently observed in porphyry-type ore-bearing systems.

Surficial geochemical evidence features were prepared by applying the catchment basins method on stream sediment geochemical data for Cu, Mo, Zn, Pb, Ag, Co, Ni, Cr, and Ba to remove the adverse impact of background lithological variations on the concentrations. Examining several univariate and multivariate analysis methods (e.g., factor analysis “FA”) on the geochemical data by targeting Cu porphyry mineralization, three evidences include Cu and Mo, as well as the main geochemical factor determined were used in the geospatial database. Moreover, to these 3 evidence layers, the lithological map of the region was also scored. The 1: 100,000 geological map was first digitized, and the rock units on the basis of their importance for hosting known porphyry Cu mineralization were then scored. A fault density map was the final evidence used; it was derived from the surface field observations reported on a geological map. It is worth noting that the presence of numerous lineaments and faults delineate structurally favorable brittle features that are suitable conduits for hypabyssal emplacement of intrusions [39] and focusing fluid flow; these places can provide suitable environments for focusing ore deposition [40-42].

Fig. 2.

There are 28 known and active porphyry-related Cu mines in this district [43], as shown in Fig. 1b, which are used in plotting the P-A curve to derive the weights of each evidence and finally in MPM through a hybrid FOWA method. According to the plotted P-A curve for each evidence layer (Fig. 2), ore prediction rate and subsequent occupied area are determined at the intersection point. Then, the weight of each evidence layer is calculated through the normalized density relationship that is the ratio of ore predication to occupied area. The parameters extracted from the P-A plot and the obtained weights for each evidence layer are summarized in Table 1.

Table 1.

3.2. Hybrid FOWA method

The OWA operator associated with the i^th alternative, which coincides with a sample point with x and y coordinates in geospatial database, has the following output [21, 32, 33],

$$OWA_i = \sum_{j=1}^{n} \left(\frac{u_j v_j}{\sum_{k=1}^{n} u_k v_k}\right) z_{ij}, i = 1,2,\ldots,m \tag{1}$$

Note that the *AND* and *OR* operators represent the limit values of the OWA which correspond to the MIN and MAX operations, respectively. Here, the ordered weights v_i are at an interval of [0,1] provided that $\sum_{j=1}^{n} v_j = 1$, and $z_{i1} \geq z_{i2} \geq \cdots \geq z_{in}$ is the sequence obtained by reordering the criterion (evidence layer) scores. In addition, u_j is the reordered criterion weight according to the criterion score z_{ij}.

Given a set of criteria (evidence) maps and a fuzzy linguistic characterizing quantity Q, a procedure for criteria integration can be accomplished by a statement about the relationship between the evaluation criteria. For instance, the combination strategy may be controlled by the following statements: most criteria must be met, at least half of the criteria must be met, all criteria must be met, and etc. This procedure depends on the qualitative-guided quantitative multi criteria evaluation [21, 32]. Yager (1998) adopted the concept of linguistic quantifier of Zadeh (1983) and introduced a quantifier guided OWA method [32, 34].

In a quantifier-guided aggregation process, the DM presents a strategy with a linguistic quantifier that specifies a set of criteria necessary for a suitable solution [34]. The conventional decision strategy is that "the criteria for Q must be satisfied by an acceptable alternative," where a linguistic quantity replaces Q. Two categories of quantifiers were used: (1) absolute quantifiers for quantifying linguistic variables such as "~5" and "~10", and (2) relative quantifiers, used for statements such as "a few," "almost", "most" and so on are operated [35]. There is no empirical evidence confirming the suitability of either of these two classes of linguistic quantifiers for MCDM problems [21, 32, 36]. These quantifiers can be represented as fuzzy sets of unit intervals [0,1]. Here, a class of relative quantifiers known as regular increasing monotone (RIM) quantifiers are used and are more common in personalized systems [21, 32]. In this approach, Q(r) for each [0, 1] ∈ r represents the membership that shows the compatibility of r with the concept represented by Q [21].

$$Q(r) = r^{\alpha}, \alpha \geq 0 \tag{2}$$

Changing the parameter α makes it possible to generate different types of quantifiers and related operators between the two states of maximum (OR operator or risk-taking) and minimum (AND operator or risk-aversion) of desired criteria for reaching a decision. For α = 1, Q(r) is proportional to r and is therefore referred to as the identity quantity. Given the criterion weights (here through the P-A plot) and the ordered weights, the hybrid FOWA operator is calculated as following [21],

$$FOWA_i = \sum_{j=1}^{n}\left(\left(\sum_{k=1}^{j} u_k\right)^{\alpha} - \left(\sum_{k=1}^{j-1} u_k\right)^{\alpha}\right) z_{ij}, i = 1,2,\ldots,m \tag{3}$$

The hybrid FOWA can then generate several outputs through considering multiple values of α, each one corresponds to level of risk-taking (lower amount of α) or risk-aversion (higher amount of α) in final decision [20, 37].

4. Results and Discussion

After preparing all the evidence layers, and determining the importance of each layer in identifying the desired target through the P-A plots summarized in Fig. 2 and Table 1, the hybrid FOWA method was executed for seven values of α. It can take different values from 0 to infinity, and the result of each must be evaluated then. For this purpose, the values 0, 0.1, 0.5, 1, 2, 10, and infinity were examined. In Fig. 3, the Cu potential maps from applying different values of the α parameter are shown, and as it is apparent for values of α= 0, 10, and infinity, the potential maps are less reliable through a visual check and were not considered for further evaluation. They are equivalent to *OR* and *AND* operators, when respectively low and high values of alpha parameter are assigned. Table 2 illustrates the extracted parameters from the P-A plots of the synthesized evidences assuming α parameters equal to 0.1, 0.5, 1, and 2.

Fig. 3.

Table 2.

According to the values of the prediction rate for each of the synthesized maps with different α values, it is clear that the prediction rate is the highest in the case where the value of the α parameter in the hybrid FOWA algorithm is equal to 0.5. Therefore, this map is selected as the final Cu favorability map. Figure 4 depicts this map while a C-A fractal model has been used to classify the continuous map into several populations. In addition, the P-A plot indicated an ore prediction rate equal to 77% in a favorable region with an occupation area of 23% for further advanced exploration investigations.

Fig. 4.

According to the intersection point of the P-A plot obtained from the final FOWA MPM, we could identify a threshold for separating background values from the values of areas of notable potential. Therefore, a two-class map is created with a threshold value of 0.58. This map, illustrated in Fig. 5, clearly shows the location of areas with exploration potential for mineralized porphyries and the relation between the known mineralization occurrences and those with Cu-bearing potential. It seems that these favorable zones follow the NW-SE structural trend (faults and lineaments). Based on this model, most areas of exploration potential are located in the western half of the area under consideration, especially the NW and SSW parts of the study area. Comparing this map with other evidences individually shows that MPM generated higher ore prediction rate in a much smaller percentage of occupied area.

Fig. 5.

5. Conclusions

Accurate selection of mineralization areas for further exploration to possible mining activity is a complex task that requires simultaneous consideration of multi-disciplinary geospatial data sets and implementing appropriate methods to outline and delimit favorable mineralized zones. In this study, it was essential to have a systematic procedure to identify porphyry copper indicators and prioritize potential areas to focus on for further studies and exploration operations within the Chahargonbad district. A hybrid FOWA method as a well-known approach in MCDM problems was utilized to synthesize evidence layers through various different strategies. A data-driven weight assignment to criteria accompanied with a fuzzy attitude toward risk-taking or -averting facilitate producing powerful and accurate synthesized maps in Cu exploration, while it uses a wide range of decision strategies to produce several porphyry Cu mineral potential/prospectivity maps (MPM). The final MPM is based upon using many available desired geospatial data sets, indicating adequately matching of high-potential zones with previous working mines and copper deposits.

The hybrid FOWA method for an alpha value equal to 0.5 produced the most appropriate potential map with an ore prediction rate of 77%, which represents just 23% of the entire area under consideration for further consideration for detailed exploration. The hybrid MCDM method applied in this study, while incorporating the location of known ore occurrences in weight assignment, solves the problem of bias weight assignment to evidence layers, improves MPM accuracy, and produces more reliable exploratory target areas, which can be used for further exploratory efforts. Focusing subsequent exploration activity on the obtained high potential areas, illustrated in Fig. 5, will save considerable time and cost.

In terms of geological evaluation, comparing the final results related to evaluating potential for mineralization, the outcrops of felsic intrusive masses show a close spatial relationship with mineralized areas. It is observed in the northern part of KouhPanj and the regions around the Chahargonbad deposits that there are potential areas of porphyry copper mineralization related to the lithological units of granodiorite and quartz diorite. After considering those empirical aspects, according to the final prospecting map, the most closely related rocks with porphyry copper mineralization areas are andesitic volcanic breccias, with lava flows and dacites and dacitic pyroclastic rocks, and intrusive dacite porphyries. Therefore, based on the results obtained and the factors affecting porphyry copper mineralization, the study area has been prioritized for exploration for porphyry Cu mineralization. The scattered areas of greatest potential are in the northwest, center, and southwest of the region considered here, supported by known mineralization occurrences.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

Data are available on reasonable request to the corresponding author via email address "shokouh.riahi@gmail.com".

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