-RESEARCH PAPER-

International Journal of Mining and Geo-Engineering

IJMGE

IJMGE 57-4 (2023) 373-380

DOI: 10.22059/ijmge.2023.357315.595050

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

Shokouh Riahi [a, *], Maysam Abedi [a] , Abbas Bahroudi [a]

[a] *School of Mining Engineering, College of Engineering, University of Tehran, Tehran, Iran.*

Article History:
Received: 03 April 2023.
Revised: 29 April 2023.
Accepted: 03 May 2023.

ABSTRACT

This research presents a case study that employs the Fuzzy Ordered Weighted Averaging (FOWA) method to develop mineral prospectivity/potential maps (MPM) for the Chahargonbad district in southeastern Iran. The primary objective of the study is to uncover intricate and concealed relationships between various evidence layers and known ore occurrences through a comprehensive analysis of multi-disciplinary geospatial data. Consequently, thirteen evidence layers were meticulously derived from existing databases, encompassing geological, geochemical, geophysical, and remote sensing data, which were then integrated using the FOWA multi-criteria decision-making approach to delineate favorable zones for porphyry Cu mineralization.

The FOWA methodology employs a diverse array of decision strategies to synthesize input geospatial evidence by incorporating multiple values for an alpha parameter. This parameter serves as the cornerstone of the algorithm, influencing experts' perspectives on MPM risk. The methodology generates seven mineral potential maps to identify the most suitable one(s). By considering a prediction-area plot for data-driven weight assignment to each evidence map, the hybrid FOWA outputs were scrutinized to pinpoint the most appropriate map for targeting significant Cu occurrences. The resulting synthesized evidence map indicates an ore prediction rate of 77%, with known Cu deposits primarily located within favorable zones occupying 23% of the entire district area.

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

1. Introduction

Mineral potential or prospectivity mapping (MPM) serves as a fundamental exploration tool, aiming to investigate all geological processes responsible for mineral deposit distribution and employ this knowledge to map areas with potential mineralization [1, 2, 3]. The growing availability of geospatial databases and the need to pinpoint areas susceptible to ore mineralization have spurred exploration teams to utilize a wide range of geospatial datasets and cutting-edge statistical techniques for systematic evaluation. These approaches are instrumental in uncovering concealed spatial patterns in the data linked to mineralization processes. However, there remains a dedicated focus on the utilization, development, and proposition of innovative and valid MPM methods [4].

Within the field of MPM, geospatial databases predominantly consist of geological, geochemical, remote sensing, and geophysical attributes. These attributes serve as key indicators that are integrated into a single favorability map targeting the desired mineralization objective [5, 6]. The primary goal of MPM revolves around the identification of regions highly conducive to ore formation, including fluid reactions and trapping processes, within prospective areas. Additionally, MPM endeavors to expand existing ore occurrences or even discover new ones [7, 8]. Simultaneously, it strives to maximize the profitability derived from mineral exploration endeavors, while concurrently minimizing the associated costs and risks associated with preliminary exploration activities [9].

In the contemporary landscape of mineral potential/prospectivity mapping (MPM), there is a notable departure from traditional categories, specifically the knowledge- and data-driven techniques. Two modern variants of MPM have garnered significant attention [10, 11].

Hybrid Approach that arises from the integration of knowledge- and data-driven methods, simultaneously incorporating expert opinions and the spatial characteristics of known mineral deposits [12, 13, 14].

On the other hand, in Data-Driven Weight Assignment, weights are assigned to continuous spatial evidence layers without relying on expert judgments. Instead, it relies on a data-driven methodology for weight calculation [15, 16].

Taking all the aforementioned factors into account, the successful implementation of MPM necessitates careful concurrent selection of the appropriate target area and meticulous preparation of input geospatial evidence/criteria (such as geological, geochemical, remote sensing, and geophysical layers) tailored to the specific type of deposit being sought. In this regard, MPM can be likened to an MCDM problem.

FOWA, recognized as one of the practical MCDM methods [21] but less commonly applied in MPM, possesses the capability to model uncertainty and risk during criteria aggregation [20]. To harness this unique feature, the study utilizes the concentration–area (C–A) fractal model [22], prediction–area (P–A) plot, and normalized density method [23, 24] for classifying, evaluating, and assigning data-driven

* Corresponding author. *E-mail address:* shokouh.riahi@gmail.com (S. Riahi).

weights to evidence layers. This enhances the evaluation and validation of the Cu favorability map.

The hybrid FOWA method is examined with varying input parameters that control experts' risk attitudes when synthesizing geospatial layers. This approach yields reliable insights into mineralized areas and can be a valuable tool in future studies and other regions of interest, offering the flexibility to produce different outputs according to expert preferences.

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 shows an 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 formed of 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 has caused the structure to be folded. Furthermore, the faulting of most rocks in this area shows a dominant NW-SE trend. The late brittle activity arrised 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.

3. Methodology

3.1. Evidence mapping

Evidence layers were derived from comprehensive processing of geological, geophysical, geochemical data, and satellite images, forming the basis of a geospatial database designed for porphyry Cu mineral potential mapping (MPM). Detailed discussions of the thirteen evidence layers are available in previous works by the authors (see [19, 29, 30, 31]). Figure 2 provides a concise and schematic flowchart illustrating the management of geospatial data within this region. This diagram succinctly elucidates all the necessary steps leading to the final stage of data integration crucial for implementing the hybrid FOWA method.

To generate the remote sensing evidence layers, satellite imagery data underwent a series of processing techniques. These methods included False color composition, band ratio analysis, Ls-Fit, principal component analysis, as well as spectral-based approaches such as spectral angle mapper and mixture tuned matched filtering. These techniques were applied to ASTER and OLI data, resulting in the creation of hydrothermal alteration layers representing argillic, phyllic, propylitic, and iron oxide mapping.

Beyond the diverse alteration types, lineament mapping was conducted using directional filters to emphasize structural features within the region.

Through a comparative analysis of various filters applied to the aeromagnetic geophysical data, two key layers, the analytic signal (AS) and total horizontal derivative (TDX), were integrated into a single map. This map was instrumental in delineating magmatic intrusive units responsible for magnetic signatures and the ore-forming processes, thus serving as a geophysical layer. Furthermore, hidden deep-seated faults and magnetic lineaments were extracted using directional derivative-based filters, specifically the total horizontal derivative of the tilt angle (THDR) and the theta angle on the aeromagnetic data. Additionally, a ratio of K/eTh, derived from airborne radiometric data (as described in Mohebi et al. 2015) [38], was computed. This ratio aided in mapping areas associated with potassic alteration, a characteristic frequently observed in porphyry-type ore-bearing systems.

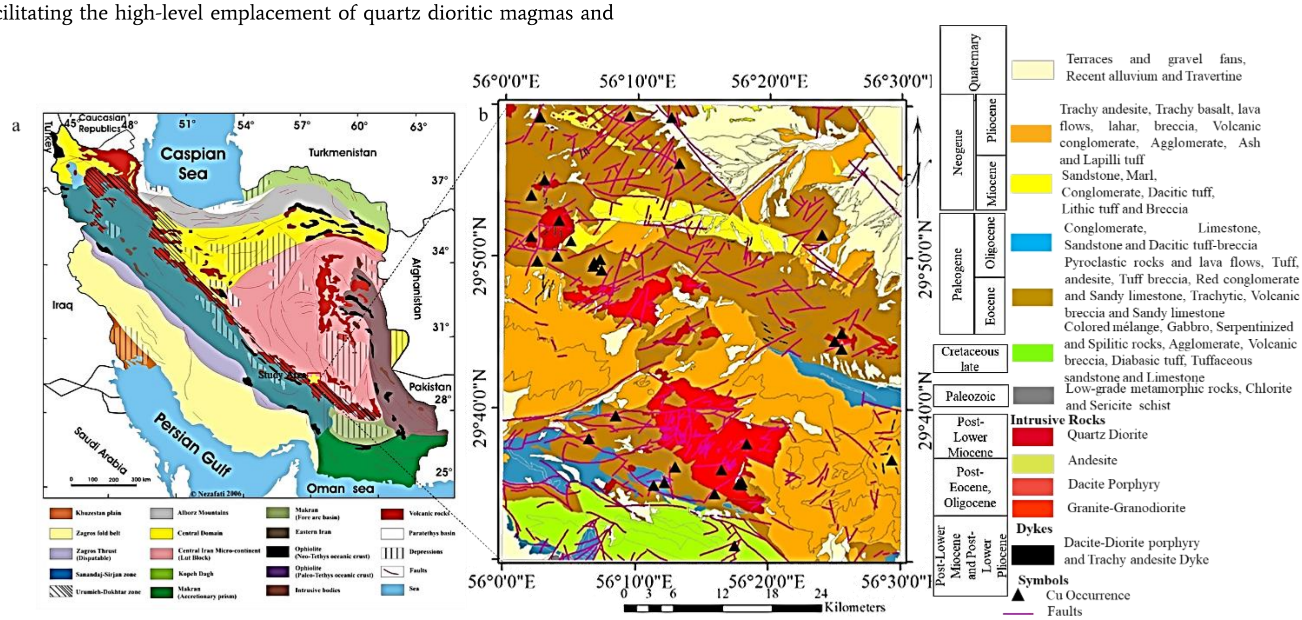

Fig. 1. (a) simplified structural geology map of Iran showing the location of the study area (modified after Alavi, 1991), and (b) detailed geological map of the Chahargonbad district at the Urumieh–Dokhtar magmatic belt in Iran (reproduced from [27]).

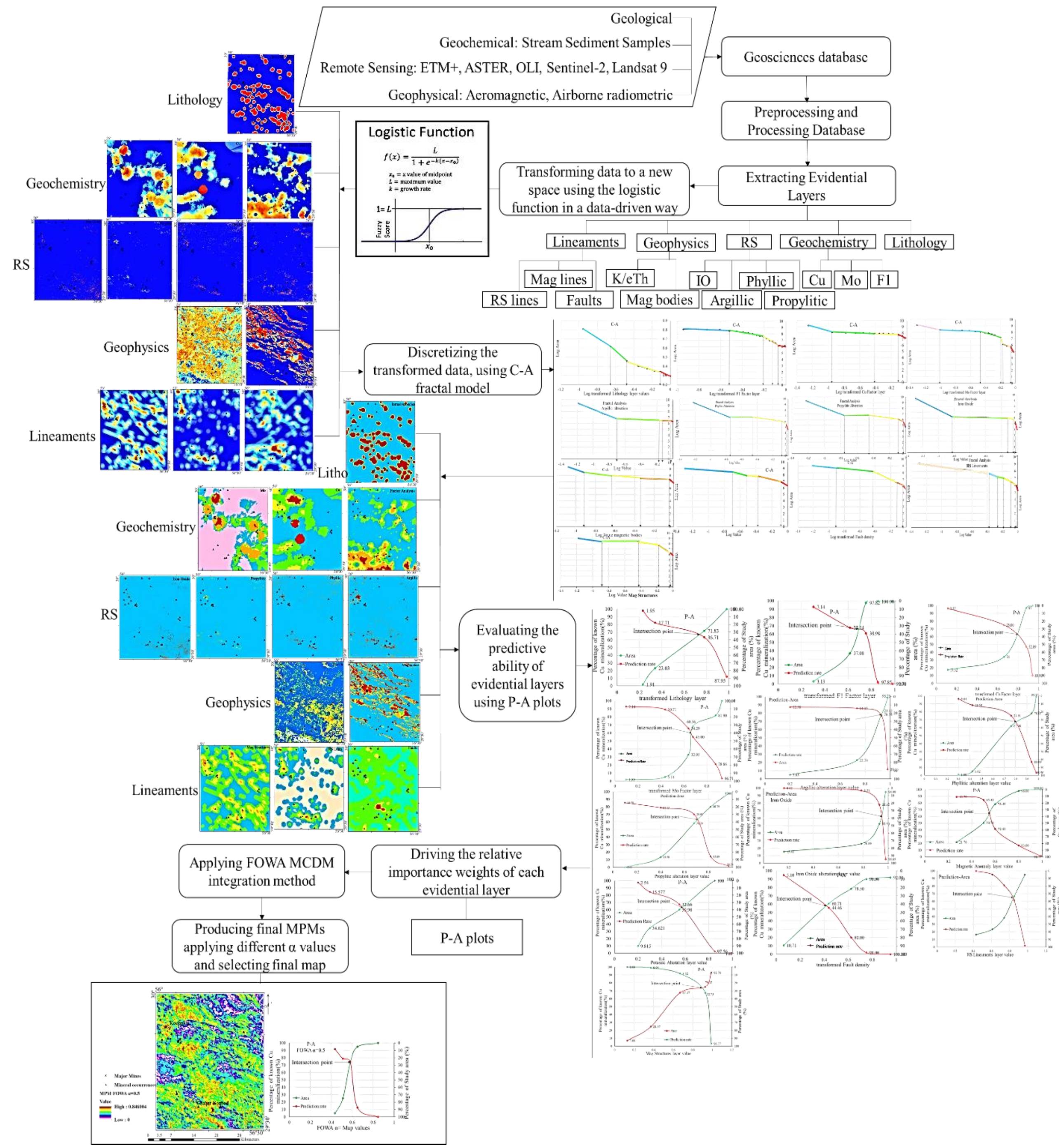

Fig. 2. A schematic flowchart of porphyry Cu potential mapping through a hybrid FOWA method.

The surficial geochemical evidence features were prepared by applying the catchment basins method to the stream sediment geochemical data for Cu, Mo, Zn, Pb, Ag, Co, Ni, Cr, and Ba to mitigate the adverse impact of background lithological variations on the concentrations. Several univariate and multivariate analysis methods, including factor analysis (FA), were employed to examine the geochemical data with a focus on Cu porphyry mineralization. Three evidence layers were selected, which encompassed Cu and Mo concentrations, as well as the primary geochemical factor determined through FA. Furthermore, the lithological map of the region was incorporated into the geospatial database. This involved digitizing the 1:100,000 geological map and scoring the rock units based on their significance for hosting known porphyry Cu mineralization. A fault density map was included as a final evidence layer, derived from surface field observations reported on the geological map. It is worth noting that structurally favorable brittle features, delineated by numerous lineaments and faults, serve as conduits for the hypabyssal emplacement of intrusions [39] and the concentration of fluid flow. These locations provide suitable environments for the concentration and deposition of ore [40-42]. In this district, there are currently 28 known and active porphyry-related Cu mines [43], as illustrated in Fig. 1b. These mines play a crucial role in plotting the P-A (prediction-area) curve, which is essential for deriving the weights of each evidence layer and subsequently conducting mineral potential mapping (MPM) using a hybrid FOWA method.

The P-A curve for each evidence layer (as depicted in Fig. 2) guides the determination of the ore prediction rate and the resulting occupied area at the intersection point. Subsequently, the weight of each evidence layer is computed based on the normalized density relationship, which involves the ratio of ore prediction to occupied area. Table 1 provides a summary of the parameters extracted from the P-A plot and the corresponding weights assigned to each evidence layer.

3.2. Hybrid FOWA method

The OWA operator linked to the ith alternative, corresponding to a sample point with x and y coordinates in the geospatial database, produces the output as following [21, 32, 33]:

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

It should be noted that the *AND* and *OR* operators represent the extreme values of the Ordered Weighted Averaging (OWA) operator, corresponding 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 represents the reordered criterion weight according to the criterion score z_{ij}.

In the context of criteria integration using a fuzzy linguistic characterization quantity Q, the process involves making statements about the relationships between the evaluation criteria. These statements govern the combination strategy, which can vary. For instance, the combination strategy might be specified as "most criteria must be met," "at least half of the criteria must be met," "all criteria must be met," and so on. This procedure aligns with the concept of qualitative-guided quantitative multi-criteria evaluation [21, 32].

Yager (1998) introduced the concept of a quantifier-guided Ordered Weighted Averaging (OWA) method, building upon Zadeh's (1983) linguistic quantifier idea [32, 34]. In a quantifier-guided aggregation process, the decision-maker (DM) provides a strategy with a linguistic quantifier that defines the criteria necessary for an acceptable solution [34]. The conventional decision strategy can be phrased as "the criteria for Q must be satisfied by an acceptable alternative," where a linguistic quantity replaces Q. There are two categories of quantifiers used: (1) absolute quantifiers for quantifying linguistic variables, such as "~5" and "~10", and (2) relative quantifiers, used in statements like "a few," "almost," "most," and so on [35]. Empirical evidence confirming the suitability of these two classes of linguistic quantifiers for multi-criteria decision-making (MCDM) problems is currently lacking [21, 32, 36]. These quantifiers can be represented as fuzzy sets within unit intervals [0, 1]. In this approach, a class of relative quantifiers known as regular increasing monotone (RIM) quantifiers is utilized, which is more commonly employed in personalized systems [21, 32]. In this context, *Q(r)* for each [0, 1] ∈ r represents the membership that indicates the compatibility of r with the concept represented by Q [21].

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

Adjusting the parameter α allows for the generation of various types of quantifiers and corresponding operators that span the spectrum between the two extreme states: maximum (OR operator, associated with risk-taking) and minimum (AND operator, associated with risk-aversion) for the desired criteria in decision-making. When α equals 1, *Q(r)* is directly proportional to *r* and is termed the identity quantity.

Given the criterion weights (determined, in this case, through the P-A plot) and the ordered weights, the calculation of the hybrid Fuzzy Ordered Weighted Averaging (FOWA) operator proceeds as follows [21],

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

The hybrid FOWA operator can produce multiple outputs by considering various values of α, with each value corresponding to a different level of risk-taking (lower values of α) or risk-aversion (higher values of α) in the final decision-making process [20, 37].

4. Results and Discussion

Once all the evidence layers were prepared, and the significance of each layer in identifying the target was determined based on the P-A plots summarized in Fig. 2 and Table 1, the hybrid FOWA method was executed for seven values of α. The α parameter can take various values ranging from 0 to infinity, and each result must be evaluated individually. To this end, the values 0, 0.1, 0.5, 1, 2, 10, and infinity were examined.

In Fig. 3, the Cu potential maps resulting from different values of the α parameter are displayed. It is evident that for α values of 0, 10, and infinity, the potential maps appear less reliable upon visual inspection and were subsequently excluded from further evaluation. These values correspond to the extreme cases of the OR and AND operators when assigning low and high values to the α parameter, respectively.

Table 2 presents the parameters extracted from the P-A plots of the synthesized evidence layers, assuming α parameters equal to 0.1, 0.5, 1, and 2.

Upon assessing the prediction rates for each of the synthesized maps with different α values, it becomes evident that the prediction rate is at its highest when the α parameter in the hybrid FOWA algorithm is set to 0.5. Consequently, this map is chosen as the final Cu favorability map. Figure 4 displays this map, and a C-A (concentration-area) fractal model has been utilized to categorize the continuous map into distinct populations.

Table 1. Extracted parameter from the P-A plots for each evidence layer.

Evidence Layer		Prediction Rate%	Occupied area%	Normalized density (Nd)	P-A method Weight
Argillic alteration		75	25	3	1.1
Phyllic alteration		67	33	2.03	0.708
Propylitic alteration		63	37	1.7	0.532
Iron Oxide		61	39	1.56	0.447
Lineaments (RS)		66	33	1.94	0. 663
Lithology		69	31	2.22	0.78
Faults		59	41	1.44	0.365
Cu enrichment		62	38	1.63	0.49
Mo enrichment		60	40	1.5	0.405
Factor Analysis		68	32	2.125	0.754
K/eTh		63	37	1.7	0.53
Magmatic bodies	Analytic Signal, TDX	65	35	1.86	0.62
Magnetic lineaments	TTHD, Theta angle	73	27	2.7	0.99

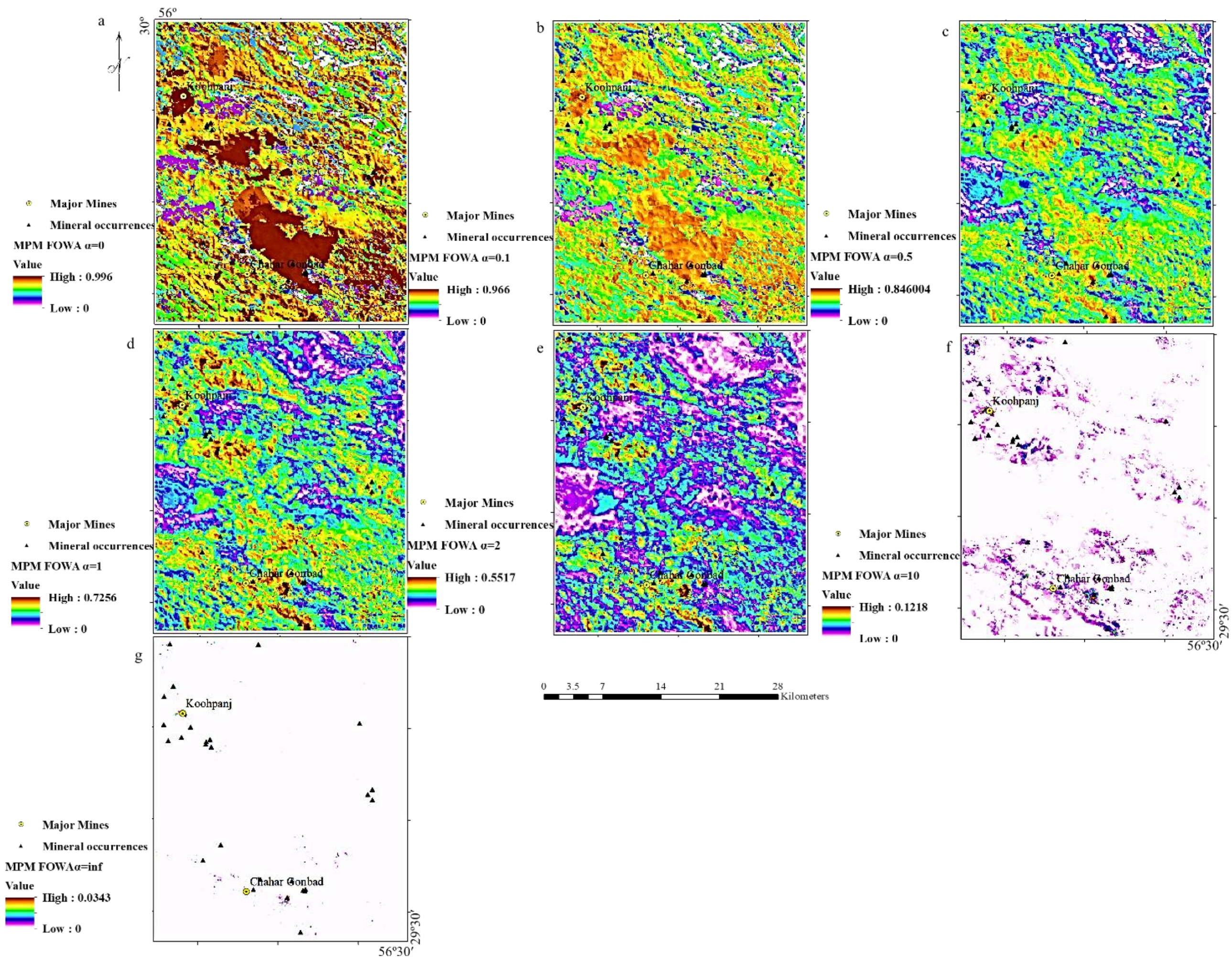

Fig. 3. Mineralization potential maps from applying the hybrid FOWA method for (a) α=0, (b) α= 0.1, (c) α=0.5, (d) α=1, (e) α=2, (f) α=10, and (g) α= infinity.

Table 2. Extracted parameters from the intersection point of the P–A plots using the hybrid FOWA method (for different α values).

Map	Prediction rate (P_r) %	Occupied area (O_a) %	Normalized density (N_d)	Weight
FOWA, α=0.1	75	25	3	1.1
FOWA, α=0.5	77	23	3.35	1.21
FOWA, α=1	76	24	3.167	1.15
FOWA, α=2	70	30	2.34	0.85

Additionally, the P-A (prediction-area) plot indicated an ore prediction rate of 77% within a favorable region occupying 23% of the total area. This information is valuable for guiding further advanced exploration investigations.

By analyzing the intersection point on the P-A plot derived from the final FOWA mineral potential mapping (MPM), a threshold value of 0.58 was identified. This threshold serves to separate background values from areas of notable mineral potential. Subsequently, a two-class map was created using this threshold value (Fig. 5). This map effectively highlights the areas with exploration potential for mineralized porphyries and establishes the relationship between known mineralization occurrences and areas with Cu-bearing potential.

Notably, these favorable zones appear to align with the NW-SE structural trend, including faults and lineaments. According to this model, the majority of areas with exploration potential are situated in the western half of the study area, particularly in the NW and SSW regions. A comparison of this map with other individual pieces of evidence reveals that the MPM generates a higher ore prediction rate within a much smaller percentage of occupied area.

5. Conclusion

The accurate selection of mineralization areas for further exploration, with the potential for future mining activities, is a complex undertaking that necessitates the concurrent consideration of multi-disciplinary geospatial datasets and the implementation of suitable methods to delineate and define favorable mineralized zones. In this study, it was imperative to establish a systematic procedure for identifying indicators of porphyry copper deposits and prioritizing potential areas for in-depth investigation and exploration activities within the Chahargonbad district.

To address this challenge, a hybrid Fuzzy Ordered Weighted Averaging (FOWA) method, well-known in the field of multi-criteria decision-making (MCDM) problems, was employed. This approach facilitated the synthesis of evidence layers through a variety of different strategies.

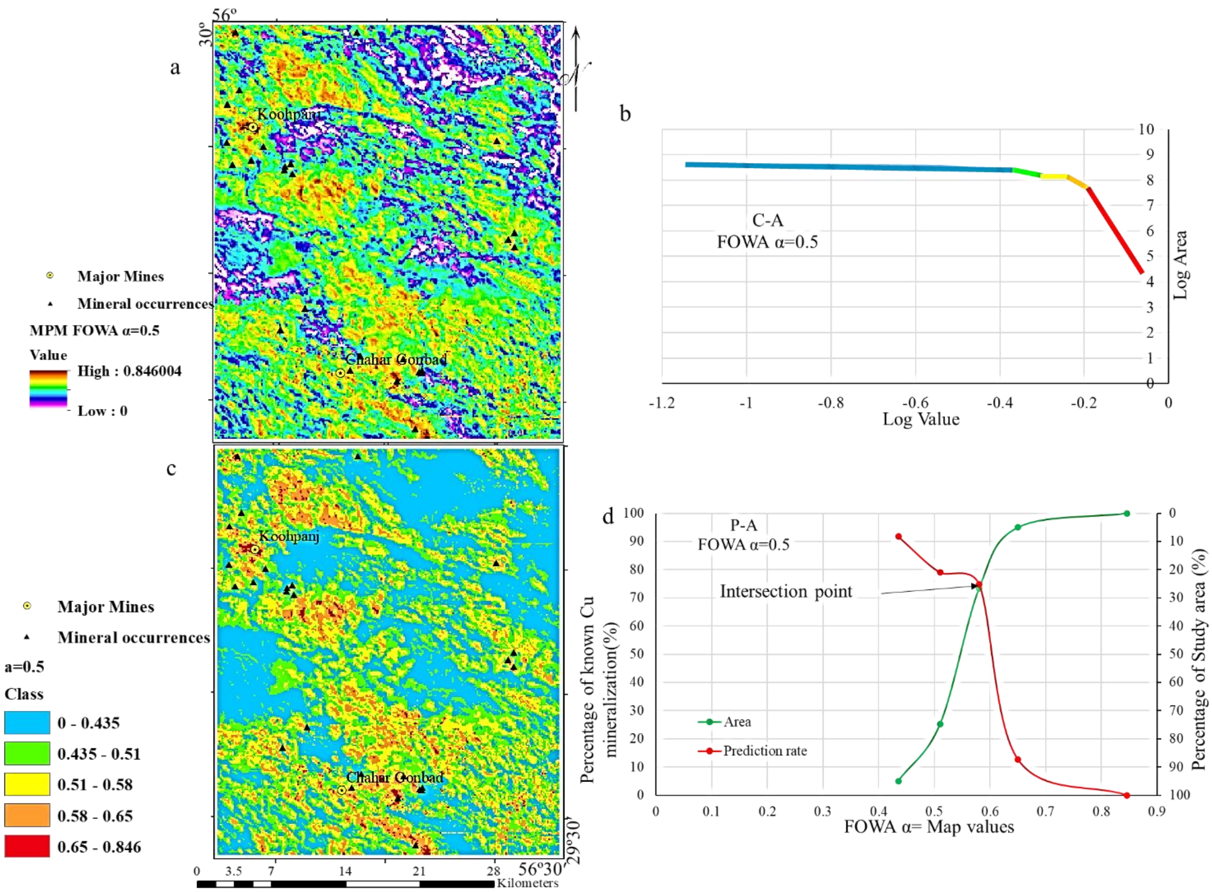

Fig. 4. (a) Hybrid FOWAα=0.5 for porphyry copper potential mapping; (b) log-log plot of concentration-area fractal model; (c) classified map based on the fractal analysis; (d) prediction-area plot.

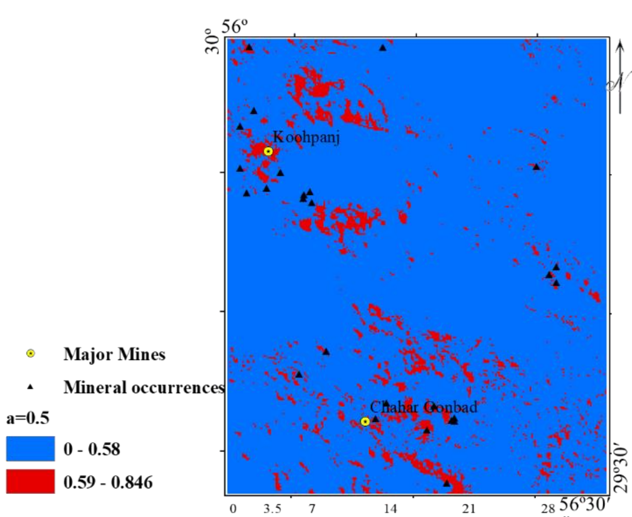

Fig. 5. Final MPM from FOWAα=0.5, classified to two classes of the favourable areas and the background.

By assigning data-driven weights to criteria and incorporating a fuzzy approach to risk assessment, the method proved effective in producing robust and accurate synthesized maps for copper exploration. It employed a broad spectrum of decision strategies, yielding several porphyry copper mineral potential/prospectivity maps (MPM). The final MPM was developed by harnessing a wealth of available geospatial datasets, showcasing a strong alignment of high-potential zones with previously known working mines and copper deposits.

The hybrid (FOWA) method, with an alpha value of 0.5, yielded the most suitable potential map in this study, achieving an ore prediction rate of 77%. This corresponds to just 23% of the total area considered, making it ideal for further detailed exploration efforts.

The hybrid multi-criteria decision-making (MCDM) method employed here, incorporating the location of known ore occurrences in weight assignment, successfully addresses the issue of biased weight assignment to evidence layers. As a result, it enhances the accuracy of mineral potential mapping (MPM) and generates more dependable target areas for exploratory purposes. By focusing subsequent exploration activities on the high-potential areas identified, as depicted in Fig. 5, significant time and cost savings can be realized.

In terms of geological evaluation and a comparison of the final results related to mineralization potential, it is evident that the outcrops of felsic intrusive masses exhibit a close spatial relationship with mineralized areas. This observation is particularly pronounced in the northern part of KouhPanj and the surrounding regions of the Chahargonbad deposits, where potential areas of porphyry copper mineralization align with lithological units composed of granodiorite and quartz diorite.

Taking these empirical observations into account and referencing the final prospecting map, the lithological units most closely associated with porphyry copper mineralization areas are andesitic volcanic breccias, lava flows, dacites, dacitic pyroclastic rocks, and intrusive dacite porphyries. Consequently, based on the results obtained and the factors influencing porphyry copper mineralization, the study area has been identified as a high-priority zone for exploration in pursuit of porphyry Cu mineralization. The scattered areas with the greatest potential are predominantly located in the northwest, center, and southwest regions of the area under consideration, aligning well with 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.

Acknowledgments

The authors gratefully acknowledge the support provided by the School of Mining Engineering, College of Engineering, University of Tehran. We also express our sincere thanks to the National Iranian Copper Industries Company (NICICo) for data provision. David Lentz (UNB) is thanked for editing an earlier version of this manuscript. Specifically, we would like to thank the Editors of the special issue and the anonymous reviewers for the invaluable comments which have served to greatly strengthen our manuscript.

Data Availability

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

REFERENCES

[1] McCuaig, T.C., & Hronsky, J. M. A. (2014). The mineral system concept: The key to exploration targeting, Applied Earth Science IMM Transactions section B 18(2):153-175.

[2] Wyman, D.A., Cassidy, K., & Hollings, P. (2016). Orogenic gold and the mineral systems approach: Resolving fact, fiction and fantasy, Ore Geol. Rev. 78, 322-335.

[3] Groves, D.I., Santosh, M., & Zhang, L. (2020). A scale-integrated exploration model for orogenic gold deposits based on a mineral system approach, Geoscience Frontiers, 11(3), 719-738.

[4] Carranza, E. J. M., & Laborte, A. G. (2016). Data-driven predictive mapping of gold prospectivity, Baguio district, Philippines: Application of random forests algorithm. Ore Geol. Rev. 71, 777–787.

[5] Agterberg, F.P. (1992). Combining indicator patterns in weights of evidence modeling for resource evaluation. Nat. Resour. Res. 1, 39–50.

[6] Bonham-Carter, G.F. (1994). Geographic Information Systems for Geoscientists, Modelling with GIS. Pergamon, New York, 398 p.

[7] Abedi, M., & Norouzi, G.H. (2012). Integration of various geophysical data with geological and geochemical data to determine additional drilling for copper exploration. J. Appl. Geophys. 83, 35–45.

[8] Parsa, M., & Maghsoudi, A. (2021). Assessing the effects of mineral systems-derived exploration targeting criteria for Random Forests-based predictive mapping of mineral prospectivity in Ahar-Arasbaran area, Iran. Ore Geol. Rev. 104399

[9] Chen, Y., & Wu, W. (2015). A prospecting cost-benefit strategy for mineral potential mapping based on ROC curve analysis. Ore Geol. Rev. 74, 26–38.

[10] Parsa, M., Maghsoudi, A., & Yousefi, M. (2017). An improved data-driven fuzzy mineral prospectivity mapping procedure; cosine amplitude-based similarity approach to delineate exploration targets. Int. J. Appl. Earth Obs. 58, 157–167.

[11] Parsa, M., Maghsoudi, A., & Yousefi, M. (2017). A Receiver Operating Characteristics-Based Geochemical Data Fusion Technique for Targeting Undiscovered Mineral Deposits. Nat. Resour. Res. 27, 15-28.

[12] Porwal, A., Carranza, E.J.M., & Hale, M. (2006). A hybrid fuzzy weights-of-evidence model for mineral potential mapping. Nat. Resourc. Res. 15, 1–14.

[13] Pazand, K., & Hezarkhani, A. (2015). Porphyry Cu potential area selection using the combine AHP-TOPSIS methods: a case study in Siahrud area (NW, Iran). Earth Sci. Inf. 8, 207–220.

[14] Yousefi, M., & Carranza, E.J.M. (2015). Prediction-area (P-A) plot and C-A fractal analysis to classify and evaluate evidential maps for mineral prospectivity modeling. Comput. Geosci. 79, 69–81.

[15] Yousefi, M., & Nykänen, V. (2016). Data-driven logistic-based weighting of geochemical and geological evidence layers in mineral potential mapping. Journal of Geochemical Exploration 164, 94–106.

[16] Bahrami, Y., Hassani, H., & Maghsoudi, A. (2019). BWM-ARAS: A new hybrid MCDM method for Cu prospectivity mapping in the Abhar area, NW Iran. Spatial Statistics, 33, https://doi.org/10.1016/j.spasta.2019.100382

[17] Yousefi, M., & Carranza, E.J.M. (2016). Union score and fuzzy logic mineral prospectivity mapping using discretized and continuous spatial evidence values. J. Afr. Earth Sci. 128, 47–60.

[18] Bahrami, Y., Hassani, H., & Maghsoudi, A. (2022). Spatial modeling for mineral prospectivity using BWM and COPRAS as a new HMCDM method. Arab J Geosci 15, 394. https://doi.org/10.1007/s12517-022-09630-1

[19] Riahi, Sh., Bahroudi, A., Abedi, M., & Aslani, S. (2022). A comparative analysis of multi-index overlay and fuzzy ordered weighted averaging methods for porphyry Cu prospectivity mapping using remote sensing data: The case study of Chahargonbad area, SE of Iran, Geocarto International 38(1), 10.1080/10106049.2022.2159068

[20] Abedi, M., Norouzi, G.H., & Fathianpour, N. (2015). Mineral potential mapping in Central Iran using fuzzy ordered weighted averaging method, Geophysical Prospecting, 63, 461–477.

[21] Malczewski, J. (2006). Ordered weighted averaging with fuzzy quantifiers: GIS-based multicriteria evaluation for land-use suitability analysis, International Journal of Applied Earth Observation and Geoinformation 8, 270–277.

[22] Cheng, Q., Agterberg, F.P., & Ballantyne, S.B. (1994). The separation of geochemical anomalies from background by fractal methods. J. Geochem. Explor. 51, 109–130.

[23] Yousefi, M., & Carranza, E.J.M. (2015). Fuzzification of continuous-value spatial evidence for mineral prospectivity mapping. Comput. Geosci. 74, 97–109.

[24] Yousefi, M., & Carranza, E.J.M. (2015). Geometric average of spatial evidence data layers: a GIS-based multi-criteria decision-making approach to mineral prospectivity mapping. Comput. Geosci. 83, 72–79.

[25] Alavi M. (1991). Sedimentary and structural characteristics of the Paleo-Tethys remnants in northeastern Iran. Geological Society of America Bulletin 103, 983-992.

[26] Berberian, F., Muir, I.D., Pankhurst, R.J. & Berberian, M. (1982). Late cretaceous and early miocene andean-type plutonic activity in northern Makran and central Iran. Journal of the Geological Society 139, 605–614.

[27] Khan-Nazer, N.H., Emami, M.H., & Ghaforie, M. (1995). Geological Map of Chahargonbad. Geological Survey of Iran publication, Tehran, Iran (1: 100,000).

[28] Kianpourian, S., Farhamandian, M., Karimi, M., & Bahroudi, A. (2013). Preparation of mineral potential map for copper deposits using mixed neuroFuzzy model: a case study of 1:100,000 sheet of Chahargonbad in Kerman province. Journal of Earth Sciences, (Rocks and Minerals), 277-286 https://sid.ir/paper/31354/fa

[29] Riahi, Sh., Bahroudi, A., Abedi, M., & Aslani, S. (2022). Hybrid Outranking of Geospatial Data: Multi Attributive Ideal-Real Comparative Analysis and Combined Compromise Solution, Chemie der Erde - Geochemistry 82(6), 10.1016/j.chemer. 2022.125898

[30] Riahi, Sh., Bahroudi, A., Abedi, M., Aslani, S., & Elyasi, G. (2021). Integration of airborne geophysics and satellite imagery data for exploration targeting in porphyry Cu systems: Chahargonbad district, Iran. Geophysical Prospecting 69(5), 1116–1137. doi:10.1111/1365-2478.13092

[31] Riahi, Sh., Bahroudi, A., Abedi, M., Aslani, S., & Lentz, D.R. (2021). Evidential data integration to produce porphyry Cu prospectivity map, using a combination of knowledge and data driven methods, Geophysical Prospecting 70(2), 421-437. https://doi.org/10.1111/1365-2478.13169

[32] Yager, R. R., & Filev, D. (1998). Operations for granular computing: mixing words and numbers, in Proceedings of the IEEE International Conference on Fuzzy Systems, 123–128, Anchorage, Alaska, USA.

[33] Malczewski, J. (1999). GIS and multicriteria decision analysis: John Wiley & Sons.

[34] Zadeh L.A. (1983). A computational approach to fuzzy quantifiers in natural languages. Computers & Mathematics with Applications 9, 149–184.

[35] Fuller R. (1996). OWA operators in decision making. In: Exploring the Limits of Support Systems, Vol. 3 (ed C. Carlsoon), pp. 85–104. TUCS General Publications, Turku Centre for Computer Science, Abo Akademi University, Turkey.

[36] Nadi, S., & Delavar, M.R. (2011). Multi-criteria, personalized route planning using quantifier-guided ordered weighted averaging operators. International Journal of Applied Earth Observation and Geoinformation 13, 322–335.

[37] Elyasi, Gh.R., Bahroudi, A., & Abedi, M. (2019). Risk-Based Analysis in Mineral Potential Mapping: Application of Quantifier-Guided Ordered Weighted Averaging Method. Natural Resources Research, 28, 931-951.

[38] Mohebi, A., Mirnejad, H., Lentz, D., Behzadi, M., Dolati, A., Kani, A., & Taghizadeh, H. (2015). Controls on porphyry Cu mineralization around Hanza Mountain, south-east of Iran: An analysis of structural evolution from remote sensing, geophysical, geochemical and geological data. Ore Geology Reviews, 69, 187-198.

[39] Yousefi, M., Kreuzer, O. P., Nykänen, V., & Hronsky, J. M. (2019). Exploration information systems-a proposal for the future use of GIS in mineral exploration targeting. Ore Geology Reviews, 5, 103005.

[40] Yousefi, M., & Hronsky, J.M.A. (2023). Translation of the function of hydrothermal mineralization-related focused fluid flux into a mappable exploration criterion for mineral exploration targeting. Applied Geochemistry, 149, 105561.

[41] Mami Khalifani, F., Bahroudi, A., Barak, S., & Abedi, M. (2019). An integrated Fuzzy AHP-VIKOR method for Gold Potential Mapping in Saqez prospecting zone, Iran. Earth Observation and Geomatics Engineering, 3 (1), 21-33.

[42] Mohammadpour, M., Bahroudi, A., & Abedi, M. (2020). Automatic lineament extraction method in mineral exploration using CANNY algorithm and hough transform. Geotectonics, 54, 366-382.

[43] Rahimi, H., Abedi, M., Yousefi, M., Bahroudi, A., & Elyasi, Gh.R. (2021). Supervised mineral exploration targeting and the challenges with the selection of deposit and non-deposit sites thereof. Applied Geochemistry, 128, 104940.