Bulletin of Geophysics and Oceanography Vol. 65, n. 4, pp. 715-740; December 2024
DOI 10.4430/bgo00462

Employing multiple prospectivity mapping and exploration targeting, a case study from the Sonajil porphyry copper deposit, north-western Iran

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(Received: 16 December 2023; accepted: 8 May 2024; published online: 12 July 2024)

ABSTRACT The main goal of this study is to demonstrate how fusion methods can be used in mineral prospectivity mapping (MPM) through a comprehensive multi criteria decision-making (MCDM) analysis. MPM plays a crucial role in mineral exploration by aiming to lower exploration expenses through identifying potential ore-bearing targets and planning detailed exploration surveys, including drilling. This study utilises various methods including index overlay, Old TOPSIS, Modified TOPSIS, Adjusted TOPSIS, Old VIKOR, Modified VIKOR, fuzzy gamma operator, fuzzy ordered weighted averaging (FOWA) with different strategies, and fuzzy inference system (FIS). The study area chosen for comparison of various fusion techniques is the Sonajil Cu-Au porphyry deposit located in the east Azerbaijan province, which is the main focus of the investigation. Geological factors, including rock units and faults, remote sensing data for alteration, geochemical analysis using soil samples, and geophysical factors from reduced to the pole magnetic data, are employed in the indicator maps to assess the potential of the region. To delineate the prospective area in terms of ore-trapping favourability, a fractal-based analysis was applied to all fusion outputs, resulting in the identification of five distinct perspective areas. The efficacy of different MPMs was assessed and compared using subsurface data from 21 boreholes, showing consistent agreement rates among all methods. The FIS showed a 79% agreement, whereas the FOWA, with its optimal strategy, exhibited an 81% agreement, emphasising their effectiveness compared to alternative approaches. The predicted maps show a close connection with the geological features of the host rock, particularly granitoid and andesite porphyry from the Sonajil formation, along with the presence of potassic and phyllic alterations. The FIS and FOWA models have successfully pinpointed new drilling sites and assisted in evaluating mining potential for future exploration and development. By utilising this comparative model, which evaluates different algorithms to determine the most accurate prediction map, significant progress has been made in exploratory studies.

Key words: index overlay, TOPSIS, VIKOR, fuzzy gamma operator, fuzzy ordered weighted averaging, fuzzy inference system, porphyry copper deposits.

1. Introduction

Mineral prospectivity mapping (MPM) plays a crucial role in exploration projects by identifying potential areas for new mineral deposits using a combination of geospatial data. The MPM, functioning as a multi criteria decision-making (MCDM) issue, greatly impacts the chance of exploration success. It is divided into two primary categories: knowledge-driven and data-driven methods, as detailed by Bonham-Carter (1994). Geological interpretations, observations, and the expertise of geoscientists play a crucial role in the former category, which focuses on exploring unknown mineral deposits in greenfield regions. On the other hand, the latter, which deals with known mineral deposits, analyses spatial correlations among geospatial patterns in brownfield regions to discover further ore-bearing zones. In the sphere of MPM, there is a growing focus on integrating knowledge- and data-driven models to identify specific areas of interest for different types of mineral deposits. This approach, exemplified by studies from researchers like Porwal *et al*. (2006), Yousefi and Carranza (2015, 2016), Barak *et al*. (2021), and Yousefi *et al*. (2021, 2023), combines the strengths of different methods through a hybrid model, effectively minimising any potential limitations or drawbacks. However, it is worth noting that these limitations are not always explicitly mentioned in the studies. In recent years, the integration of extensive and diverse data sets across various scales has led to significant advancements in MPM techniques, which have been a central focus for many scientists. Determining the most suitable method or technique for MPM is not governed by a universally applicable rule. Instead, researchers have successfully utilised various fusion methods, showcasing a range of approaches. Various methodologies have been employed in the field of MPM, such as fuzzy logic demonstrated in works by Knox-Robinson (2000), Barak *et al*. (2018a, 2018b), and Sanusi and Amigun (2020). Furthermore, fuzzy inference systems (FISs) have been investigated in studies by Barak *et al*. (2018a, 2018b, 2020, 2021), while fuzzy outranking techniques have been utilised in works by Abedi *et al*. (2012, 2013). Fuzzy analytical hierarchy process (AHP) was used according to Zhang *et al*. (2017), along with other approaches like fuzzy weights of evidence (Cheng and Agterberg, 1999), fuzzification of continuous-value data (Yousefi and Nykänen, 2016), and the ordered weighted averaging approach pioneered by Yager (1988). Each method brings unique perspectives and capabilities to the field of MPM. Porphyry copper deposits are created by hydrothermal fluids from a magma reservoir deep below the deposit, serving as crucial sources of copper, molybdenum, and gold for industrial and societal needs (Park *et al*., 2021). Studies show that these deposits are linked to various mineral occurrences, including high-sulfidation epithermal deposits with copper, gold, and silver, as well as intermediate-sulfidation polymetallic deposits hosting lead, manganese, zinc, and silver (Sillitoe, 2010). Moreover, porphyry copper deposits can also play a role in forming distal skarn deposits, showcasing the diverse mineral associations and complex nature of their formations (Hedenquist *et al*., 1994).

The Sonajil region has been extensively explored for Cu-porphyry deposits, by ESPEER (2007). Despite these endeavours, no economically viable mineral reserves have been found. This study aims to create mineral potential maps for the Sonajil deposit using integration techniques such as index overlay, TOPSIS, VIKOR, fuzzy gamma operator, fuzzy ordered weighted averaging (FOWA), and FIS. These methodologies utilise a fuzzy approach to integrate geospatial data, consistent with previous research by Abedi *et al*. (2017) on multi-method data integration in MPM. MPM techniques' effectiveness relies heavily on the quality of geospatial data sets used. This study merged criterion layers derived from various types of data, such as geological, geochemical, geophysical, and remote sensing data, to achieve comprehensive data integration. The resulting mineral potential maps were, then, compared to each other. To validate the accuracy of the copper favourability maps, data from 21 boreholes were utilised. The significance of this research lies in identifying the most efficient MPM approach for mapping Cu-Au favourability. Ultimately, the maps generated from this study highlight the effectiveness of the FIS and FOWA.

2. Geology and mineralisation of the Sonajil area

The study area is located in the north-eastern region of the 1:100,000 geological map of Ahar and is part of the Urmieh-Dokhtar Magmatic Arc as classified by Iran's structural geology zones (Stocklin, 1968) (Figs. 1a and 1b). The geological formations in this area consist of various rock

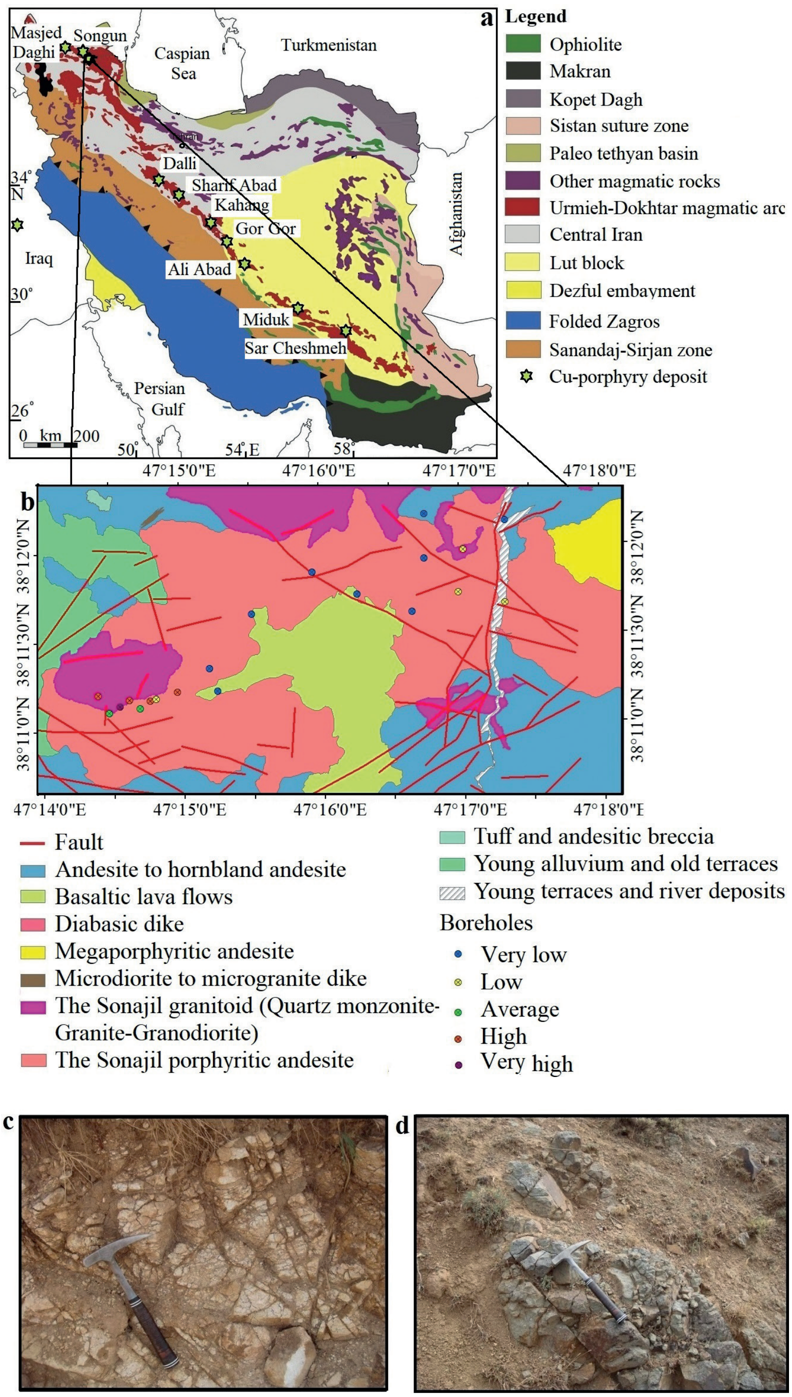

Fig. 1 - The Sonajil geological map with a scale of 1:10,000, within the Iran structural map (a, b); the intrusive unit included granite to highly altered and leached granodiorite (c); and the malachite mineral traces on the surface mineralised area (d).

units, such as Eocene lava, Oligocene intrusive masses of granodiorite to monzodiorite, diorite to diabase dykes, Quaternary basic lava, and Quaternary sediments, all at a scale of 1:1000. It is important to highlight that these volcanic activities have greatly impacted the geological characteristics of the region, including magma formation and placement, fault formation, regional uplift, and rotational movements (Imamalipour and Barak, 2019; Barak *et al.*, 2023).

The Eocene lava formations in the area consists of andesitic to latite-andesitic lava, which often show propylitic alteration. The intrusive unit is composed of granodiorite, which has undergone extensive alterations and exhibits copper mineralisation. Argillic alteration has been observed, and pyrite and other sulphide minerals have undergone significant washing and leaching processes. When the granodiorite mass comes into contact with the Eocene lavas, it undergoes alterations with the presence of numerous silica veins. Within the altered granodiorite mass, patches of more basic masses with micro-monzodiorite to micro-diorite compositions have been observed. These rocks show comparatively less alteration and have a darker coloration in manual samples. Mineralisation is predominantly observed within these rocks, with traces of malachite visible in the rock texture. Manual samples also show the presence of secondary biotites and orthosis. Potassic alteration is the prevailing alteration, although partial occurrences of propylitic alteration (secondary biotites transforming into chlorite and epidote) have been noted.

The diabase to diorite dykes intersects both the igneous mass and Eocene rocks, displaying green to dark colours with a micro-granular texture. Mineralisation in these dykes is minimal, with only traces of malachite minerals visible in certain outcrops (see Fig. 1d). The Quaternary volcanic rock unit consists of basaltic to basaltic andesite lava formations, mainly found in the southern and western regions, showing a lack of mineralisation. Additionally, Quaternary pyroclastic rocks are present at the base of this unit.

3. Geospatial data set

The predictive model for ore mineralisation was developed by utilising various evidence layers from the geospatial data set in line with the porphyry mineralisation conceptual model. These layers included a geochemical map from previous studies (Barak *et al.*, 2018a, 2018b, 2020, 2021), a magnetometry map by Ranjbar *et al.* (2004), intrusive igneous rock units focusing on metalogenic factors, and significant alteration types associated with porphyry deposits (Lickfold *et al.*, 2007; Sillitoe, 2010). Lineament and fault indicator maps served as conduits for Cu-bearing fluids (Campos *et al.*, 2002). Furthermore, various alteration types commonly linked to porphyry deposits such as potassic, phyllic, argillic, and propylitic alterations were employed in this research (Sillitoe, 2010; Barak *et al.*, 2021).

Four primary criteria were utilised in this research. Table 1 presents an overview of these criteria, including the layers of indicators and the normalised scores assigned to each criterion within the Sonajil region. It is important to mention that all indicator maps were created using a cell size of 20×20 m^2.

3.1. Geological indicators

Sillitoe's (2010) research was consulted to assess the importance of rock units and fault zones in the Sonajil deposits, revealing that the predominant host rocks are part of the acidic internal igneous rock group, including granite, granodiorite, tonalite, quartz monzonite and diorite. The construction of the rock unit layer for the Sonajil area involved considering the

Table 1 - The normalised scores assigned to factor layers in the Sonajil area.

Criteria	Scores	Evidence layer	Scores	Reason of using
Geology	0.269	Rock units	0.700	Suitable area for ore–metal occurrence
		Fault areas	0.300	
Remote sensing	0.260			Alteration zones
Geochemistry	0.320	Copper (Cu) anomaly	0.550	Ore–metal enrichment
		Gold (Au) anomaly	0.450	
Magnetic (RTP)	0.151			Reflect the location of alteration zones

relevance of surrounding rocks in relation to ore body formation in porphyry deposits, leading to the assignment of scores. Consistent with Sillitoe's (2010) findings, granitoid units like quartz monzonite, granite, and granodiorite were given higher scores, while basaltic lava flows, young alluvium, old/young terraces, and river deposits received lower scores as depicted in Fig. 2a. Sillitoe (2010) has highlighted the significance of fractures in porphyry-type copper mineralisation areas as indicators for exploration due to their role as conduits for ore fluids. Faults, fractures, shear zones, and spatial stresses play a crucial role in magma concentration and movement in shallow crustal regions (Dewey and Ryan, 1990). Geological faults were identified from the geological map and analysed using remote sensing imagery data. A buffering technique was utilised to score faults, with areas near faults given higher weights for their influence (Fig. 2b). To gain a deeper understanding of the methodologies used in creating geological and faults maps, readers are recommended to review the research conducted by Barak *et al*. (2023).

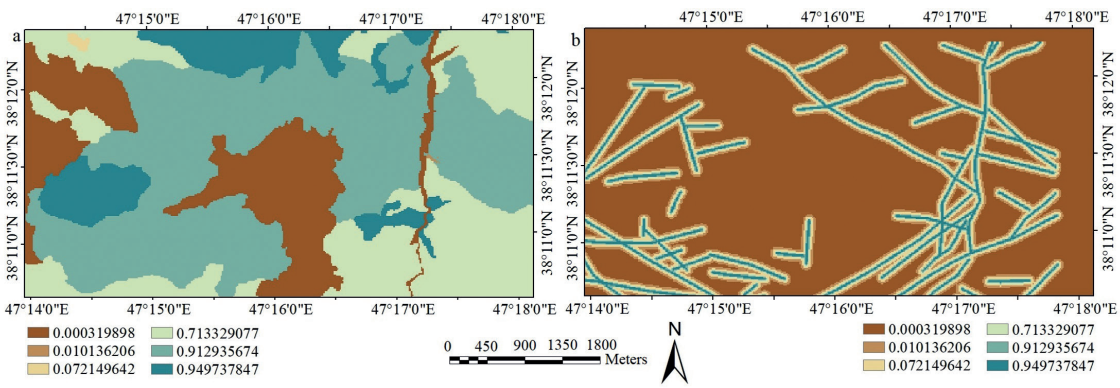

Fig. 2 - Geological evidential layers of: a) rock units, and b) faulted area map.

3.2. Alteration indicator

Satellite image data analysis can detect hydrothermal alteration zones, with ENVI 4.8 software used for processing an ASTER image in Sonajil. Techniques including both spectrum-based methods (Spectral Angle Mapper, Spectral Feature Fitting, Mixture Tuned Matched Filtering) and image-based approaches [RGB analysis, Relative Absorption Band Depth (RBD), Principal Component Analysis] were employed to identify alterations.

Applying satellite scenes to diagnose data by integrating various bands rather than individual band presentation is called false-colour composite (RGB). According to Rajendran *et al*. (2011), the use of RGB composites, specifically RGB (456), RGB (468), and RGB (468), is effective in identifying phyllic, argillic, and propylitic alteration zones. The RBD is an extremely basic and popular approach in remote sensing. Its idea is to highlight or overstate the anomaly of the target (Abrams *et al*., 1983). The technique employed here aims to create distinct mineral zones from ASTER images. By dividing the maximum reflection by the maximum absorption, an indicator map is generated. This map helps identify alteration zones by analysing the spectral properties of the constituent minerals. The detection of phyllic alteration in this study involved the use of sericite and the [(Band5+Band7) / Band6] ratio. To identify kaolinite mineral and argillic alteration, the [(Band4+Band6) / Band5] ratio was utilised. Lastly, chlorite was employed for extracting propylitic alteration through the band ratio [(Band7+Band9) / Band8]. The outcrops of the main alteration have been effectively identified in recent decades using the ASTER image, which benefits from three distinct spectral systems and a total of 14 bands (Tommaso and Rubinstein, 2007; Esmaeilzadeh *et al*., 2023). Tommaso and Rubinstein (2007) demonstrated that, by examining particular silicate and carbonate mineral outcrops in thermal bands (8-12 μm), quartz presence can be identified within the potassic zone, showing absorption in the 10 and 12 bands and reflection in the 11 band. Therefore, by the inverse of Q_i ratio $\{[(b_{11}\times b_{11})/(b_{10}\times b_{12})]\times(-1)\}$ the potassic alteration can be detected in porphyry deposits (Ninomiya, 2003). PCA, also known as principal component analysis, serves as a technique for reducing the dimensionality of extensive data sets. It achieves this by converting a multitude of variables into a smaller set that retains the majority of the original information (Fauvel *et al*., 2009). By examining the absorption and reflection bands associated with sericite mineral, the 4, 6, and 7 bands are identified as indicators of phyllic alteration. The detection of kaolinite (argillic) is achieved using bands 4, 5, and 7, while chlorite (propylitic) can be identified through bands 1, 6, 7, and 9.

In this study, spectrum-based techniques were used to map alterations. Reference spectra of pyrite, kaolinite and chlorite, were selected for phyllic, argillic and propylitic alterations, respectively. The Spectral Angle Mapper method was employed to assess the spectral similarity between the image spectra and the reference spectra by calculating the angles between them. Smaller angles indicate a higher degree of resemblance, while larger angles signify a lower degree of resemblance (Girouard *et al*., 2004). For the Sonajil porphyry deposit, optimal angles for phyllic, argillic, and propylitic alterations were determined to be 0.085, 0.17, and 0.16 respectively. These angles were found to be the most suitable to accurately identify and characterise these specific types of alterations within the deposit area.

Spectral Feature Fitting (SFF), introduced by Clark *et al*. (1991), leverages absorption features in spectra and employs a sequential elimination approach along with square fitting algorithms to detect mineral substances. While SFF is frequently applied in hyperspectral imagery analysis to identify intriguing targets, it does not consistently guarantee superior accuracy in extracting image data under all conditions, as highlighted by Pan *et al*. (2013) in comparison to other remote sensing analysis techniques. Mixture Tuned Matched Filtering (MTMF) represents an extension of Matched Filtering (MF) by incorporating an infeasibility image into the results. The introduction of this infeasible image aims to mitigate the occurrence of false positives that may arise when utilising MF alone. Pixels demonstrating high infeasibility are more likely to be classified as false positives. Validly mapped pixels exhibit a higher score compared to the background distribution around zero, while unreasonably low values indicate potential false positives. These infeasibility values are measured in sigma noise units, which differ on the DN (Digital Number) scale from the MF score. MTMF is designed to enhance the spectral resolution of hyperspectral imagery, thereby facilitating the identification of the presence and potential frequency of specific phenomena within a defined region of interest. With advancements in remote sensing and image analysis, the detection and mapping of phenomena within a scene using satellite data and sophisticated software have become more achievable for land managers (Boardman, 1998; Williams and Hunt, 2002; Harris and Bryant, 2009). These methodologies and technological advancements contribute to more refined and precise analyses of phenomena within given regions using satellite imagery and advanced processing tools.

Porphyry systems are commonly accompanied by various hydrothermal alterations, including potassic, phyllic, argillic, and propylitic alterations, as per the conceptual model. Among these alterations, the potassic zone is predominantly associated with porphyry systems and plays a crucial role in their exploration, often containing the primary portion of the ore body. Consequently, it has been assigned the highest score compared to other alteration zones. The phyllic, argillic, and propylitic alterations have received subsequent scores based on their significance in porphyry deposits. The final alteration indicator layer, shown in Fig. 3, was generated using this methodology. For more detailed information on the creation of alteration maps and exported ASTER images, interested readers are referred to the research conducted by Barak *et al*. (2023).

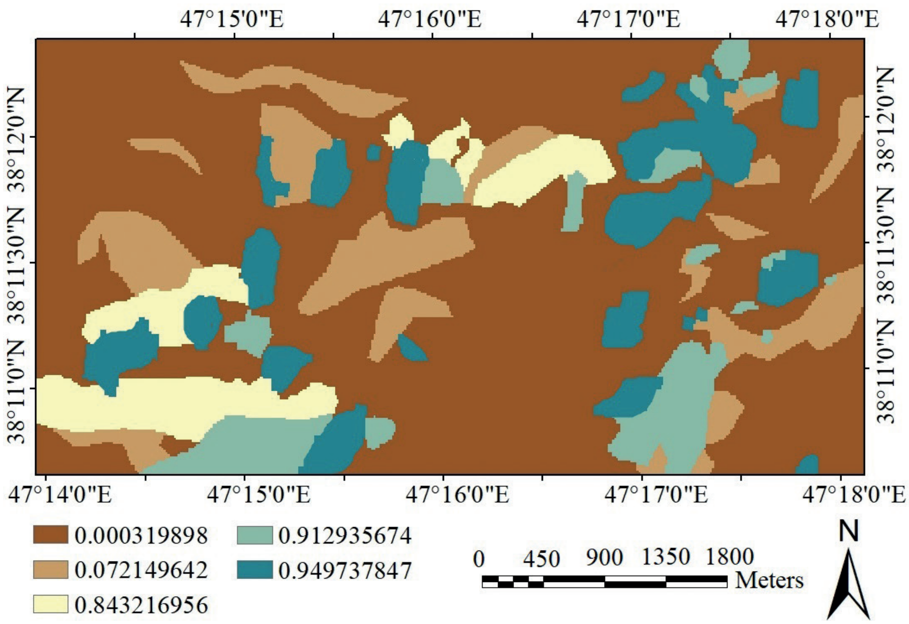

Fig. 3 - Alteration evidential layer of the Sonajil area.

3.3. Geochemical indicator

A total of 1,248 lithogeochemical samples were collected by KCE (2006) to generate the geochemical layer. The AMDEL laboratory in Australia conducted the analysis using ICP-Mass analysis for 43 elements and fire assay analysis for gold. After data pre-processing steps, including identifying censored data, adjusting outlier values, and normalising skewed data, the descriptive statistical characteristics of the geochemical Cu and Au elements were examined (Imamalipour *et al*., 2019, 2020). The results are given in Table 2. In addition, histograms, box plots, and quantile-quantile (q-q) plots (Figs. 4a, 4b, and 4c) were used to illustrate the skewed nature of the data, indicating the potential presence of ore mineralisation in the Sonajil area. The Pearson correlation coefficient, a statistical measure used to assess the relationship between several variables, showed a correlation coefficient of 0.42 between Cu and Au (as stated in Table 3). Cluster analysis, a multivariate statistical technique, was conducted on the data following the methodology outlined by Barak *et al*. (2016, 2018a, 2018b). The analysis, depicted in Fig. 5, revealed a close relationship between Cu and Au among all 43 elements. To differentiate anomalous regions from the background in terms of Cu and Au elements, the concentration-number (C-N) fractal method was employed. This method was utilised for the classification and scoring of different geochemical populations for each element (Afzal *et al*., 2013; Hassanpour and Afzal, 2013; Barak *et al*., 2017; Mami Khalifani *et al*., 2019). The resulting geochemical indicators were generated and plotted (as shown in Figs. 6a and 6b). For more detailed information, readers can refer to the study conducted by Barak *et al*. (2023).

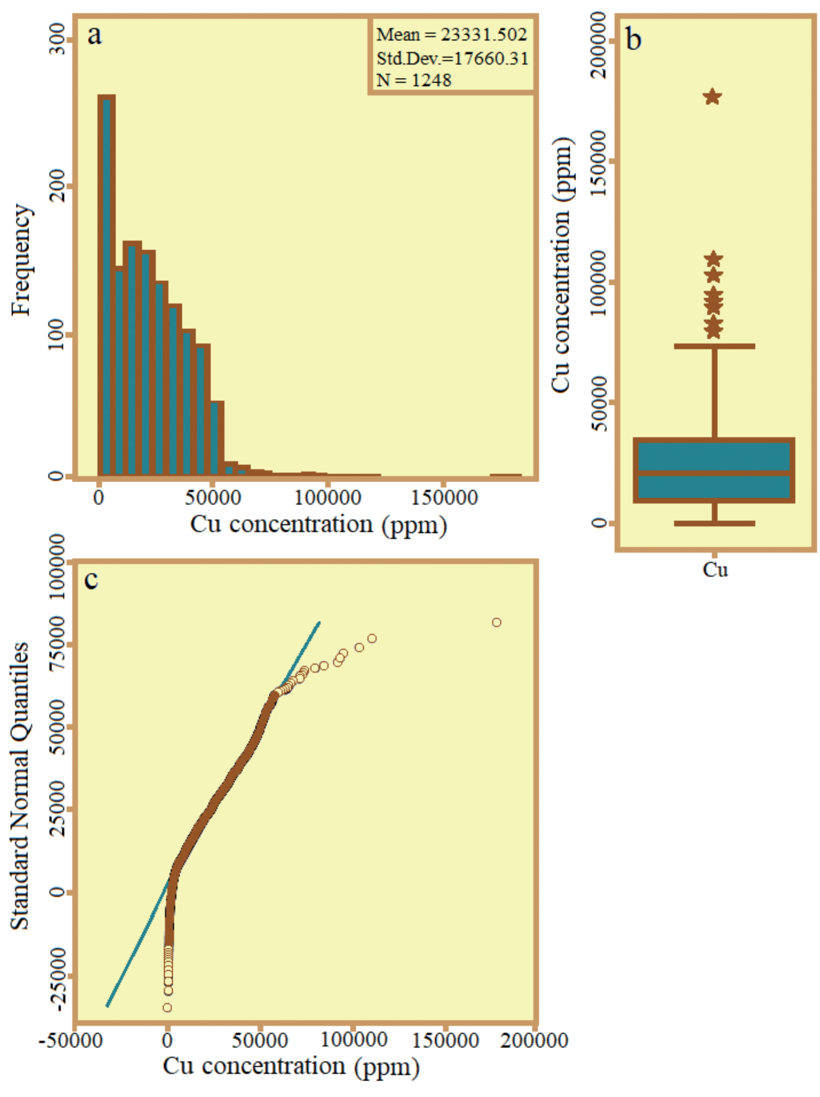

Fig. 4 - Statistical graphs of raw data including: a) histogram, b) boxplot, and c) q-q plots.

Table 2 - Descriptive statistics of geochemical Cu and Au element of the Sonajil area.

Element	Minimum	Maximum	Mean	Standard deviation	Variance	Skewness	Kurtosis
Cu	7.100	9890	230.8019	789.9465	624015.5	7.96198	72.09288
Au	0.000	8890	24.38862	283.4842	80363.29	26.16065	781.8694

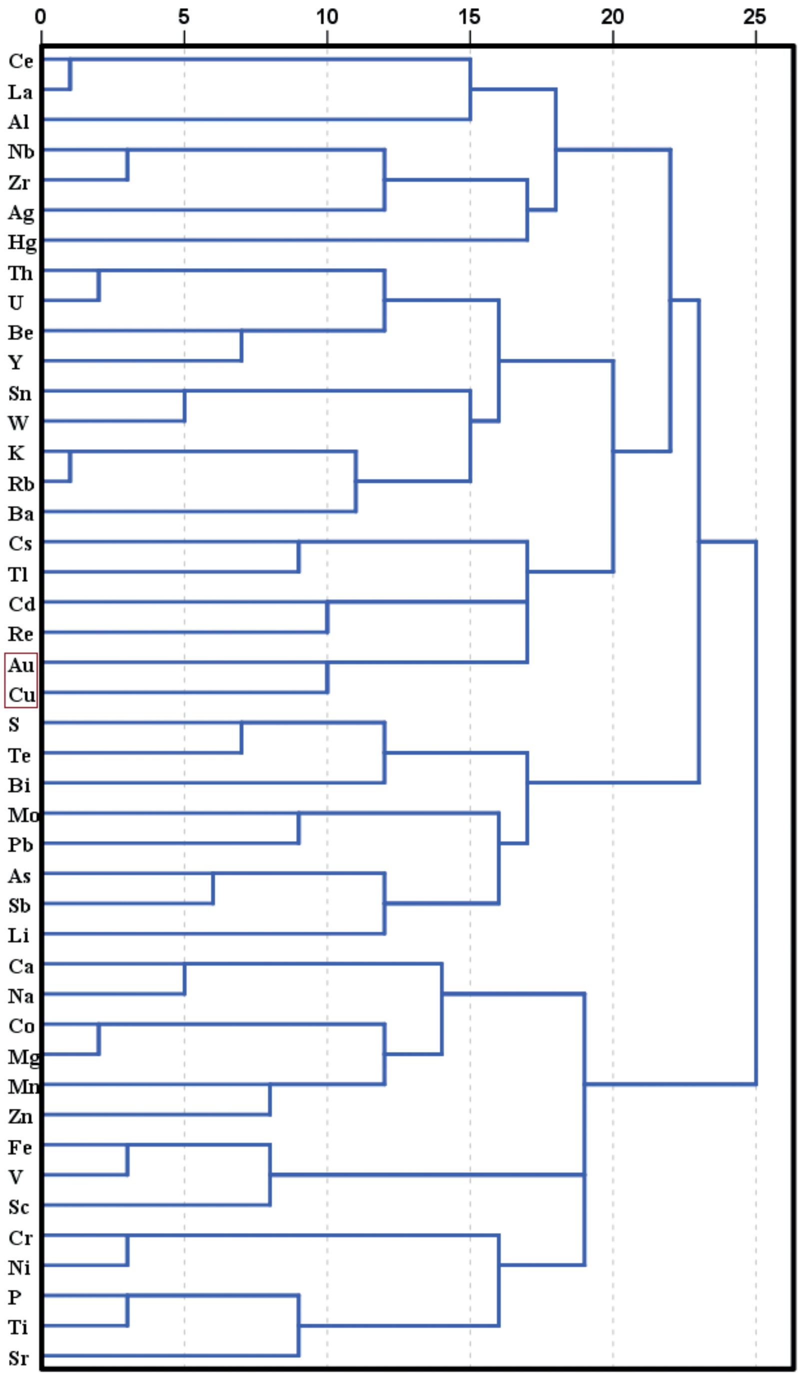

Fig. 5 - Cluster analysis of normalised geochemical soil sample data from the Sonajil area.

Table 3 - The Pearson correlation coefficient of selected minerals of the Sonajil area.

Element	Ag	Au	Cu	Mo	Pb	Zn
Ag	1.00					
Au	0.04	1.00				
Cu	-0.04	0.42	1.00			
Mo	0.01	0.27	0.23	1.00		
Pb	0.03	0.23	0.12	0.45	1.00	
Zn	0.06	0.10	0.32	-0.19	-0.08	1.00

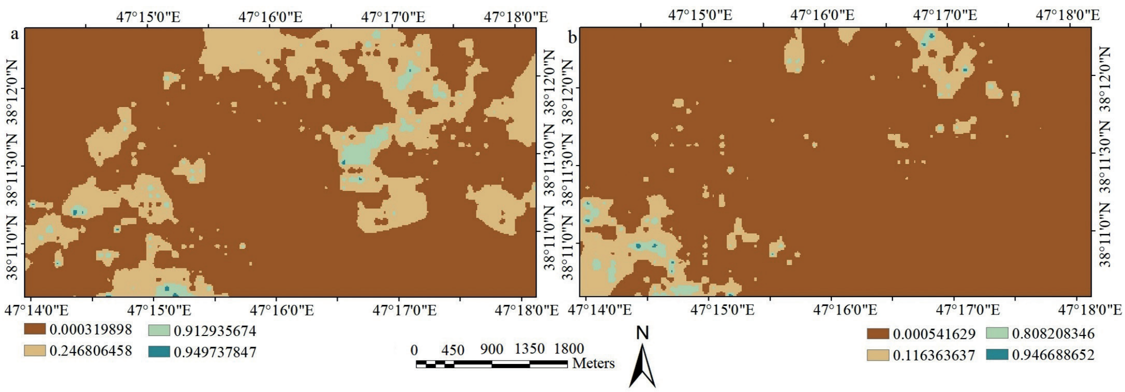

Fig. 6 - Geochemical evidential layers of: a) Cu, b) Au.

3.4. Geophysical indicator

Porphyry copper systems commonly have a central region of Cu mineralisation that is surrounded by various alteration zones. Each of these zones is distinguished by different magnetic intensity fluctuations. According to Clark *et al.* (2004), the potassic zone, which is enriched with iron-oxide, typically exhibits higher magnetic intensity. On the other hand, the phyllic zones, which contain sericite, generally show a decrease in magnetic intensity. The propylitic zone, however, experiences a gradual increase in magnetic intensity. These magnetic variations are significant focal points for detection in magnetometry studies. The dimensions of the surveying grid used were 20×50 m^2, with magnetic data showing a significant difference between the minimum and maximum values, totalling around 2,400 nT. The Earth's magnetic field intensity in the area was measured at approximately 48,920 nT, with data collected using the SCINTREX ENVI pro-proton magnetometer device. The collected data were processed with the International Geomagnetic Reference Field and diurnal correlations using the Geosoft Oasis montaj 6.4.2 software, resulting in the creation of a total field magnetic map. The analysis of the magnetic map revealed the presence of two distinct poles, positioned approximately in the middle of the anomaly. This bipolar behaviour added a level of complexity to the analysis. To address this complexity, a reduced-to-pole (RTP) filter was utilised. The RTP filter adjusts the magnetic data to align with the magnetic pole. At the Earth's magnetic north pole, the positive pole directly above the source becomes stronger, while the negative pole weakens and shifts towards the periphery of the anomaly. This simplifies the overall complexity of the magnetic field intensity map by aligning the magnetic origins with the positive pole. This filtering technique aids in identifying mineralisation zones based on the positions of maximum anomalies (Schattner *et al.*, 2019). Different classes were assigned weights to contribute to the creation of the final geophysical map, shown in Fig. 7. This map offers a detailed representation of magnetic anomalies, assisting in pinpointing mineralisation zones in the surveyed region. To delve deeper into geophysical layer preparation, readers are advised to refer to the research by Barak *et al*. (2023).

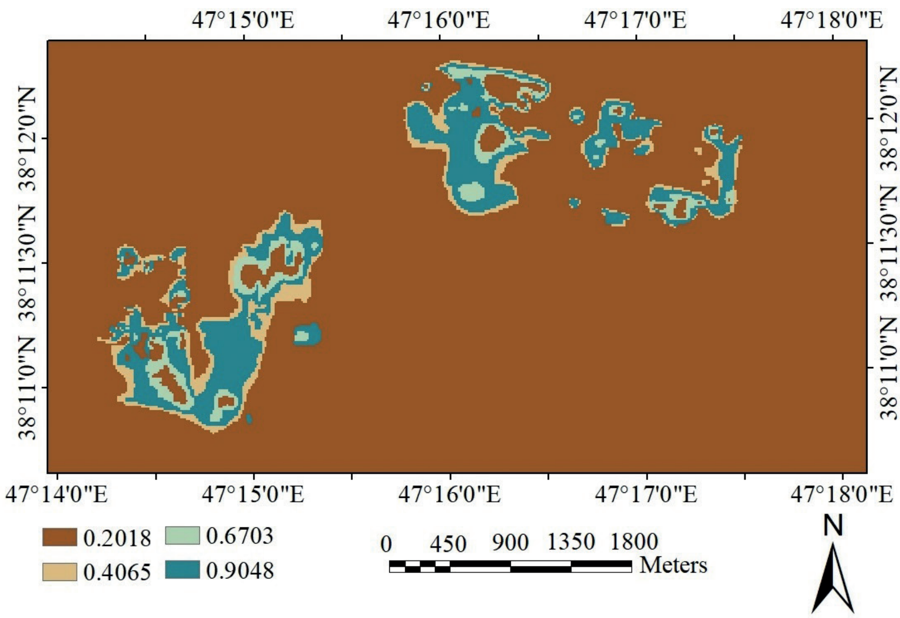

Fig. 7 - Geophysical magnetometry evidential layers of the RTP.

4. Geospatial data fusion methodologies

Fusion techniques were integrated into the Sonajil region by creating a detailed collection of six exploration proxies based on the exploratory geo-data set. The proxies included geology, remote sensing, geophysics, and geochemistry criteria layers, which underwent meticulous curation and assessment by a team of knowledgeable experts and geologists familiar with the study area's intricacies. The decision-making process was visualised using a decision tree diagram (Fig. 8), which showed that the final potential maps were created by combining: 1) two layers containing fault and rock type maps, 2) two layers obtained from Cu and Au factors extracted from soil sample geochemical data, 3) a layer generated from reduced-to-pole magnetics data, and 4) an alteration layer derived from remote sensing data. The Sonajil area utilised the Delphi technique, a well-known knowledge-based weighting approach, to assign normalised values to each exploratory layer. This allowed for the evaluation of the relative importance and contribution of each layer in the overall analysis. Various methods were employed in the study, including index overlay, Old TOPSIS, Modified TOPSIS (M-TOPSIS), Adjusted TOPSIS (A-TOPSIS), Old VIKOR, Modified VIKOR, fuzzy gamma operator, FOWA with different α parameters, and FIS. The advantages and disadvantages of these methods are discussed in Table 4. The subsequent sections provide a comprehensive overview of these methods.

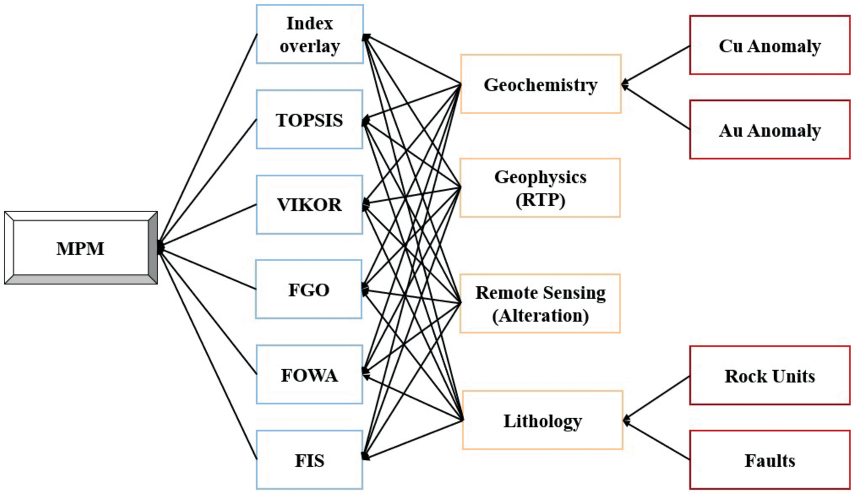

Fig. 8 - The decision tree flowchart for generating final prospectivity map.

4.1. Index overlay

The initial method utilised in this research is referred to as the multi-class index overlay, a knowledge-based technique commonly employed during the preliminary exploration stage, especially in regions with limited known mineral occurrences or in greenfield areas (Carranza, 2008). This technique involves transforming all fractal layers into a grid format and integrating them using a Boolean operation. Each layer contains various classes with assigned weights, which are multiplied by corresponding values to produce scores for individual elements, whether they are polygons or pixels. Subsequently, these scores are aggregated across the layers, integrated, and normalised. Notably, index overlay offers flexibility in presenting the priority or weightage assigned to the studied factors (Bonham-Carter, 1994). Hence, this approach is valuable for comparing and evaluating fusion models in assessing mineral potential.

The Sonajil data set underwent analysis using the index overlay fusion technique in this research. The delineated zones, categorised into five classes based on potential grades, were

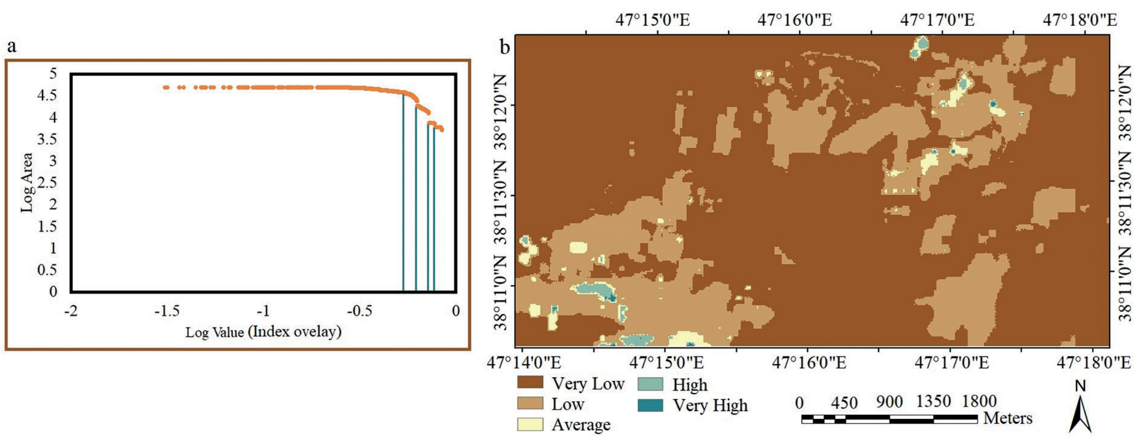

Fig. 9 - The generation of MPM through the index overlay approach (b) is informed by a fractal-based curve computation (a).

Table 4 - The advantages and disadvantages of the methods applied in this study.

Method	Advantages	Disadvantages
Index Overlay (e.g. Bonham-Carter, 1994; Carranza, 2008).	Simple and easy to understand. Allows combining different criteria into a single index.	Assumes linear relationships between criteria, which may not always hold. Difficulties in assigning appropriate weights to criteria.
Old TOPSIS (Hwang and Yoon, 1981; Chen and Hwang, 1992).	Provides a ranking of alternatives based on their proximity to an ideal solution. Considers both the best and worst performance of alternatives.	Sensitive to the choice of normalisation methods. Assumes that the distance to the ideal and non-ideal solutions are equally important.
M-TOPSIS (Ren *et al.*, 2007).	Addresses some of the limitations of the original TOPSIS method. Offers more flexibility in handling different types of data and preferences.	Increased complexity compared to the original TOPSIS. Requires careful consideration of modifications for specific applications.
A-TOPSIS (Deng *et al.*, 2000).	Incorporates adjustments to better account for uncertainties and preferences. Offers improved robustness compared to standard TOPSIS.	May require additional data or information for adjustment parameters. Complexity might increase with adjustments, making it more challenging to implement.
Old VIKOR (Opricovic, 1998).	Provides a compromise solution that balances conflicting criteria. Allows for the consideration of both the distance to the ideal solution and the proximity to the negative ideal.	May not handle uncertainties well. Complexity increases with the number of criteria and alternatives.
Modified VIKOR (Chang, 2010).	Offers improvements on the original VIKOR method, such as addressing uncertainties and preferences more effectively. Provides a compromise solution considering multiple conflicting objectives.	Increased complexity compared to the original VIKOR. Requires careful consideration of modifications for specific applications.
Fuzzy gamma operator (Zadeh, 1965).	Allows for the modelling of uncertainty and vagueness in decision-making. Can handle imprecise or qualitative data effectively.	Choice of membership functions and gamma operator parameters can affect results significantly. Interpretation of fuzzy logic results might be challenging for some decision-makers.
FOWA (Yager, 1988).	Offers a flexible framework for aggregating criteria with different importance levels. Allows adjusting aggregation strategies using α parameters.	Complexity increases with the number of criteria and alternatives. Selection of appropriate α parameters may require expert knowledge or sensitivity analysis.
FIS (e.g. Mamdani and Assilian, 1975; Porwal *et al.*, 2015; Barak *et al.*, 2021).	Provides a systematic approach to handle uncertainty and vagueness in decision-making. Can model complex relationships between criteria and alternatives.	Requires significant computational resources, especially for large decision problems. Construction and tuning of fuzzy rules and membership functions can be subjective and time-consuming.

represented clearly through a curve derived from fractal computations (Figs. 9a and 9b). This classification assists in identifying and prioritising areas for further exploration and analysis by showcasing different levels of mineral potential within the surveyed region.

4.2. Technique for Order Performance by Similarity to Ideal Solution (TOPSIS)

Hwang and Yoon (1981) introduced the TOPSIS algorithm, later refined by Chen and Hwang (1992) and further enhanced by Chen (2000) in a fuzzy environment. This method is widely recognised as a leading technique for addressing MCDM problems, as highlighted by Opricovic and Tzeng (2004) and Tavana and Hatami-Marbini (2011). TOPSIS operates on the principle that the selected alternative should be closest to the positive ideal solution (PIS) and farthest from the negative ideal solution (NIS). The PIS aims to maximise benefit criteria and minimise cost criteria, while the NIS aims to maximise cost criteria and minimise benefit criteria, as explained by Wang and Elhag (2006). The traditional TOPSIS method determines criteria weights based on precise data, while the fuzzy TOPSIS method considers fuzzy conditions and linguistic variables to better reflect real-world decision-making scenarios. Notably, there exist three prevalent variants of the TOPSIS method: 1) the old TOPSIS (Hwang and Yoon, 1981), 2) the A-TOPSIS (Deng *et al.*, 2000), and 3) the M-TOPSIS (Ren *et al.*, 2007).

This research drew inspiration from Abedi and Norouzi's (2016) study and applied three different versions of TOPSIS in MPM. The variations combined evidential layers from the Sonajil area data set, resulting in successful identification of high-potential zones. The MPMs generated by the TOPSIS variants categorised the layers into five classes using a fractal-based curve, offering a clear depiction of mineral potential levels in the surveyed area (Fig. 10).

4.3. VIKOR

Introduced by Opricovic (1998), VIKOR is an MCDM method specifically designed for decision-making scenarios involving contradictory and non-commensurable criteria. The technique aims to identify the alternative that best approximates the ideal solution by evaluating all criteria. VIKOR prioritises multi-criteria and determines the approach that is closest to an optimal solution. Opricovic (2011) later developed fuzzy VIKOR to handle fuzzy concepts, where criteria and values are assessed within the 0 to 1 range. This extension of VIKOR simplifies real-life problems by accommodating linguistic variables. There are two primary variations of the VIKOR method: the original Old VIKOR, introduced by Opricovic (1998), and the Modified VIKOR, developed by Chang (2010). Abedi *et al*. (2016) successfully utilised this method in MPM. In this particular study, both the original and modified versions of the VIKOR method were applied to evidential layers, as shown in Figs. 11a to 11d. These techniques have aided in the prioritisation and classification of potential zones within the Sonajil area, offering valuable insights into varying levels of mineral prospectivity throughout the surveyed region.

4.4. Fuzzy gamma operator

Zadeh (1965) introduced the fuzzy set theory which differs from Boolean set theory as it allows objects in a set to have varying degrees of membership instead of strict categorisation. Fuzzy logic operates on a scale from 0 to 1, representing degrees of membership, unlike the binary nature of traditional set theory. In fuzzy logic analysis, assigning membership values between 0 and 1 is essential, as the chosen weights for different factors should align with the extent of

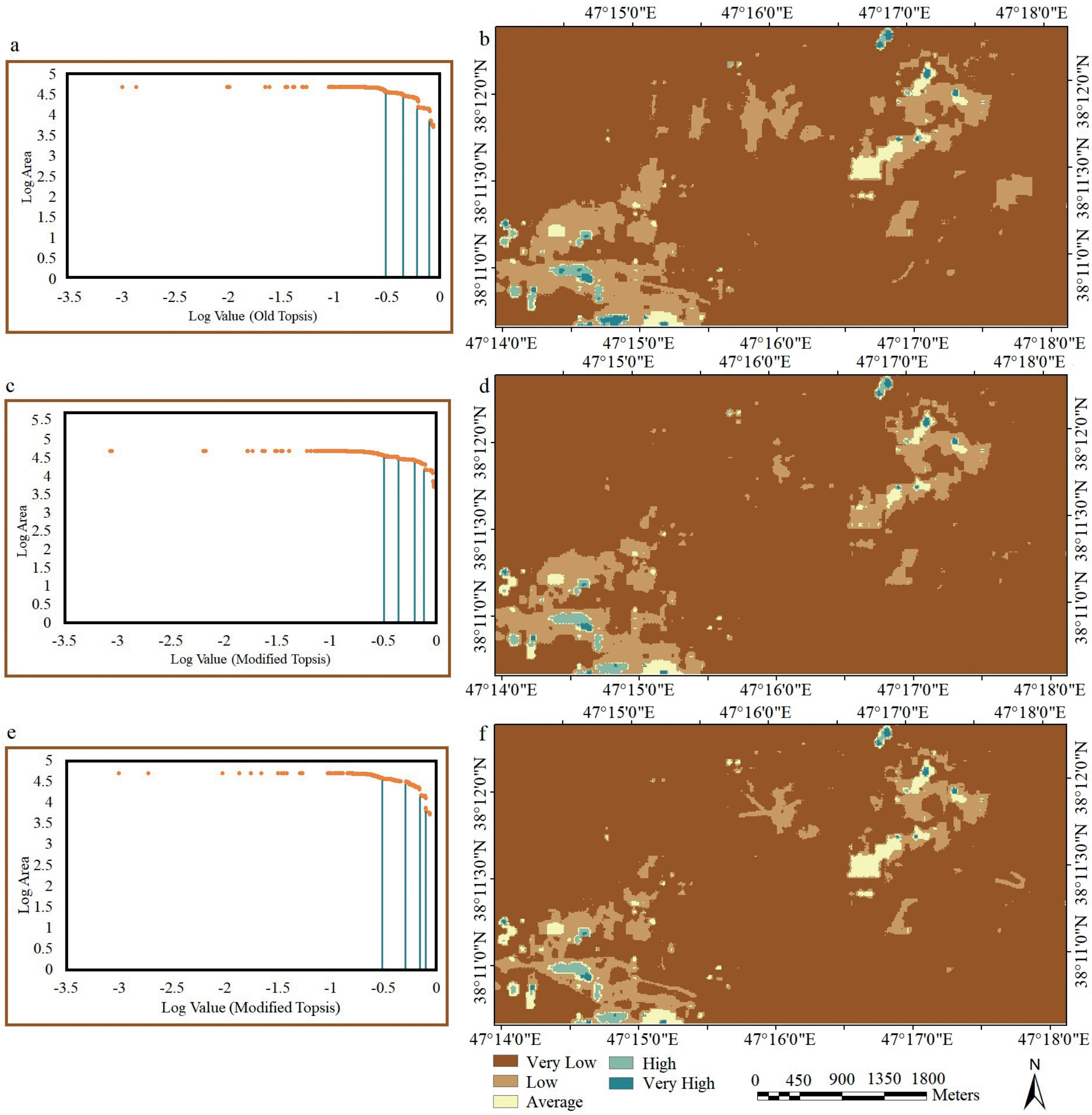

Fig. 10 - The mineral prospectivity map resulting from the utilisation of Old TOPSIS (a, b), M-TOPSIS (c, d), and A-TOPSIS (e, f) methodologies is presented. The left column illustrates the curve based on fractal computation, while the right column showcases the fusion outputs.

membership in a set, which can be influenced by user experience and considerations (Kanungo *et al.*, 2009). The fuzzy gamma operator is utilised as an efficient integration technique, allowing for adaptability in weighted maps and seamless implementation in the ArcGIS platform. Following the assignment of scores to the criteria and indicators (Table 2), the gamma weight of 0.87 was determined using a trial-and-error approach in this research. This specific value was selected for the MPM integration in the study region. Subsequently, the resulting mineral favourability map was categorised into five classes based on a curve obtained from fractal computation, as illustrated in Figs. 12a and 12b. This classification offers a detailed depiction of various levels of mineral favourability throughout the Sonajil area.

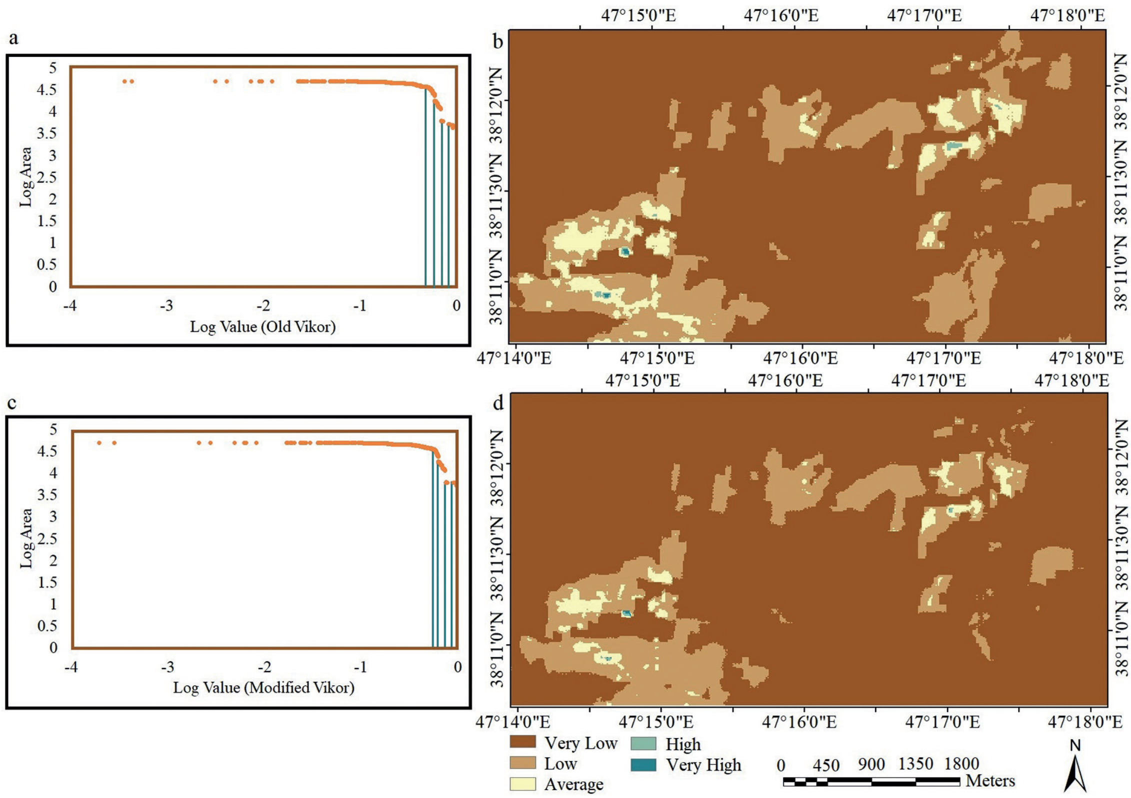

Fig. 11 - The mineral prospectivity map generated through the application of Old VIKOR (a, b) and Modified VIKOR (c, d) methodologies is illustrated. The left column displays the curve based on fractal computation, while the right column presents the fusion outputs.

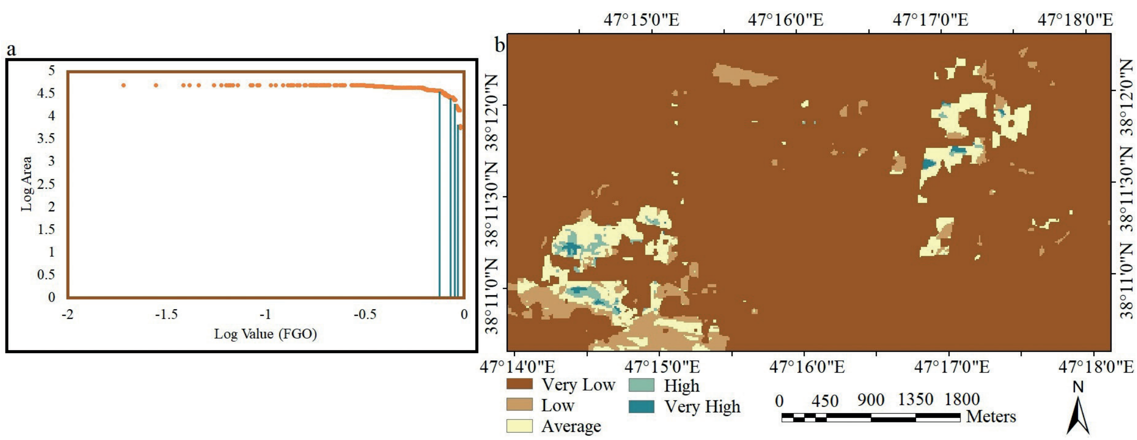

Fig. 12 - The curve based on the fractal computation (a) for generating the MPM by utilising fuzzy gamma operator (b).

4.5. Fuzzy Ordered Weighted Averaging (FOWA) method

The process of applying FOWA involves sequential stages and modifications, aiming to achieve optimal outcomes by utilising the α parameter. This α parameter serves as a degree scale for decision-makers to adopt different strategies in MCDM problems (Yager, 1988). Essentially, it allows decision-makers to shift from a pessimistic state to an optimistic one.

In the study conducted in the Sonajil region, a total of seven α parameters were tested: 0.001, 0.1, 0.5, 1, 2, 10, and 1000. These parameters were adjusted based on the assigned weights to indicators. The fusion layers obtained from these parameters were, then, classified into five classes using a curve derived from fractal computation, as shown in Figs. 13a to 13n. This classification provides a detailed insight into the different levels of mineral prospectivity in the surveyed region, depending on the α parameter values applied in the FOWA method.

4.6. Fuzzy Inference System (FIS)

The FIS stands out as a knowledge-driven technique for MPM (Porwal *et al*., 2015). It operates through four primary steps: fuzzification, rule evaluation, aggregation, and defuzzification (Mamdani and Assilian, 1975; Porwal *et al*., 2015; Barak *et al*., 2021). The FIS method was utilised in this research across four distinct layers, with a tailored algorithm incorporating four criteria layers to simplify inferencing rules, ultimately reducing complexity and time consumption (Alaei Moghadam *et al*., 2015). These layers encompassed geology (employing a weighted overlay technique with a 70% participation percentage for rock units and 30% for faults within ArcGIS 10.8 software), geochemistry (merging Cu and Mo using an OR operator), alteration, and geophysics (RTP filter). Trapezoidal memberships were selected as fuzzy functions to align with the preliminary exploration phase in the Sonajil area, applied to input layers such as geological, remote sensing, geochemical and geophysical layers (Mamdani and Assilian, 1975). The process of defining fuzzy "if-then" rules is a critical step in FIS fusion techniques. In this study, a total of 81 "if-then" rules have been carefully established, taking into account the available information from the Sonajil area and the conceptual model of porphyry deposits. These rules can be found in Table 5 and Fig. 15. Following a similar approach as Barak *et al*. (2020), the FIS integrated layer was created, and the resulting integration was divided into five classes using a curve obtained from fractal computation (Figs. 16a and 16b). This classification offers a detailed representation of the mineral prospectivity levels in the Sonajil area, based on the FIS technique and the specific ruleset developed for this study.

Table 5 - Examples of "if-then" rules in FIS.

Rule	Geology	Alteration	Geochemistry	Geophysics	Mineral potential
1	Poor	Poor	Poor	Poor	Very poor
2	Poor	Poor	Average	Poor	Poor
3	Average	Strong	Poor	Average	Average
4	Poor	Average	Strong	Strong	Above average
5	Strong	Strong	Strong	Average	Strong
6	Strong	Strong	Strong	Strong	Very strong

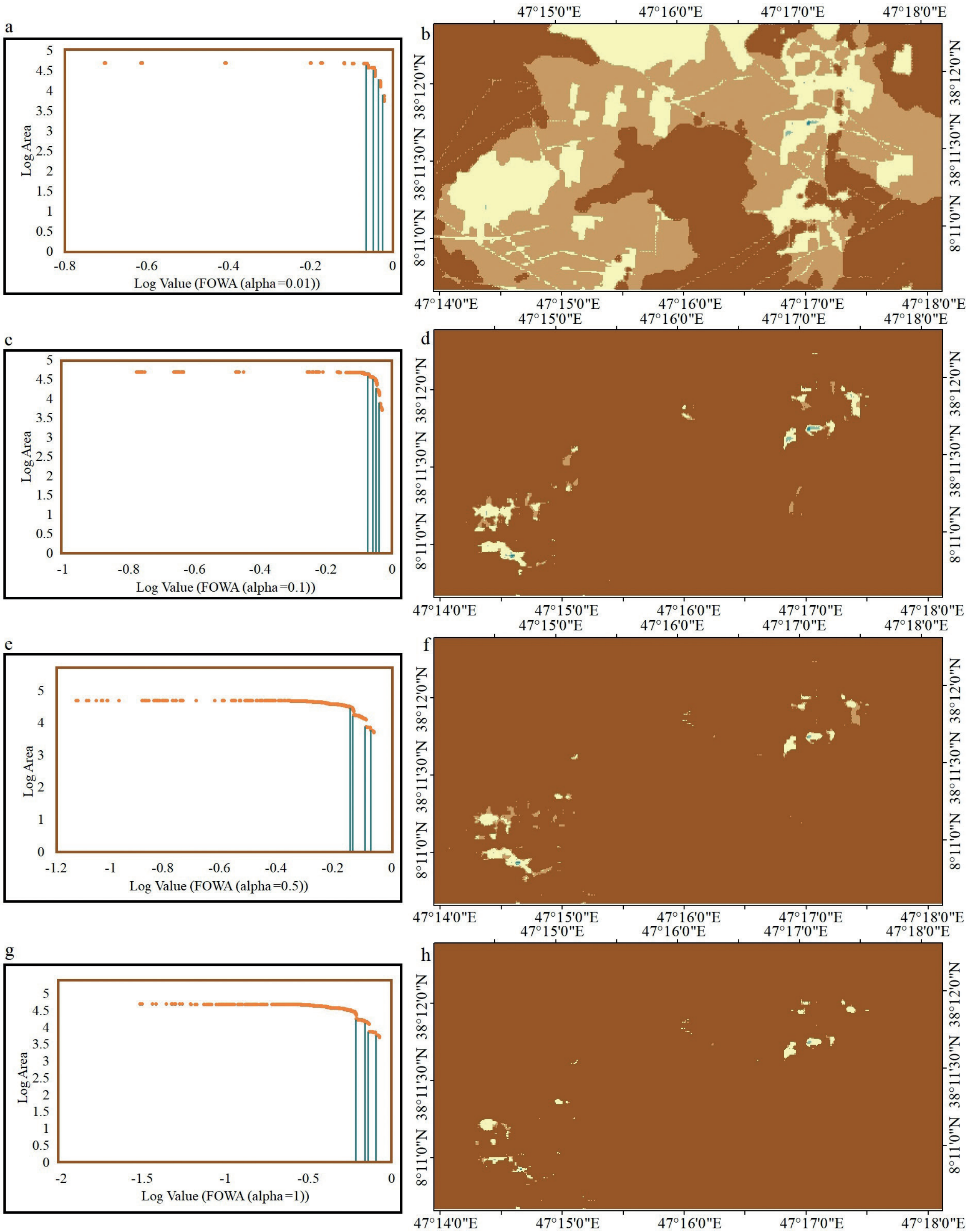

Fig. 13 - MPMs created by using the FOWA technique for seven values of α. Left column depicts the curve based on the fractal computation and the right column depicts the fusion outputs: a-b) α = 0.01, c-d) α = 0.1, e-f) α = 0.5, g-h) α = 1, i-j) α = 2, k -l) α = 10, and m-n) α = 100.

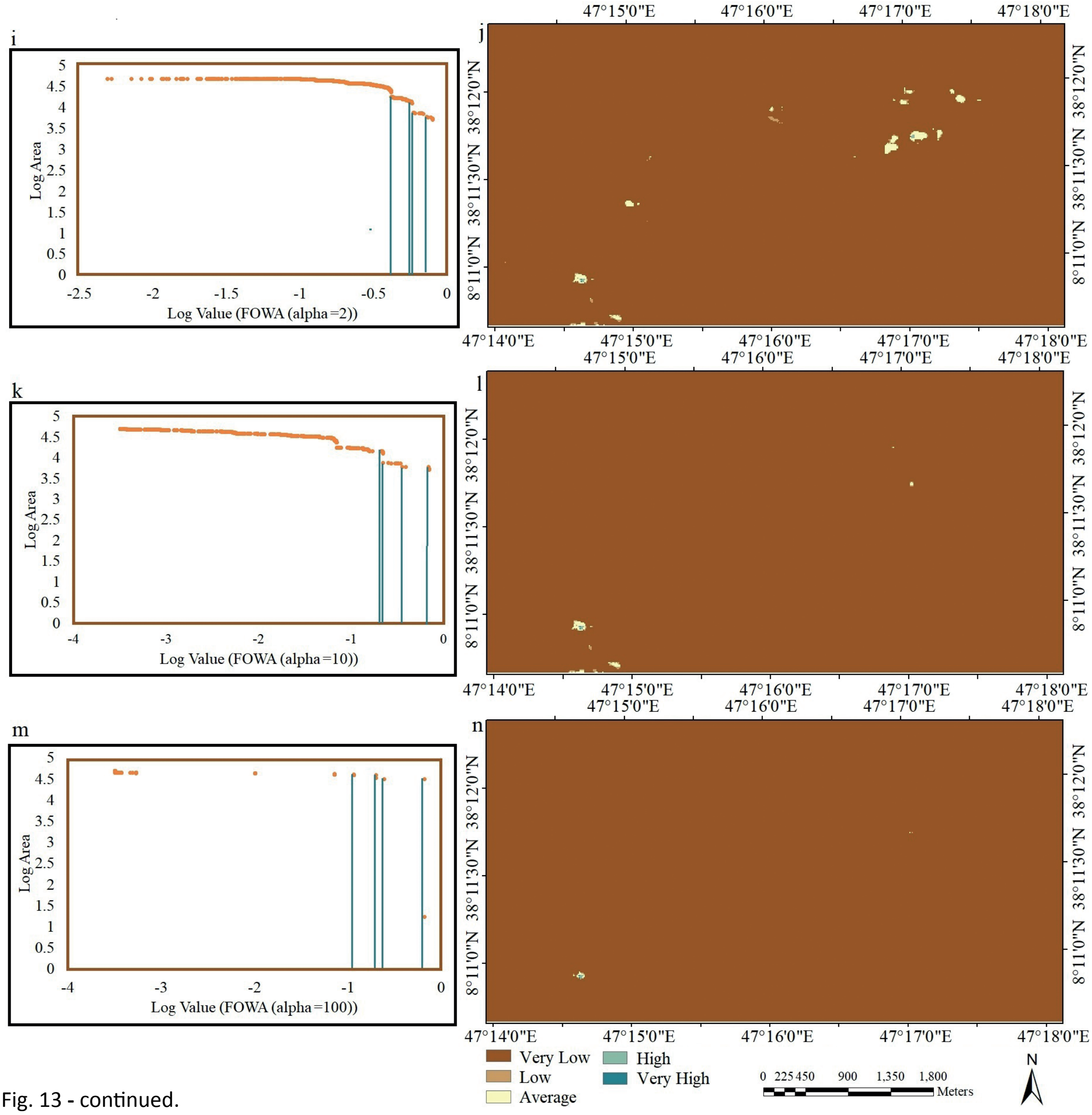

Fig. 13 - continued.

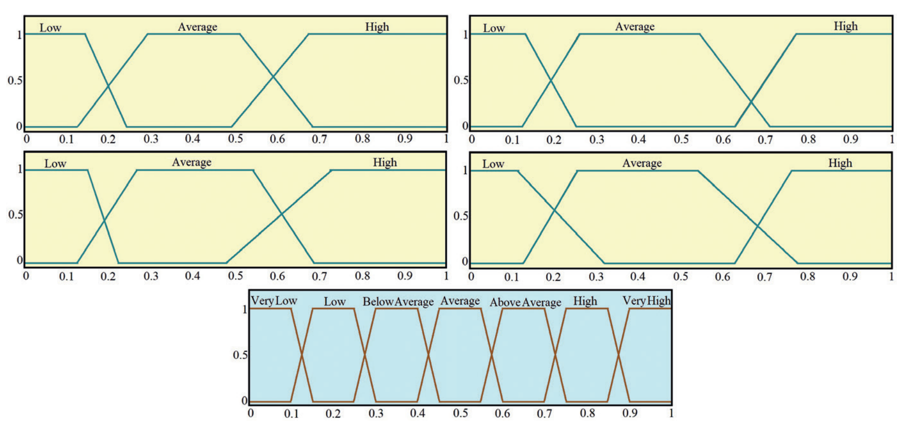

Fig. 14 - Membership functions taken into account for: a) geological factor, b) remote sensing factor, c) geochemical factor, d) magnetics factor, and e) output factor (MPM).

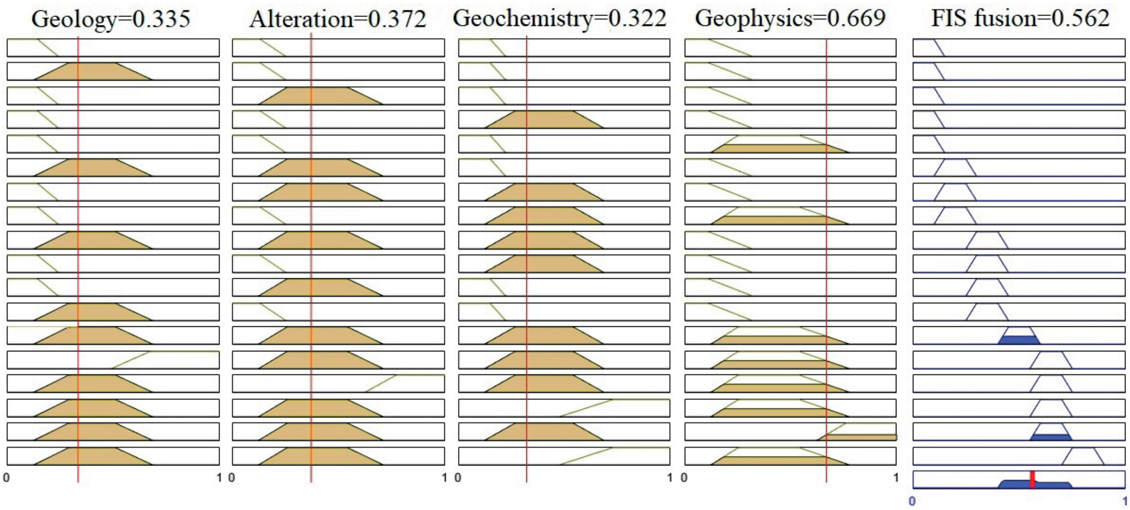

Fig. 15 - Simplified processing of “if-then” rules in FIS.

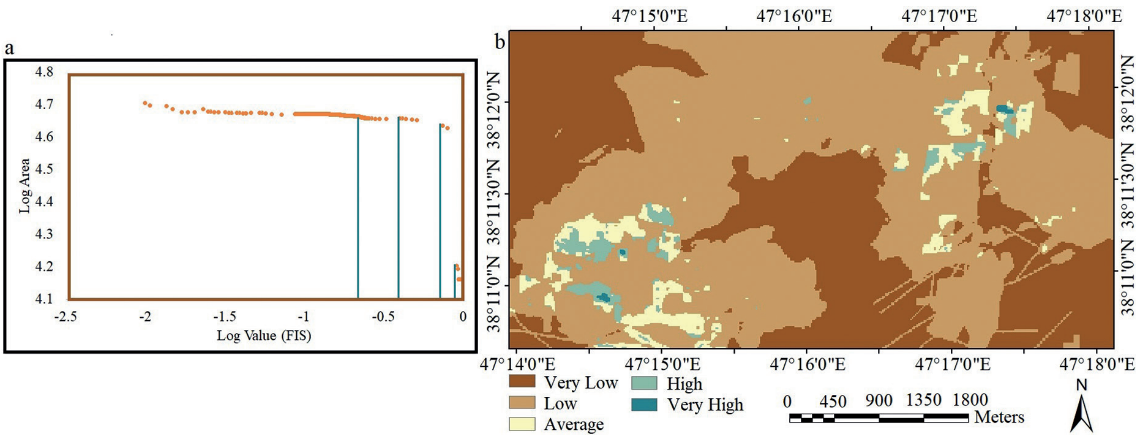

Fig. 16 - The mineral prospectivity map generated through the application of the FIS technique: a) the curve based on fractal computation, b) the fusion outputs.

5. Result and discussion

The primary objective of this research is to give priority and identify Cu-Au porphyry deposits in the Sonajil region using MPM methods. These methods, widely used in recent mineral processing studies, involve combining various data sets from geological, remote sensing, geochemistry, and geophysics sources. This integration provides a thorough understanding of the mineral potential in the Sonajil area. Various fusion techniques were employed to generate MPM maps, encompassing index overlay, Old TOPSIS, M-TOPSIS, A-TOPSIS, Old VIKOR, Modified VIKOR, fuzzy gamma operator, FOWA (with different α parameters), and FIS. Different fuzzy fusion methods were used to analyse the MPM outcomes (Figs. 9 to 13 and 16), and they consistently revealed similar results. These results highlighted the areas with high potential, which are mainly linked to Sonajil’s granitoid rocks (quartz monzonite-granite-granodiorite) and

Sonajil andesite porphyry. These rock formations are known to be the primary hosts for Cu mineralisation.

To evaluate the effectiveness of the methods used, productivity values were calculated by multiplying ore grade with ore thickness for all 21 drilled boreholes, using a copper cut-off value of 0.2%. The results showed a clear link between higher productivity values in the boreholes and the prospectivity values from the MPMs, highlighting the significance of these areas for copper mineralisation. Furthermore, linear correlation coefficients (R^2) between the productivity values of the boreholes and the prospectivity values from MPMs were computed. Notably, FOWA (α = 10) showed an agreement of 81%, while FIS exhibited 79% agreement, signifying the highest consistency among the applied techniques in the region (Fig. 17). The comparison of R^2 values for all fusion techniques (Fig. 18) reinforced the prominence of the NE and SW portions of the Sonajil area as primary sources of porphyry deposits, particularly evident in the dark blue zones in the models created by FOWA (α = 10) and FIS. These findings suggest that the utilisation of FOWA (α = 10) and FIS techniques could guide and prioritise further exploration and drilling efforts in the identified favourable zones, particularly in the NE and SW regions of the Sonajil deposit.

Table 6 - The productivity values of all boreholes assuming a cut-off value of 0.2% of Cu grade.

x	y	Productivity
696182	4228889	125.84
696294	4228709	73.68
696405	4228777	46.48
696505	4228845	43.13
697004	4228934	85.40
696725	4228842	21.15
696784	4228860	62.30
696619	4228757	3.65
698409	4230184	4.03
699934	4229985	3.99
698877	4229961	30.80
699579	4230335	4.25
699453	4229779	0.00
699575	4230800	13.51
700423	4229875	3.09
700419	4230738	3.00
699983	4230425	18.85
697427	4228946	21.94
697339	4229180	4.40
697780	4229748	2.22

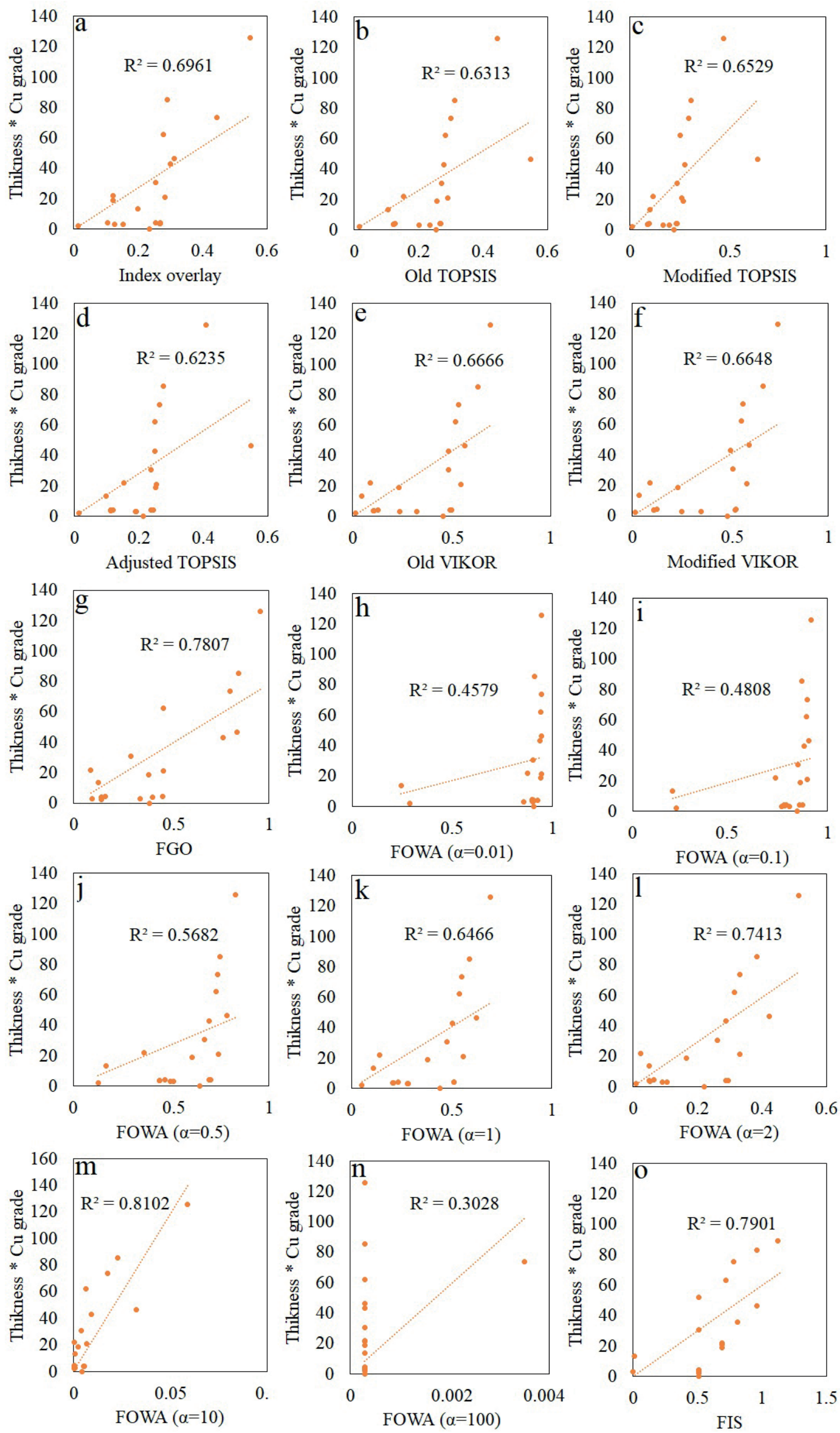

Fig. 17 - The curve of the productivity values of the drilled boreholes versus the MPM values for the prepared MPMs of: a) index overlay, b) Old TOPSIS, c) M-TOPSIS, d) A-TOPSIS, e) Old VIKOR, f) Modified VIKOR, g) fuzzy gamma operator, and FOWA for different values of: h) α = 0.01, i) α = 0.1, j) α = 0.5, k) α = 1, l) α = 2, m) α = 10, n) α = 100, and o) FIS.

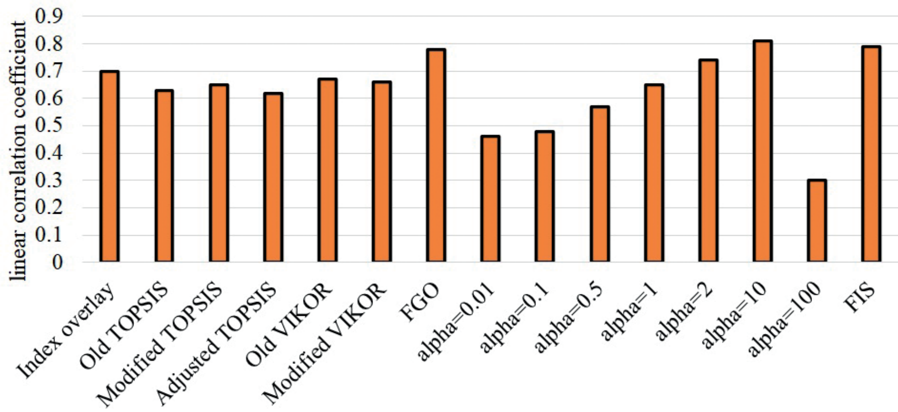

Fig. 18 - The linear correlation coefficient between the productivity values of the drilled boreholes and MPM values for various fuzzy-based techniques applied.

6. Conclusions

The research utilised various fusion techniques such as index overlay, Old TOPSIS, M-TOPSIS, A-TOPSIS, Old VIKOR, Modified VIKOR, fuzzy gamma operator, FOWA, and FIS, to assess the mineral potential of a Cu-Au porphyry deposit in the Sonajil area. Six indicators were created and examined, incorporating fractal-based curves to enhance anomaly zones and classify the findings into five zones for improved precision. The precision of the fuzzy fusion techniques was confirmed by identifying high potential areas that match with granitoid and andesite porphyry units. These findings, supported by geological data, suggest the possible existence of a Cu-Mo porphyry deposit in the Sonajil region, as evidenced by information from 21 boreholes utilised in the validation process. Within the study area, different fusion methods were utilised, with results indicating a 79% agreement for FIS and 81% for FOWA. These results strongly indicate the potential of using FIS and FOWA for future exploration, which could aid in identifying Cu-Au mineralisation and delineating the geometry in the Sonajil region.

Acknowledgments. This research was made possible with the help of the office of the vice-chancellor for Research and Technology, at the Urmia University. We acknowledge their support. Furthermore, the exploration works were conducted by the Koomeh Mine Pars Company on the Sonajil region. The authors would like to acknowledge the exploration group of this company, particularly Mr Gholamreza Asgarizadeh, manager and Mr Jamshid Habibi, engineer of the Sonajil project for their sincere support.

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