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Comparison of various knowledge-driven and logistic-based mineral prospectivity methods to generate Cu and Au exploration targets Case study: Feyz-Abad area (North of Lut block, NE Iran)

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Abstract
Motivated by the recent successful results of using GIS modeling in a variety of problems related to the geosciences, some knowledge-based methods were applied to a regional scale mapping of the mineral potential, special for Cu-Au mineralization in the Feyz-Abad area located in the NE of Iran. Mineral Prospectivity Mapping (MPM) is a multi-step process that ranks a promising target area for more exploration. In this work, five integration methods were compared consisting of fuzzy, continuous fuzzy, index overlay, AHP, and fuzzy AHP. For this purpose, geological maps, geochemical samples, and geophysics data were collected, and a spatial database was constructed. ETM $^+$ images were used to extract the hydroxyl and iron-oxide alterations, and to identify the linear and fault structures and prospective zones in regional scale; ASTER images were used to extract SiO_2 index, kaolinite, chlorite, and propylitic alterations in a district scale. All the geological, geochemical, and geophysical data was integrated for MPM by different analysis. The values were determined by expert knowledge or logistic functions. Based upon this analysis, three main exploration targets were recognized in the Feyz-Abad district. Based on field observation, MPM was proved to be valid. The prediction result is accurate, and can provide directions for future prospecting. Among all the methods evaluated in this work, which tend to generate relatively similar results, the continuous fuzzy model seems to be the best fit in the studied area because it is bias-free and can be used to generate reliable target areas.

Keywords: *Mineral Prospectivity Mapping, Fuzzy, AHP, Index Overlay, Feyz-Abad.*

1. Introduction

Lut block in eastern Iran is located along the Alpine-Himalayan orogenic and metalogenic belt. The tectonic setting, type of magmatism, and history of ancient mining suggest a great potential for different types of mineral deposits in the Lut block. Due to the unsystematic mineral exploration and lack of modern exploration techniques, there are still several unexplored outcropping of ore deposits in this area.

The Feyz-Abad area lies in the north of the Lut block, NE Iran, with an approximate area of about 2500 km^2. The sedimentary rocks in this area belong to Paleozoic. A suite of ophiolitic rocks (Cretaceous) is exposed in the northern part. Pyroclastic and volcanic rocks (mainly intermediate to felsic) are widespread all over in this area. Volcanic activities occurred during the Eocene time [1]. Post-Eocene magmatism is mostly manifested by intrusion of granodiorite, granite, and diorite into the volcanic rocks (Figure 1). There are three trends of faulting in this area: east-west, north-east, and north-west. Mineralization is mainly structurally controlled and found along the faults and within the fault zones [2].

Magmatism and metamorphic belt relate to arc volcanism, with Late Mesozoic to Neogene volcanic rocks distributed within. Different types of porphyry, hydrothermal, and iron oxide deposits have been identified along the Khaf-Dorouneh volcanic and plutonic belt in north-eastern Iran. Kuh-e-Zar is one of these ore deposits known as an Fe-oxide gold deposit [3]. The gold and copper deposits in this structure zone are strongly controlled by a large-scale fault system.

The purpose of this work was to use the GIS techniques to perform the analysis and to provide maps for a better understanding of the geochemical anomalies and mineral potentials within the Feyz-Abad area, and to indicate the best target for Mineral Prospectivity Mapping (MPM) to specify the prospective regions. MPM was recognized according to the metallogenic conceptual model for the Au-Cu deposits.

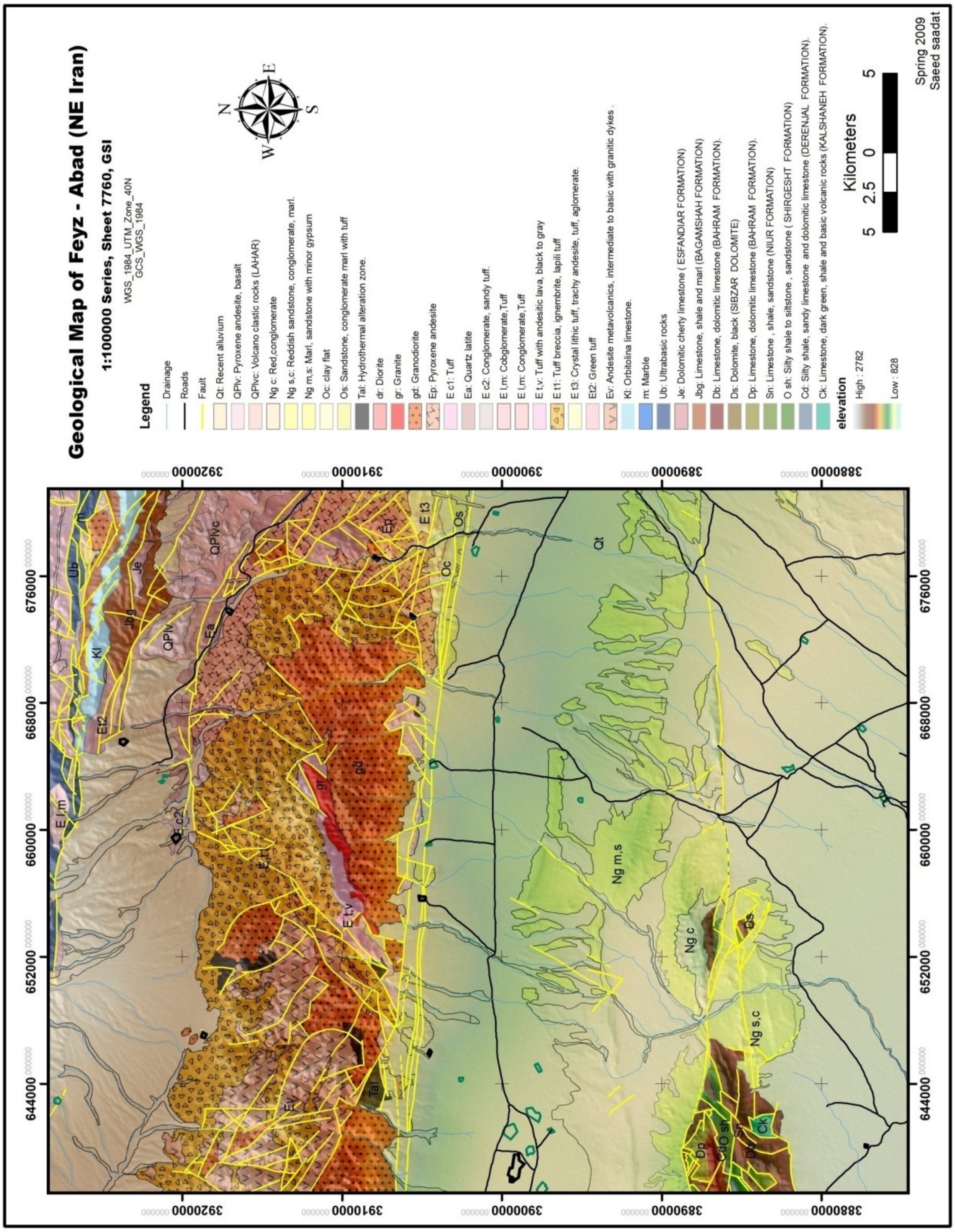

Figure 1. Simplified geological map of Feyz-Abad area (original map from [1]).

2. Modeling

Several approaches are applied for MPM, which are classified as data-driven and knowledge-driven methods [4-6]. Knowledge-driven predictive mapping of mineral prospectivity is suitable in the regions that are less-explored geologically, where no or very few known mineral deposits occurred [7]. In knowledge-driven prediction, the assigned weights to every spatial evidence layer are based upon a geoscientist's knowledge. In contrast, data-driven predictive mapping of mineral prospectivity is suitable in the regions that are moderately-to-well explored, where the main objective is to restrict new targets in order to explore undiscovered mineral deposits of the type sought (e.g. [8]). Some examples of these methods are Boolean logic [9], index overlay [9], Dempster-Shafer belief theory [10], and fuzzy logic [11]. In the recent years, fuzzy method has been applied to MPM in several ways such as fuzzy logic, fuzzy AHP [12], and fuzzy weights of evidence [13, 14]. The fuzzy analytic hierarchy process is useful when the act of decision-making is faced with several options and decision criteria. Recent works on fuzzy methods are based upon a combination of data and knowledge such as Neuro-fuzzy [15] and Fuzzification of continuous-value [16].

In the data-driven methods, the assigned weights to every spatial evidence layers are quantified. Spatial relationships between the known deposits and particular datasets were used to represent the prospectivity recognition criteria [17]. Data-driven contains different methods such as weight of evidence [9], logistic regression [18], neural networks [19, 20], evidential belief functions [21, 22], and Bayesian network classifiers [23].

3. Methods and result

3.1. Data

Geological, geochemical, and geophysical datasets were available and used as sources of evidence for MPM. To prospect the metalogenic zones for the Au-Cu deposits, the important layers were determined as pyroclastic rocks, intrusive bodies, alteration zone, volcanic rocks, faults, high magnetic zone, Fe-Oxide outcrops, ore occurrences, and Au, As, Ag, Cu, Mo, Pb, and Zn geochemical anomalies.

The geological maps contained information on igneous rocks, sedimentary formations, faults, and dikes, which were mapped at a scale of 1:100,000. A simplified geological map was constructed (Figure 1). The lithology layer consisted of 35 units. The selective rocks and ore occurrences indicate that the northern part is most important for MPM (Figure 2).

Faults play a role in enabling fluid passage during mineralization. The objective of fault density analysis is to determine the distribution of faults over the entire region, and the degree of fault convergence. As the gold and copper deposits in this area are controlled by a large-scale fault system, the density of faults was determined (Figure 3). A separate fault layer was also constructed based on the distance from faults. Buffer analysis was performed for faults and ore occurrences in a radius to 1500 m with intervals of 500 m.

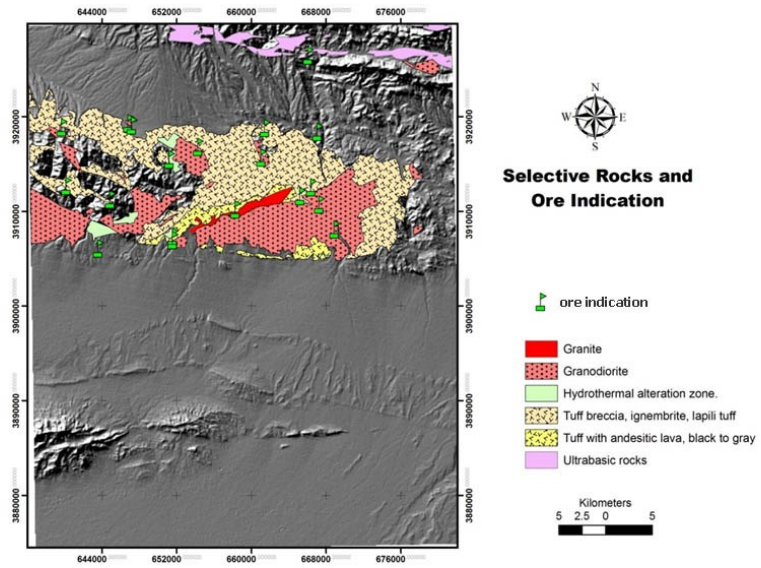

Figure 2. Selective rocks and ore indicators in Feyz-Abad area.

The geochemical data includes 2066 sample analysis from 28 major and trace elements. The geochemical anomaly map of some elements is shown in Figures 4 and 5. There are still some challenging aspects in generating stream sediment geochemical evidential maps. Some researchers have combined fuzzy with data-driven methods. For instance, [25] used ilr-transformation and staged Factor Analysis (FA) of stream sediment geochemical data for fuzzy membership scores to prepare a geochemical anomaly map.

The higher efficiency of staged FA over ordinary FA in extracting significant multi-element geochemical signature for the mineral deposit has been demonstrated by [24]. In this work, it was found that ilr-transformation resulted in approximately symmetric distributions for the stream sediment element data.

To examine the ilr-transformed data in factor analysis, Principal Component Analysis (PCA) was utilized for the extraction of factors. Furthermore, varimax rotation of factors was applied [25]. The findings here indicate that the ilr-transformed data for Ni, Cr, and Co in factor analysis can extract components representing anomalous multi-element geochemical signatures. However, for Cu and Au mineralization and their assemblage elements, there are no significant factors, which may be due to their different genesis and type of mineralization. As a result, separate raster images were produced for each indicator element. Pixel size of 100 m × 100 m has been used in all maps in this work. Figure 6 shows an example for Cu and Au anomalies.

The geophysical data includes regional air-borne magnetometry data, and shows a high magnetic potential in the northern part of the studied area.

Alteration zones are gained by processing satellite images. A scene of Landsat Enhanced Thematic Mapper plus (ETM$^+$ data, path 159, row 36, date 2000) and advanced space-borne thermal emission and reflection radiometer (ASTER, 2001) are used for an enhancing alteration.

These images are geometrically corrected using control points from topographic sheets. Data processing has been done by the ENVI (Environment for Visualizing Images) software. Band Ratios, PCA, and Spectral Angel Mapper (SAM) method were used to delineate the associated zones of hydrothermal alteration and iron oxide minerals. SAM is a procedure that determines the similarity between a pixel and each one of the reference spectra based on the calculation of the "spectral angle" between them [26]. Aster images are used for mapping hydrothermal alteration minerals such as Pyrophyllite, Kaolinite, Illite, Muscovite, Sericite, and carbonate. Enhanced kaolinite and phyllic zones by SAM methods are shown in Figure 7.

Argillic, Phyllic, and Propylitic alterations were determined with the aid of SWIR bands in aster imagery but iron oxide composites such as magnetite and hematite appeared by Landsat Imagery.

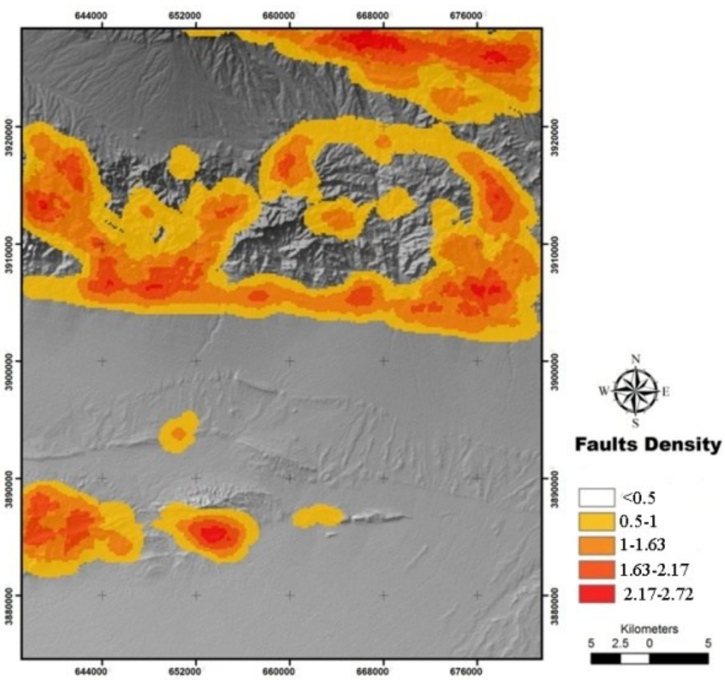

Figure 3. Density map of faults in Feyz-Abad area.

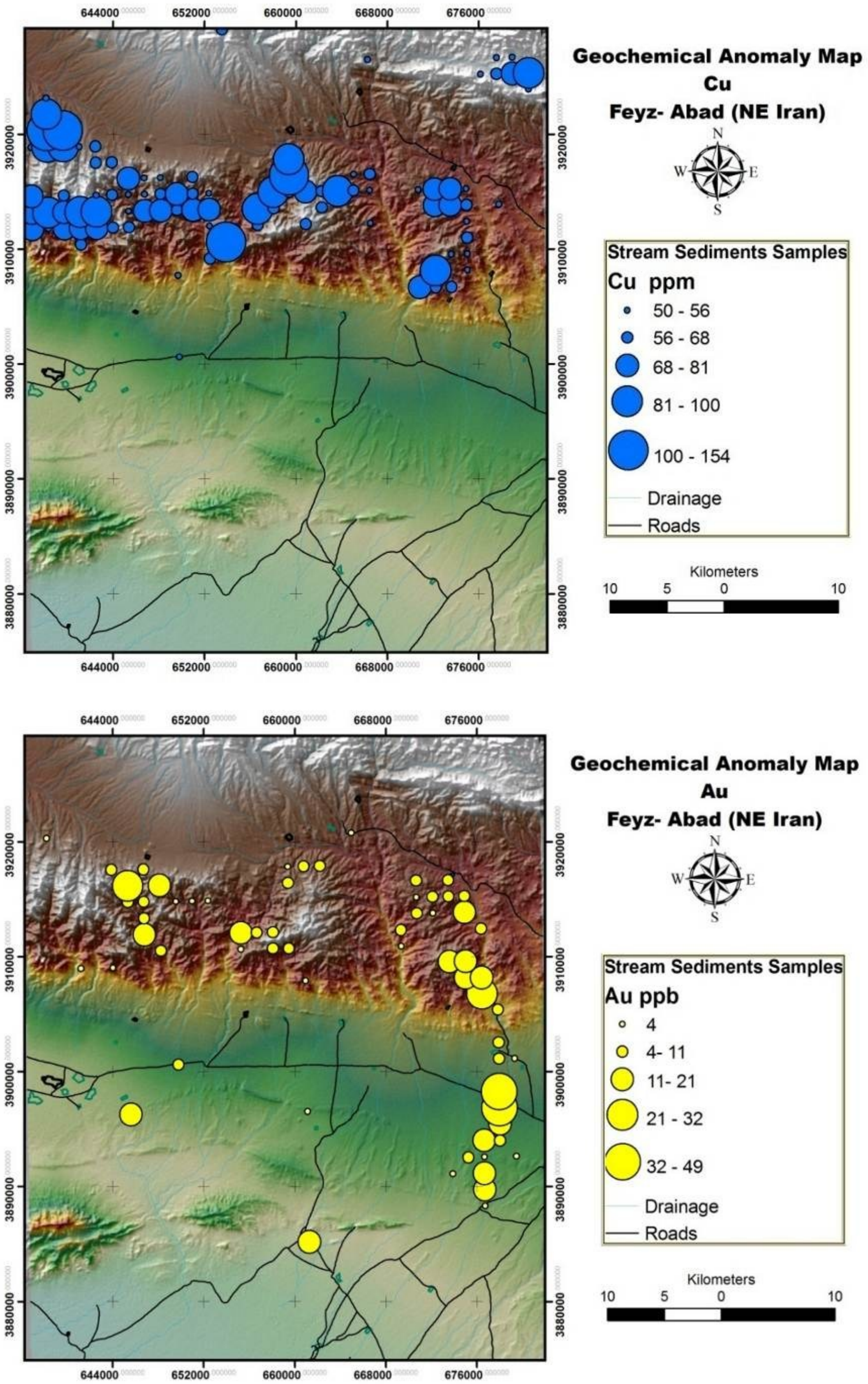

Figure 4. Distribution of Au and Cu in Stream sediments in Feyz-Abad area.

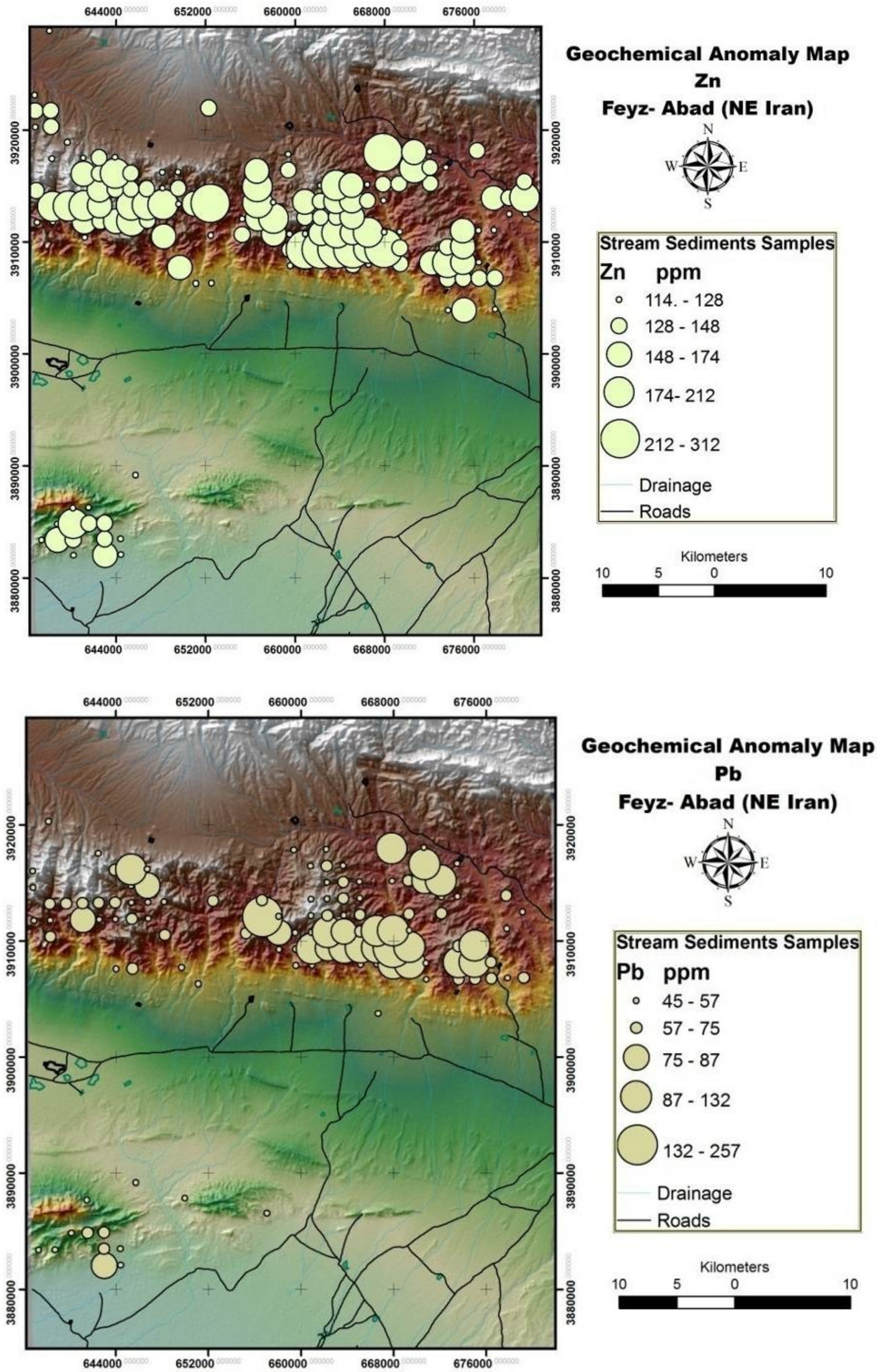

Figure 5. Distribution of Zn and Pb in Stream sediments in Feyz-Abad area.

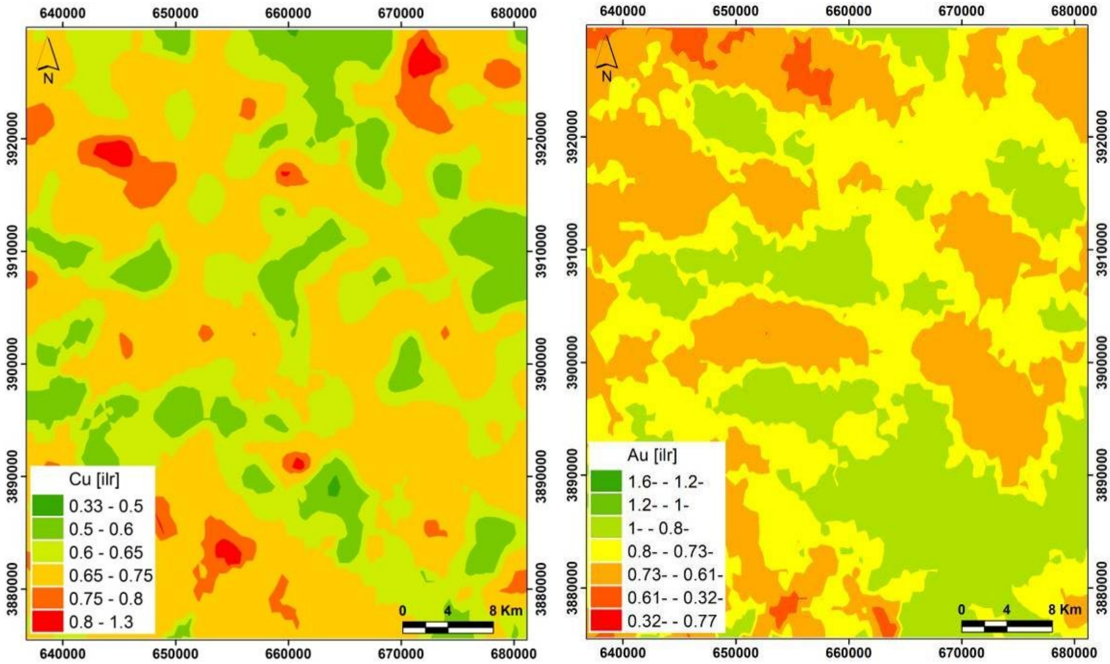

Figure 6. Distribution map of Cu and Au anomalies in Feyz-Abad area (based on ilr data).

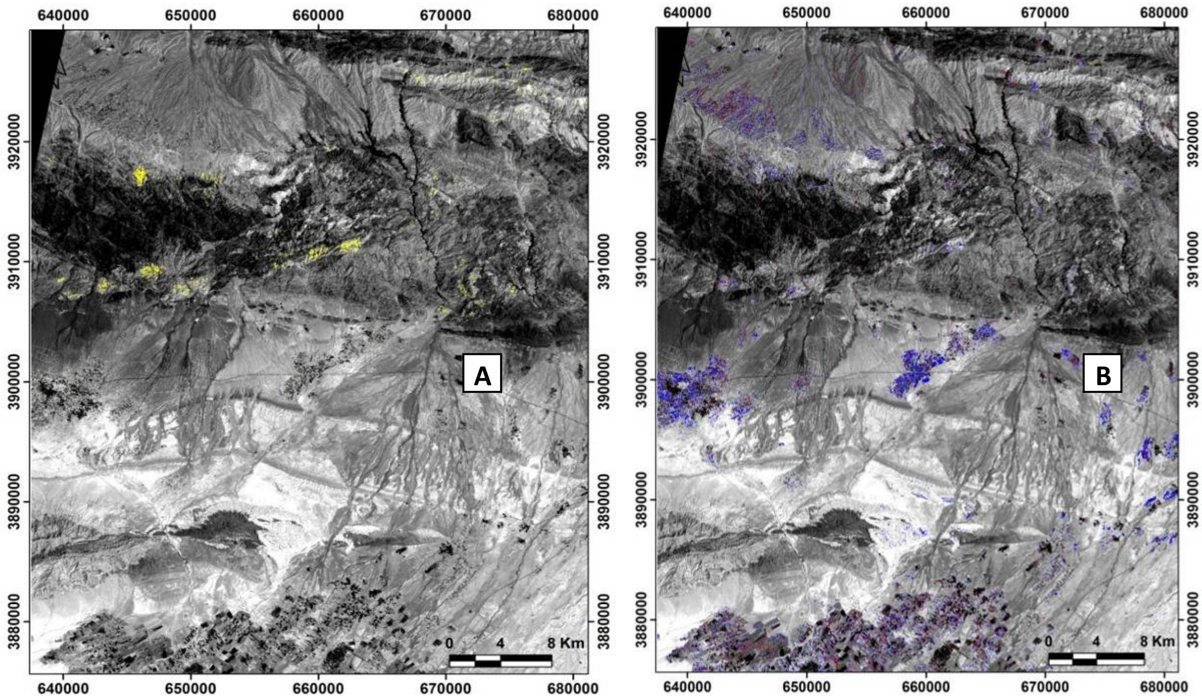

Figure 7. Results of enhanced Phyllic zone (left) and kaolinite zone (right).

3.2. Methodology of integration

Mineral exploration is a complex process in which the main purpose is to discover a new mineral deposit in the region of interest. To achieve this goal, various thematic (e.g. geological, geophysical, geochemical) geo-datasets should be collected, analyzed, and integrated for MPM (Figure 8). Five different methods have been used to extract the favorable area for more exploration, as shown below.

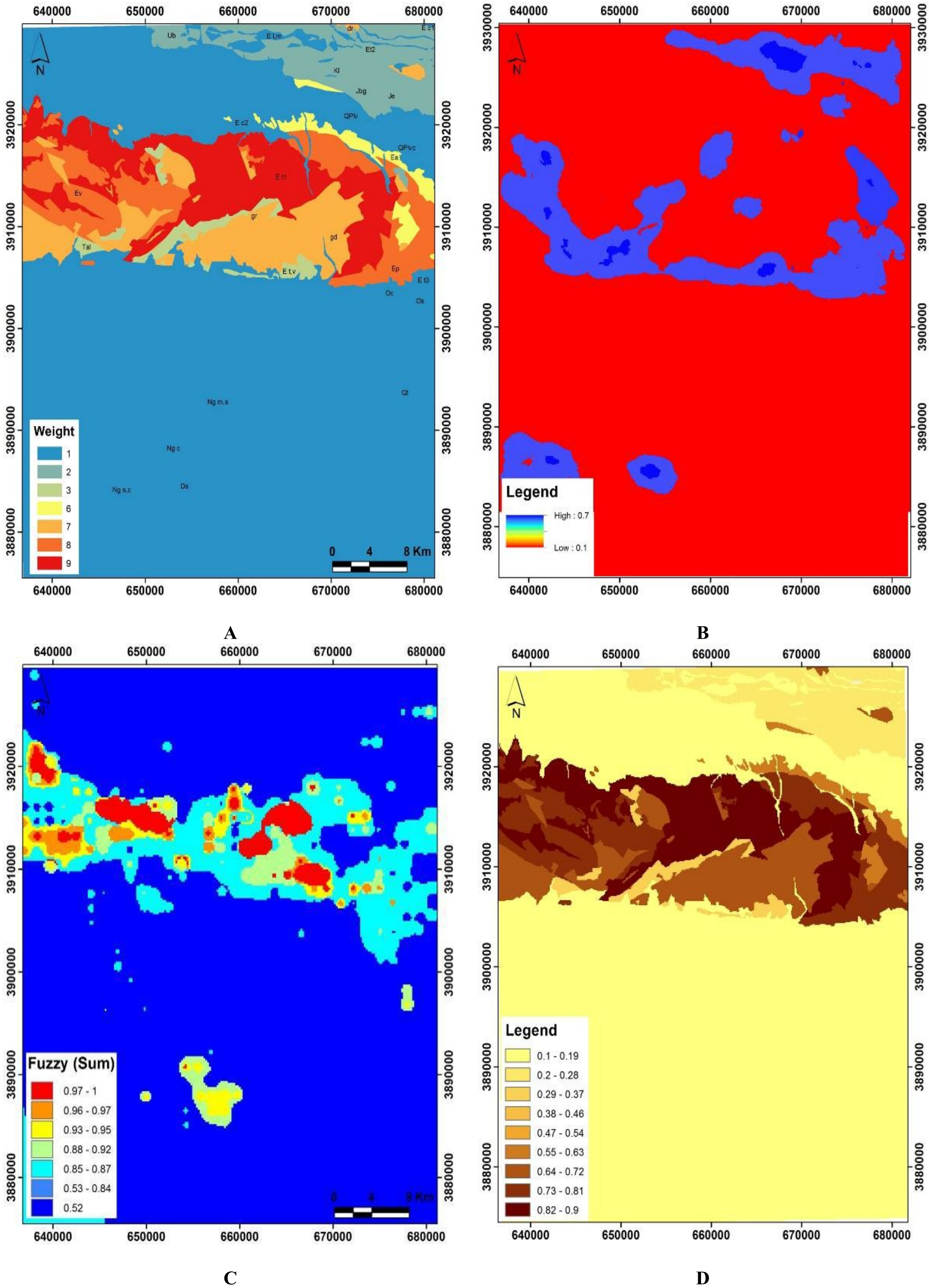

Figure 8. Some weighted evidential layers: A) geology (for AHP) B) fault intersection (for fuzzy) C) geochemistry (fuzzy sum operator) D) geology (fuzzy).

3.2.1. Fuzzy

The fuzzy method allows weights to be assigned to each layer based upon expert opinions. The fuzzy-set theory defines a degree of membership in a set represented by a value between 0 and 1. The value of the membership function can be determined by two methods. One method is to calculate according to the membership function curve; the other is to assign values artificially according to geological knowledge. The fuzzy model in mineral prediction consists of two steps: (1) fuzzification of data (2) fuzzy synthesis of fuzzified data. Fuzzy weights for different evidential layers are shown in Table 1. Fuzzy synthesis is executed using the operator. The most basic fuzzy operators are: fuzzy AND; fuzzy OR; fuzzy algebraic product; fuzzy algebraic sum; and fuzzy gamma.

The fuzzy Sum operator highlights the maximum values available for all conditions. This operator was used for geochemical and lithological events. The sum fuzzy operator assumes that the more favorable input is better. The resulting sum is an increasing linear combination function that is based upon the number of criteria entering the analysis. The fuzzy gamma operator was used to calculate the final prospectivity map in the current work (Figure 9). The fuzzy Gamma type is an algebraic product of fuzzy Product and fuzzy Sum, which are both raised to the power of gamma. The generalize function is as follows: $\mu(x) = (\text{FuzzySum})^{\gamma} * (\text{FuzzyProduct})^{1-\gamma}$.

The final prospective map was prepared with fuzzy $\gamma = 0.9$ operator. This map shows the prospective area for the Au-Cu deposits (Figure 14).

Table 1. Score for different evidential layers.

(Layer)		(Weight)	(Layer)		(Weight)
Geochemical anomalies	Au	0.9	Lithology	Intrusive	0.9
	Cu	0.85		Volcanic	0.8
	Pb	0.5		Sedimentary	0.3
	Zn	0.5		Alluvium	0.1
	As	0.8	Ore occurrences	Buffer 500	0.7
	Mo	0.7		Buffer 1000	0.6
	Ag	0.9		Buffer 1500	0.5
Faults density	Buffer 50	0.7	Alteration and oxidation	Silisification	0.9
Air-borne magnetic	Buffer 50	0.7		Serisitic	0.8
				Argillic	0.7
Faults	Buffer 500	0.8		Propylitic	0.5
	Buffer 1000	0.6		Fe oxide	0.6

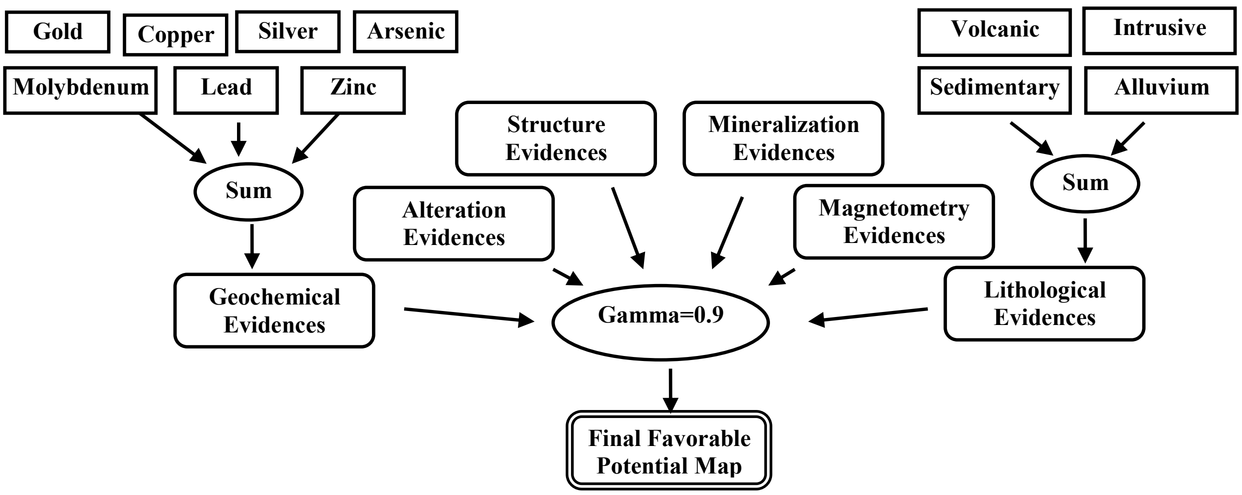

Figure 9. Schematic inference network for MPM in Feyz-Abad area.

3.2.2. Integration of Continuous Fuzzy Weighted Evidence Layer

To transform data into the [0, 1] range, logistic functions are used in order to generate fuzzified evidential maps. Moreover, to transform a dataset into a logistic space based on the minimum and maximum data values and slope variations between them, some logistic functions can be utilized [15]. Recently, researchers [16] have applied an equation to assign continuous weights to individual evidential layers into the same space for more efficiency. In this research work, the following equation, as mentioned by [16], was used to determine suitable values for i and s in the logistic function for transforming continuous dataset into fuzzy space:

$$F_{Ev} = \frac{1}{1+e^{-s(Ev - i)}} \quad (1)$$

where F_{Ev} is a score in the [0, 1] range, fuzzy weight in a logistic space, i and s are the inflection point and slope, respectively, of the logistic function, and E_v is the evidential value of each pixel in an input map from which F_{Ev} is estimated. The parameters i and s determine the shape of the logistic function, and hence, the output fuzzy weights. The above-mentioned equation is written two times to make a system of equations, as [15]:

$$\begin{cases} F_{Ev\,(\min)} = \dfrac{1}{1+e^{-s(Ev_{\min}-i)}} \\ F_{Ev\,(\max)} = \dfrac{1}{1+e^{-s(Ev_{\max}-i)}} \end{cases} \quad (2)$$

where $F_{Ev\ (min)}$ and $F_{Ev\ (max)}$ are the lowest and highest fuzzy scores of evidential values, and Ev_{min} and Ev_{max} are their corresponding minimum and maximum values in the input dataset. The i and s values are calculated based on the corresponding minimum, Ev_{min}, and maximum, Ev_{max}, evidential values in the input dataset as [16]:

$$s = \frac{9.2}{Ev_{\max} - Ev_{\min}} \quad (3)$$

$$i = \frac{Ev_{\max} + Ev_{\min}}{2} \quad (4)$$

Table 2 shows the calculated i and s values defined using the above equations. Some continuous weighted maps are shown in Figure 10. Fuzzified layers have integrated with fuzzy gamma operator with a high value of gamma (= 0.9).

3.2.3. Index overlay

In the index overlay method, each class of maps is given a different score, allowing for a flexible weighting system from 1 to 9. The table of scores and the map weights can be adjusted to reflect the judgment of experts in the domain of the application under consideration [4].

In order to use the index-overlay combination method, spatial relationships are quantified as maps that comprise nine distinct levels of prospectivity (Tables 3 and 4). In this work, each one of the layers has been integrated based on their priority. The integration has been done using the Arc GIS software, and the evaluation of these layers has been done in the Expert Choice software (Tables 2 and 3). All the evidential layers converted to raster and combined by raster calculation. A mineral prospectivity map based on this model is illustrated in Figure 14.

Table 2. Calculated i and s values for different datasets of evidential values, defined by solving a system of equations.

	Evidential value	s	i
Geology	geology	11.5000	0.5000
Geochemical anomalies	Au	11.5000	0.5000
	As	13.1429	0.4500
	Ag	13.1429	0.4500
	Pb	14.1538	0.4250
	Mo	15.3333	0.4000
	Zn	14.1538	0.4250
	Cu	11.5000	0.5000
Structures	Faults	13.1429	0.4500

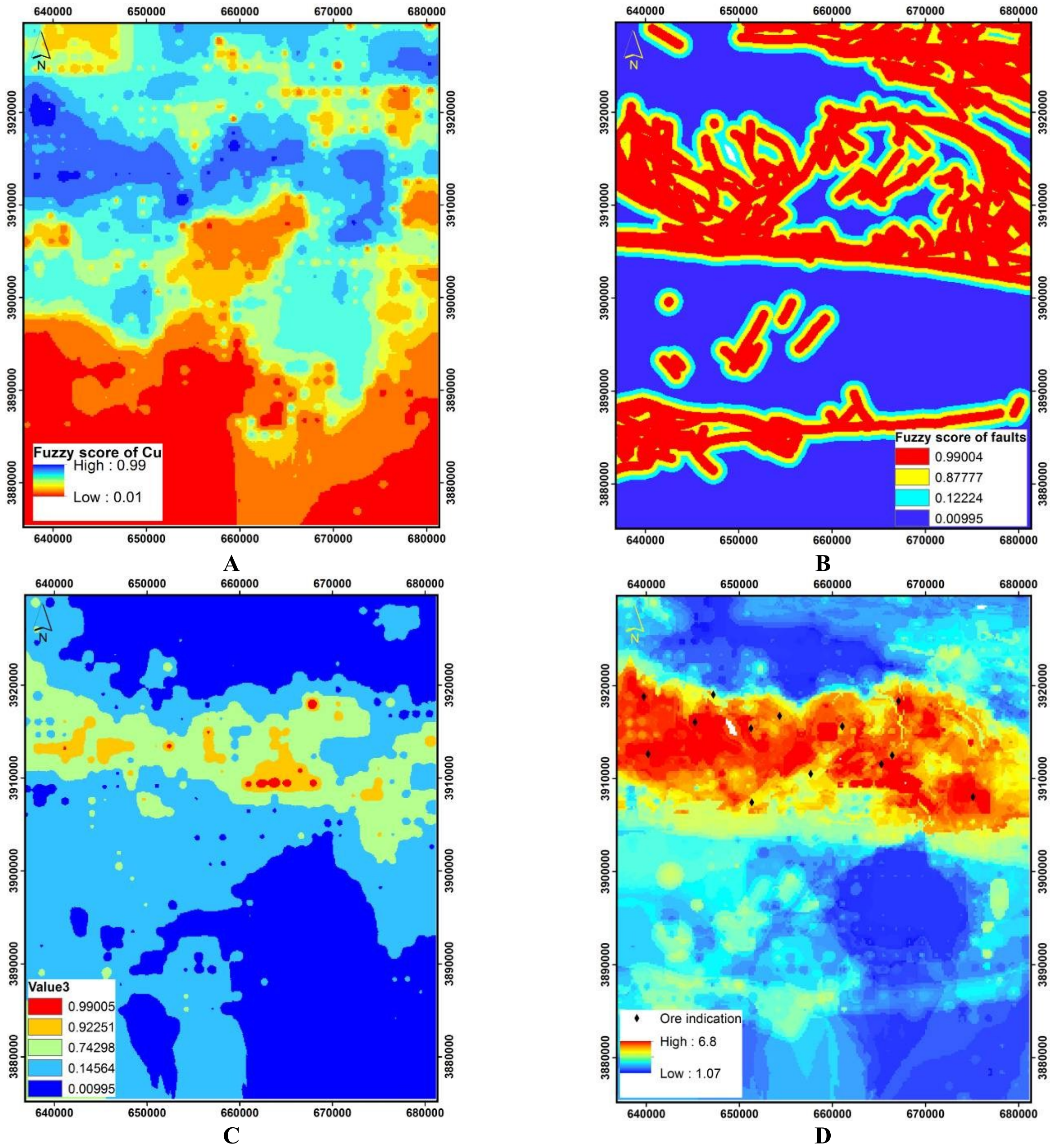

Figure 10. Fuzzy evidence layer of (A) Cu geochemical signature, (B) fault density, (C) Zn geochemical signature (D) fuzzy prospectivity model generated by integration evidence layers.

Table 3. Score for different evidential layers.

(Layer)		(Weight)	(Layer)		(Weight)
Geochemical anomalies	Au	9	Lithology	Intrusive	9
	Cu	9		Volcanic	8
	Pb	6		Sedimentary	3
	Zn	6		Alluvium	1
	As	8	Ore occurrences	Buffer 500	7
	Mo	7		Buffer 1000	6
	Ag	9		Buffer 1500	5
Faults density	Buffer 50	7	Alteration and oxidation	Silisification	9
Air-borne magnetic	Buffer 50	7		Serisitic	8
				Argillic	7
Faults	Buffer 500	8		Propylitic	5
	Buffer 1000	6		Fe Oxide	6

Table 4. Final score for evidential layers.

(Layer)	(Weight)
Faults	8
Geochemistry	7
Lithology	9
Mineralization	9
Alteration	8
Geophysical Anomaly	6

3.2.4. AHP

The Analytical Hierarchy Process (AHP) is one of the best ways for deciding among the complex criteria structure in different levels. The concept of AHP was developed for pairwise analysis of priorities in multi-criteria decision-making [24]. It aims to derive a hierarchy of criteria based on their pairwise relative importance with respect to the objective of a decision-making process. The method adopts a nine point continuous pairwise rating scale for judging which criteria is less or more important than another (Figure 11). The AHP method is used in this research work to evaluate the weight of data and compare the results with fuzzy and fuzzy AHP.

In this work, all data is classified based on their relative importance. Then pairwise comparison has been prepared in expert choice software. A hierarchy has been constructed based on expert opinions. The hierarchy tree is shown in Figure 12. The consistency ratio was less than 0.1 after pairwise comparisons, so the result was correct for MPM. AHP weights Multiple to layers and integration of the all final layers have been done in ArcGIS. The final prospectively map shows the prospective area for Au-Cu deposits (Figure 14). The mineral potential map was classified into five major classes including very poor to very good potentiality. Most favorable potential areas are shown in Figure 14.

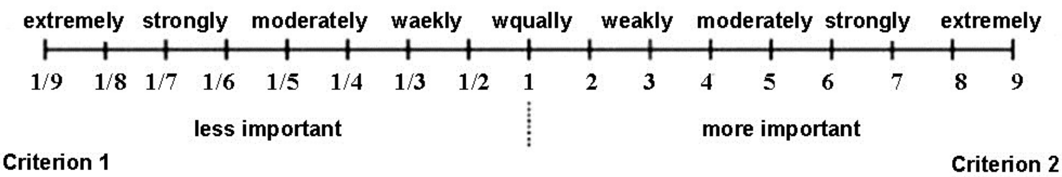

Figure 11. Continuous rating scale for pairwise comparison of relative importance with respect to a proposition (adapted from [27]).

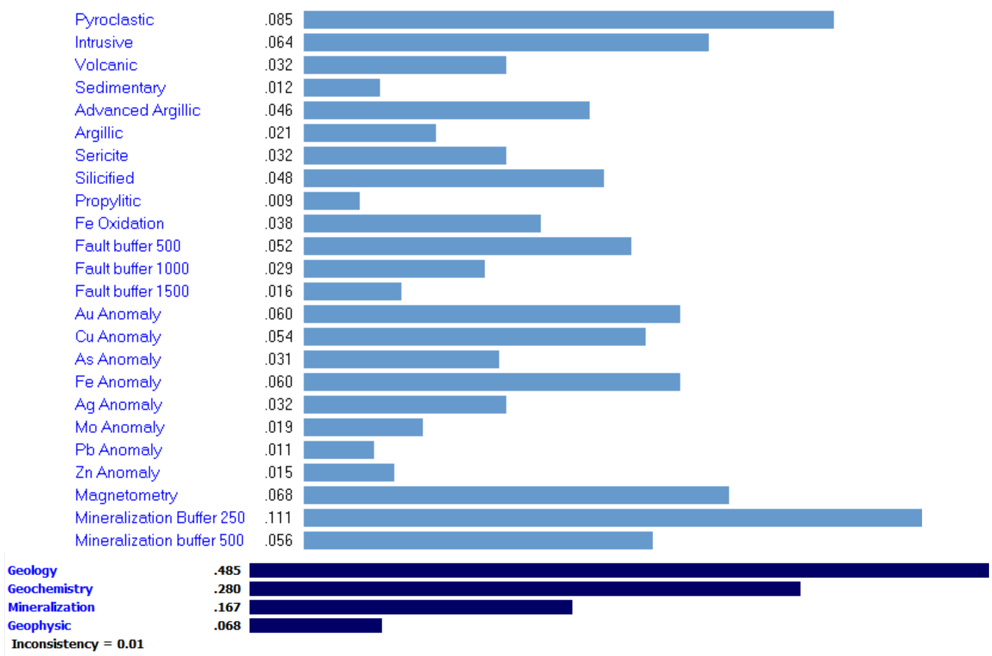

Figure 12. Parameter weighting of different data and structure layer based on AHP with inconsistency = 0.01.

3.2.5. Fuzzy AHP

The fuzzy analytic hierarchy process is one of the most accepted multi-criteria decision-making techniques. The fuzzy AHP is a synthetic extension of the classical AHP method when the fuzziness of the decision-makers is considered. This technique can be viewed as an advanced analytical method developed from the traditional AHP. A number of methods have been developed to handle the fuzzy AHP. Chang [25] has introduced a new method for fuzzy AHP using triangular fuzzy numbers for pairwise comparison scale of fuzzy AHP and the use of the extent analysis method for the synthetic extent values of the pairwise comparisons. The weights of the nine-level fundamental scales of judgments are expressed via triangular fuzzy numbers (TFNs) in order to represent the relative importance among the hierarchy's criteria [28].

The MPM steps involve (1) construction of a hierarchy, (2) preparation of important layers, (3) creation of pairwise comparison matrix, (4) calculation of consistency ratio, (5) construction of fuzzy evaluation matrix, (6) calculation of normalized weights, and (7) using fuzzy operators.

Construction of a hierarchy is the first step involved in doing fuzzy AHP (Figure 13). Evaluation hierarchy for MPM is divided into three levels, namely goal (MPM), multiple criteria (geology, geochemistry, and geophysics), and alternatives (Figure 13). In this work, pairwise comparison matrices were done using fuzzy AHP solver and excel software, utilizing the expert opinions. Matrix of fuzzy paired comparisons for goal is shown in Table 5. The CR value for criteria is 0.01; for geology alternative, CR=0.02; and for geochemical alternative, CR=0.03, all less than 0.1, so the pairwise comparison matrix is consistent. Map layers were prepared in a GIS environment as raster layers.

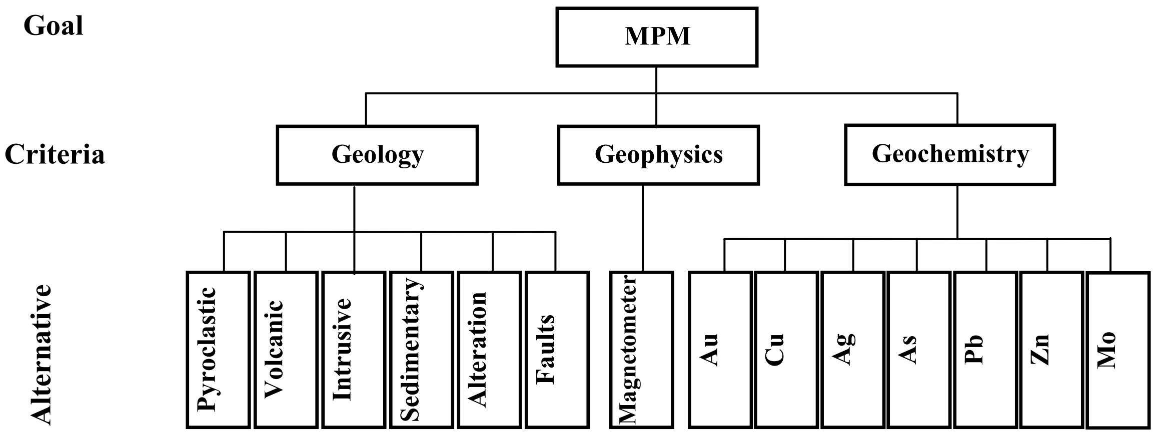

Figure13. Hierarchy trees used in this paper.

After the matrix of paired comparisons, the relative and final weights must be calculated by the extent analysis method. The value for the fuzzy synthetic extent with respect to the i-th object is defined by:

$$S_i = \sum_{j=1}^{M} M_{gi}^{i} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{i} \right]^{-1} \qquad (5)$$

In the above equation, S_i is a triangular number. All M^j_{gi}($j = 1, 2, \ldots, m$) are triangular fuzzy numbers. As $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ are two triangular fuzzy numbers, the degree of possibility of $M_1 \geq M_2$ is defined by:

$$V(M_2 \geq M_1) = \begin{cases} 1 & \text{if } m_2 \geq m_1 \\ 0 & \text{if } l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} & \text{otherwise} \end{cases} \qquad (6)$$

To compare M_1 and M_2, the values for both $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ are required. The probability that a convex fuzzy number is greater than k, convex fuzzy numbers Mi (1,2, …,k) can be defined by:

$V(M \geq M_1; M_2 \ldots M_K) = V(M \geq M_1)$ and $(M \geq M_2)$ and … $(M \geq M_k)$

$= \text{Min } V(M \geq M_i)$ i=1, 2,…,k

Assume that: $d(B_i) = \min V(S_i \geq S_k)$ for $k = 1, 2, \ldots, m$; $k \neq i$. Then the weight vector is given by: $W' = (d'(B_1), \ldots, d'(B_m))^T$, where B_i($i = 1,\ldots, m$) are m elements. Via normalization, the normalized weight vectors are given by: W = (d'(B_1), d'(B_2), ..., d'(B_m))^T, where W is a non-fuzzy number.

S_i for any criteria (Table 5) was calculated: The results obtained are as follow:

S_1 (Geological Criteria) = (0.276, 0.466, 0.727)
S_2 (Geochemical Criteria) = (0.158, 0.276, 0.463)
S_3 (Geophysics Criteria) = (0.163, 0.259, 0.485)

S_i for geological alternative (Table 6) was calculated: The results obtained are as follow:

S_1 (Intrusive Alternative) = (0. 138, 0.249, 0.415)
S_2 (Volcanic Alternative) = (0.121, 0.201, 0.331)
S_3 (Sedimentary Alternative) = (0.077, 0.118, 0.2)
S_4 (Alteration Alternative) = (0.156, 0.266, 0.462)
S_5 (Faults Alternative) = (0.105, 0.166, 0.269)

Si for geochemical alternative (Table 7) was calculated: The results obtained are as follow:

S_1 (Au Alternative) = (0.123, 0.217, 0.356)
S_2 (Cu Alternative) = 0.1, 0.15, 0.256)
S_3 (As Alternative) = (0.083, 0.15, 0.256)
S_4 (Ag Alternative) = (0.095, 0.168, 0.31)
S_5 (Mo Alternative) = (0.07, 0.121, 0.218)
S_6 (Pb Alternative) = (0.049, 0.087, 0.166)
S_7 (Zn Alternative) = (0.046, 0.075, 0.141)

Matrix of fuzzy paired comparisons for geological criteria is shown in Table 6, and fuzzy evaluation matrix for geochemical alternatives is shown in Table 6. Additional reclassification of the data was performed according to the weight assigned. Weights of criteria and alternatives are shown in Table 8. The final prospectivity map is created upon integration of data for all the alternative layers with weights using gamma fuzzy operators (Figure 14).

Table 5. Fuzzy evaluation matrix with respect to criteria.

	Geology	Geochemistry	Geophysics
Geology	(1,1,1)	(1,1.5,2)	(1.5,2,2.5)
Geochemistry	(0.5,0.667,1)	(1,1,1)	(0.5,1,1.5)
Geophysics	(0.4,0.5,0.667)	(0.667,1,2)	(1,1,1)

Table 6. Matrix of fuzzy paired comparisons for geological criteria.

	Intrusive	Volcanic	Sedimentary	Alteration	Faults
Intrusive	(1,1,1)	(1.5,2,2.5)	(1.5,2,2.5)	(0.5,1,1.5)	(1,1.5,2)
Volcanic	(0.4,0.5,0.667)	(1,1,1)	(1,1.5,2)	(0.5,0.667,1)	(1.5,2,2.5)
Sedimentary	(0.5,0.667,1)	(0.5,0.667,1)	(1,1,1)	(0.4,0.5,0.667)	(0.4,0.5, 667)
Alteration	(0.667,1,2)	(1,1.5,2)	(1.5,2,2.5)	(1,1,1)	(1.5,2,2.5)
Faults	(0.5,0.667,1)	(0.4,0.5,0.667)	(1.5,2,2.5)	(0.4,0.5, 667)	(1,1,1)

Table 7. Fuzzy evaluation matrix for geochemical alternatives.

	Au	Cu	As	Ag	Mo	Pb	Zn
Au	(1,1,1)	(0.5,1,1.5)	(1,1.5,2)	(0.5,1,1.5)	(1.5,2,2.5)	(2.5,3,3.5)	(2.5,3,3.5
Cu	(0.667,1,2)	(1,1,1)	(1.5,2,2.5)	(1,1.5,2)	(0.5,1,1.5)	(1.5,2,2.5)	(1.5,2,2.5
As	(0.5,0.667,1)	(0.4,0.5,0.667	(1,1,1)	(0.5,1,1.5)	(1.5,2,2.5)	(1,1.5,2)	(1.5,2,2.5
Ag	(0.667,1,2)	(0.5,0.667,1)	(0.667,1,2)	(1,1,1)	(1.5,2,2.5)	(0.5,1,1.5)	(2.5,3,3.5
M	(0.4,0.5,0.667)	(0.667,1,2)	(0.4,0.5,0.667	(0.4,0.5,0.667)	(1,1,1)	(1.5,2,2.5)	(1,1.5,2)
Pb	(0.286,0.333,0.4	(0.4,0.5,0.667	(0.5,0.667,1)	(0.667,1,2)	(0.4,0.5,0.667	(1,1,1)	(0.5,1,1.5
Zn	(0.286,0.333,0.4	(0.4,0.5,0.667	(0.4,0.5,0.667	(0.286,0.333,0.4	(0.5,0.667,1)	(0.667,1,2	(1,1,1)

Table 8. Weights of criteria and alternatives.

Criterion	Weight	Alternative	Weight	Final Weight
Geological data	0.4405	Intrusive	0.2734	0.120
		Volcanic	0.2128	0.094
		Sedimentary	0.0670	0.029
		Alteration	0.2921	0.128
		Faults	0.1547	0.068
Geochemical data	0.3926	Au Anomaly	0.2401	0.094
		Cu Anomaly	0.2043	0.080
		Ag Anomaly	0.1901	0.075
		As Anomaly	0.1601	0.063
		Pb Anomaly	0.0594	0.023
		Zn Anomaly	0.0264	0.010
		Mo Anomaly	0.1197	0.047
Geophysical data	0.1668	Aeromagnetic	1	0.167

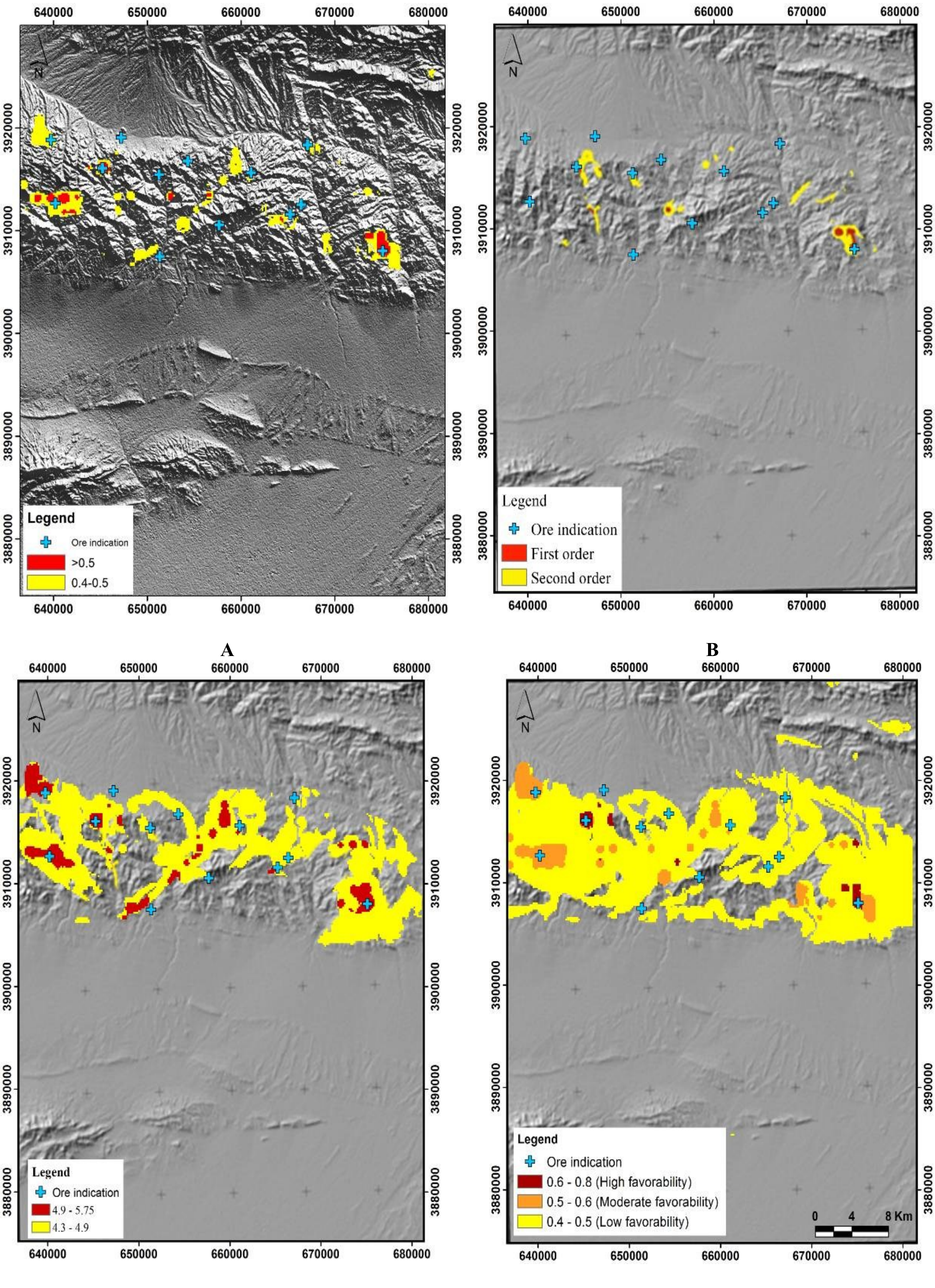

Figure14. Promising areas for MPM in Feyz-Abad area based on a) fuzzy method, b) index overlay integration, C) AHP method, and D) Fuzzy AHP.

3.2.6. Evaluation of prospectivity model

Feyz-Abad area has a high potential for Au–Cu mineralization. Four MPM methods have been applied to show prospectivity maps (Figure 14). After generation of prospectivity models, locations of known mineral deposits and field observations have been used to evaluate the precision of these methods. The prospectivity map obtained by the integration of these models indicates a strong correlation between areas of high posterior probabilities and known Au and Cu deposits, indicating that the evidential layers used in the studied area are valid.

Some percentages of favorable areas are located close to the Tannurjeh and Kuh-e-Zar deposits that are well-known mineral deposits.

C–A fractal model, as proposed by [29], was applied to classify the weighted maps. Thresholds were obtained for creating classified maps, and then the models were evaluated by locations of known mineral deposits in prediction-area plots. In the P-A plot, the cumulative percentage of known occurrences predicted by integration evidential classes and their corresponding cumulative occupied areas (with respect to the total studied area) are plotted versus the prospectivity values. Thus the prediction ability of the evidence layer and its ability to delimit the studied area for further exploration are evaluated in a scheme [30].

Comparison of the prediction rates in the P-A plots (Figure15) ~~shows~~ the importance of analyzing the predictability of prospectivity models.

The intersection point in the P-A plot (Figure 15a) of the continuous fuzzy prospectivity model shows 80% of the known Cu occurrences predicted in 20% of the studied area, while the intersection point in the P-A plot (Figure 15b) of the logic fuzzy prospectivity model shows 75% of the known Cu occurrences predicted in 25% of the studied area.

The intersection point in the P-A plot (Figure 15c) of the AHP prospectivity model shows 60% of the known Cu occurrences predicted in 40% of the studied area, and the intersection point in the P-A plot (Figure 15d) of the AHP-fuzzy prospectivity model shows 82% of the known Cu occurrences predicted in 18% of the studied area.

The intersection point in the P-A plot (Figure 15e) of the index overlay prospectivity model shows 70% of the known Cu occurrences predicted in 30% of the studied area.

Comparison of the presented data demonstrates a higher efficiency of the prospectivity models generated using AHP fuzzy and continuous weighted fuzzy integration over other prospectivity models.

4. Discussion

The predicted regions of the index overlay and fuzzy methods are similar in distribution but the fuzzy result shows a more favorable area. AHP was applied successfully in this work with the consistency rate being equal to 0.01, which represents a very good value for the evaluation of the importance of each criterion to the other. Fuzzy AHP also has a result comparable with the fuzzy result.

The prediction results of these studies provide a prospecting direction for this region. The result of integrating the data is a map depicting the favorable area for exploring Au-Cu deposits (Figure 14). Based on this work, there are three strong anomalies of Au-Cu exploration in the east and west of the Feyz-Abad sheet (Figure 14). The legends show the favorability values for the areas.

It must be mentioned that for using this method, due to the different geochemical behaviors of some elements, it is better to produce different maps based on the geochemical characteristics of elements and different types of ore deposits related to these elements. In the promising map for gold, the area for placer gold exploration is not visible because it does not depend on rocks and faults that were given values in this model.

As demonstrated by [29], the parameters of the intersection point of the two curves (prediction rate and occupied area curves) in the P-A plots are used to evaluate and weight the maps. In the P-A plot, if the intersection point shows a greater prediction rate in comparison with the P-A plot of other maps, it means that the former represents a smaller area containing a larger number of mineral deposits. The parameters of the intersection points in the P-A plots of the integrated maps are shown in Table 9. The order of the prediction rate of the models generated using different MPM methods is: 80% for continuous weighting approach (continuous fuzzy logic); 80% for fuzzy AHP; 75% for fuzzy logic; 70% for index overlay; and 60% for AHP. Based on Table 9, integration from continues fuzzy and fuzzy AHP methods have the best results for prospecting the deposit-type.

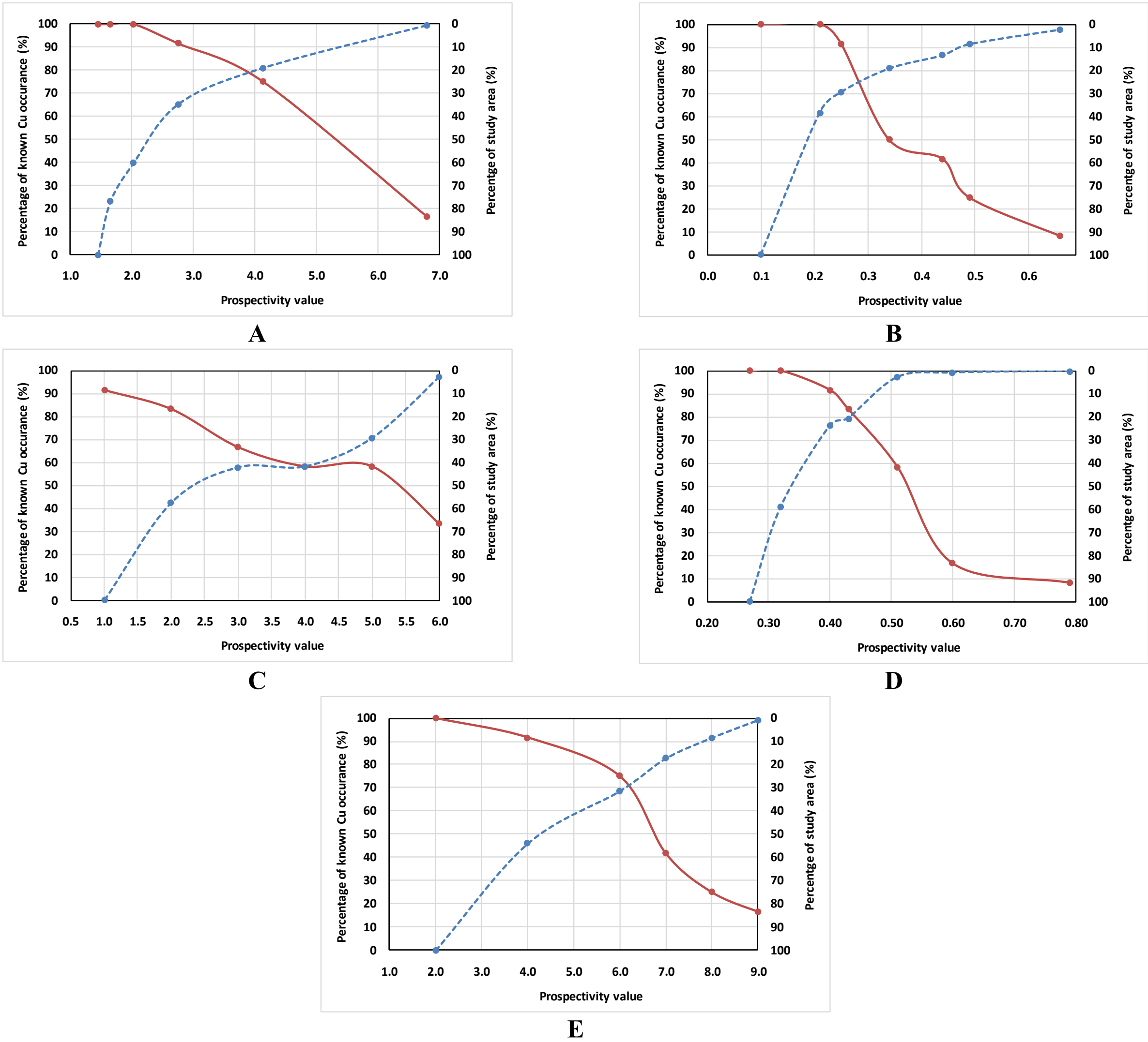

Figure 15. P-A plot for prospectivity model generated by integration of A) continuous fuzzy, B) logic fuzzy, C) AHP, D) fuzzy AHP, and E) index overlay.

Table 9. Extracted parameters from intersection point of P-A plots.

Integration model	Prediction rate (%)	Occupied area (%)
Continuous fuzzy	80	20
Fuzzy	75	25
AHP	60	40
Fuzzy AHP	80	20
Index Overlay	70	30

The prediction rate of the prospectivity model generated using the continuous weighting approach and fuzzy AHP is around 80%, the highest value compared to other models generated in this work.

Excluding continuous fuzzy methods, all other mentioned methods are knowledge-driven MPM. In knowledge-driven methods, the analyst's judgments are used in assigning weights. Thus most models generated by these methods carry exploration bias and random error. In these methods, the analyst changes the weights until a model with the highest prediction rate of mineral deposits in areas with some known mineral deposits is obtained. Furthermore, in green-fields, there is no agreement in defining evidential weights. Thus every analyst can assign his arbitrary weights to exploration features, which bears exploration bias as well.

On the other hand, the continuous fuzzy MPM method is a powerful approach by which the exploration bias including systematic and random errors are avoided. This is because the method does not use the location of known mineral deposits (such as data-driven MPM) or the analyst's judgments (i.e. knowledge-driven MPM) in assigning weight of evidence data. Thus it can be used for both green-fields and brown-fields. The continuous fuzzy model is the best one in the studied area because it is bias-free and can be used to generate reliable target areas.

5. Conclusions

In this work, various GIS techniques of generating maps were evaluated to better understand the geochemical anomalies and mineral potentials within Feyz-Abad area of the Lut block, eastern Iran, in order to indicate the best target for more mineral exploration activities. For that purpose, the following layers were used: (1) lithology, (2) alteration zones, (3) density of fault, (4) geochemical anomaly of indicator elements, and (5) air-borne magnetic anomaly.

Five knowledge/data-driven models were practiced in the current research work. In the index overlay method, all weights were calculated within 1-10 ranges, both for layers and data within. In fuzzy and fuzzy continuous integration, the features dataset are categorized in fuzzy order from 0 to 1. Then the relative importance with AHP was calculated within the [1, 9] range. In fuzzy AHP, a combination of AHP score and fuzzy method were used. The classes were assigned with new weights to evaluate their importance for prospecting the deposit type.

The index overlay method is very simple and fast but the result is not very different from the other methods. Fuzzy and fuzzy AHP both integrate fuzzy mathematics into weight calculation and involve three-step data processing, weight calculation, and layer integration. However, weight calculation using fuzzy is easier than using fuzzy AHP based on triangular fuzzy numbers. On the other hand, in fuzzy AHP, expert scores might need to be adjusted to the probability of $CR \leq 0.1$, which will evaluate relative scores. Field investigation showed that the final result could better match the known deposits in the Feyz-Abad area.

Based on the basic spatial analysis method, around 20% of the total studied area was selected as suitable for more exploration. In general, the majority of a suitable area was located in the north and NW of the Feyz-Abad region. According to the available data and field observation, the results of the index overlay method are similar to those for fuzzy, AHP, and fuzzy AHP integration.

While the other methods generate relatively similar results, the continuous fuzzy model seems to be the best fit in the studied area because it is bias-free and can be used to generate reliable target areas.

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References

[1]. Behrouzi, A. (1987). Geological map of Feyz-Abad 1:100000 series. Sheet 7760. Geological Survey of Iran (GSI).

[2]. Saadat, S., Karimpour, M.H., Ajayebi, K. and Stern, C. (2007). Petrology, Fluid Inclusion, thermometry, and geochemistry of Tannurjeh porphyry Cu-Au, North Eastern Iran. GSA annual meeting and exploration. Denver. Colorado.

[3]. Saadat, S. and Ghoorchi, M. (2009). Primary Analysis for Enhancing the Iron Oxide and Alteration Minerals, Using ETM^+ Data (A case study of Kuh-e-Zar gold deposit, north east of Iran). Iranian journal of Earth Science. 1 (1): 73-83.

[4]. Bonham-Carter, G.F. (1994). Geographic Information Systems for Geoscientists: Modeling with GIS. Pergamon. Ontario. 398 P.

[5]. Carranza, E.J.M. and Laborte, A.G. (2014). Data-driven predictive mapping of gold prospectivity, Baguio district, Philippines: Application of Random Forests algorithm. Ore Geology Reviews. 71: 777-787.

[6]. Pan, G. and Harris, D.P. (2000). Information Synthesis for Mineral Exploration. Oxford Univ. Press. New York. 461 P.

[7]. Lusty, P.A.J., Scheib, C., Gunn, A.G. and Walker, A.S.D. (2012). Reconnaissance-scale prospectivity analysis for gold mineralization in the southern Uplands-Down-Longford Terrane, Northern Ireland. Nat. Resour. Res. 21: 359-382.

[8]. Mejía-Herrera, P., Royer, J.J., Caumon, G. and Cheilletz, A. (2014). Curvature attribute from surface restoration as predictor variable in Kupferschiefer copper potentials. Natural Resources Research. 24 (3): 275-290.

[9]. Bonham-Carter, G.F., Agterberg, F.P. and Wright, D.F. (1989). Weights of evidence modelling: a new approach to mapping mineral potential. In: Agterberg, F.P. and Bonham-Carter, G.F. (Eds.), Statistical Applications in the Earth Sciences. Geological Survey of Canada. 89 (9): 171-183.

[10]. Moon, W.M. (1990). Integration of geophysical and geological data using evidential belief function. IEEE Trans. Geosci. Remote Sens. 28 (4): 711-720.

[11]. Molan, Y.E. and Behnia, P. (2013). Prospectivity mapping of Pb-Zn SEDEX mineralization using remote-sensing data in the Behabad area, Central Iran. Int. J. Remote Sens. 34 (4): 1164-1179.

[12]. Najafi, A., Karimpour, M.H. and Ghaderi, M. (2014). Application of fuzzy AHP method to IOCG prospectivity mapping: acase study in Taherabad prospecting area, eastern Iran. Int. J. Appl. Earth Observation Geoinformation. 33: 142-154.

[13]. Cheng, Q., Chen, Z. and Khaled, A. (2007). Application of fuzzy weights of evidence method in mineral resource assessment for gold in Zhenyuan District, Yunnan Province, China. Earth Sci. J. China Univ. Geosci. 32 (2): 175-184 (In Chinese with English Abstract).

[14]. Pazand, K., Hezarkhani, A. and Ghanbari, Y. (2014). Fuzzy analytical hierarchy process and GIS for predictive Cu porphyry potential mapping: a case study in Ahar-ArasbaranZone (NW, Iran). Arab. J. Geosci. 7: 241-251.

[15]. Lin, C.T. and Lee, C.S.G. (1996). Neural Fuzzy Systems: A Neuro-Fuzzy Synergism to Intelligent Systems. Upper Saddle River, NJ: Prentice Hall.

[16]. Yousefi, M. and Carranza, E.J.M. (2015). Fuzzification of continuous-value spatial evidence for mineral pro spectivity mapping. Computers and Geosciences. 74: 97-109.

[17]. Theodoridis, S. and Koutroumbas, K. (2006). Pattern Recognition. 2nd Ed. Academic Press. Elsevier. USA.

[18]. Agterberg, F.P. and Bonham-Carter, G.F. (1999). Logistic regression and weights of evidence modeling in mineral exploration. In: Proceedings of the 28th Inter- national Symposium on Applications of Computer in the Mineral Industry (APCOM). Golden. Colorado. pp. 483-490.

[19]. Singer, D.A. and Kouda, R. (1996). Application of a feedforward neural network in the search for Kuruko deposits in the Hokuroku district, Japan. Mathematical Geology. 28: 1017-1023.

[20]. Porwal, A., Carranza, E.J.M. and Hale, M. (2003). Artificial neural networks for mineral- potential mapping: a case study from Aravalli Province, Western India. Natural Resources Research. 12 (3): 156-171.

[21]. Carranza, E.J.M. (2008). Geochemical anomaly and mineral prospectivity mapping in GIS. In: Handbook of Exploration and Environmental Geochemistry. Vol. 11. Elsevier. Amsterdam. 351 P.

[22]. Carranza, E.J.M. and Hale, M. (2002). Wildcat mapping of gold potential, Baguio district, Philippines. Transactions of the Institution of Mining and Metallurgy (Section B-Applied Earth Science). 111 (2): 100-105.

[23]. Porwal, A., Carranza, E.J.M. and Hale, M. (2006). A hybrid fuzzy weights-of-evidence model for mineral potential mapping. Natural Resources Research. 15 (1): 1-14.

[24]. Yousefi, M., Kamkar-Rouhani, A. and Carranza, E.J.M. (2012). Geochemical mineralization probability index (GMPI): A new approach to generate enhanced stream sediment geochemical evidential map for increasing probability of success in mineral potential mapping. Journal of Geochemical Exploration. 115: 24-35.

[25]. Kaiser, H.F. (1958). The varimax criteria for analytical rotation in factor analysis. Psychometrika. 23: 187-200.

[26]. Kruse, F.A., Lefkoff, A.B., Boardman, J.W., Heidebrecht, K.B., Shapiro, A.T., Barloon, P.J. and Goetz, A.F.H. (1993). The Spectral Image Processing System (SIPS) Interactive Visualization and Analysis of Imaging Spectrometer Data. Remote Sensing of Environment. 44: 145-163.

[27]. Saaty, T. L. (1977). A scaling method for priorities in hierarchical structures. J. Math. Psychol. 15 (3): 234-281.

[28]. Chang, D.Y. (1996). Applications of the extent analysis method on fuzzy AHP. Eur. J. Oper. Res. 95 (3): 649-655.

[29]. Yousefi, M. and 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. Computers and Geosciences. 79: 69-81.

[30]. Yousefi, M. and Carranza, E.J.M. (2016). Data-driven index overlay and Boolean logic mineral prospectivity modeling in Greenfields exploration. Natural Resources Research. 25 (1): 3-18.

مقایسه به کارگیری روش‌های مختلف دانش‌محور و تلفیق داده محور- دانش‌محور در مدل‌سازی پتانسیل‌های معدنی و معرفی نواحی امیدبخش کانی سازی مس و طلا مطالعه موردی: منطقه فیض‌آباد (شمال بلوک لوت، شمال شرق ایران)

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چکیده:

بر اساس نتایج موفقیت‌آمیز به کارگیری مدل‌سازی سیستم اطلاعات جغرافیایی در مسائل مربوط به علوم زمین در سال‌های اخیر، برخی از روش‌های دانش‌محور برای معرفی مناطق امیدبخش و به ویژه کانی‌سازی مس و طلا در مقیاس ناحیه‌ای در منطقه فیض‌آباد (شمال شرق ایران) در این تحقیق به کار گرفته شد. مدل‌سازی پتانسیل معدنی یک فرآیند چند مرحله‌ای است که مناطق امیدبخش مورد نظر را برای اکتشافات بعدی رده‌بندی می‌کند. در این تحقیق، پنج روش ادغام شامل فازی، فازی پیوسته، وزن‌های نشانگر، تحلیل سلسله مراتبی و تحلیل سلسله مراتبی فازی مورد مقایسه قرار گرفته است. برای این منظور، نقشه‌های زمین‌شناسی، داده‌های ژئوشیمیایی و ژئوفیزیک جمع‌آوری و یک پایگاه داده مکانی ساخته شد. تصاویر لندست برای استخراج آلتراسیون، تغییرات اکسید آهن و شناسایی ساختارهای خطی و گسل‌ها و تصاویر استر برای استخراج شاخص‌های اکسید سیلیسیم، کائولینیت، کلریت و آلتراسیون پروپیلیتیک در مقیاس منطقه‌ای مورد استفاده قرار گرفت. داده‌های زمین‌شناسی، ژئوشیمیایی و ژئوفیزیک با روش‌های مختلف مدل‌سازی پتانسیل معدنی تلفیق شدند. ارزش‌گذاری وزن‌ها توسط دانش تخصصی و یا توابع استدلالی مشخص شدند. بر اساس این تحلیل، سه ناحیه اکتشافی اصلی در منطقه فیض‌آباد مشخص شد و بر اساس مشاهدات میدانی، صحت و دقت نتایج مدل‌سازی پتانسیل معدنی مورد تائید قرار گرفت که می‌تواند برای جستجوهای اکتشافی آینده مفید واقع شود. روش‌های ارزیابی شده در این پروژه نتایج نسبتاً مشابهی را نشان می‌دهند ولی به نظر می‌رسد که روش مدل‌سازی فازی پیوسته مناسب‌ترین روش در منطقه مورد مطالعه است زیرا مانع اختلال و یا پیش‌داوری می‌شود و می‌تواند به خوبی برای مشخص کردن مناطق امیدبخش قابل اتکا مورد استفاده قرار گیرد.

کلمات کلیدی: مدل‌سازی پتانسیل معدنی، فازی، تحلیل سلسله مراتبی، وزن‌های نشانگر، فیض‌آباد.