-RESEARCH PAPER-
International Journal of Mining and Geo-Engineering
IJMGE
IJMGE 57-3 (2023) 251-258
DOI: 10.22059/IJMGE.2023.355380.595037

Recognition coefficient of spatial geological features, an approach to facilitate criteria weighting for mineral exploration targeting

Mahyar Yousefi [a,*], Saeed Yousefi [b], Abolghasem Kamkar-Rouhani [c]

[a] *Faculty of Engineering, Malayer University, Malayer, Iran.*
[b] *Faculty of Engineering, University of Birjand, Birjand, Iran.*
[c] *School of Mining, Petroleum and Geophysics, Shahrood University of Technology, Shahrood, Iran.*

Article History:
Received: 13 February 2023.
Revised: 20 April 2023.
Accepted: 03 May 2023.

ABSTRACT

The different methods for the delineation of favorable areas for mineral exploration utilize exploration criteria in regard to targeted mineral deposits. The criteria are elicited according to conceptual model parameters of the targeted mineral deposits. The selection of indicator criteria, the evaluation of their comparative importance, and their integration are critical in mineral prospectivity modelling. In data-driven methods, indicator features are weighted using functions whereby the importance of certain indicator criteria may be ignored. In this paper, a data-driven method is described for recognizing and converting exploration criteria into quantitative coefficients representing favorability for the presence of the targeted mineral deposits. In this approach, all indicator features of the targeted mineral deposits are recognized and incorporated in the modelling procedure. The method is demonstrated for outlining favorable areas for a Mississippi valley-type fluorite deposit in an area, north of Iran. The method is developed by studying and modelling the geological characteristics of known mineral occurrences. The degree of prediction ability of each exploration criterion is quantified as a recognition coefficient, which can be used as a weight attributed to the criterion in mineral exploration targeting to outline favorable areas.

Keywords: *Weighting, Exploration features, Exploration targeting, Recognition coefficient.*

1. Introduction

In the mineral prospectivity modelling (MPM) for generating exploration targets, a set of prospectivity criteria is used, considering the type of targeted mineral deposits. The prospectivity criteria are elicited based on a conceptual model of the targeted type of mineral deposit. In a study area, each prospectivity criterion represents the presence or absence of certain features in a corresponding exploration data set that would indicate the existence or lack of the targeted deposit. For example, lithology is a prospectivity criterion representing the presence or absence of favorable host rocks as depicted in geological maps. Hence, favorable host rocks are among the indicative features of the mineral-deposit type sought. One of the most important challenging issues in MPM is the recognition of indicative features and the evaluation of the relative importance of each of them [1, 2]. Assessment of the relative importance of an indicative feature compared to other indicative features is usually depicted as a numerical prospectivity weight that is assigned to each set of indicative features.

Assignment of prospectivity weights to indicative features can be made in various ways. In the MPM, knowledge- and data-driven methods are two general techniques for assigning prospectivity weights to indicative features [1, 2]. The weighting of indicative features in data-driven MPM in a particular area is generally accomplished according to the known mineral occurrences (KMOs) in that area. Many examples of applications of data-driven methods of MPM exist in the literature (e.g., [1-11]). In the cited previous studies, the importance of classes of geosciences data, for example a geological map, is defined by the quantification of the spatial associations of the KMOs with the individual classes of geosciences data. In the data-driven MPM, the analysis consists of quantification of the spatial association of the KMOs with the evidence features. This analysis produces some statistical values or weights that evaluate the spatial association between KMOs and indicator features, thus, determining the relative importance of the individual classes of geoscience data as predictor of mineral prospectivity. Theses weights are a cornerstone for accepting or rejecting a feature or class of geoscience data as an indicator or predictor [1, 12]. Based on the acceptance and/or rejection (or assigning weights comparatively, i.e., neither completely rejecting nor completely accepting) of a feature as an indicator, a weighted evidence map is generated. Generally, in some of the data-driven MPM methods, for example the weight of evidence method [3, 13, 14] and data-driven evidential belief functions [7], the weights of spatial evidence are allocated in respect of the locations of KMOs through mathematical and statistical functions such as those proposed by [15-17]. In these methods, two types of weights for each spatial evidence (E) are calculated with respect to a certain sought mineral deposit-type (D), namely the weight for the presence of E with respect to D and the weight for the absence of E with respect to D. In the evaluation of the relative importance of the classes of spatial evidence data, there may be some classes having a few KMOs; however, these classes are comparatively classified as completely non-predictive or less predictive, and given a score equal to or less than 0. Hence, in such data-driven methods of weighting geological features, the favorability of some indicator features or locations is neglected. Such a problem exists in logistic regression (e.g.,

* Corresponding author: *Tel.*: +98 9113385443, *E-mail address:* m.yousefi@malayeru.ac.ir (M. Yousefi).

[6, 7, 18-21]) and discriminant analysis (e.g., [2, 6, 18, 20, 22, 23]) and other methods of MPM techniques as well. In these methods, the independent variables are modeled as binary evidential maps, in which the classes of evidence (i.e., encoded by 0 or 1) have positive or negative associations with mineral deposits. In classical artificial neural networks (ANN) for MPM (e.g., [6, 9, 10, 11, 24, 25]), all of the input maps are also binary; hence, the same problem exists. Moreover, in logistic regression, discriminant analysis, and ANN for MPM, several unit cells are defined as completely non-favorable, i.e., encoded with 0 value for training but this is not a certain/reliable value for those cells, because their locations may not have been explored by subsurface exploration yet. The assigned value of 0 is based just on surface information (cf. [26]).

Furthermore, in all of the data-driven weighting methods, the presence of E compared to its absence provides stronger evidence of D. In this paper, we believe that in such situations there is no need to estimate a weight for the absence of E with respect to D, because the absence of one spatial evidence (e.g., E_1) is equivalent to the presence of other spatial evidence/feature (e.g., E_2), which may be an indicator. Hence, the weight of the presence of E_2 can be calculated with respect to D. Using this method, all spatial indicator features containing some KMOs are given positive weights, depicting relevant degrees of prospectivity for the targeted mineral deposit. Hence, negative weights are not allocated to certain spatial evidence that contains some KMOs.

Yousefi and Hronsky (2023) [27] explored a new mappable geological feature representing mineral deposits and applied it to MPM. This illustrates the importance of using geological features in mineral exploration. In this research, the assumption isthat if in a study area, there is a mapped geological feature that contains at least one KMO, it is considered as an indicator feature in the modelling procedure as an indicator feature. Therefore, a question that arises is which method can be used for assigning the weight of every indicator feature that contains at least one KMO? The main logic behind this question is that if an attribute is present in a certain KMO, it has the potential to be an indicator of the deposit type sought. Moreover, Bonham-Carter (1994) [1] posed two important questions with regard to MPM: (1) what are the characteristics of a mineralization type (i.e., special positions), and (2) where are these characteristics localized (i.e., spatial positions)? A special position, namely the position of each KMO, represents a location where some favorable conditions or indicator features of the targeted type of mineral deposits exist. The kinds of indicator features can be elicited from the characteristics of KMOs of the same type as the targeted type of mineral deposits (e.g., [28, 29]). Therefore, each attribute of a KMO can be used as a basis for prospecting similar locations to answer the second question of Bonham-Carter (1994) [1] mentioned above. Several exploration methods (e.g., geological, geophysical, geochemical, remote sensing) can be used for prospecting mineral deposits. However, this study is focused on the recognition of indicator features and converting their importance into quantitative coefficients based on geological map information, which includes lithostratigraphic units and structural features. For this, we developed a new method to contribute and weight all indicator features, that contain at least one KMO. By using this method, not only all indicator features that contribute to the modelling are considered, but also uncertainty in assigning the weights of indicator features is considered; because weight is given for each features. In this method, each geological feature that contains at least one KMO is classified as an indicator feature. Thus, in this paper, an attempt is made to convert recognition criteria (indicator features) from a geological map into quantitative coefficients representing favorability for the presence of the targeted mineral deposits. In the method introduced in this paper, classes (features) of each geological or structural map are divided into two subsets, indicator and non-indicator features. Then, the indicator features are ranked and given weights. The weight, called the recognition coefficient (*RC*), is assigned based on data. The method was developed by studying and modelling the geological characteristics of eight known fluorite mining areas in an area in the Mazandaran province, north of Iran. In this regard, indicator and non-indicator features were first recognized based on the geological attributes of KMOs. Then, by calculating the *RC*s of individual indicator features, the relative importance of each of them was evaluated. Therefore, some important indicator features, which can be used in subsequent exploration stages, were quantitatively weighted. In this research, a data-driven weighting approach was developed to quantify geological exploration criteria and to create weighted geological evidence maps.

2. Descriptive modelling of fluorite mineralization in the study area

The study area, covering 4379 km^2, is located in the south of the 1:250,000 scale geological map of Sari and in the north of the 1:250,000 scale geological map of Semnan, eastern region of the Alborz zone north of Iran (Figure 1). In this district, some known F-Ba-Pb-Zn deposits exist, in which fluorite is the major economic mineral. Due to the mining activities on these fluorite deposits, they have also been called fluorite mines. In the study area, outcrops of different types of igneous (plutonic and volcanic), sedimentary and metamorphic rocks exist [30, 31]. The ages of the lithological features vary from the Precambrian to Recent. In the eastern district of the Alborz, several fluorite mining areas and a number of less significant fluorite, lead and zinc mines exist. Modelling of KMOs has demonstrated that the Triassic Elika Formation (dolomitic limestone) and the Lower Cretaceous Tizkooh Formation (orbitolina-bearing limestone) are the main host lithostratigraphic units for fluorite mineralization, which is deposited in lens forms in the spaces of faults [32, 33]. The fluorite mineralization has been diffused in lens forms into fracture zones (related to faults) that are widespread in limestones and dolomites of the Elika and Tizkooh Formations [33]. In this research, we used the spatial positions of 30 individual outcrops of fluorite mineralization in the mining areas to calculate *RC*s of indicator features.

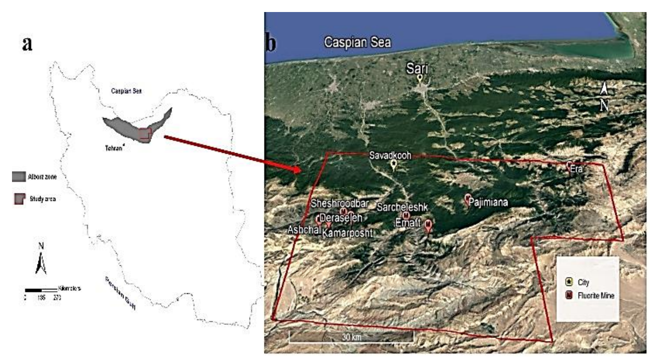

Figure 1. Location of the study area a) in central Alborz zone, north of Iran and b) with magnification along with the location of major fluorite mine.

3. Methods

3.1. RCs of exploration criteria

A given type of mineral deposit in a certain study area with a number of KMOs, has generally several characteristics, one or more of which may be present or absent in a given KMO. That is, not all of the characteristics of a certain type of mineral deposit are present in each of the KMOs. Therefore, the degrees of presence or absence of the attributes of a targeted type of mineral deposit in all of the KMOs are not the same. For this reason, every attribute of the deposit type sought is an indicator feature, and the locations where the features are present can be elicited from geoscience data (e.g., [28, 29, 34, 35]). In this regard, if at least one attribute of the targeted type of mineral deposit is present in at least one KMO, it is incorporated in the modelling. In this approach, the key point is the KMO, and the attributes of the KMOs are important. Therefore, first, all of the KMOs in the study area are arranged in rows, and then, the presence or absence of each attribute of the mineral deposit-type sought is given in columns with a score of 1 or 0, respectively (Table 1).

Considering Table 1, the percentage of the presence of each attribute in each KMO (denoted as P_{Aij}), which is the initial weight of each

Table 1. Process of quantifying the characteristics of "k" number of the KMOs for "m" number of attributes in "n" number of evidential maps (e.g., geological map and fault map). The presence or absence of an attribute of the targeted mineral deposit in a KMO is, respectively, encoded with 1 and 0, respectively.

KMO	A_{11}	A_{12}	...	A_{1j}	...	A_{1m}	A_{21}	A_{22}	...	A_{2j}	...	A_{2m}	...	A_{ij}	...	A_{nm}
KMO_1	1	0	...	1	...	0	0	1	...	1	...	1	...	0	...	1
KMO_2	1	1	...	0	...	1	1	1	...	0	...	1	...	1	...	0
KMO_3	0	0	...	1	...	1	0	1	...	1	...	1	...	0	...	1
. .	. .	. .	. .	. .	. .	. .	. .	. .	. .	. .	. .	. .	. .	. .	. .	. .
KMO_k	1	0	...	0	...	1	1	1	...	0	...	0	...	1	...	0
	P_{A11}	P_{A12}	...	P_{A1j}	...	P_{A1m}	P_{A21}	P_{A22}	...	P_{A2j}	...	P_{A2m}	...	P_{Aij}	...	P_{Anm}

indicative feature/attribute, is calculated as follows:

$$P_{A_{ij}} = \frac{N1_{Aij}*100}{k} \quad (1)$$

where A_{ij} represents the attribute, $N1_{Aij}$ is the sum of values in column A_{ij}, and k is the number of KMOs used in the modelling. After calculating P_{Aij}, to assign attribute weights for modelling the prospectivity of the mineral deposit- type sought in the study area, P_{Aij} is divided by the percentage area of spatial evidence with respect to the total area of the region being studied. This is the procedure to obtain the RC of an attribute considered as an indicator feature (RC_{Aij}). It is emphasized that the areal proportion of the indicator feature must be considered when calculating the RC with respect to mineral deposit occurrences (cf. [3, 7, 13, 15, 16, 17]). The main reason for that can be realized in a situation where two different classes of spatial evidence with different areal proportions contain an equal number of mineral deposits. In this situation, the percentage of deposits in both of the spatial features is equal, and thus, one may think that their coefficients should be the same. However, the equal coefficients based simply on the number of deposits contained are meaningless, because the two classes of spatial evidence have different area proportions. In such a situation, the class of spatial evidence with a smaller area should intuitively have a higher coefficient, because it is "easier" to find undiscovered mineralization within a smaller area than within a larger area. Hence, the RC of an indicator feature, RC_{Aij}, for modelling the prospectivity of the targeted mineral deposit is calculated as follows:

$$RC_{A_{ij}} = \frac{P_{A_{ij}}}{S_{A_{ij}}} \quad (2)$$

where P_{Aij} is the percentage of KMOs in which Aij is present, and S_{Aij} is the percentage area occupied by the spatial indicator feature A_{ij} with respect to the total study area.

Equation (3) is a summative function, because an area with higher degree of the presence of indicator attributes, and with higher RC value with respect to the targeted mineral deposit, has higher prospectivity. By using equation (3), KMOs with a higher degree of presence of attributes to the sought deposit-type, have a higher influence on MPM, depicted as the distribution map of the *US*. Another reason to use a summative function is that, in the method described in this paper, the RC is allocated only to indicator features; hence, the simultaneous presence of indicator features has a summative effect on prospectivity for the sought mineral deposit type.

3.2. Separation of indicator and non-indicator features

For prospecting different types of mineral deposits, different kinds of exploration methods, for example, geochemical, geophysical, remote sensing, and geological methods (e.g., [37-41]) are used to elicit corresponding indicator features of mineral deposits. By considering the mineral deposit type sought, some exploration methods may not be suitable. For instance, because of the nonmetallic nature of fluorite, the aeromagnetic geophysical survey is not directly used for prospecting fluorite deposits. Thus, in the preliminary stage of fluorite deposit exploration, the definition of geological recognition criteria would be more important than applying a geophysical method to outline favorable areas.

Here, we used a geological map to recognize the locations where indicator features are present for MPM for two reasons. Firstly, the purpose of this paper is the conversion of recognition criteria (for occurrences of mineral deposits) into quantitative coefficients based on geological map information. Secondly, according to the descriptive model of fluorite deposits in the study area, host rock lithology and structural features are two important exploration criteria for prospecting this type of mineralization [33], and the locations where these two features exist can be elicited from a geological map. In the study area, there are eight important fluorite mining areas (Fig. 2), namely Pajimiana, Kamarposht, Era, Emaft, Sarcheleshk, Sheshroodbar, Ashchal, and Deraseleh fluorite mines exist, of which Pajimiana is the largest. For recognizing the indicator host rock, the presence or absence of the host lithostratigraphic units of fluorite mineralization in each mining area is recorded in Table 2 following the example in Table 1.

Considering Table 2, two indicator host lithostratigraphic units, namely the Elika and Tizkooh Formations, out of the different lithostratigraphic units are depicted by the geological map of the study area. Because there is no other lithostratigraphic unit in which at least one KMO exists, all the remaining lithostratigraphic units were classified as non-indicator features. The indicator lithostratigraphic features for modelling prospectivity for Mississippi valley-type (MVT) fluorite deposit in the study area are shown in Figure 2.

Table 2. Presence or absence of the host lithostratigraphic units of fluorite mineralization in mining areas of the study region.

Mining area	Host lithostratigraphic unit	
	Elika[a]	Tizkooh[b]
Era	1	0
Pajimiana	1	0
Emaft	0	1
Sarcheleshk	1	0
Kamarposht	1	0
Sheshroodbar	1	0
Ashchal	1	0
Deraseleh	1	0

[a]Elika Formation: Triassic limestone and dolomite rocks. [b]Tizkooh Formation: Lower Cretaceous Orbitolina-bearing limestone.

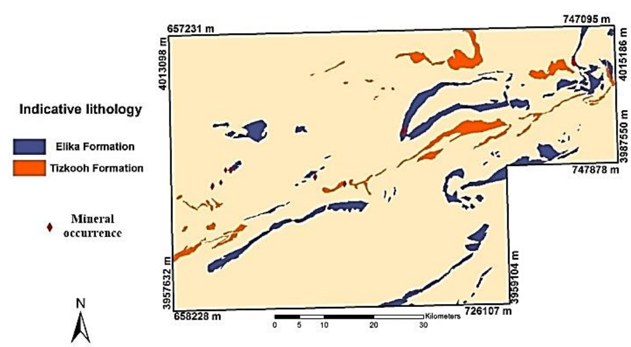

Fig.ure 2. The indicator lithostratigraphic features of MVT-fluorite mineralization, Elika formation: limestone and dolomite rocks with the age of Triassic. Tizkooh formation: Orbitolina limestone with the age of lower Cretaceous.

According to the descriptive model, structural features are indicators for modelling the prospectivity of MVT-fluorite deposits in the study area as well. Hence, we used proximity analysis from faults to recognize the indicator features. The number of mineral occurrences per class of proximity is recorded in Table 3. Considering Table 3, five classes of proximity, namely 0-150, 150-300, 450-600, 900-1050, and 1050-1200 m, out of the 11 proximity classes from faults, were elicited as indicator features based on the geological map of the study area. Therefore, all the remaining proximity classes (i.e., 300-450, 600-750, 750-900, 1200-1350, 1350-1500 and >1500 meter) were classified as non-indicator features (Figure 3).

Table 3. The number of mineral occurrences in different classes of proximity from faults.

Proximity from faults (m)	The number of mineral occurrences
0-150	17
150-300	6
300-450	0
450-600	1
600-750	0
750-900	0
900-1050	1
1050-1200	5
1200-1350	0
1350-1500	0
>1500	0

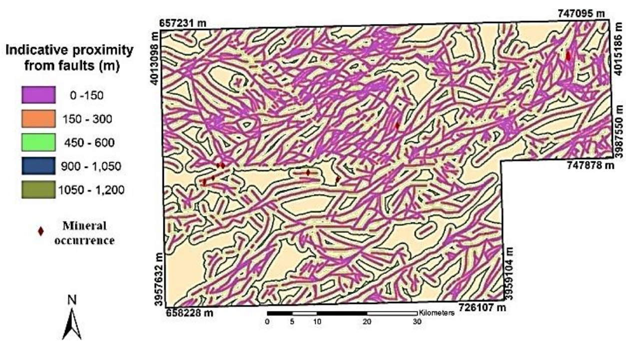

Figure 3. The indicator classes of proximity from faults to prospect MVT-fluorite deposit.

3.1. Conversion of descriptive information to quantitative data

After identification of the indicator features, the relative importance of each of them should be evaluated. As the importance of individual indicator features vary varies with respect to the targeted type of mineral deposit, it is necessary to quantify the degree of importance in order to determine which indicator feature is superior or inferior. Hence, equations (1) and (2), and Tables 2 and 3 were used to calculate the RCs of the individual indicator features. After calculating the RCs, we used a logistic membership function (e.g., [7, 9, 38, 42]) to assign a fuzzy weight between 0 and 1, to each indicator feature, thus:

$$\mu_{A_{ij}} = \frac{1}{1+e^{-a(RC_{Aij}-b)}} \quad (3)$$

where "b" is an inflexion point, "a" is the slope of the logistic function, and RC_{Aij} is the RC of the indicator feature A_{ij} for the j^{th} class in the i^{th} evidential map. The parameters "b" and "a" determine the shape of the function and, hence, the output of the fuzzifier. These parameters are chosen based on subjective assessment. Table 4 indicates the RC of each indicator feature and its corresponding fuzzy weight, $\mu_{A_{ij}}$ (data-driven fuzzy weight), for modelling the prospectivity of MVT-fluorite deposit in the study area.

4. Results

4.1. Generation of evidential maps

After recognizing the indicator features and calculating their corresponding weights, RC_{Aij} and $\mu_{A_{ij}}$, we generated weighted evidential layers. These evidential layers, namely a map of host lithostratigraphic features and a map of structures, are shown in Figure 4. In these maps, the RC of each indicator feature is a weight between 0 and 100 (Figures. 4a and 4c), and the RC-based fuzzy score ($\mu_{A_{ij}}$) is a weight between 0.01 and 1 (Figures. 4b and 4d).

Table 4. Weights, P_{Aij}, RC_{Aij}, and $\mu_{A_{ij}}$ of indicator features for modelling the prospectivity of MVT-fluorite deposit in the study area.

	Host lithology		Proximity from fault (m)				
Indicative feature	Elika formation[a]	Tizkooh formation[b]	0-150	150-300	450-600	900-1050	1050-1200
P_{Aij}	87.5	12.5	56.67	20	3.33	3.33	16.7
RC_{Aij}	15.54	4.17	2.17	1.23	0.37	0.75	4.97
$\mu_{A_{ij}}$	0.75	0.24	0.17	0.15	0.13	0.14	0.27

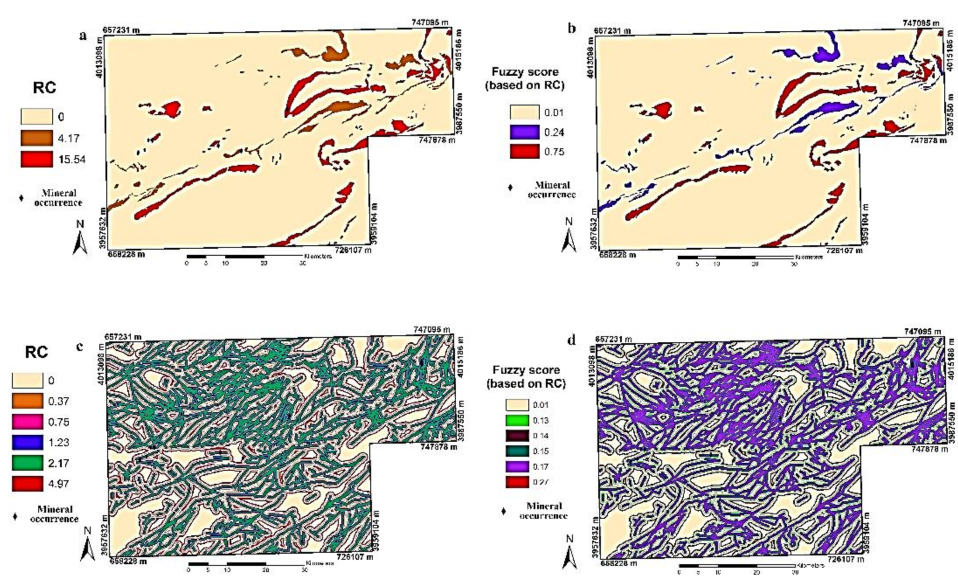

Figure 4. The evidence layers of (a) map of host lithostratigraphic units weighted on the basis of RC, (b) the map of host lithostratigraphic units weighted based on $\mu_{A_{ij}}$, (c) the map of proximity to faults weighted based on RC, and (d) the map of proximity to faults weighted based on $\mu_{A_{ij}}$.

4.2. Integration of evidential maps

After generating the weighted evidential maps, i.e., the maps of host lithostratigraphic units and structures, they were integrated. We used three methods to combine them in order to generate a final predictive model of prospectivity for MVT-fluorite deposit in the study area as described below.

4.2.1. Union score mineral potential model

Considering the descriptive model of MVT-fluorite deposits, the simultaneous presence of indicator host lithologies and structures has a summative effect on the formation of this type of mineral deposits. Hence, equation (3), a summative function, is proper to calculate the *US* for generating a mineral prospectivity model in this case study. The mineral prospectivity model for MVT-fluorite deposit in the study area, generated using the *US* is shown in Figure 5. In this figure, areas with higher *US* have priority for further exploration.

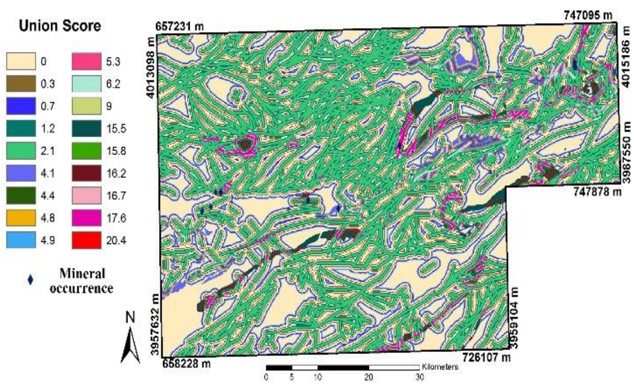

Figure 5. Mineral potential model of the MVT-fluorite deposit generated using the US function.

4.2.2. RC-based index overlay

The classical index overlay [1] is a knowledge-driven method for prospectivity mapping whereby each of the j^{th} classes of the i^{th} evidence layer is given a score, shown as S_{ij}. The class scores can be positive integers or positive real values. There is no limitation on the range of the scores, except that the range of class scores in evidential maps must lie between the same minimum and maximum values), meaning that it is impossible to control the relative weight of an evidential map by making the range of its class scores differently from the range of class scores in other evidential maps. The relative weight of an evidential map in comparison with other evidence layers is quantified through the weight W_i, which is a positive integer. The weighted layers are then integrated to determine an average weighted score (S) for each spatial unit in the study area [1, 2]. In this case, we used the following index overlay equation as a data-driven index overlay method (e.g., [43]):

$$S = \frac{\sum_{i=1}^{n} Rc_{Aij}\, W_i}{\sum_{i}^{n} W_i} \tag{5}$$

In fact, equation 5 is a knowledge-guided data-driven index overlay, in which the weight of each indicator feature is assigned using *RC*. In this method, the weight of j^{th} indicator class of the i^{th} evidence map is in fact RC_{Aij}, equivalent to S_{ij} in the knowledge-driven multi-class index overlay method. Similar to the knowledge-driven multi-class index overlay, the relative importance of an evidential map compared to other layers is realized by setting the weights W_i, but in this case, setting the weights is based on the nature of the data. The weight for each evidence map, W_i, varies between 0 and 10, and is obtained from division of the maximum *RC* value of its indicator features in the corresponding evidential map to 10 in Table 4. Hence, for the study area, the weights of the evidential geological map and structural map are 8.7 and 5.6, respectively. Fig. 6 shows the mineral prospectivity model for the MVT-fluorite deposit using the data-driven index overlay.

Unlike the ordinary multi-class index overlay (e.g., [1, 44, 45, 46]), in the theoretical function of the *RC*-based index overlay (Figure 6), the output, *S*, varies between 0 and 100, but in fact generally *S*, at least for the study area, has no values near 100. The reason for this is the low values of *RC*, because there is no class of evidential feature in which the highest number of KMOs was present in the lowest percentage area with respect to the total study area, meaning that there were no values of P_{Aij} equal to 100 and no values of S_{Aij} equal to 1 for an indicator feature. In the map of Figure 6, areas with higher values of *S* have more priority for prospecting the targeted deposit.

4.2.3. RC-based fuzzy logic modeling

Weights assigned within the [0, 1] range are similar to probabilities; thus, the score of indicator features, μ_{Aij}, is a fuzzy or probabilistic weight as well. The fuzzy logic modelling (e.g., [7, 47-51]) is a kind of knowledge-driven method for MPM. Here, we used fuzzy logic modelling, but as a data-driven method. In fact, this is a knowledge-guided data-driven fuzzy logic modelling, in which the weights of indicator features (fuzzy membership) are assigned based on data, i.e., the *RC* values. After generating fuzzy evidence maps (Figs. 4b and 4d), we used the fuzzy sum operator to generate the fuzzy favorability map shown in Figure 7.

According to Figure 7, all parts of the study area have been ranked by a favorability degree between 0.01 and 1 for prospecting the MVT-fluorite deposit. The fuzzy algebraic sum operator has an 'increasive' effect, and its output is larger than or equal to the maximum fuzzy score at every spatial unit. Thus, this operator is appropriate to combine sets of indicator feature [2]. In this research, the 'increasive' effect of the fuzzy algebraic sum operator is necessary, because in the *RC* method only indicator features of the targeted deposit are incorporated in assigning their weights based on their presence in KMOs, while all of non-indicator features have the same weight equal to 0.01. Therefore, in an area where there is an indicator feature with a fuzzy score higher than 0.01 (because the weights more than 0.01 are assigned just to indicator features), the area has the potential to be prospected. In such a situation, the simultaneous presence of indicator features has an increasing effect on prediction.

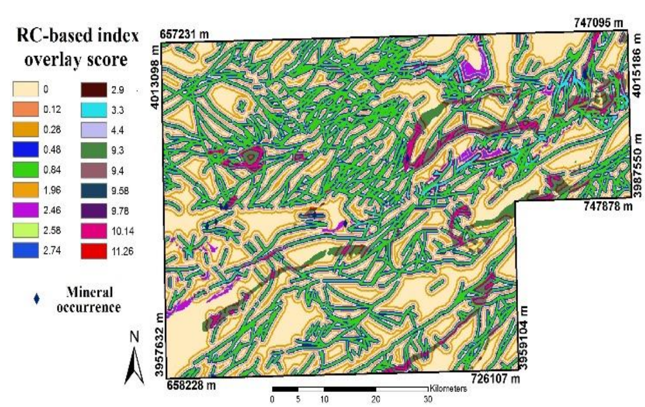

Figure 6. Mineral potential model of the MVT-fluorite deposit, generated using the RC based on the index overlay function.

In this method, if in a KMO has a higher presence of indicator features (with higher *RC*), that KMO has higher importance for prediction than the KMOs with fewer presence of indicator features (i.e., with a smaller value of *RC*). Hence, a higher presence of indicator features (i.e., with higher *RC*) in an area indicates a higher prospectivity for that area.

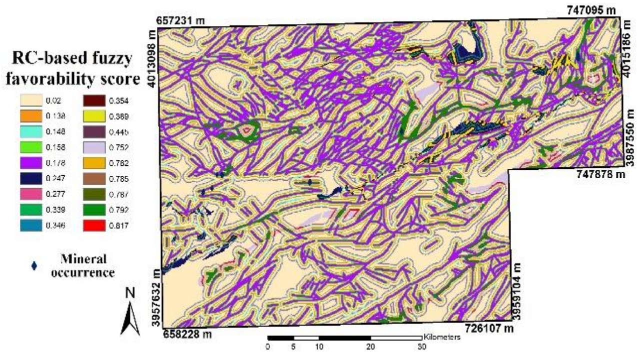

Figure 7. Mineral prospectivity model for the MVT-fluorite deposit, generated using the *RC*-based fuzzy logic modelling with fuzzy sum operator.

5. Discussion

The new concept, *RC*, introduced in this paper, is a weight allocated to each indicator feature of mineral deposits and illustrates their relative importance in comparison with other indicator features. Considering that the indicator degree of an attribute (exploration feature) may be different from other attributes (other exploration features), by using the proposed method we can quantify the relative importance of a feature compared with other features in order to determine which one is superior or inferior. In this method, the importance of any indicator feature is not lost, because if an attribute is present in even one KMO, it contributes to the calculation of the weights of indicator features. In this method, classes of evidential maps are categorized into two subsets, indicator and non-indicator features. In this approach, indicator features are ranked and allocated by fuzzy weights (assigned based on data), but the weights of all non-indicator features are the same, equal to 0 or 0.01. In this situation, uncertainty for the indicator features is considered; hence, relative importance of the features is evaluated, but for non-indicator features uncertainty and comparative importance cannot be evaluated. To address this problem, a fuzzy weight can be assigned to non-indicator features based on expert judgment, but the value of maximum weight allocated to a non-indicator feature should be less than the value of minimum weight, i.e., minimum *RC*, allocated to indicator features. By the *RC* approach, indicator and non-indicator features are discriminately recognized based on data, i.e., the characteristics of KMOs given in Table 1. The calculation of *RC* is worthwhile for assigning fuzzy weights to indicator features based on data.

6. Conclusion

The findings of this study are as follows.

- By using a recognition coefficient (RC), all indicator features are incorporated in the procedure for weight assignment.

- By using RC, uncertainty for the indicator features is considered; hence, the relative importance of indicator features is evaluated.

- By using RC, an approach to calculate fuzzy weights of indicator features is introduced.

- The RC approach is a data-driven weighting method to quantify the prediction ability of geological exploration criteria.

- By using RC, a data-driven approach to generate weighted evidence maps (here weighted lithostratigraphic and structural evidential maps) is developed.

- By using RC, a data-driven index overlay method is developed.

- By using RC, the subjective judgment of the analyst is not incorporated in assigning the weight of evidence features, at least for ranking indicator features.

- Finally, according to the results of this research, data-driven fuzzy logic modelling, .i.e., RC- based fuzzy logic modelling, is more effective for generating a mineral prospectivity model that is because of ranking the study area within the [0, 1] range with respect to probability. Hence, the RC approach can be used efficiently in the MPM to assign weights of exploration features with the contribution of all indicator features of the mineral deposit-type sought and without subjective judgment. The application of the proposed RC method in the study area has shown some promising areas with high values of prospectivity (Fig.7). These promising areas show a Mississippi valley-type fluorite type mineralization belt with a NE-SW trend that should be considered in further exploration stages.

Acknowledgment

We express our sincere gratitude to Professor John Carranza for his constructive comments and editions on our paper.

REFERENCES

[1] Bonham-Carter, G. F. and Bonham-Carter, G. (1994). Geographic information systems for geoscientists: modelling with GIS (No. 13). Elsevier.

[2] Carranza, E. J. M. (2008). Geochemical anomaly and mineral prospectivity mapping in GIS. Elsevier.

[3] Bonham-Carter, G. F. (1989). Weights of evidence modeling: a new approach to mapping mineral potential. Statistical applications in the earth sciences, 171-183.

[4] Agterberg, F. P., Bonham-Carter, G. F. and Wright, D. F. (1990). Statistical pattern integration for mineral exploration. In Computer applications in resource estimation (pp. 1-21). Pergamon. doi: https://doi.org/10.1016/B978-0-08-037245-7.50006-8

[5] Cheng, Q. and Agterberg, F. P. (1999). Fuzzy weights of evidence method and its application in mineral potential mapping. Natural resources research, 8(1), 27-35. doi: https://doi.org/10.1023/A:1021677510649

[6] Pan, G. and Harris, D. P. (2000). Information synthesis for mineral exploration. Oxford University Press.

[7] Carranza, E. J. M. (2002). Geologically-Constrained Mineral Potential Mapping: Example from the Philippines. International Institute of Aerospace Survey and Earth Science (ITC) (Doctoral dissertation, PhD Thesis. 88: 1-474).

[8] Carranza, E. J. M. and Hale, M. (2003). Evidential belief functions for geologically constrained mapping of gold potential, Baguio district, Philippines. Ore Geology Reviews, 22(2), 117-132. doi: https://doi.org/10.1016/S0169-1368(02)00111-7

[9] Porwal, A. K. (2006). Mineral potential mapping with mathematical geological models, Ph.D thesis. (Vol. 130). Utrecht University (Doctoral dissertation, PhD Thesis).

[10] Harris, J. R. and Sanborn-Barrie, M. (2006). Mineral potential mapping: examples from the Red Lake greenstone belt, northwest Ontario. GIS for the Earth Sciences, 44, 1-21.

[11] Nykänen, V. (2008). Radial basis functional link nets used as a prospectivity mapping tool for orogenic gold deposits within the Central Lapland Greenstone Belt, Northern Fennoscandian Shield. Natural Resources Research, 17(1), 29-48. doi: https://doi.org/10.1007/s11053-008-9062-0

[12] Boleneus, D. E., Raines, G. L., Causey, J. D., Bookstrom, A. A., Frost, T. P. and Hyndman, P. C. (2001). Assessment method for epithermal gold deposits in northeast Washington State using

weights-of-evidence GIS modeling (No. 2001-501). doi: https://doi.org/10.3133/ofr01501

[13] Good, I. J. (1950). Probability and the Weighing of Evidence, London, Charles Griffin.

[14] Carranza, E. J. M. (2004). Weights of evidence modeling of mineral potential: a case study using small number of prospects, Abra, Philippines. Natural Resources Research, 13(3), 173-187. doi: https://doi.org/10.1023/B:NARR.0000046919.87758.f5

[15] Jaccard, P. (1908). Nouvelles recherches sur la distribution florale. Bulletin Societe Vaudoise des Sciences Naturelles, 44, 223-270.

[16] Yule, G. U. (1912). On the methods of measuring association between two attributes. Journal of the Royal Statistical Society, 75(6), 579-652. doi: https://doi.org/10.2307/2340126

[17] Bayes, T. (1763). An essay towards solving a problem in the doctrine of chances. By the late Rev. Mr. Bayes, FRS communicated by Mr. Price, in a letter to John Canton, AMFR S. Philosophical transactions of the Royal Society of London, (53), 370-418. doi: https://doi.org/10.1098/rstl.1763.0053

[18] Bonham-Carter, G. F. and Chung, C. F. (1983). Integration of mineral resource data for Kasmere Lake area, Northwest Manitoba, with emphasis on uranium. Journal of the International Association for Mathematical Geology, 15(1), 25-45. doi: https://doi.org/10.1007/BF01030074

[19] Chung, C. F. and Agterberg, F. P. (1988). Poisson regression analysis and its application. In Quantitative analysis of mineral and energy resources (pp. 29-36). Springer, Dordrecht. doi: https://doi.org/10.1007/978-94-009-4029-1_2

[20] Harris, D. and Pan, G. (1999). Mineral favorability mapping: a comparison of artificial neural networks, logistic regression, and discriminant analysis. Natural Resources Research, 8(2), 93-109. doi: https://doi.org/10.1023/A:1021886501912

[21] Daneshfar, B., Desrochers, A. and Budkewitsch, P. (2006). Mineral-potential mapping for MVT deposits with Limited data sets using Landsat data and geological evidence in the Borden Basin, Northern Baffin Island, Nunavut, Canada. Natural Resources Research, 15(3), 129-149. doi: https://doi.org/10.1007/s11053-006-9020-7

[22] Chung, C. F. (1977). An application of discriminant analysis for the evaluation of mineral potential. In Application of computer methods in the mineral industry, Proceedings of the 14th APCOM Symposium, 1977 (pp. 299-311). Society of Mining Engineers of American Institute of Mining, Metallurgical, and Petroleum Engineers.

[23] Harris, J. R., Sanborn-Barrie, M., Panagapko, D. A., Skulski, T. and Parker, J. R. (2006). Gold prospectivity maps of the Red Lake greenstone belt: application of GIS technology. Canadian Journal of Earth Sciences, 43(7), 865-893. doi: https://doi.org/10.1139/e06-020

[24] Brown, W. M., Gedeon, T. D., Groves, D. I., & Barnes, R. G. (2000). Artificial neural networks: a new method for mineral prospectivity mapping. Australian journal of earth sciences, 47(4), 757-770. https://doi.org/10.1046/j.1440-0952.2000.00807.x

[25] Oh, H. J. and Lee, S. (2010). Application of artificial neural network for gold–silver deposits potential mapping: A case study of Korea. Natural Resources Research, 19(2), 103-124. doi: 10.1007/s11053-010-9112-2.

[26] Rahimi, H., Abedi, M., Yousefi, M., Bahroudi, A., Elyasi, G.R., 2021. Supervised mineral exploration targeting and the challenges with the selection of deposit and non-deposit sites thereof. Applied Geochemistry, 128, 104940. https://doi.org/10.1016/j.apgeochem.2021.104940.

[27] Yousefi, M., Hronsky, J.M.A., 2023. Translation of the function of hydrothermal mineralization-related focused fluid flux into a mappable exploration criterion for mineral exploration targeting. Applied Geochemistry, 149, 105561. https://doi.org/10.1016/j.apgeochem.2023.105561

[28] Yousefi, M., Kreuzer, O.P., Nykänen, V., Hronsky, J.M.A., 2019. Exploration information systems-a proposal for the future use of GIS in mineral exploration targeting. Geology Reviews, 111, 103005. https://doi.org/10.1016/j.oregeorev.2019.103005

[29] Yousefi, M., Carranza, E.J.M., Kreuzer, O.P., Nykänen, V., Hronsky, J.M., Mihalasky, M. J., 2021. Data analysis methods for prospectivity modelling as applied to mineral exploration targeting: state-of-the-art and outlook. Journal of Geochemical Exploration, 229, 106839. https://doi.org/10.1016/j.gexplo.2021.106839

[30] Vahdatidaneshmand, F. & Saidi, A. (1991). 1:250000 scale geological quadrangle map of the sari, geological survey of Iran (in Persian).

[31] Aghanabati, A. and Hamidi, A. R. (1994). 1:250000 scale geological quadrangle map of the Semnan. geological survey of Iran (in Persian).

[32] Ghazban, F. & Moritz, R., (2001). Nature of carbonate-hosted F-BA-Pb deposits in central Alborz Iran: Genetic relationships, XVIECROFI European current research on fluid inclusion, Porto.

[33] Vahabzadeh, Gh., 2008. Mineralogy and geochemistry of Fluorite mineralization in eastern district of central Alborz, Savadkooh area, Iran, Shahidbeheshti University (Doctoral dissertation, PhD Thesis. in Persian).

[34] Abedi, M., Mostafavi Kashani, S. B., Gholam-Hossain Norouzi, G.H., Yousefi, M., (2017). A deposit scale mineral prospectivity analysis: A comparison of various knowledge-driven approaches for porphyry copper targeting in Seridune, Iran. Journal of African Earth Sciences, 128, 127-146. https://doi.org/10.1016/j.jafrearsci.2016.09.028

[35] Kreuzer, O.P., Yousefi, M., Nykänen, V., 2020. Introduction to the special issue on spatial modelling and analysis of ore forming processes in mineral exploration targeting. Ore Geology Reviews, 119, 103391. https://doi.org/10.1016/j.oregeorev.2020.103391

[36] Yousefi, M., Carranza, E.J.M., 2017. Union score and fuzzy logic mineral prospectivity mapping using discretized and continuous spatial evidence values. Journal of African Earth Sciences, 128, 47-60. https://doi.org/10.1016/j.jafrearsci.2016.04.019

[37] MamiKhalifani, F., Bahroudi, A., Aliyari, F., Abedi, M., Yousefi, M., Mohammadpour, M. 2019. Generation of an efficient structural evidence layer for mineral exploration targeting. Journal of African Earth Sciences, 160, 103609. https://doi.org/10.1016/j.jafrearsci.2019.103609

[38] Yousefi, M., Nykänen, V., 2016. Data-driven logistic-based weighting of geochemical and geological evidence layers in mineral prospectivity mapping. Journal of Geochemical Exploration, 164, 94-106. https://doi.org/10.1016/j.gexplo.2015.10.008

[39] Ghasemzadeh, S., Maghsoudi, A., Yousefi, M., Mihalasky, M. J., (2019). Stream sediment geochemical data analysis for district-scale mineral exploration targeting: Measuring the

performance of the spatial U-statistic and C-A fractal modeling. Ore Geology Reviews, 113: 103115. https://doi.org/10.1016/j.oregeorev.2019.103115

[40] Ghasemzadeh, S., Maghsoudi, A., Yousefi, M., Mihalasky, M. J., (2022a). Recognition and incorporation of mineralization-efficient fault systems to produce a strengthened anisotropic geochemical singularity, Journal of Geochemical Exploration, 235, 106967. https://doi.org/10.1016/j.gexplo.2022.106967

[41] Ghasemzadeh, S., Maghsoudi, A., Yousefi, M., Mihalasky, M.J., (2022b). Information value based geochemical anomaly modeling: a statistical index to generate enhanced geochemical signatures for mineral exploration targeting. Applied Geochemistry, 136, 105177. https://doi.org/10.1016/j.apgeochem.2021.105177

[42] Zimmermann-Tansella, C., Donini, S., Lattanzi, M., Siciliani, O., Turrina, C., & Wilkinson, G. (1991). Life events, social problems and physical health status as predictors of emotional distress in men and women in a community setting. Psychological Medicine, 21(2), 505-513. https://doi.org/10.1017/S0033291700020614

[43] Yousefi, M., Carranza, E. J. M., 2016. Data-driven index overlay and Boolean logic mineral prospectivity modeling in greenfields exploration. Natural Resources Research, 25, 3-18. https://doi.org/10.1007/s11053-014-9261-9

[44] Billa, M., Cassard, D., Lips, A. L., Bouchot, V., Tourlière, B., Stein, G. and Guillou-Frottier, L. (2004). Predicting gold-rich epithermal and porphyry systems in the central Andes with a continental-scale metallogenic GIS. Ore Geology Reviews, 25(1-2), 39-67. doi: https://doi.org/10.1016/j.oregeorev.2004.01.002

[45] Chica-Olmo, M., Abarca, F. and Rigol, J. P. (2002). Development of a decision support system based on remote sensing and GIS techniques for gold-rich area identification in SE Spain. International Journal of Remote Sensing, 23(22), 4801-4814. doi: https://doi.org/10.1080/01431160110104656

[46] De Araújo, C. C. and Macedo, A. B. (2002). Multicriteria geologic data analysis for mineral favorability mapping: application to a metal sulphide mineralized area, Ribeira Valley Metallogenic Province, Brazil. Natural Resources Research, 11(1), 29-43. doi: https://doi.org/10.1023/A:1014235703541

[47] D'ercole, C., Groves, D. I. and Knox-Robinson, C. M. (2000). Using fuzzy logic in a Geographic Information System environment to enhance conceptually based prospectivity analysis of Mississippi Valley-type mineralization. Australian Journal of Earth Sciences, 47(5), 913-927. doi: https://doi.org/10.1046/j.1440-0952.2000.00821.x

[48] Knox-Robinson, C. M. (2000). Vectorial fuzzy logic: a novel technique for enhanced mineral prospectivity mapping, with reference to the orogenic gold mineralisation potential of the Kalgoorlie Terrane, Western Australia. Australian Journal of Earth Sciences, 47(5), 929-941. doi: https://doi.org/10.1046/j.1440-0952.2000.00816.x

[49] Carranza, E. J. M. and Hale, M. (2001). Geologically constrained fuzzy mapping of gold mineralization potential, Baguio district, Philippines. Natural Resources Research, 10(2), 125-136. doi: https://doi.org/10.1023/A:1011500826411

[50] Porwal, A., Carranza, E. J. M. and Hale, M. (2003). Knowledge-driven and data-driven fuzzy models for predictive mineral potential mapping. Natural Resources Research, 12(1), 1-25. doi: https://doi.org/10.1023/A:1022693220894

[51] Nykänen, V., Groves, D. I., Ojala, V. J., Eilu, P. and Gardoll, S. J. (2008). Reconnaissance-scale conceptual fuzzy-logic prospectivity modelling for iron oxide copper–gold deposits in the northern Fennoscandian Shield, Finland. Australian Journal of Earth Sciences, 55(1), 25-38. doi: https://doi.org/10.1080/08120090701581372