Journal of Geomine (2023), 1(1), 13-21
DOI: 10.22077/jgm.2023.6377.1004

Application of multivariate decision-making algorithms in the mineral potential mapping; Case study: West Basiran, South Khorasan Province

Hamid Geranian[1], Malieh Nakhaei[1]

Recived: 2023 May 14, Revised: 2023 Jun. 12, Online Published: 2023 Jun. 18

ABSTRACT

Identifying composite geochemical anomalies is one of the most essential goals in regional-scale exploration studies. In this paper, the results of the chemical analysis of 18 elements in 191 geochemical stream sediment samples have been used to evaluate potential for poly-metallic mineralization in an exploration area. The study area is located in the western part of Basiran 1:100000 scale geological map in the south of Birjand, South Khorasan Province. In terms of the geological-structural division of Iran, this area is located in the Lut block, and for this reason, it is very promising for various mineralization. Composite geochemical anomalies were determined by three multivariate decision-making methods such as Simple Additive Weighting (SAW), Integrated Determination of Objective Criteria Weights (IDOCRIW), and Weighted Aggregated Sum Product Assessment (WASPAS) algorithms in the study area. The results of SAW, IDOCRIW, and WASPAS algorithms show five geochemical anomalies with a total area of 30.4, 26.8 and 24.8 square kilometers, respectively. These anomalies have the same locations and shapes. The II and V anomalies are the most significant mineralization zones in the study area. The I anomaly, located in the southwest of the study area, is related to diorite and micro granodiorite igneous rocks, while the II anomaly is related to acidic tuffs rocks. The II, IV and V anomalies are also associated with deep to semi-deep acidic to intermediate rocks in the north to northeast of Bisheh village. The surface and core drilling studies show high concentrations of Fe, Cu, Au, Zn, Pb, Ti, W, Co and Bi elements in these anomalies. This point can confirm the correctness of the algorithms used in identifying composite geochemical anomalies. Therefore, this paper proposes the abovementioned algorithms as an exploration data integration method.

KEYWORDS

Composite geochemical anomaly, multivariate decision-making method, IDOCRIW algorithm, WASPAS algorithm, Basiran region

I. INTRODUCTION

Mineral exploration on a regional scale is considered one of the most important infrastructure projects in identifying mineral potential mapping, in which remote sensing data, airborne geophysics, stream sediments geochemical sampling, and medium-scale geological exploration maps are used. In this regard, the identification of composite (multi-element) geochemical anomalies is one of the important techniques in the processing of regional exploration data. To determine multi-element geochemical anomaly, one can use (1) the visual or mathematical integration method of single-element geochemical anomalies (Zhizhong et al., 2014; Chen et al., 2016), (2) the conversion of multi-element data into one variable, and then use the single-element threshold determination method (Hosseini-Dinani et al., 2015; Cao and Lu, 2015) or (3) clustering methods (Geranian, 2018; Ellefsen & Smith, 2016). Multivariable decision-making (MDM) methods are part of the second group, in which by giving weight to each variable, the data combine, and the final result will be in the form of a quantity value. The MDM methods mainly use as algorithms for choosing the best option in economics, agriculture, industrial engineering and management studies. These methods were only used in a few exploration studies as an integration method. Among these studies, compare the performance of TOPSIS and VIKOR methods in finding copper mineralization potential in the central part of the Kerman metallurgical belt (Maghsoudi Moud, 2016), determining the optimal dimensions of the block in Angoran mine (Hayati et al., 2015) and identifying potential exploration areas in a volcanic-sedimentary belt of central Iran (Abedi et al., 2016) can be mentioned. The purpose of this paper is to introduce new algorithms of the MDM methods and study the possibility of their application in determining composite geochemical anomalies.

[1] Department of Mining Engineering, Birjand University of Technology, Birjand, Iran
H. Geranian: h.geranian@birjandut.ac.ir

The study area, in the 1:100,000 Basiran sheet, is located in the Lut block in the geological-structural division of Iran (Berberian and King, 1981). Due to the many magmatic activities and special tectonic conditions in the Lut block at different times, this block is economically very capable and can expect to form different deposits of various metallic and non-metallic minerals. Some researchers have linked the occurrence of magmatism and the formation of deposits in eastern Iran with subduction (Camp and Griffis 1982). In contrast, others have rejected this theory and attributed these processes to the existence of tensile conditions (Tarkian et al., 1983). In the following, two MDM algorithms will be introduced and their application will be investigated on the exploration data of the Basiran region to determine composite geochemical anomalies and the mineral potential mapping of this part of Iran.

II. THE MDM METHODS

A. IDOCRIW ALGORITHM

The Integrated Determination of Objective Criteria Weights (IDOCRIW) algorithm was introduced in 2016 by Zavadskas et al. (2016). This method, a combination of entropy and Criterion Impact LOSs (CILOS) methods, is mainly used as an algorithm in multivariable decision-making problems. If the data set, D, contains n samples (or options) that for each sample m variables (or characteristics or criteria) are also measured, this multi-dimensional data set can be defined as follows:

$$D = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} \quad (1)$$

The steps of the IDOCRIW algorithm are (Zavadskas and Podvezko, 2016; Cereška et al., 2016, Trinkuniene et al., 2017; Zavadskas et al., 2017; Cereška et al., 2018; Vinogradova et al., 2018):

1. Unscaling the data matrix: To eliminate the effect of the measurement units of variables, the first step is to normalize the data matrix, which is done by the following equation:

$$\tilde{x}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \;\; ; i = 1, 2, \dots, n \;\; ; j = 1, 2, \dots, m \quad (2)$$

2. Determining the entropy of each variable or criterion: The following equation is used to calculate it:

$$E_j = -\frac{1}{Ln(n)} \sum_{i=1}^{n} \tilde{x}_{ij} Ln(\tilde{x}_{ij}) \;\; ; j = 1, 2, \dots, m \;\; ; 0 \leq E_j \leq 1 \quad (3)$$

3. Determining the uncertainty or degree of deviation of each variable as follows:

$$d_j = 1 - E_j \;\; ; \;\; j = 1, 2, \dots, m \quad (4)$$

4. Determining the weight of each variable: The entropy method is used to determine the weight of each variable by the following equation:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \;\; ; \;\; j = 1, 2, \dots, m \quad (5)$$

5. Forming a square matrix: The maximum values of each column of the normalized matrix data are selected to form this matrix. So we have:

$$a_j = \max_i \tilde{x}_{ij} = a_{k_i j} \;\; ; \; i = 1, 2, \dots, n \;\; ; j = 1, 2, \dots, m \quad (6)$$

Where $a_{k_i j}$ equals the highest criterion value or the jth column taken from the sample or row k_i. In order to form a square matrix with the $m \times m$ dimensions, $a_{ij} = a_{k_i j}$ and $a_{jj} = a_j$. Therefore, the ith row of the square matrix will contain the elements of the k_i row of the normalized matrix.

6. Forming the lost impact matrix: The square matrix of the lost impact of the criteria formed by using the square matrix of the previous step and as follows:

$$p_{ij} = \frac{a_{jj} - a_{ij}}{a_{jj}} ; i, j = 1, 2, \dots, m \;\; ; \;\; p_{jj} = 0 \quad (7)$$

Where p_{ij} represents the loss of the relative effect of the criterion or j variable, if the ith criterion is chosen as the best criterion.

7. Calculating the matrix of the weight system: The square matrix of the weight system is formed according to the loss values of the relative effect as follows:

$$F = \begin{bmatrix} -\sum_{i=1}^{m} p_{im} & p_{12} & \cdots & p_{1m} \\ p_{21} & -\sum_{i=1}^{m} p_{i2} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & -\sum_{i=1}^{m} p_{im} \end{bmatrix} \quad (8)$$

8. Determining the weight of each criterion using the criterion impact loss method (CILOS): If the weight of each criterion or variable is considered equal to q_j, these weights obtain from the following equation:

$$Fq^T = 0 \quad (9)$$

Where q^T is the linear vector of weights (i.e. $q = [q_1 \,, \; q_2 \,, \dots, q_m]$). From the solution of equation 9, the weights calculated by the CILOS method in such a way that $\sum_{j=1}^{m} q_j = 1$.

9. Calculating the weight of each criterion by the cumulative method: Finally, the weight of each criterion obtain by combining the weights obtained by the entropy method (w_j) and CILOS method (q_j) by the following equation:

$$\omega_j = \frac{q_j w_j}{\sum_{j=1}^{m} q_j w_j}\, ;\ j = 1, 2, \dots, m \qquad (10)$$

Where ω_j is the final weight of the jth criterion by the IDOCRIW method.

B. WASPAS ALGORITHM

The Weighted Aggregated Sum Product Assessment (WASPAS) method was first introduced in 2012 by Zavadskas et al. (2012). This method mainly uses as an algorithm in multivariable decision-making problems. The steps of the WASPAS algorithm are (Zavadskas et al., 2012; Chakraborty et al., 2015; Chakraborty and Zavadskas, 2014; Zavadskas et al., 2016; Zavadskas et al., 2013):

1. Normalizing the data matrix: To eliminate the effect of the measurement units of the variables, the method of dividing each data by the largest data of each column can use the following equation:

$$\bar{x}_{ij} = \frac{x_{ij}}{max_i x_{ij}}\ \ ;\ \ i = 1, 2, \dots, n\, ; j = 1, 2, \dots, m \qquad (11)$$

Where $\bar{x}_{ij}$ is the normalized value of the ith sample for the jth variable.

2. Calculating the relative importance of each sample: This importance is obtained based on the weighted sum model (WSM) from equation 12 and based on the weighted product model (WPM) from equation 13 to the following formulas:

$$Q_i^{(1)} = \sum_{j=1}^{m} \bar{x}_{ij} w_j\ \ ;\ \ i = 1, 2, \dots, n \qquad (12)$$

$$Q_i^{(2)} = \prod_{j=1}^{m} (\bar{x}_{ij})^{w_j}\, ;\ \ i = 1, 2, \dots, n \qquad (13)$$

Where $Q_i^{(1)}$ and $Q_i^{(2)}$ are the relative importance of the ith sample and w_j is the weight of the jth variable. In order to calculate the weight of each variable, three methods such as equal weights, data-oriented (for example the Chalon entropy method) and knowledge-oriented methods, can be used (for more details, refer to the source (Asgharpour, 2011)). The weights, in all three categories of methods, should be chosen in such a way that:

$$\sum_{j=1}^{m} w_j = 1\ \ ;\ \ 0 \le w_j \le 1 \qquad (14)$$

3. Calculating a joint generalized criterion: To calculate the final score of each sample, the total importance and the weighte of each sample must add together. The following equation is used for this purpose:

$$Q_i = \lambda Q_i^{(1)} + (1-\lambda) Q_i^{(2)} = \lambda \sum_{j=1}^{m} \bar{x}_{ij} w_j + (1-\lambda) \prod_{j=1}^{m} (\bar{x}_{ij})^{w_j}\, ;\ \ \lambda = 0, 0.1, 0.2, \dots, 1 \qquad (15)$$

So finally, the samples or options will rank in descending order based on the Q_i values. The λ parameter determines the accuracy of the WASPAS algorithm in ranking the samples. If λ is equal to zero, the WASPAS algorithm will work similarly to the WPM model, and if λ is chosen equal to 1, this algorithm will convert to the WSM model. In most operations, the λ is usually considered equal to 0.5. Over the past few years, several revisions have been made to the WASPAS algorithm, including the use of this algorithm on fuzzy data (Turskis et al., 2019), single-value intuitive fuzzy data (Stanujkić and Karabašević, 2018), intuitive fuzzy data with distance values (Mishra1 and Rani, 2018) and WASPAS-G model (Zavadskas et al., 2015).

III. GEOLOGY SETTING OF THE STUDY AREA

The study area is located 196 km south of Birjand, east of Iran, between 59° 01' 56" to 59° 12' 32" E and 31° 39' 31' to 31° 49' 55" N. Jurassic Shale and sandstone units are the oldest rocks that are present in east part in the study area and other rocks are placed on them unconformity. Paleocene conglomerate with brown color beside massive and thick cream color limestones with Paleocene microfossils are exposed after Jurassic rocks. These limestones are outcropped in the northeast of Bishe village and north-northeast of Chah-e- shur village. Tertiary magmatic units, such as volcanic and plutonic rocks are the other rocks in the study area. They have included andesite, basalt, tuff with black color, dacitic tuffs along with trachyandesite -trachyte lavas and pyroxene andesite. Eocene volcanic units are cut by intrusive and sub-volcanic felsic and intermediate rocks. In the north of Bishe village, Neogene conglomerate with 40-50-meter thickness and 10-degree dip are exposed on Eocene lavas and tuffs. There is recent alluvium in the southeast parts and some parts of the northwest of the area that are included low terraces, younger gravel fans, high terraces and old fans.

The processing of aster satellite data showed that the most important alteration in the region includes sericitic, propylitic and argillic. Also, iron oxides and hematite, have been widely identified in the study area. The presence of iron oxide and hydroxides can be a sign of iron mineralization or the company of sulfides that have altered into iron oxide.

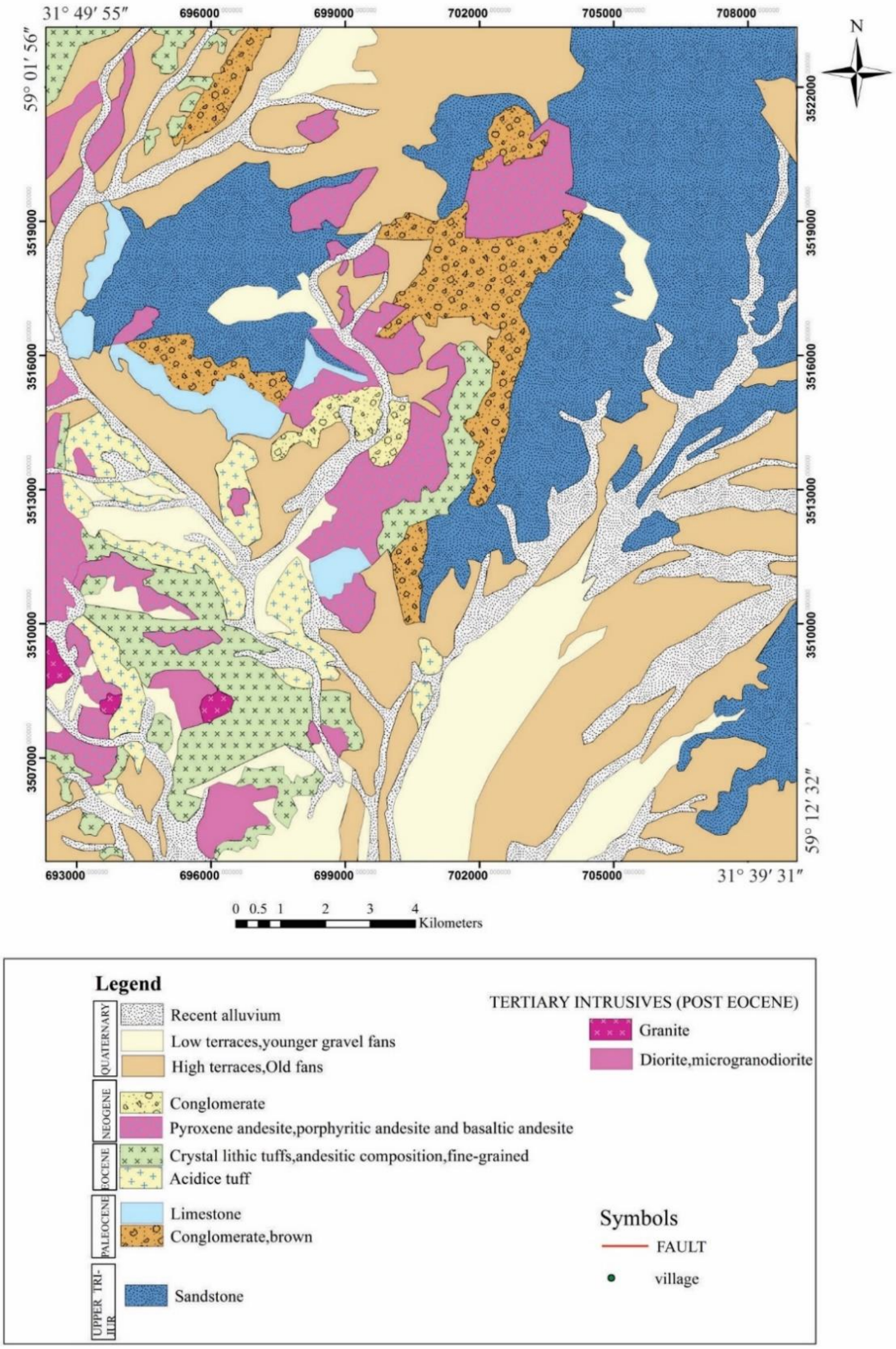

Fig. 1. Geological map of the study area (Behrouzi and Nazer, 1992)

IV. Geochemical data of the study area

The geochemical data of the study area includes 191 samples of stream sediments collected from an area of 224 Km^2. These data are a part of the stream sediment samples of the west of Basiran, a 1:100,000 scale Basiran sheet, which were collected by the experts of the Geological Survey & Mineral Explorations of Iran. The samples were analyzed in the Laboratory of the Geological Survey & Mineral Explorations of Iran. The sediment fraction smaller than 80 mesh was selected for the chemical analysis of 44 elements by inductively coupled plasma-optical emission spectroscopy. Fig. 2 shows the distribution map of these samples, mostly taken from the middle of the study area. In this paper, the results of the chemical analysis of the 18 elements have used that are related to hydrothermal mineralization. These elements and their descriptive statistics parameters are presented in Table 1. The data was obtained after replacing the censored data with 3/4 of the respective detection limits and adjusting the outlier data. The skewness and kurtosis indicate that the data distribution is non-normal for most of the elements. Also, comparing the mean data with the Clark value shows the enrichment of the samples in all elements except for Co, Cu and Ni elements. Therefore, the data in Table 1 indicates the multiple populations of the data and the presence of multi-element geochemical anomalies, which will determine in three algorithms.

V. Mineral potential mapping of the study area

In order to combine the geochemical contour maps of the elements with each other and prepare a composite geochemical contour map as a mineral potential map, firstly, the primary data should be normalized, and secondly, the data of each sample should combine with a linear or non-linear equation to get a quantity value. In this paper, the range of each variable transfered to [1, 0] and the data combine by three linear equations. In the first linear equation, which adapts from the collective composite anomaly method, the weight of all variables is considered the same. Therefore, the normalized data of each sample is only added together. This method is one of the multivariate decision-making methods and is known as Simple Additive Weighting (SAW) algorithm. Fig. 3 shows the resulting contour map with the continuous (Fig. 3A) and classified (Fig. 3B) scales. Classification of the data or separation of the statistical populations is done by the concentraion-area fractal method. The data have been divided into three classes: the first population as a low-grade area, the second population as a high-grade area, and the third population as an anomaly or mineralization probability area. The mineralization probability area can be seen in the southwest-northeast direction of the study area and 5 zones (Fig. 3). The extent of these zones are as I, V, II, III and IV from large to small. The total area of these zones, or anomaly areas in Fig. 3B, is estimated to be almost 30.4 km^2.

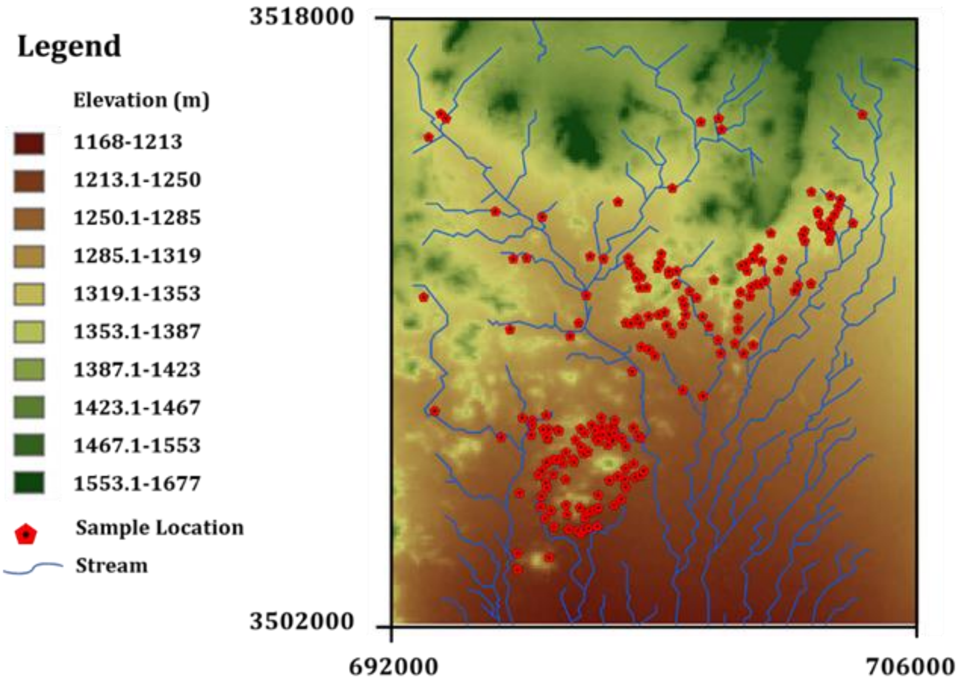

Fig. 2. Locations of stream sediment geochemical samples (red dots) overlain on a digital elevation model of the study area

Table 1. Descriptive statistical parameters of the elements in the study area

Variable	Mean	StDev	Minimum	Median	Maximum	Skewness	Kurtosis
Ag (ppm)	0.2385	0.1977	0.075	0.23	2.33	7.19	69.52
As (ppm)	26.50	19.04	9.0	20.0	141.0	2.72	9.69
Au (ppb)	1.341	2.374	0.001	1.0	16.0	3.87	17.78
Ba (ppm)	422.61	65.6	245.0	423.0	643.0	0.16	0.22
Bi (ppm)	0.624	0.9248	0.075	0.30	6.90	3.50	15.87
Co (ppm)	16.561	2.934	10.0	16.6	24.0	0.10	-0.32
Cr (ppm)	181.05	81.87	68.00	157.0	601.0	2.01	5.17
Cu (ppm)	33.71	14.24	9.0	33.5	123.0	2.67	12.33
Fe (%)	4.996	1.124	3.00	4.83	9.31	1.05	1.57
Hg (ppm)	0.0348	0.0543	0.013	0.013	0.39	4.22	21.61
Mo (ppm)	1.1745	0.3286	0.04	1.10	2.80	0.70	5.32
Ni (ppm)	48.937	11.522	22.0	50.0	78.0	-0.25	-0.14
Pb (ppm)	21.447	8.138	7.0	20.6	56.0	0.96	1.13
Sb (ppm)	2.267	1.319	1.00	1.90	8.50	1.58	3.19
Sn (ppm)	2.18	1.433	1.00	1.90	10.90	3.68	17.41
Sr (ppm)	372.24	39.81	272.0	370.0	458.0	-0.02	-0.74
W (ppm)	3.248	7.415	0.30	1.0	39.0	3.38	10.37
Zn (ppm)	81.21	16.81	49.60	79.0	149.0	0.63	0.62

The IDOCRIW algorithm is the second linear equation used in this paper to prepare the mineral potential map of the study area. Table 2 shows the weight of each variable in this linear equation calculated by the mentioned algorithm. The w_i and q_i are respectively, the weight of each variable obtained by the entropy and CILOS methods, and ω_i is the final weight estimated by the IDOCRIW algorithm. Table 2 shows that Au and Ti elements have the highest weights and Sr and Ba elements have the lowest weights. Also, the weights in this table indicate that the IDOCRIW algorithm moderates the disadvantages of the entropy method to some extent, so it slightly reduces the high weights and slightly increases the low weights. One of the significant points in preparing the mineral potential map by the linear equation is the influence of the grade and weight of elements in the final value.

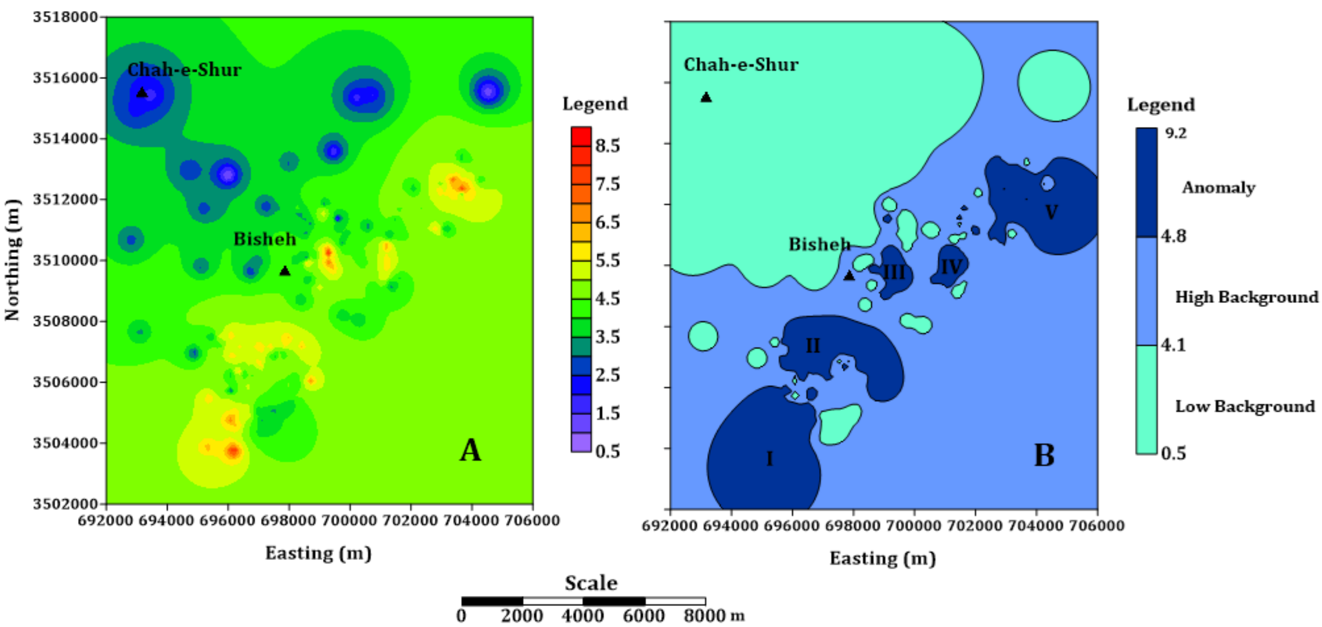

Fig. 3. Maps of composite geochemical anomalies using (A) the SAW method with continuous scale and (B) classified scale

Table 2. The weight of the elements in the mineral potential map using the IDOCRIW algorithm

Method	Ag	As	Au	Ba	Bi	Co	Cr	Cu	Fe
w_i	0.042	0.043	0.211	0.003	0.150	0.004	0.019	0.017	0.005
q_i	0.033	0.039	0.029	0.085	0.037	0.139	0.034	0.051	0.060
ω_i	0.040	0.048	0.174	0.007	0.160	0.014	0.019	0.024	0.009
	Hg	Mo	Ni	Pb	Sb	Sn	Sr	W	Zn
w_i	0.142	0.009	0.006	0.015	0.033	0.034	0.001	0.261	0.005
q_i	0.030	0.044	0.066	0.041	0.039	0.040	0.136	0.033	0.064
ω_i	0.123	0.012	0.012	0.018	0.037	0.038	0.005	0.250	0.009

Fig. 4 shows the composite geochemical contour maps in the study area, delineated with two continuous (Fig. 4A) and classified (Fig. 4B) scales. The anomaly areas obtained in Fig. 4 can be seen in 5 zones and in the same direction as in Fig. 3. The location of the more important zones, i.e., zones I and V, are almost the same in both Figures. While the extent and location of zones II, III and IV are different from each other. The area of the composite geochemical anomaly zones in Fig. 4 is about 26.8 km^2. Zone V is the largest area, followed by zones II, I, IV, and III, respectively.

In the next step, the composite geochemical contour map is determined by the WASPAS algorithm. For this purpose, the weight of each variable is estimated by the Chalon entropy method. Table 3 shows the estimated weights, in which W and Au elements have the highest weights and Ba and Sr elements have the lowest. Elements based on weights are effective in the composite geochemical contour map. So, if the weight of a variable is higher, its impact on the composite geochemical contour map will be more significant.

Then, the value of the composite geochemical anomaly (Q_i) is estimated by the WASPAS algorithm as the third linear equation. Fig. 5 shows the contour map of this anomaly with the continuous (Fig. 5A) and the classified (Fig. 5B) scales. The classification of data in this map has also been done by the concentration-area fractal method. In this map, as in Figs. 3 and 4, five anomalous zones have been identified in which the probability of mineralization is higher. Of course, the extent and location of these zones are slightly different forms, as shown in Figs. 3 and 5, except for zone V. The distribution of these zones is in one strike and the southwest-northeast direction. The extent of these anomalies is zones V, II, I, IV, and III from large to small, respectively. However, the total area of these zones is about 24.8 km^2.

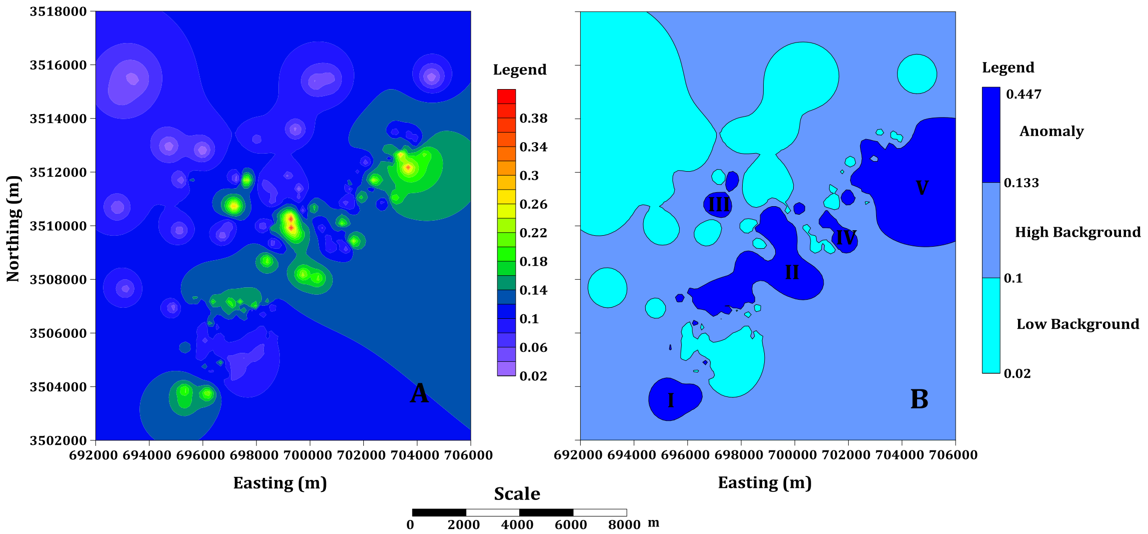

Fig. 4. Maps of composite geochemical anomalies using the IDOCRIW algorithm with continuous scale (A) and classified scale (B)

Table 3. The weight of each variable is estimated by the Chalon entropy method

Variable	Fe	Cu	Cr	Co	Bi	Ba	Au	As	Ag
Weight	0.00537	0.016707	0.019219	0.003526	0.14956	0.002698	0.211436	0.042703	0.042392
Variable	Zn	W	Sr	Sn	Sb	Pb	Ni	Mo	Hg
Weight	0.004675	0.261041	0.001282	0.033508	0.032771	0.015208	0.006483	0.00941	0.142009

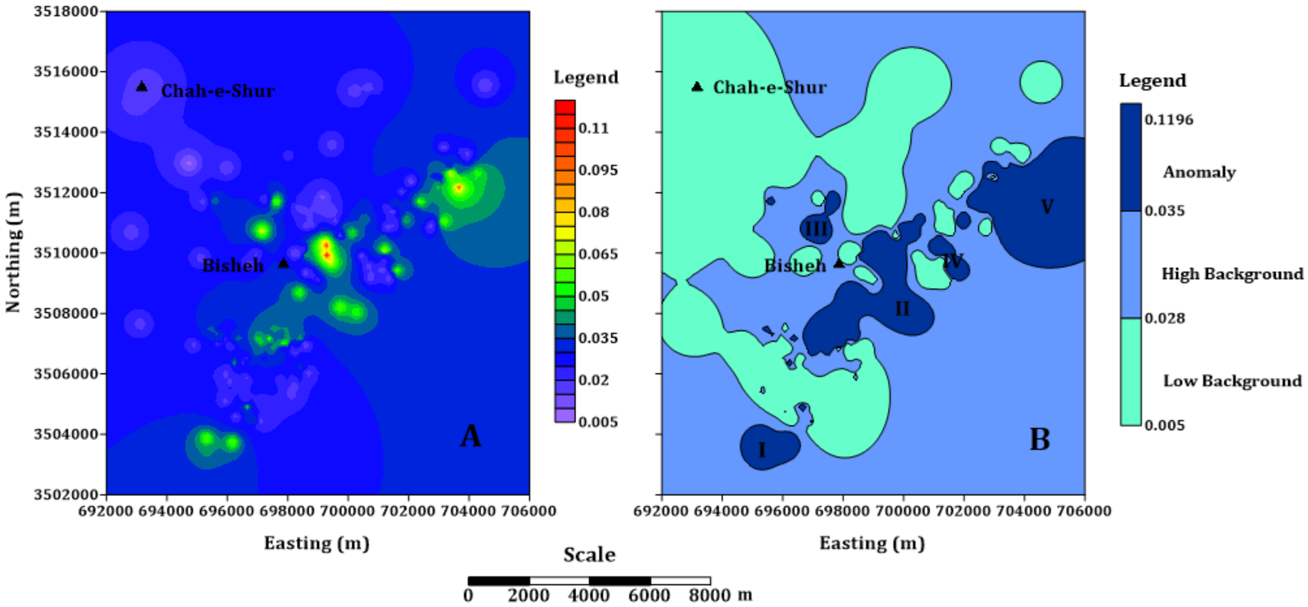

Fig. 5. Maps of composite geochemical anomalies using the WASPAS algorithm with continuous scale (A) and classified scale (B)

Although there are no igneous rocks in the Basiran 1:100,000 geological map in the east of the study area, field studies have shown that in the west of zone V, granitoid masses of the ilmenite series have outcropped and caused this anomaly. In the Bisheh region, the incursion of Tertiary intrusive-semi-intrusive masses into Paleocene limestones has caused the formation of skarn and Fe mineralization in the study area (Nakhaei, 2015). In this region, Cu, Au, Zn, Pb, Ti, W, Co, and Bi anomalies can be seen on the earth's surface and cores (Nakhaei et al., 2015). Zone II, the second identified anomaly in terms of area, corresponds to the rocks and minerals of this region. The geological map of the study area shows that diorite and micro granodiorite igneous masses are exposed in the southwest of the study area, and zone I is related to the existence of these rocks. The zone III overlaps with acid-tuff rocks, and detailed geological studies in this zone can lead to identifying deep or semi-deep masses that cause this anomaly. The zone IV includes a relatively small area to the east of the zone II. The cause of this anomaly can be related to the deep and semi-deep masses of the Bisheh region (Figs. 1, 4, and 5). Better adaptation of the composite geochemical anomalies obtained in the IDOCRIW and WASPAS algorithms with the geological and mineralization conditions of the study area indicates the relative superiority of the results obtained in Fig.s 4 and 5 compared to Fig. 3. This is also true in the case of the similarity of the shapes and locations of these anomalies.

VI. Conclusions

The eastern part of Iran, especially the Lut block, has created various mineralizations due to special tectonomagmic conditions at different times. In this paper, three multivariate decision-making algorithms are used to determine the mineral potential map in the Basiran sheet. The IDOCRIW algorithm can reduce the negative effect of the entropy method in determining the weight of variables due to the use of the CILOS method. Applying this algorithm to the geochemical data of the west Basiran introduced five zones with the probability of mineralization, which was confirmed by detailed geological and mineralogical studies for zones V, II, and IV. These anomalies are related to the deep to semi-deep acidic to intermediate rocks with high Fe, Cu, Au, Zn, Pb, Ti, W, Co, and Bi anomalies. The WSPAS algorithm also determined the same five composite geochemical anomaly zones with a slightly smaller area. Therefore, the results of this paper show that multivariate decision-making methods can used as an algorithm for determining composite geochemical anomalies in addition to integrating the exploration data.

References

Abedi, M., Mohammadi, R., Norouzi, G.H., & Mir Mohammadi, M.S. (2016). A comprehensive VIKOR method for integration of various exploratory data in mineral potential mapping. Arabian Journal of Geoscience, 9, 482.

Asgharpour, J. (2011). Multi-criteria Decision-Making, Tehran Universtiy Publication.

Behrouzi A., & Nazer N. Kh. (1992). Geological Map of Basiran at 1:100000 scale. GSI, Tehran.

Berberian, M. & King, G.C. (1981). Towards a paleogeography and tectonics evolution of Iran. Canadian Journal of Earth Science, 18(2), 210–265.

Camp, V.E., & Griffis, R.J. (1982). Character, genesis and tectonic setting of igneous rocks in the Sistan Suture Zone, Eastern Iran. Lithos, 15(3), 221-239.

Cao, M., & Lu, L. (2015). Application of the multivariate canonical trend surface method to the identification of geochemical combination anomalies. Journal of Geochemical Exploration, 153(1), 1–10.

Cereška, A., Podvezko, V., & Zavadskas, E.K. (2016). Operating Characteristics Analysis of Rotor Systems Using MCDM Methods. Studies in Informatics and Control, 25(1), 59-68.

Cereška, A., Zavadskas, E.K., Bucinskas, V., Podvezko, V., & Sutinys, E. (2018). Analysis of Steel Wire Rope Diagnostic Data Applying Multi-Criteria Methods. Applied Science, 8, 1-22.

Chakraborty, S., & Zavadskas, E.K. (2014). Applications of WASPAS method in manufacturing decision making. Informatica, 25(1), 1–20.

Chakraborty, S., Zavadskas, E.K., & Antucheviciene, J. (2015). Applications of waspas method as a multi-criteria decision-making tool. Economic computation and economic cybernetics studies and research, 49, 1-17.

Chen, X., Zheng, Y., Xu, R., Wang, H., Jiang, X., Yan, H., Cai, P., & Guo, X. (2016). Application of classical statistics and multifractals to delineate Au mineralization-related geochemical anomalies from stream sediment data: a case study in Xinghai-Zeku, Qinghai, China. Geochemistry: Exploration, Environment, Analysis, 16(3–4), 253–264.

Ellefsen, K.J., & Smith, D.B. (2016). Manual hierarchical clustering of regional geochemical data using a Bayesian finite mixture model. Applied Geochemistry, 75, 200–210.

Geranian, H. (2018). Application of clustering methods in determining the Multi-elements anomalies in regional geochemical exploration; A Case study: 1/100000 Kordagan Sheet, South Khorasan Province. Iranian Journal of Mining Engineering, 12(37), 81-94 (In Persian with English Extended Abstract).

Hayati, M., Rajabzadeh, R., & Darabi, M. (2015). Determination of Optimal Block Size in Angouran Mine Using VIKOR Method. Journal of Materials and Environmental Science, 6(11), 3236-3244.

Hosseini-Dinani, H., Aftabi, A., Esmaeili, A., & Rabbani, M. (2015). Composite soil-geochemical halos delineating carbonate-hosted zinc–lead– barium mineralization in the Irankuh district, Isfahan, west-central Iran. Journal of Geochemical Exploration, 156, 114–130.

Maghsoudi Moud, F. (2016). Comparing operation of TOPSIS and VIKOR methods in Cu mineralization potential mapping at central part of Kerman metallogenic arc. MS Thesis, Isfahan University of Technology, (In Persian).

Mishra1, A.R., & Rani, P. (2018). Interval-Valued Intuitionistic Fuzzy WASPAS Method: Application in Reservoir Flood Control Management Policy. Group Decision and Negotiation, 27(6), 1047-1078.

Nakhaei, M. (2015). Skarn mineralogy, exploratory geochemistry, magnetometry, dating, Rb-Sr, Sm-Nd isotopic studies of intrusive masses of Bisheh iron mineralization area, Birjand. Ph.D. Thesis, Mashhad Ferdowsi University (In Persian with English Abstract).

Nakhaei, M., Mazaheri, S.A., Karimpour, M.H., Farmer, G.H., Stern, C.R., Zarrinkoub, M.H., & Haidarian Shahri, M.R. (2015). Petrogenesis and zircon U-Pb dating of skarnified pyroxene-bearing dioritic rocks in Bisheh area, south of Birjand, eastern Iran. Journal of Economic Geology, 6(2), 393-409 (In Persian with English Abstract).

Stanujkić, D., & Karabašević, D. (2018). An extension of the WASPAS method for decision-making problems with intuitionistic fuzzy numbers: a case of website evaluation. Operational Research in Engineering Sciences: Theory and Applications, 1, 29-39.

Tarkian, M., Lotfi, M., & Baumann, A. (1983). Tectonic, magmatism and the formation of mineral deposits in the central Lut, east Iran, 357-383.

Trinkuniene, E., Podvezko, V., Zavadskas, E.K., Joksiene, I., Vinogradova, I., & Trinkunas, V. (2017). Evaluation of quality assurance in contractor contracts by multi-attribute decision-making methods. Economic Research (EkonomskaIstrazivanja), 30(1), 1152–1180.

Turskis, Z., Goranin, N., Nurusheva, A., & Boranbayev, S. (2019). A Fuzzy WASPAS-Based Approach to Determine Critical Information Infrastructures of EU Sustainable Development. Sustainability, 11, 1-25.

Vinogradova, I., Podvezko, V., & Zavadskas, E. K. (2018). The recalculation of the weights of criteria in MCDM methods using the bayes approach. Symmetry, 10(6), 1–18.

Zavadskas, E. K., & Podvezko, V. (2016). Integrated determination of objective criteria weights in MCDM. International Journal of Information Technology & Decision Making, 15(2), 267–283.

Zavadskas, E. K., Cavallaro, F., Podvezko, V., Ubarte, I., & Kaklauskas, A. (2017). MCDM assessment of a healthy and safe built environment according to sustainable development principles: A practical neighborhood approach in Vilnius. Sustainability, 9(5), 702–712.

Zavadskas, E.K., Antucheviciene, J., Saparauskas, J., & Turskis, Z (2013). Multi-criteria Assessment of Facades' Alternatives: Peculiarities of Ranking Methodology. Procedia Engineering, 57, 107–112.

Zavadskas, E.K., Bausys, R., Stanujkic, D., & Magdalinovic-Kalinovic, N. (2016). Selection of lead-zinc flotation circuit design by applying WASPAS method with single-valued neutrosophic set. Acta Montanistica Slovaca, 21(2), 85–92.

Zavadskas, E.K., Turskis, Z., & Antucheviciene, J. (2015). Selecting a Contractor by Using a Novel Method for Multiple Attribute Analysis: Weighted Aggregated Sum Product Assessment with Grey Values (WASPAS-G). Studies in Informatics and Control, 24(2), 141-150.

Zavadskas, E.K., Turskis, Z., Antucheviciene, J., & Zakarevicius, A. (2012). Optimization of weighted aggregated sum product assessment. Electronic and Electrical Engineering, 122(6), 3-6.

Zhizhong, C., Xie Xuejing, X., Wensheng, Y., Jizhou, F., Qin, Z., & Jindong, F. (2014). Multi-element geochemical mapping in Southern China. Journal of Geochemical Exploration, 139, 183–192.