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Spatial modelling of zonality elements based on compositional nature of geochemical data using geostatistical approach: a case study of Baghqloom area, Iran

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Abstract
Due to the existence of a constant sum of constraints, the geochemical data is presented as the compositional data that has a closed number system. A closed number system is a dataset that includes several variables. The summation value of variables is constant, being equal to one. By calculating the correlation coefficient of a closed number system and comparing it with an open number system, one can see an increase in the values of the closed number system, which is false. Such features of this data prevent the application of standard statistical techniques to process the data. Therefore, several methods have been proposed for transforming the data from closed to open number systems. There are various geostatistical methods consisting of estimation and simulation methods in order to model a deposit. Geostatistical simulations can produce various models for a deposit with different probability percentages. The most applicable geostatistical simulation method is the sequential Gaussian simulation technique, which is highly flexible. In this work, 392 Litho-geochemical data of the Baghqloom region of Kerman in Iran consisting of 20 elements were at first converted using an open number system. Afterwards, the elements that were helpful for exploring the area and were normally standard were simulated for 100 times. After the simulations, the valid output was chosen using geostatistical validation. The maps derived from the simulations revealed the enriched concentrations of mineralization elements in the central regions.

Keywords: *Compositional Data, Closed and Open Number System, Geostatistical Simulation, Sequential Gaussian Simulation, Baghqloom-Kerman.*

1. Introduction

Considering the geochemical data as a closed number system is important in data processing. A closed number system is a dataset of several variables that applies one or more constraints on the data. In closed number systems, the variables are not independent from each other, i.e. they are expressed as parts per million or percent [1-3]. In fact, the sum of variables in a closed numerical system is constant. This fixed value is a restriction, and varies depending on the measuring units of variables. Standard statistical techniques are designed for the data that change in negative to positive infinity range. Thus these techniques cannot be implemented on the data with a closed number system because in such a system, the value of any combination is positive, and this value is between 0 and 100 [4-7]. In most conducted works, disregarding this issue has caused incorrect results. There are various methods available to convert the data from closed to open number systems. Despite the closed numerical systems, in an open numerical system, the variables are independent. As a result, each variable can be individually examined. The most important methods are additive logratio transform (ALR), centered logratio transform (CLR), and isometric logratio transform (ILR) [8-11]. The output logarithmic coefficients are random

variables that are in positive and negative infinity range; as a result, statistical techniques can be performed on them.

In mining activities, the samples taken cover a limited part of the area. Several geostatistical investigations have been conducted to design sampling plans, in most of which, the estimation variance has been used as an uncertainty measurement. The estimation variance only depends on the position of the sample in space [12, 13]. However, it should be noted that in the case of modeling the deposits and geochemical halos, calculating various realizations of a deposit is more useful rather than having an average image of the deposit that is achieved from kriging [14] because in this case, the smoothing effect of kriging will be lost and the local variability can be observed.

Geostatistical simulation methods are powerful tools used to achieve this purpose. These methods remove the problems of kriging method, and the variability of the concentrations in the area will be easily recognized using a series of taken points. An accurate and appropriate perspective of the variability of area is useful for starting a geochemical exploration. These methods were introduced in 1970 by Journel, and are now used in various industries including mining, oil, and environment [15]. The principles of the geostatistical simulation method are based upon the principles of the Monte Carlo simulation method. However, the difference is that in geostatistical simulation, in addition to the initial histogram data, the recreation of the variogram data is also important. Moreover, the most important feature of geostatistical simulation is the production of a series of realizations that include the domains of possible modes. In conditional simulation, the amount of simulation data in certain points will be equal to the actual amount [13, 16]. In other words, showing the accuracy of a simulation, if one considers a point with an absolute value as an unknown value and simulates it using the surrounding points, the simulated and the real values are equal, and as a result, the error is zero.

The sequential Gaussian simulation (SGS) method is among the most important and most widely used geostatistical simulation methods, which nowadays is used to simulate many geological parameters such as mineral grade, porosity, and permeability [17]. Gaussian simulation is an algorithm that sequentially simulates the nodes, and the simulated values are used as the conditioning data. Gaussian standardized values are necessary to be used in the Gaussian simulation method. Therefore, it is necessary to transform the data into the Gaussian space [18, 19].

2. Methodology

2.1. Compositional data

In order to conduct a geostatistical operation on the geochemical data, it is absolutely necessary to convert the data to an open numerical system, in which the elements are independent from each other. Data conversion makes it possible to separately examine each element or variable in terms of statistical and geostatistical analyses. The important methods of data conversion are presented in the following sections.

For analyzing the correlation coefficient of the compositional data, first of all, the data should be opened by ALR or CLR. ILR cannot be used to determine the correlation coefficient because in this method, the relationship between the main variables is completely deflected from a straighten system. As a result, the calculated correlation coefficient is unrealistic [20, 21]. When CLR is used to open the system, the correlation coefficient is related to the geometric mean of the variables. Moreover, when the selection of element is not considered, this transformation can be used as well. When ALR is used to open the system, the correlation coefficient is related to the selected element (denominator).

2.1.1. Additive logratio transformation (ALR)

The ALR method was first developed by Aitchison in 1982. In this method, a variable is selected from the existing variables as denominator, and the values for other variables are divided into this variable. Then a logarithm is applied on these values so that the variables are transformed from closed to open systems and the denominator is deleted from variables (Equation 1) [22].

$$alr(x) = [\log\frac{x_1}{x_j}, ..., \log\frac{x_{j-1}}{x_j}, \log\frac{x_{j+1}}{x_j}, \log\frac{x_D}{x_j}] \quad (1)$$

where x_1, x_2,…, x_D are the available variables (elements) and x_j is the denominator.

It should be noted that the denominator should not be one of the main variables (major elements); otherwise, it will create a false correlation. In geochemistry, the denominator belongs to trace elements because if these elements are removed from the dataset, they will not cause an important problem in the mineral exploration projects [22].

2.1.2. Centered logratio transform (CLR)

The CLR method was also developed at first by Aitchison in 1986. In this method, a logarithm is applied on all variables (Equation 2) [23].

$$clr(x) = [\log(\frac{x_1}{g(x)}),...,\log(\frac{x_D}{g(x)})] \quad (2)$$

where x_1, x_2,…, x_D are the available variables, and the fraction denominator is the logarithm of the geometric mean ($g(x)$) of variables. The advantage of this method is that no variable will be removed from the set of variables. On the other hand, the disadvantage of this method is that the matrix of covariance is irreversible; therefore, various multivariate statistical analyses cannot be implemented on open data using this transformation [23].

2.1.3. Isometric logratio transform (ILR)

The ILR method was developed by Egozcue in 2003. As an advantage of this transformation, it is possible to calculate the inverse covariance matrix; therefore, it excels the previous method. This method is slightly more complicated than the above-mentioned two methods, and there are different rules for its conduction. In this method, each variable is divided on total roots of other variables, then a logarithm is applied on the outcome values, and finally, it is multiplied by a coefficient that is dependent on the number of variables (Equation 3) [24].

$$ilr(x) = \sqrt{\frac{D-i}{D-i+1}} \log \frac{x_i}{\sqrt[D-i]{\prod_{j=i+1}^{D} x_j}} \quad (3)$$

where x_1, x_2,…, x_D are the available variables and x_j is the studied variable. D is the number of variables and i is the number of studied variables. The fraction denominator is the total root of variables (except for the variable in the numerator).

2.2. Sequential gaussian simulation (SGS)

After transforming data from the closed to the open mode, geostatistical simulation can be performed on the data. According to the previous studies, simulations are applied to the alr-transformed data [25]. Unlike all estimation methods based on moving average, geostatistical simulation is considered as an algorithm to adjust the smoothing effect of such methods [26].

Kriging is able to produce non-skewed estimations through minimizing the estimation variance. However, the smoothing effect of the kriging method impedes to show the variability of the region. Geostatistical simulation with its available tools can rebuild different states for each point or block, and can provide a distribution of data. In general, the simulation and estimation have two different objectives. The purpose of kriging is to calculate the features of probability of distribution function such as the mean value, and to achieve a minimum estimation error based on the available data (actual facts). However, the purpose of simulation is the creation of unrealized possible scenarios by maintaining the data structure elements (accomplished facts) [27, 28].

Geostatistical simulations have different methods, of which sequential simulation is one of the most important methods. Sequential simulation is a stochastic modeling process that is based upon the input data that creates numerous realizations [29, 30]. For this simulation, the input data can be continuous or definite. Based on the type of data, sequential simulations can be divided into the three Gaussian, indicator, and direct groups [31]. The SGS method is the most flexible and performable simulation method. In this method, the Gaussian standard data is used with a mean of zero and a variance of one. Therefore, at first, data must be transformed as described earlier [32, 33]. In the simplest expression, this algorithm starts the simulation from a random point and will continue randomly to simulate all points of a block.

Simple kriging estimation helps to create a local distribution function. Then a value is selected from the distribution and is assigned to the point as a full-scale. This operation is repeated as long as all the spots on this route are simulated. In the simulation of a region one will be faced with many realizations that are different the other ones because except for the areas that have been sampled, the rest are facing with uncertainty. Therefore, each realized case can be a product of simulation. The main objective of the simulation process can be seen as restoring the changes of the original data space.

Therefore, the basic steps involved to perform this simulation can be expressed as follow [27, 34]:

1. Transforming data to a standard normal distribution,
2. Variography for the transformed data,
3. Random selection of one of the nodes,
4. Estimation of the nodes using kriging, the transformed data, and the simulated values,
5. Forming a normal distribution function using the estimation variance and the value of

estimation, and random sampling of the distribution function, and then putting this value in the node,

6. Repeating steps 3-5 until all nodes are selected,
7. Reversing data transformation,
8. Repeating the simulation.

Perhaps the biggest problem for the sequential Gaussian simulation method is to select a search radius (a part of region for doing the calculation). Selecting a small neighborhood radius leads to a poor conditioning of data [27].

3. Study area

The Baghqloom exploration area is located about 41 Km East of Jiroft and about 12.5 km west of the Gomrokan village in Kerman, Iran (Figure 1b); this area is called Sangestan. From a geological viewpoint, Baghqloom is located in the southern part of the Barez Mountains. The dominant lithology in the studied area is alkaline granite, diorite, granodiorite, and a set of intrusive dykes. The post-mineralization parts of the region are of stockwork and shear zone types that occur in different rock types (sub-volcanic and intrusive units). It seems that most of the mineralization was introduced by dikes. The mineralization has been formed only around the dikes, in a way that the veinlets that contain ore minerals are not uniform everywhere. Formation of an ore deposit depends on various factors, of which, the major ones are structural, hydrothermal, lithological, and chemical elements. In the Kerver and Baghqloom regions, the faults, fractures, and veinlets were created due to the structural forces or hydrothermal fluid pressures (stockwork framework). These have created a proper space for circulation of hydrothermal fluids, and eventually, formation of an ore deposit. The lithology brittleness plays an important controlling role in the development of veins. The lithological units of the area consist of a wide range of Eocene units including the pyroclastic rocks that are inter-bedded between the volcanic lavas, conglomerate, sandstone, and green tuff of sedimentary units. The dikes of acidic to mafic composition have affected the area in several stages. The mineralization in this area has a stockwork form, and is scattered over a large area. It has a porphyritic texture, and the mineralogical paragenesis (pyrite and chalcopyrite) has been introduced as porphyry copper mineralization. From the copper mineralization perspective, the Baghqloom area is less important than the Kerver region, which is located 2 km away from Baghqloom. Systematic sampling was carried out on the studied area that is enriched with granite, granodiorite, and quartz diorite rocks. Figure 1a shows the geological map of the studied area and the sample position.

4. Results

4.1. Dataset

After determining 20 elements of the collected data from the Baghqloom region in Kerman, the important elements for exploration operations were recognized. In the last few decades, researchers have tried to analyze the mineralization and depth of the erosion level, especially to detect the hidden reserves, using the exploration and geochemical indicators. For porphyry deposits, the indirect exploration methods (that do not directly deal with the studied mineral deposit) were used to achieve better and more accurate results, and also to avoid wasting huge costs of different exploration methods. These indirect methods are based upon the geochemical data [35-38]. The method of geochemical zonation pattern core of elements is an appropriate method to apply. Analyzing the geochemical zonality using the litho-geochemical halo method above and under the deposits reveals important implications in relation to the erosion of the deposits and mineralization level [39-42]. Usually in porphyry deposits, elements such as Cu, Mo, Pb, and Zn are introduced as the zonality index elements and tried to detect the mineralization and depth of the erosion level using Equation 4 [38-41]. After analyzing the transformed data, Cu, Mo, Pb, and Zn were selected. The other exploration operations were performed on these elements as well.

$$Zonality\ Index = \frac{Pb \times Zn}{Cu \times Mo} \quad (4)$$

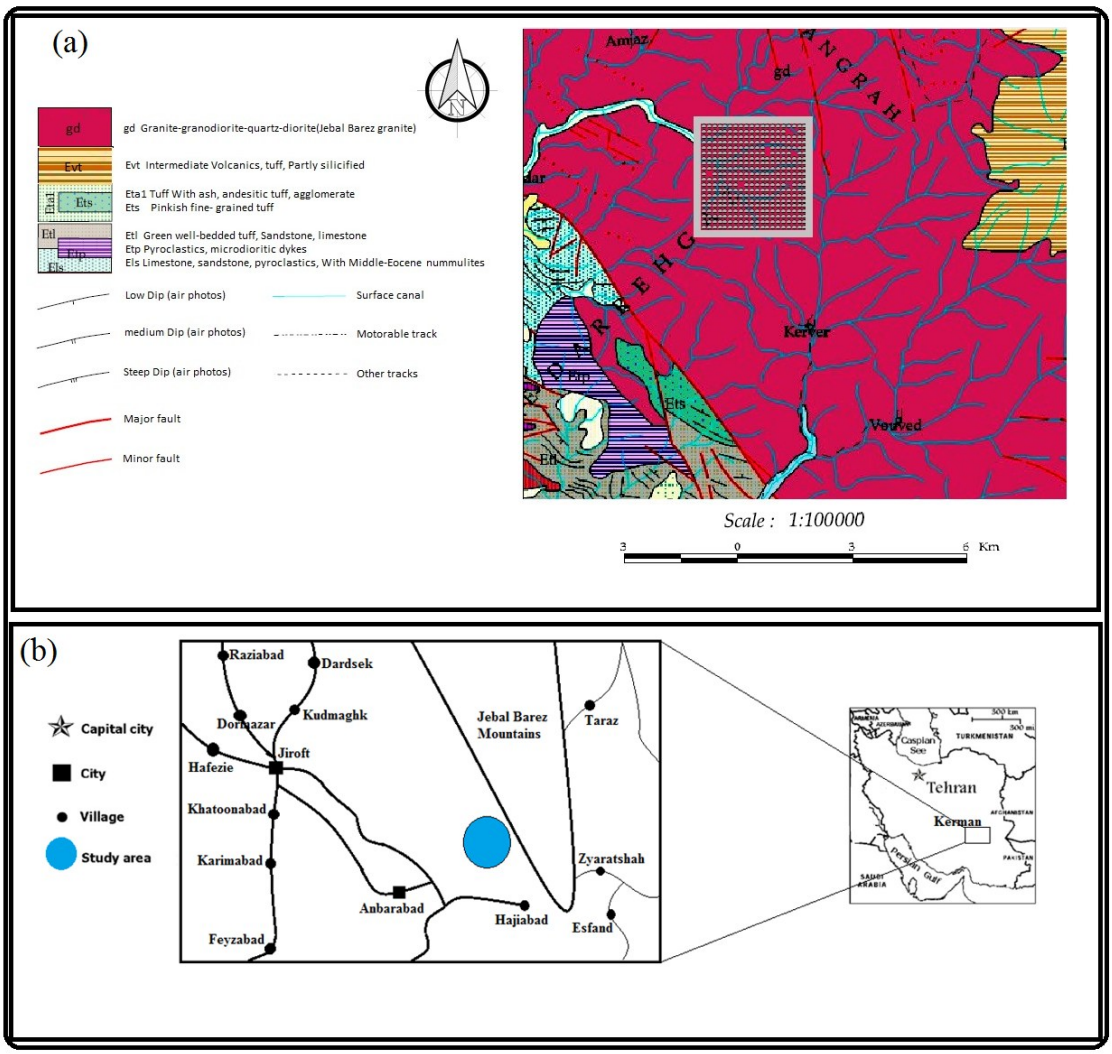

Figure 1. (a) Geological map of studied area with a scale of 1:100000 (the marked part with a gray border shows location of sampling points) (b) Geographical situation of studied area.

4.2. Correlation coefficient of data

Since in this study the selected element has the minimum value compared to the other elements, application of the ALR method is really appropriate. On the other hand, by analyzing the other conducted research works, the calculated correlation coefficients can be interpreted right after the transformation [25, 43]. In the additive logratio transformation method, the elements that have small values can be removed. The purpose of applying the multivariable analysis on the geochemical data is to find the relationship between the major and minor elements and the possibility of using this correlation to achieve a specified pattern. Data processing was performed by the two methods of cluster analysis and principal component analysis in order to remove the desired element.

Cluster analysis is a chart that shows the relationship between the elements under the maximum correlation coefficient. First, by using the clustering chart, the relationships between the paragenetic elements were determined and the elements were divided into different groups.

As it can be seen in Figure 2, the elements were divided into four groups. Using this analysis, one can conclude that the elements in the first branch and the first group are the mineralization elements, and are independent from the other ones. After carrying out the cluster analysis, the principal component analysis determined the factor that resulted in the variability of concentration. The purpose of analyzing the major element is to analyze the components variance of multivariate data in which the first component causes most of the variance in the data, and gradually the next components justify the lower variance of changes [44]. In this method, each component is independent from the other factors. This means that there is no correlation between the resulting components. In the analysis of the main components, the first and second

components are of high importance. Generally, the elements in each component whose values are approximately equal to or more than 0.5 will be identified as its main component elements. It can be concluded from Table 1 that copper, gold, silver, molybdenum, arsenic, bismuth, and mercury are the major elements of the first component, and antimony and tin are the major elements of the second component. The results of the cluster analysis and principal component are overlapping well. In fact, by using both methods at the same time, it can be realized that the results are true. Accordingly, nickel is the least important element whose maximum and minimum concentration values are very low. As a result, nickel can be selected as the denominator element.

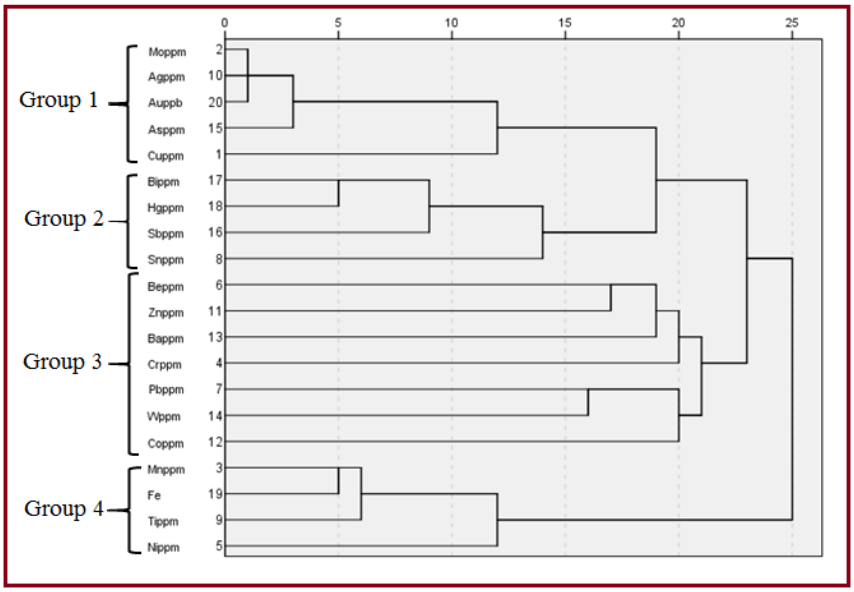

Figure 2. Dendrogram of cluster analysis elements and categorizing elements based on cluster analysis (closed system).

Table 1. Results of principal component analysis (closed system).

	Component					
	1	**2**	**3**	**4**	**5**	**6**
Cu (ppm)	0.678	0.205	-0.338	0.412	-0.017	-0.173
Pb (ppm)	0.875	0.045	-0.333	-0.083	0.077	-0.046
Mn (ppm)	0.449	-0.739	0.211	-0.005	0.087	-0.032
Cr (ppm)	-0.108	0.289	0.065	-0.092	0.053	-0.561
Ni (ppm)	0.188	-0.566	0.448	-0.012	0.003	-0.282
Be (ppm)	-0.081	0.388	0.104	0.129	0.481	-0.205
Mo (ppm)	0.623	0.377	-0.010	-0.023	-0.043	-0.115
Sn (ppm)	0.236	0.353	0.547	0.303	0.147	0.102
Ti (ppm)	0.371	-0.684	0.143	0.318	0.103	0.182
Ag (ppm)	0.905	0.048	-0.318	-0.056	0.031	-0.053
Zn (ppm)	0.191	0.085	0.131	-0.027	0.766	-0.011
Co (ppm)	-0.019	0.006	-0.072	-0.150	-0.112	0.403
Ba (ppm)	-0.154	0.159	-0.203	0.008	0.419	0.555
W (ppm)	-0.030	0.152	-0.040	0.669	-0.229	0.151
As (ppm)	0.904	0.131	-0.100	-0.083	-0.057	0.003
Sb (ppm)	0.254	0.553	0.573	-0.180	-0.170	0.122
Bi (ppm)	0.672	0.404	0.295	-0.075	-0.137	0.158
Hg (ppm)	0.716	0.368	0.337	-0.155	-0.106	0.058
Fe (%)	0.551	-0.593	0.0241	0.228	0.005	0.056
Au (ppb)	0.874	0.051	-0.332	-0.072	0.015	-0.052

Table 2 shows the correlation coefficient data in a closed number system and the correlation coefficient ALR and CLR transformed data. The correlation coefficient in ALR can be interpreted significantly more than CLR. According to Equation 4, the correlation coefficient between Pb and Zn, which are in the numerator, should be high. Also the correlation coefficient between Cu and Mo, which are in the denominator, should be high. According to the results obtained, the correlation coefficient between Cu and Mo as the mineralization elements in the closed number system (Table 2) is 0.461. In ALR, the correlation is equal to 0.825, which is closer to the amount of interest. In the clr transformed data, this amount is 0.128, which is really different from the closed number system. Therefore, it can be concluded that the correlation coefficient obtained from ALR is interpretable and more accurate than the correlation coefficient obtained from CLR

4.3. Geostatistical studies

In this work, the SGeMS software was used for the geostatistical studies. Statistical analysis (histogram) of 392 raw data based on Figure 3a indicates a skewed and non-normal data. After transforming the data with the desired norm (the mean of data is close to zero and the variance is almost one), the histogram of data for all elements is illustrated in Figure 3b.

Table 2. Correlation coefficient elements in rock samples (closed system) in upper part and correlation coefficient of elements based on results of additive logratio transform (low diagonal) and a centered logratio transform (up diagonal) in a lower part.

	Pb	**Zn**	**Cu**	**Mo**
Pb	1			
Zn	0.186	1		
Cu	0.224	0.041	1	
Mo	0.046	-0.009	0.461	1
	Pb	**Zn**	**Cu**	**Mo**
Pb	1	0.300	-0.258	0.458
Zn	0.696	1	-0.396	0.483
Cu	-0.036	-0.026	1	0.128
Mo	-0.025	-0.012	0.825	1

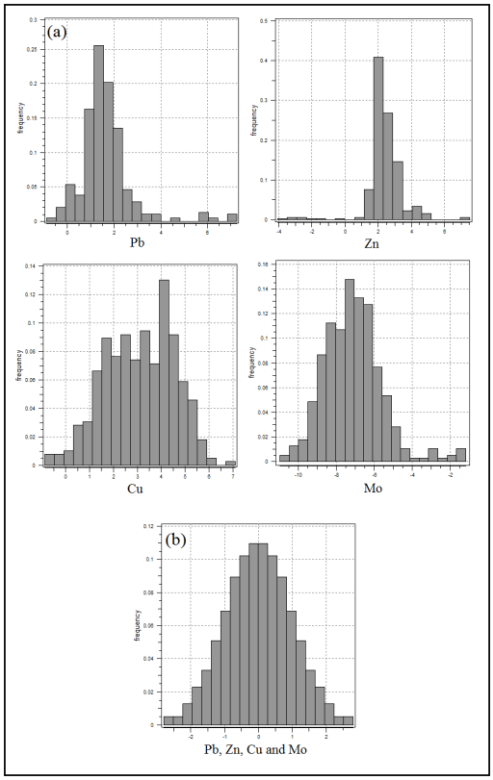

Figure 3. (a) Histogram of data in non-normal mood that shows skewedness and abnormality among them (b) Histogram of data frequency after becoming normal standard (for all four elements under study).

4.3.1. Variography and structural analysis

After normalizing the data, in order to determine the direction of anisotropy, the variography in different directions was conducted for each four selected elements. After carrying out the variography and fitting a spherical model on the data, the isotropy was identified for each one of the four elements. Figure 4 shows the variography in the isotropic direction for the elements, and Table 3 shows the parameters of the variogram model. According to the definition of isotropy, anisotropy is the direction in which the concentration or grade has the highest variability, and therefore, it is expected that the fitted model has the least impact range and it is a model with a high slope. According to the definition of azimuth, the direction of isotropy and anisotropy together will build the angle of 90°. In other words, the most variability of concentration or grade happens in the direction that is perpendicular to the direction of mineralization. That is because the ore minerals directly enter the waste zone, and vice versa.

The best model that can be fitted on the variogram model is spherical. According to Figure 4, the experimental variograms show the spherical nested structures. Actually, a nested structure is the sum of several variograms having various ranges and sills. In this case study, the spherical model equation for lag distance h is as follows [45]:

$$\gamma(h)=\gamma_1(h)+\gamma_2(h)+\gamma_3(h)$$

$$\gamma_1(h)=C_0$$

$$\gamma_2(h),\gamma_3(h)=\begin{cases} C\left(\frac{3h}{2a}-\frac{h^3}{2a^3}\right), h\le a \\ C, h>a \end{cases} \quad (5)$$

where C stands for the ceiling of variogram when it is added to the nugget effect (C_0), a stands for the impact range of variogram, which is very small in this interval. Also lag h determines the distance between the studied samples.

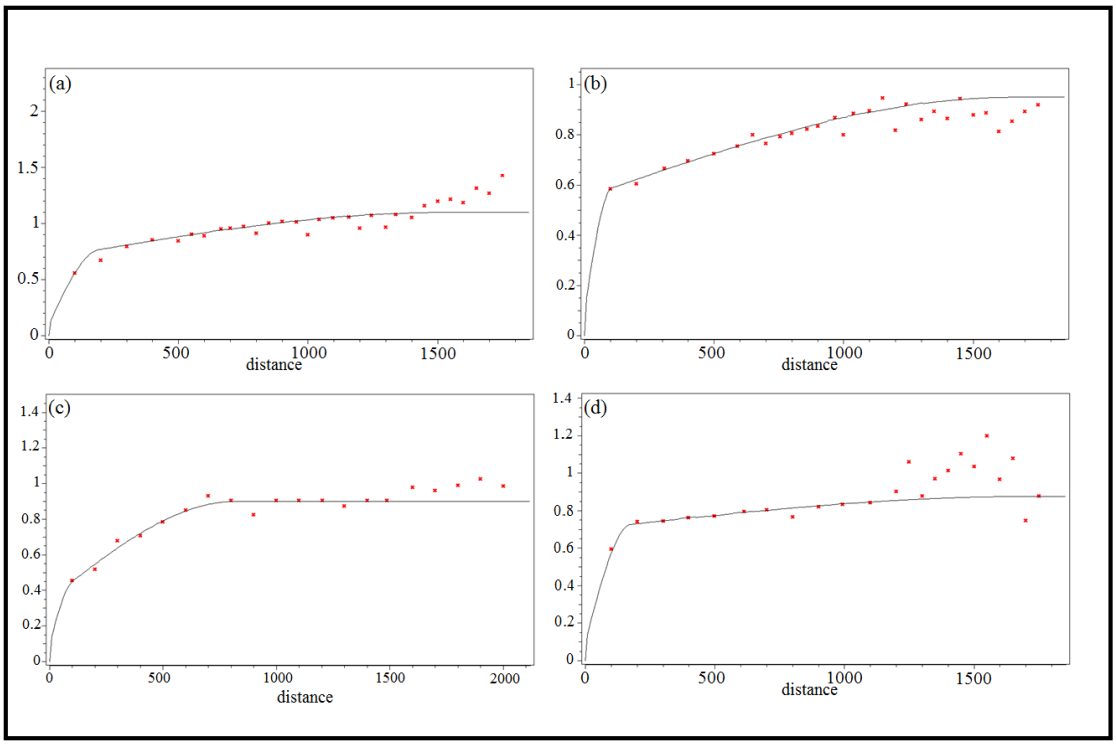

Figure 4. Variography of four elements in isotropy direction a) Pb element in azimuth of 90° b) Zn element in azimuth of 90° c) Cu element in azimuth of 90° d) Mo element in azimuth of zero degrees.

Table 3. Parameters of variogram model.

Element	Direction	Nugget (C_0)	Sill ($C+C_0$)	Range (a)
Pb	90°	0.1	0.59, 0.41	192.5, 1540
Zn	90°	0.1	0.45, 0.4	105, 1662.5
Cu	90°	0.1	0.55, 0.25	820, 100
Mo	0°	0.1	0.6, 0.176491	175, 1715

The unit of range is in m

4.3.2. Kriging

Using the variogram model and normalized data, the elements were estimated using ordinary kriging. In order to perform the ordinary kriging as an estimator, the data should be independent from coordinates (the stationary-lack of trend), and their average value has to be unknown. After analyzing the data and ensuring that these two conditions are met, the results of this method are shown in Figure 5 for all four elements. It should be noted that for a better view of the area, before opening the numerical system, we changed the stage (the code on Matlab software) to real space. Also the kriging results changed to a non-Gaussian distribution.

Copper and molybdenum in the central parts of the region show enriched values (Figure 5). This can prove that these two elements were the mineralization elements, and the correlation coefficient between these two elements was very high. Lead, as the zonality index element in the western and northwestern and northeastern and southwestern parts of the region, is enriched. Zinc, as the zonality index element in the western, northwestern, and southwestern parts, is enriched as well. According to these maps, we can use these elements to check the status of mineral exploration and to locate the mineralization.

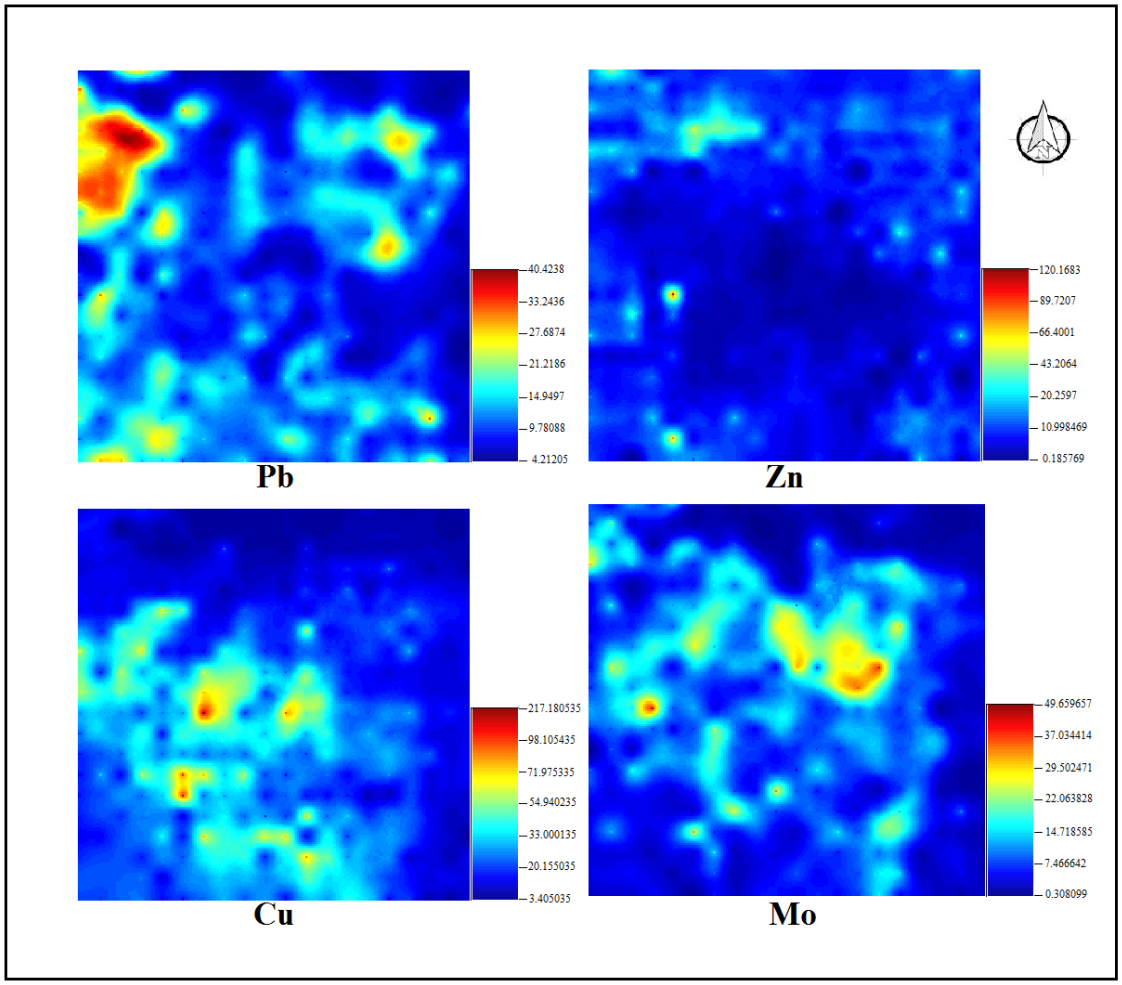

Figure 5. Maps of ordinary kriging (ok), respectively, for the four elements Pb, Zn, Cu, and Mo (data using an inverse logarithmic transform from open mood has become the primary mode).

4.3.3. Sequential gaussian simulation

Application of an appropriate method is really important to show the variability of concentrations in the upper and lower parts of the deposits. The SGS method illustrates the variability of the concentration of the elements by eliminating the smoothing effect of the kriging method.

In this work, for each element, to obtain 100 realizations on data, the simulation was repeated for 100 times. Using the average of all simulation maps, the E-type map was obtained. After the simulation and validation of all simulations, an appropriate simulation was selected for each element, which was very similar to the normal and

raw data in the statistical and geostatistical viewpoints (Table 4, Figures 6 and 7). The Omni-directional variograms of three randomly selected realizations of the zonality elements and also the raw data and kriging maps are displayed in Figure 7. Comparing these Omni-directional variograms of realization with the raw data and kriging variogram shows that the realization reproduction is reasonably well (Figure 7). Figure 8 shows suitable simulations for each element. After simulation, the simulated data for each element were back-transformed.

According to Figure 8, increasing the concentration of the selected elements is almost like the OK maps. In the simulation map, increase in concentration is different, which is due to the removal of the smoothing effect of OK. In fact, in the conducted simulations, local variability (sudden increase in concentration) obviously contradicts the OK method. It is clear that the correlation coefficient between molybdenum and copper (as the mineralization elements) is very high. Copper and molybdenum enrichment is almost visible throughout the region. If these elements are required to be explored in this area, it can be supposed that the deposits of interest are of porphyry mineralization type. The reason is that the mineralization in this area is hosted in granitic, granodioritic, and quartz dioritic rocks.

Table 4. Statistical parameter of zonality elements and output grid for selected realization. Comparing these results of selected realization with raw data shows that the realization reproduce data for high values.

	Raw Data					Simulated Data			
	Pb	Zn	Cu	Mo	Selected realization	Pb	Zn	Cu	Mo
						38	86	32	38
Mean	148.7	128.3	227.8	41.5		148.5	127.9	227.1	41.2
Variance	10.26	34.3	12.9	16.8		10.22	34.25	12.45	16.75

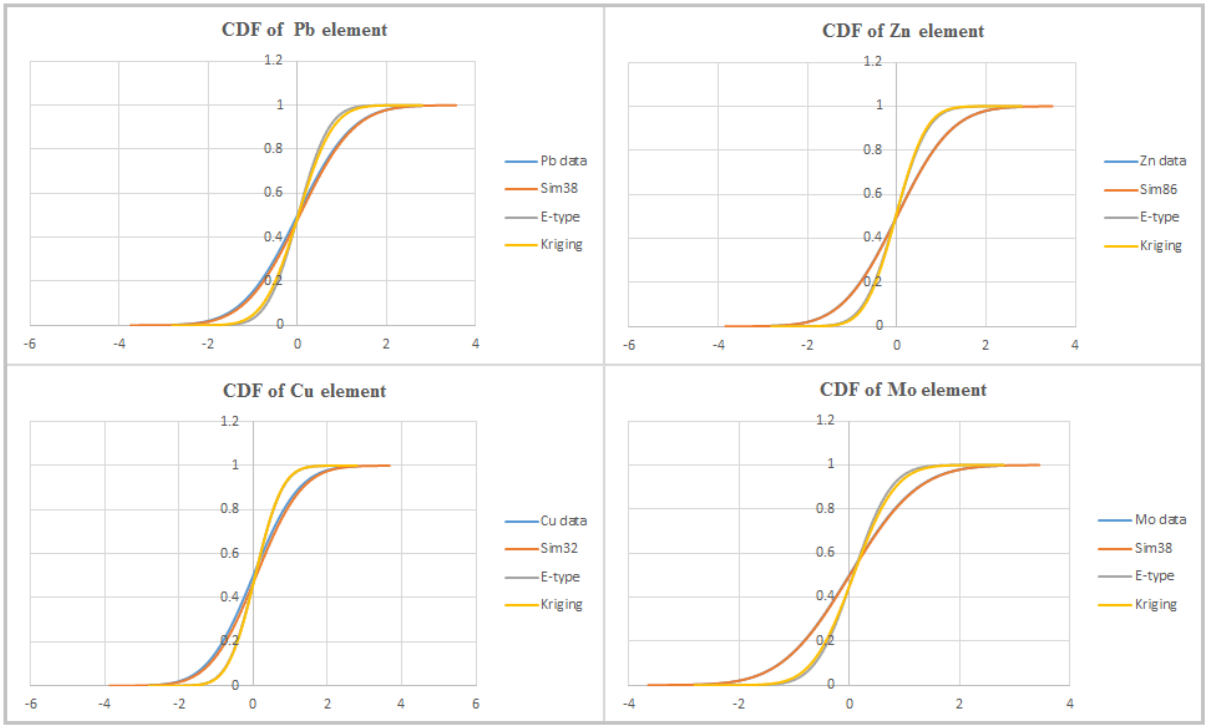

Figure 6. Cumulative distribution function of selected realizations reproducing sample zonality element histogram. Cumulative distribution function of E-type and kriging could not reproduce data for high values.

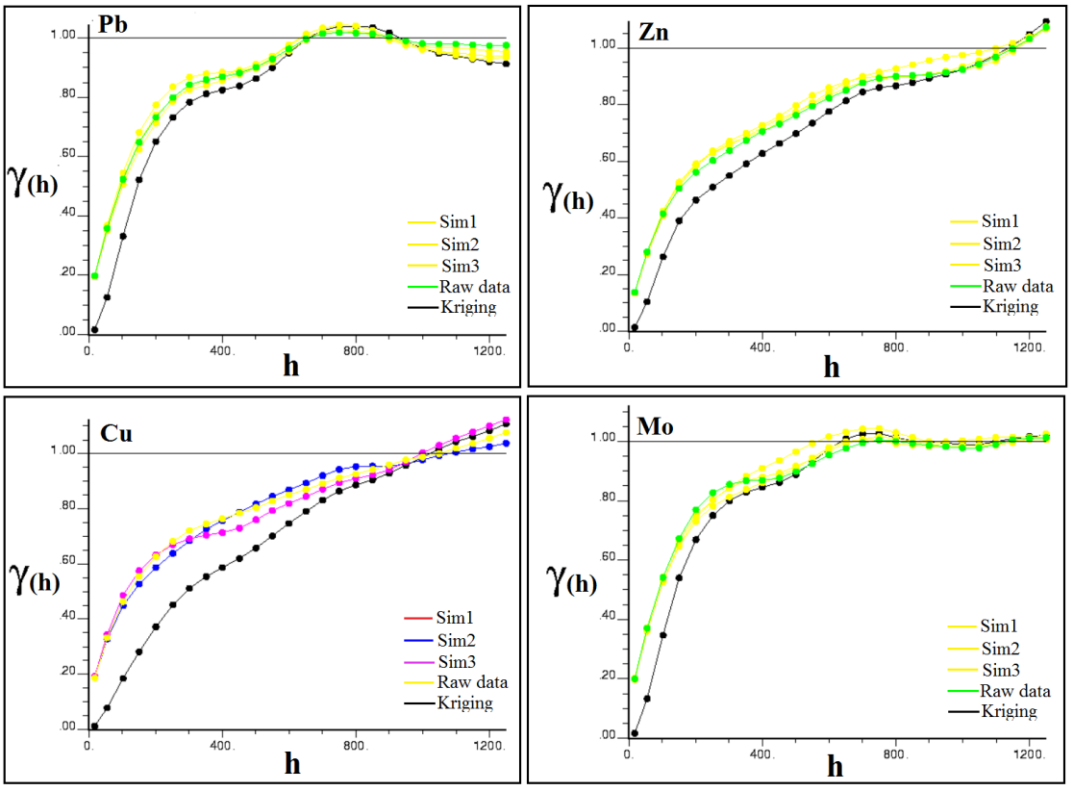

Figure 7. Omni-direction variograms of three randomly-selected realizations and raw data and kriging map.

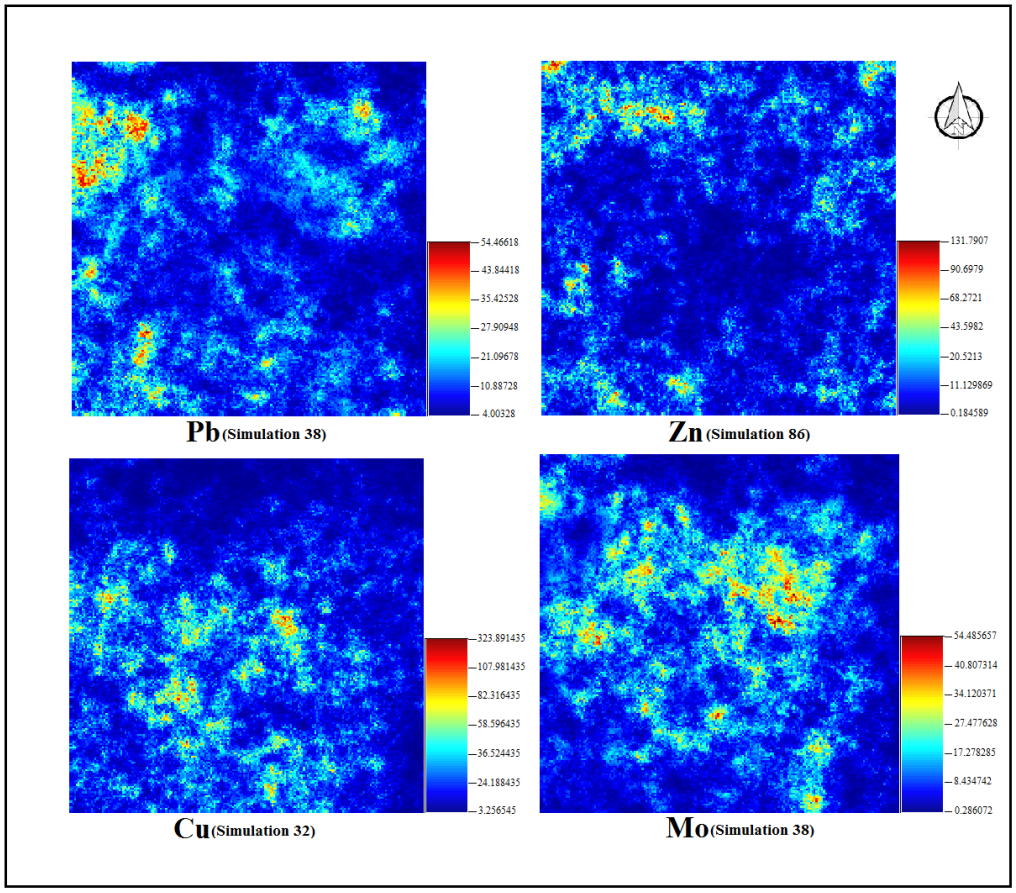

Figure 8. Maps of sequential Gaussian simulation to achieve the best realization among 100 realizations, respectively, for four elements Pb, Zn, Cu, and Mo (using an inverse logarithmic transform, data was changed from open mood to initial state).

5. Discussion

According to the simulation maps of elements obtained, an appropriate model of geochemical halos can be produced. According to the SGS results, copper is enriched in the central parts of the region. Also this element shows low and medium concentrations in the northwestern and southern parts, respectively (Figures 5 and 8). Lead and zinc, as the front halo elements, are enriched in the northwestern part of the region. Most likely, the central part is located in or nearby the mineralization region. In order to achieve better and more accurate results, it is required to evaluate the erosion level in the southern and northwestern parts of the studied area. Analyzing the geochemical zonality reveals important implications in relation to the deposit erosion and mineralization level. In order to calculate the zonality coefficients, K-coefficient of mineralization (K) and coefficient of productivity were obtained for each element. In K-coefficient of mineralization, the concentration of element from each sample is divided into the mean of the element in the anomalous zone. In the coefficient of productivity approach, the K-coefficient of mineralization is multiplied by the mean from each element (Table 5).

According to the classification of erosion level for this zonality index (Table 6) and the results of Table 5, the northwestern, southern, and central parts of the studied area are located in the supper-ore and lower-ore, respectively. Actually, the deposit is strongly eroded in the southern part of the area so that the under deposit elements are remained. Also there are two hidden mineralizations of Pb-Zn (northwestern part) and Cu porphyry (central part) in the Baghqloom area. Furthermore, the zonality index of the deposit was compared with different types of standard models in order to investigate the potential of Cu mineralization in the Baghqloom zone (Figure 9).

According to Figure 9, the zonality index of the central and northwestern parts are located above the surface of the western part of the Sungun deposit zonality pattern. Thus it is expected that the Cu porphyry mass is in shallower depths of 150-200 m. Also there is a hidden mineralization of Pb-Zn deposit in a higher depth. From a topographical viewpoint, the studied region has a general slope. According to the geological map (Figure 1), the streams flowing from the east to the west show that the slope region is towards the west. According to the created mineralization model, it can be concluded that the hidden mineralization is located in the central and northwestern regions (Figure 10).

Table 5. Coefficient zonality of central, northwestern, and southern parts of Baghqloom area.

Area	Element	K	Productivity	Cu.Mo	Pb.Zn	Pb.Zn/Cu.Mo
Central	Cu	0.38	90.3	120.1	……..	23.22
	Mo	0.24	1.33			
	Pb	0.86	86.6	…….	2788.5	
	Zn	0.29	32.2			
Northwestern	Cu	0.75	609.15	9.12	……..	131455.31
	Mo	0.008	0.015			
	Pb	1	2965.3	…….	119872.5	
	Zn	0.75	404.25			
Southern	Cu	0.85	305	1515.85	……..	0.0288
	Mo	0.39	4.97			
	Pb	0.08	4.22	…….	43.76	
	Zn	0.122	10.37			

Table 6. Geochemical zonality model for Cu porphyry based on different types of standard models [42].

Erosion Level	Pb.Zn/Cu.Mo
Supra-ore	>100
Upper-ore	100-10
Ore	10-1
Ore	1-0.1
Lower ore	0.1-0.01
Sub-ore	<0.01

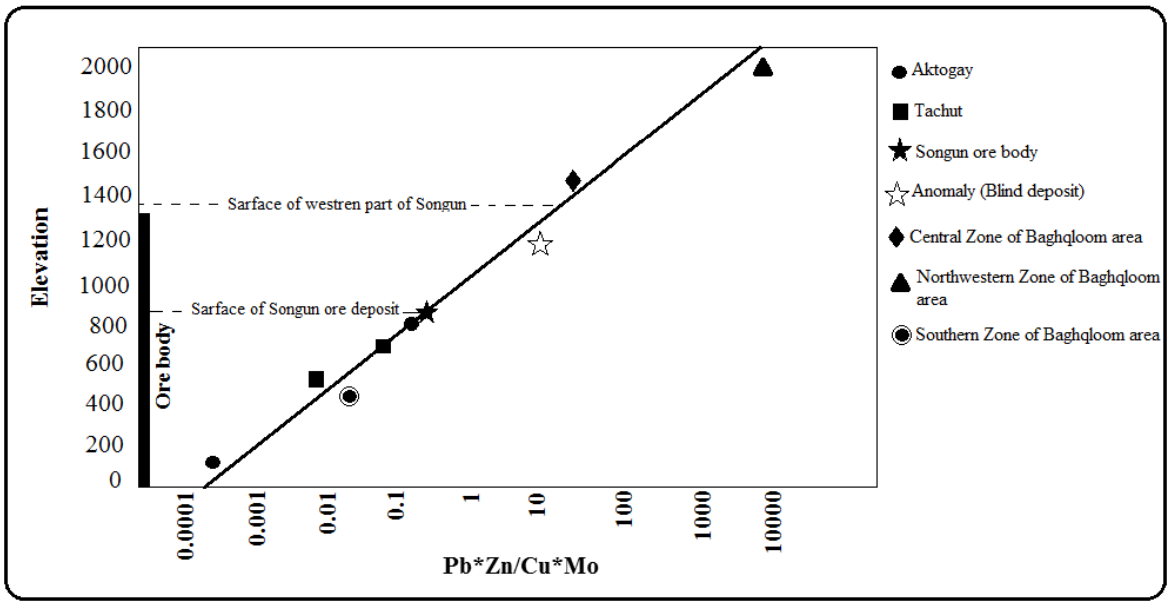

Figure 9. Standard chart of different types of Cu porphyry models.

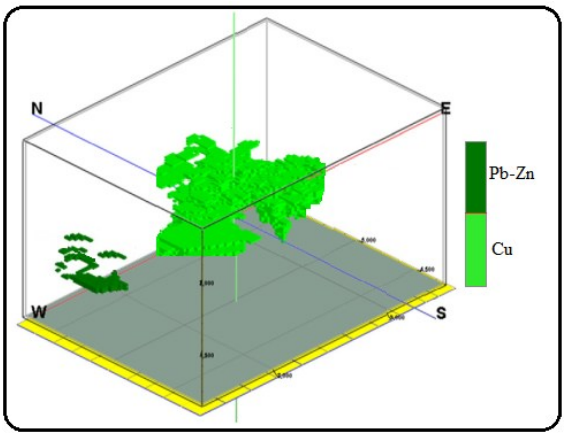

Figure 10. Geochemical zonality modeling of Baghqloom deposit based on geological map.

6. Conclusions

In the exploration studies, when conducting statistical processing, it is important to take into account the compositional nature of the compositional data, and transform it from a closed system (due to false correlation coefficient) to an open system using centered, isometric, and additive logratio transformations. Among transformations, the additive logratio is more common because it is simpler both in application and in interpretation. Also due to the small size of the sampled area compared to the whole studied area, it is recommended to use the geostatistical simulation methods that are able to predict the best and worst events. Among these methods, the SGS method is the most efficient and flexible method that examines all the possible scenarios. The results of the kriging and Gaussian simulations are compatible to a considerable extent, and both results represent significant concentrations of copper and molybdenum mineralization, especially in the central part of the

deposit. Since the case study is a porphyry type deposit, this increase is sporadic. This shows that the correlation between these two elements is substantial in additive logratio transformation. Geochemical exploration using geochemical halo modelling has introduced the central regions as suitable areas for a detailed exploration of copper mineralization, which was found based on the available shallow depth evidence. Enormous fracture in the altered zones of the Baghqloom area shows that this mineralization has occurred as a result of hydro-fracturing caused by high pressured hydrothermal fluids. In general, according to the geological studies, it can be concluded that this area has a high mineralization potential.

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مدل‌سازی فضایی عناصر زونالیته بر اساس ماهیت ترکیبی داده‌های ژئوشیمیایی با استفاده از رویکرد زمین‌آمار: مطالعه موردی منطقه باغ‌غلوم، ایران

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چکیده:

داده‌های ژئوشیمیایی به علت وجود قید مجموع ثابت، معمولاً به صورت داده‌های ترکیبی که دارای سیستم عددی بسته هستند، مطرح می‌شوند. سیستم عددی بسته به مجموعه داده‌هایی گفته می‌شود که شامل چند متغیر می‌باشند. مجموع مقادیر متغیرها معمولاً ثابت و برابر واحد است. با محاسبه ضریب همبستگی سیستم عددی بسته و مقایسه آن با سیستم عددی باز یک افزایش در مقادیر سیستم عددی بسته دیده می‌شود که غیرواقعی و کاذب است. ویژگی این چنین داده‌هایی، مانع از به کارگیری تکنیک‌های آماری استاندارد بر روی آن‌ها می‌شود. بدین منظور روش‌های مختلفی برای تبدیل داده‌ها از حالت بسته به باز وجود دارد. به منظور مدل‌سازی کانسار، روش‌های زمین‌آماری مختلفی شامل روش‌های تخمین و شبیه‌سازی وجود دارند. شبیه‌سازی‌های زمین‌آماری می‌توانند مدل‌های مختلفی از کانسار با درصد احتمال رخداد هر کدام را تولید کنند. قابل اجرایی‌ترین روش شبیه‌سازی زمین‌آماری که دارای انعطاف‌پذیری بالایی است، روش شبیه‌سازی گاوسی متوالی است. در این پژوهش، در منطقه باغ‌غلوم کرمان ۳۹۲ داده لیتوژئوشیمیایی، متشکل از ۲۰ عنصر در ابتدا با استفاده از تبدیلات به سیستم عددی باز تبدیل شده‌اند. سپس عناصری که در اکتشاف منطقه کمک شایانی می‌کنند، به استاندارد نرمال تبدیل شده و سپس شبیه‌سازی با ۱۰۰ تحقق بر روی آن‌ها انجام گرفت. پس از شبیه‌سازی با استفاده از اعتبار سنجی آماری و زمین‌آماری تحقق معتبر انتخاب شد. نقشه‌های حاصل از شبیه‌سازی‌ها نشان دهنده غلظت غنی از عناصر کانی‌سازی در مناطق مرکزی است.

کلمات کلیدی: داده‌های ترکیبی، سیستم عددی باز و بسته، شبیه‌سازی زمین‌آماری، شبیه‌سازی گوسی متوالی، باغ‌غلوم- کرمان.