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Research article

Identification of anomalies using multivariate fractal modeling in the Maleksiahkuh region, SE Iran

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Abstract

Anomaly separation based on stream sediment data is an important step for mineral exploration. In this article, three methods of cluster analysis, factor analysis and fractal geometry have been used to separate the anomalous and suspected mineralization areas from the background areas. By combining these three methods, a possible mineralization was found in the Maleksiahkuh area. In addition, the relationship between the anomalies and the anomaly's host rocks was discussed. Maleksiahkuh is located 35 kilometers north of Zahedan and in the eastern part of the Flysch zone, Iran. Multivariate statistical analysis was performed. The results show a positive correlation between copper and molybdenum. The amount of chromium from the field is relatively high. Chromium is rich in the host mafic rocks. The presence of large concentrations of chromium in the region can be attributed to the presence of mafic rocks. The highest positive correlation was observed between manganese and cobalt, which is about 0.997. In addition, iron with titanium has a correlation of 0.984. Cobalt with iron has a correlation of 0.975. The cluster analysis for the region confirmed the existence of three clusters. The third cluster containing elements As, Sr, Sn, Sb, Pb, Cu, and Ag is probably related to the base-metal mineralization. Factor analysis was performed on the elemental concentrations. The sixth factor, which Cu and Ag elements have the highest weightage, was considered as another mineralization factor. The location of the most concentrated copper in the map derived from the Number-size (N-S) fractal method corresponds to the highest score in the factor rating map. There is a good match between copper anomalies and mafic rocks. Green crests have always been associated with mineralization, and studies show that there is a good relationship between mineralization and these rocks.

1. INTRODUCTION

The study area is located in Sistan and Baluchestan province, near Zahedan city, Iran. The study area is located in the Zahedan 1: 250,000 scale geology map. The difference in temperature overnight throughout the year is high in the area. The most important mountain in the region is the Maleksiahkuh with a height of 1605 meters and the lowest points in the area are river sediments, flood plains, and alluvial altitudes.

The results of traditional methods based on classical statistics have long been used as the only methods of analysis that have defects such as the normal distribution condition, the deletion of some data as outliers, the failure considering the spatial distribution of the data, and the lack of attention to the geometric shape of the anomalies [1]. In addition, while processing geochemical data using classical statistical methods, a large number of data are deleted as values outliers. These issues, together with the lack of attention to the geometric shape of the anomaly, make it obscure and, even in some cases, the removal of some actual anomalies or, in some cases, poorly illustrated them [1].

Cluster analysis is one of the statistical methods used to reduce data and find real groups. The cluster analysis aims to divide the dataset into distinct groups based on the similarity or difference between the groups. A good outcome of cluster analysis will result in several clusters where the observations within a cluster are as similar as possible while the differences between the clusters are as large as possible [2]. This method has many applications in earth sciences and has been used by many researchers [3, 4, 2].

Factor analysis is one method that can help identify more simple patterns within a set of variables. Specifically, this method seeks to discover a much smaller number of variables in cases where we can explain the observed changes with them [1]. One of the main goals of the factor analysis technique is the reduction of data dimensions [1]. The basic hypothesis in using this technique is the presence of a subsurface pattern or specific model in determining the complex communication concepts between variables, which appears as an agent in this hypothetical model. In general, the purpose of factor analysis is to determine the main coordinator variables among a geochemical data series and to evaluate the relative contribution of different variables to the development of the distribution of elements [5, 6].

Fractals have been widely applied in various disciplines to understand and analyze complex processes. In the field of geochemistry, fractal methods have gained attention for their ability to explain and quantify anomaly patterns in geochemical data. This literature review aims to provide an overview of the applications of fractal methods in geochemical studies, focusing on their role in anomaly separation, characterizing mineral distributions, understanding self-organization processes, and predicting geochemical behavior.

Fractal analysis has been utilized to characterize the spatial and temporal distribution of geochemical parameters, such as element concentrations. These studies often utilize fractal dimension (FD) to quantify the degree of complexity and heterogeneity of pattern distributions. Fractal analysis has been applied in investigations of mineral deposits, and hydrothermal systems. The fractal approach has proven valuable in describing the distributions of minerals within rocks and soils. Fractal models have been employed to characterize ore body geometries, investigate porosity and permeability in reservoir rocks, and identify trends in mineral zoning patterns.

Fractal models have also been employed to predict and simulate geochemical behavior, especially when dealing with complex systems. Fractal models, combined with probability-based approaches and geostatistical techniques, have been utilized to simulate [x]. The utilization of fractal methods in geochemical fields has remarkably advanced our inspection of complex patterns, and predictability of geochemical behavior. However, more research is needed to refine and develop fractal methodologies to address specific geochemical challenges and improve the integration of fractal analysis with other statistical and machine-learning techniques.

Fractal geometry is a nonlinear mathematical technique which was established by Mandelbrot (1983). Methods based on fractal geometry are useful for anomaly separation. These methods include the concentration-area (C-A) and concentration-perimeter (C-P) fractal models [7,8], spectrum-area (S-A) fractal model [9,10], concentration-volume (C-V) fractal model [11], spectrum-volume (S-V) fractal model [12], wavelet-number (W-N) fractal model and simulated size-number (SS-N) fractal model, Monte Carlo simulation algorithm (GSS-N) [13]. The C-A fractal model that was presented by Cheng et al. (1994) has been applied by many geoscientists [14, 15, 16, 11, 17, 18, 19; 20, 21, 22, 23,24, 25, 26, 27].

Stream sediment samples (n=192) were used to identify geochemical anomalies. Stream sediment samples of the −80 mesh (0.18 mm) fraction were collected from the center of the streams. Concentrations of the elements were measured by X-ray fluorescence spectrometry and atomic absorption spectrometry (AAS). The main purpose of this article is to identify potential areas for mineralization. Multivariate statistical methods and fractal geometry have been used for this purpose. Cluster analysis, factor analysis, and fractal number-size (N-S) methods were used and the results were compared. The geology of the area was first studied. Observations were made on the field. The morphology of the study area, its topography, and all the different types of rocks in the area were studied. Stream sediment samples were taken in the study area. The histogram of the elements was plotted. The distribution of elements was tested for normality or non-normality. Then, elements were classified by cluster analysis method. Factor analysis was also performed and the map with related mineralization factor was drawn. Finally, by using the Number-Size (N-S) method, the anomaly areas of the Maleksiahko area were suggested.

2. GEOLOGY OF THE STUDIED AREA

Maleksiahkuh is located in 35 Km north of Zahedan in the flysch zone of eastern Iran. The most notable elevation of the region is the volcanic Maleksiahkuh mountain with a height of 1605 meters. The lowest points of the region are rivers, flood plains, and alluvial barracks. Because the relative elevation and topography determine erosion processes' speed, most rivers are scattered and extend over broad areas. The flysch zone of eastern Iran has a rift between the Afghan block and the Lut block, which is Upper Cretaceous in age [23]. The main rocks of this zone are Cretaceous ophiolite and ophiolitic mélanges (remnants of an oceanic crust) and Late Cretaceous to Paleogene flysch-like marine sedimentary rocks that were intruded by rocks of subduction, collision, and post-collision events. Fig. 1 shows the map of structural zones of Iran [24] in which the Maleksiahkuh region lies in the Nahbandan-Khash zone.

The geology of the Maleksiahkuh is shown in the Zahedan geological map (1/2500000) (Fig. 2). The geological units in this area are flysch-like rocks such as shale, sandstone, mudstone, marl, and limestone associated with conglomerate and several types of igneous rocks. The sedimentary rocks were locally metamorphosed or altered in contact with intrusive plutons. The igneous rocks occur as stock, dike, sill, and lava. Biotite and amphibole separated from the rocks of Maleksiahkuh yielded approximate K-Ar ages of 27-28 Ma. [25]. The igneous rocks in the study area are intermediate to mafic rocks, such as andesite, dacite, granodiorite, and gabbro (Fig. 3). Sedimentary rocks in the area include sandstone, marl, shale, and limestone, with shales typically interbedded with sandstones. The sandstone layers in the shales are generally of different thicknesses and commonly have ripple marks. Sandstones are also associated with shale and marl in most places. Conglomerate is sparsely distributed in the coarser sandstones, and include sandstone, shale, slate, and phyllite along with rarer igneous fragments. Limestones locally occur with calcareous sandstones often containing reefal fossils. The igneous rocks are mainly calc-alkaline shoshonite and are related to post-collisional tectonic-magmatic settings [26]. The generation and emplacement of such magma are assumed to be related to the movements of the Zahedan fault, a post-collisional strike-slip fault situated at the eastern margin of the flysch zone [26].

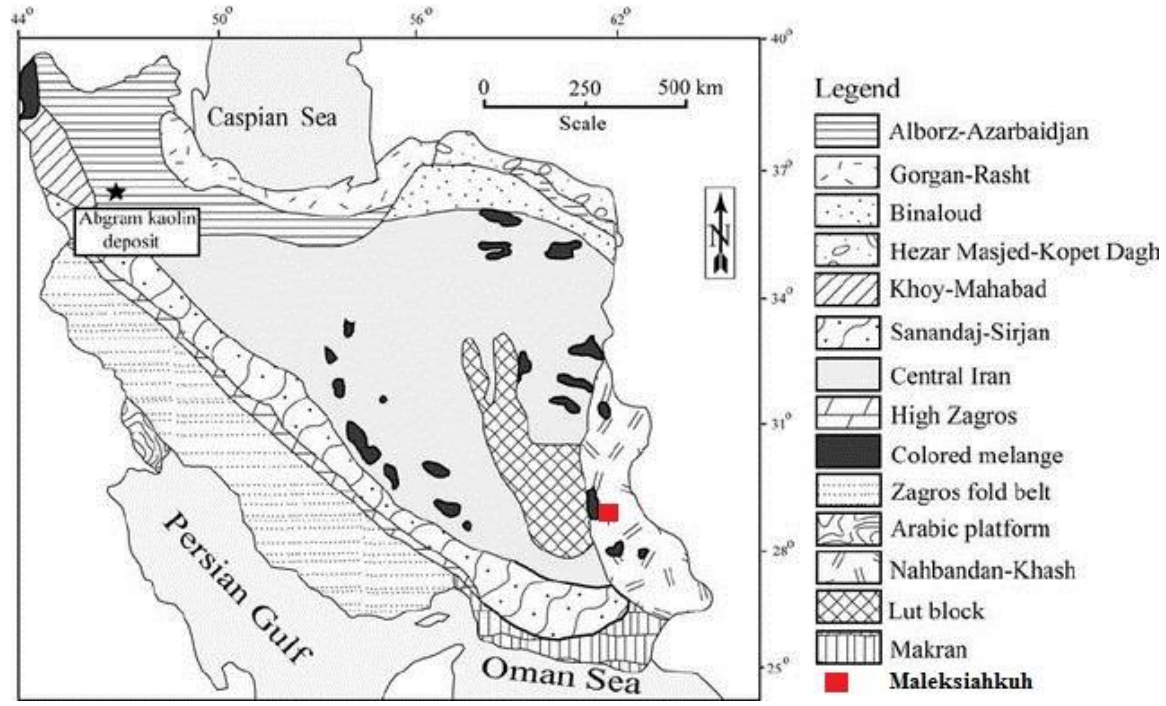

Fig. 1. Map of structural zones of Iran in which the Maleksiahkuh region lies in the Nahbandan-Khash zone [22].

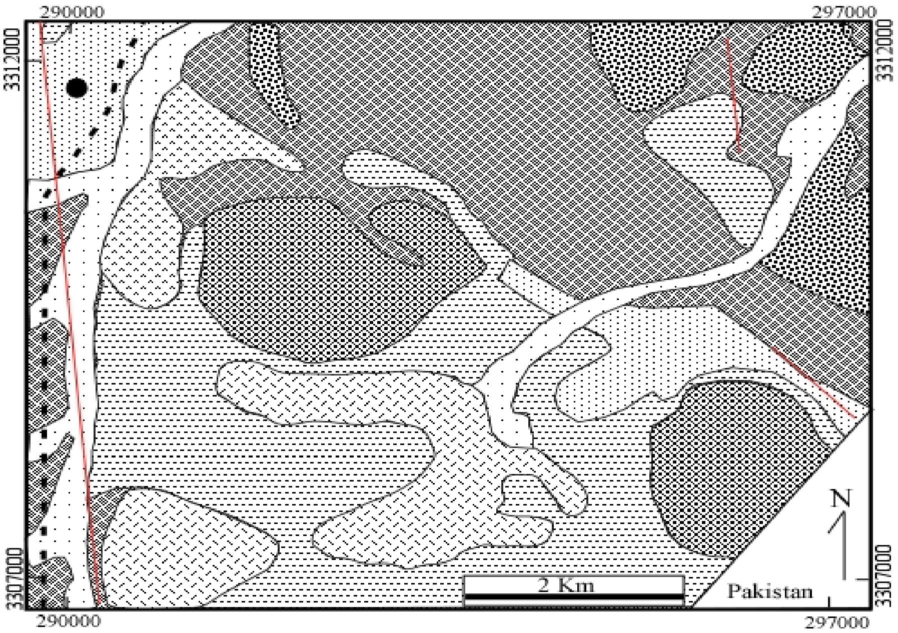

Fig. 2. Geological map of the Maleksiahkuh area (modified from geological map of Zahedan).

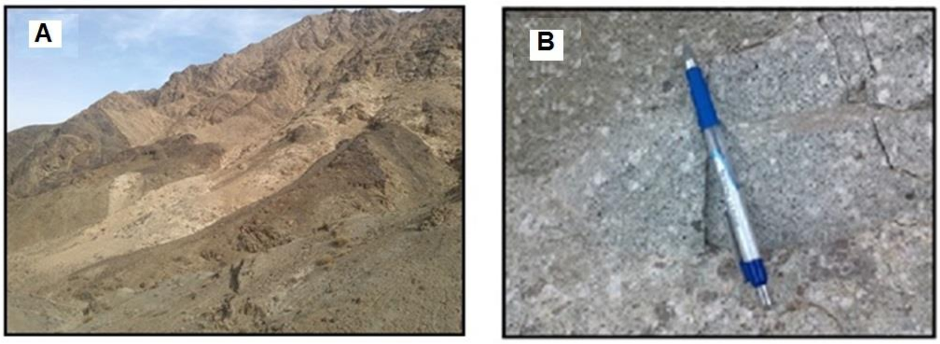

Fig. 3. Field photographs for the local granodiorite intrusion "A" and related subvolcanic dacite porphyry "B" in the study area.

3. METHODOLOGY

3.1. Cluster Analysis

The principle of cluster analysis is that n different samples are regarded as n different classes, and the two classes with the closest properties (or the shortest distance) can be merged into the same class. Then, the next two classes with the closest properties (or the shortest distance), from the n−1 classes, are combined [1]. This process continues until all the samples have been merged into a single class. The basic algorithm steps of cluster analysis are shown below [1]:

In the beginning, each sample is a separate class, and the distance matrix between two pairs of n classes is calculated, denoted as:

$$D_0 = \begin{bmatrix} 0 & & & & \\ d_{21} & 0 & & & \\ d_{31} & d_{32} & 0 & & \\ \vdots & \vdots & \vdots & & \\ d_{n1} & d_{n2} & d_{n3} & \cdots & 0 \end{bmatrix}$$

1. Find the minimum distance value dij in the distance matrix, and denoted as di1j1 , and combine the i1 and j1 classes into the n − 1 class.

2. Calculate the distance between class n −1 and other classes;
3. Merge rows i1, j1 in the initial distance matrix D0 into a new row, and columns i1, j1 into a new column, the number of classes is reduced by one. We can get the new distance matrix D1.
4. Repeat steps (2) (3) and (4) until n samples are clustered into one class.
5. The clustering process was made into a cluster analysis diagram. The original samples were screened according to the cluster analysis diagram to eliminate the samples that did not meet the requirements [1].

3.2. Factor Analysis

Factor analysis assumes that relationships within a set of variables reflect correlations with a smaller number of underlying factors. The main applications of factor analytical techniques are to diminish the number of variables and to distinguish structure in the relationships between variables, or to classify them [1]. A special feature of this technique is that it extracts factors or principal components which are linear combinations of all variables that can explain the maximum of total variance successively. Thus the first factor explains the maximum variance; the remaining factors define the maximum of the residual variability. The factors extracted are uncorrelated or orthogonal to each other. The variances extracted by the factors are called the eigenvalues. Since the first factor explains maximum variance it has the highest eigenvalue. The sum of the values of all factors will be equal to the total number of variables [1].

3.2. Fractal Number-Size (N-S) Model

Number–size (N–S) method can be utilized to describe the distribution of geochemical populations. This model shows a relationship between desirable attributes and their cumulative numbers of samples. A power-law frequency model has been proposed to explain the N–S relationship according to the frequency distribution of elemental concentrations and cumulative number of samples with those attributes (Daya, 2015a):

$$N(\geq \partial) = K\partial^{-D} \quad (1)$$

where ∂ denotes elemental concentration, $N(\geq \partial)$ denotes the cumulative number of samples with concentration values greater than or equal to ∂, K is constant, and D is the fractal dimension of the distribution of elemental concentrations. Log-log plots of $N(\geq\partial)$ versus ∂ show straight line segments with different slopes −D corresponding to different concentration intervals [18].

4. STATISTICAL SURVEY OF DATA

One of the essential steps of each geochemical exploration phase is the design of sampling network, so, it is necessary to design it with a high degree of accuracy. Basically, in the stream sediments geochemical exploration, optimal sampling is performed to obtain the desired result. Considering the aforementioned factors, 192 geochemical samples were taken from an area of 49 km2 and the concentration of important elements was determined. Stream sediment samples of the −80 mesh (0.18 mm) fraction were collected from the center of the streams. Concentrations of the elements were measured by X-ray fluorescence spectrometry (XRF) and atomic absorption spectrometry (AAS). International standard samples (JSD1, JSD2) and replicates were analyzed after every 10 samples for checking accuracy and precision. Mean deviations between the measured concentrations and reference values were less than 10%. Fig. 4 shows the location of these samples. Table 1 shows the statistical parameters of selected elements of 317 stream sediment samples from the Maleksiahkuh region. Preparation and chemical analysis of the samples took place. In geochemical data extracted from the study area, most elements had sensor data. Since the number of sensor data in the study area was insignificant (less than 10%), the simple replacement method was used. In the case of identifying outlier values in this paper, it is assumed that the high values are anomalous and are not considered outlier values and are used in statistical calculations.

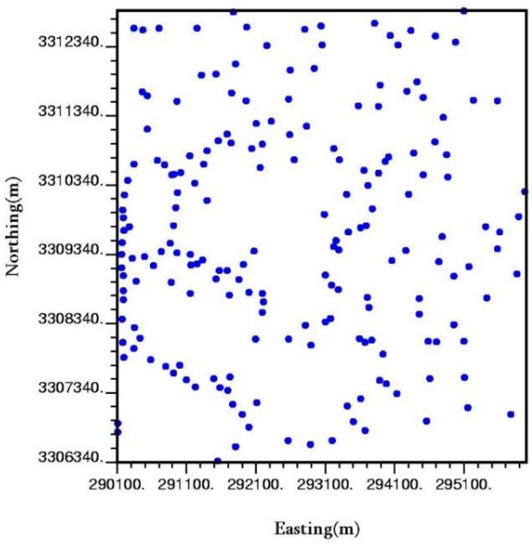

Fig. 4. Location of the sediment samples taken in the Maleksiahkuh area.

Table 1. Statistical parameters of selected elements of 317 stream sediment samples from Maleksiahkuh region

	Cr (ppm)	Fe (ppm)	Co (ppm)	Ni (ppm)	Sn (ppm)	Zn (ppm)	Pb (ppm)	Mo (ppm)	Cu (ppm)	As (ppm)
Mean	116.50	2.75	13.50	48.25	2.15	46.20	18.50	1.30	28.10	18.11
Median	112	2.50	13	49	2	67	10	1.26	25.64	15.94
Std. Deviation	32.55	1.60	13.95	5.80	0.76	33.52	13.03	0.56	1.64	7.95
Variance	1059.20	2.50	15.51	33.74	0.58	1127.80	176025	0.31	266.25	63.081
Skewness	3.971	6.9	6.13	0.167	1.82	-0.30	-0.972	0.55	11.331	1.582
Kurtosis	32.171	51.90	46.50	1.042	8.75	-1.47	0.60	-0.92	143.4	3.35
Minimum	50	1.65	9	36	0.75	5	1	0.25	19.55	0.001
Maximum	342	16.72	48	74	7	106	73	3	273.30	52.12

A statistical survey on the data of the Maleksiahkuh showed that the arsenic, copper, molybdenum, zinc, lead, and chromium elements are notably higher than their Clark values. Fig. 5 shows the frequency (histogram) of these elements. One of the applications of the Q-Q plot diagrams is to evaluate the frequency distribution of elements. The closer the curve to the line is, the distribution becomes normal. The Q-Q plot for these elements is also shown in Fig. 6. From these shapes and diagrams, it can be deduced that the molybdenum, chromium, and arsenic elements have a normal distribution, and lead, copper, and zinc elements have no normal distribution. The lead and zinc analyses yield histograms showing a bimodal distribution.

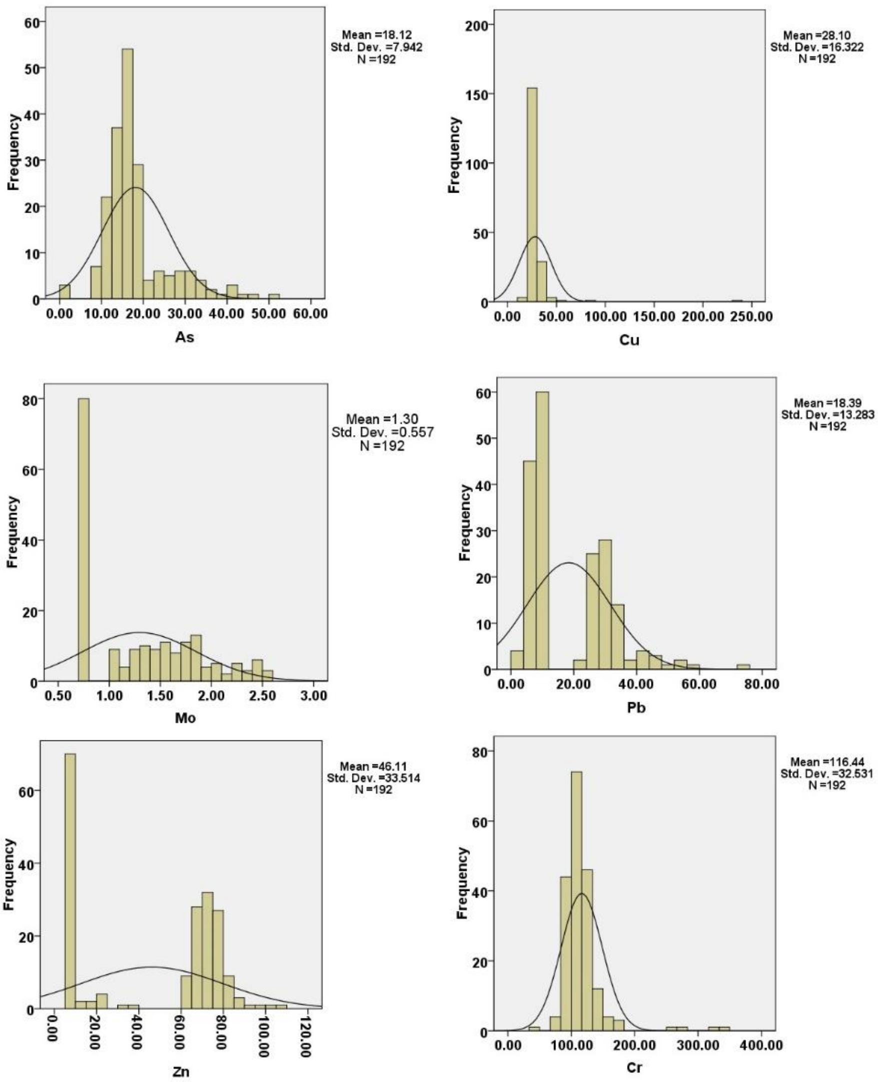

Fig. 5 .Histogram for arsenic, copper, molybdenum, lead, zinc, and chromium (in ppm or g/t) in the Maleksiahkuh area.

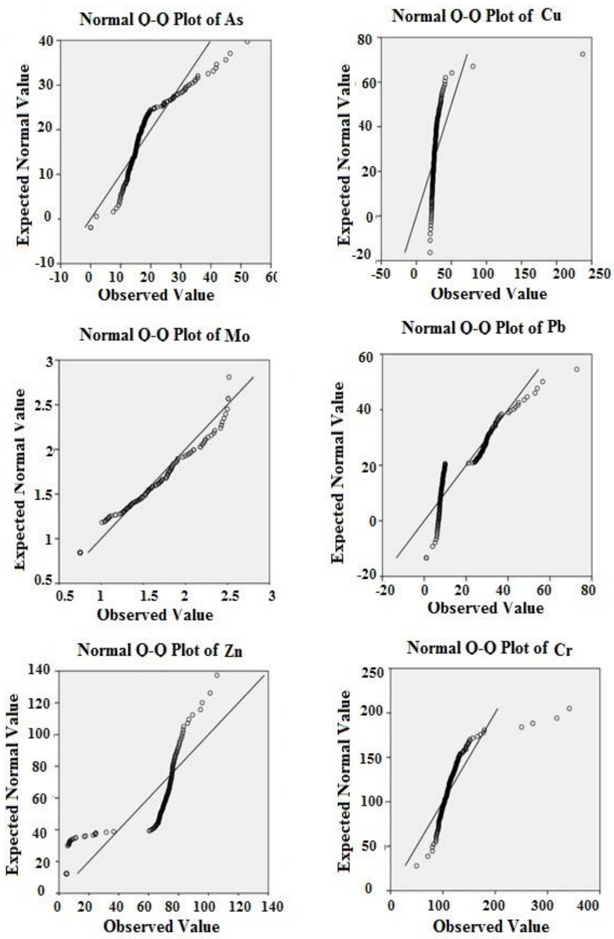

Fig. 6. The Q-Q plot for the studied elements.

In geochemical surveys, important elements of the samples are often measured. Since any given group of elements exhibits a similar sensitivity to specific environmental conditions, recognizing the existing genetic correlations between different elements can be used to better understand the changes in geochemical environments. In addition, the genetic accumulation of some elements may be used as a direct guide to determining the type of deposit that is probably present in the area. The correlation coefficients of the Pearson method for the main elements of the Maleksiahkuh area are presented in Table 2. This was done using SPSS 16 software.

Table 2. Correlation matrix between important elements in the stream sediment of the Maleksiahkuh area

Ag	1													
As	.035	1												
Co	.070	.091	1											
Cr	.092	.086	.887**	1										
Cu	.113	.030	.170*	.113	1									
Fe	.123	.100	.975**	.894**	.126	1								
Mn	.061	.110	.979**	.882**	.151*	.954**	1							
Mo	-.092	-.054	.143*	.142	.017	.051	.215**	1						
Ni	-.093	-.072	.064	.054	.111	-.089	.074	.596**	1					
Pb	-.029	.285**	.428**	.308**	.170*	.371**	.420**	.110	.203**	1				
Sb	-.055	.066	.055	.021	.098	.055	.100	.133	.020	.170*	1			
Sn	-.072	.246**	.234**	.148*	.119	.214**	.226**	-.063	.103	.462**	.585**	1		
Ti	.089	.073	.972**	.891**	.107	.984**	.954**	.035	-.070	.363**	.046	.226**	1	
Zn	-.060	-.022	.334**	.269**	.101	.201**	.405**	.752**	.691**	.243**	.059	-.002	.207**	1
Elements (ppm)	Ag	As	Co	Cr	Cu	Fe	Mn	Mo	Ni	Pb	Sb	Sn	Ti	Zn

4. DISCUSSION

It can be concluded from Table 2 that the highest positive correlation was observed between the manganese and cobalt (the main origin is the sea floor) elements, which is about 0.979, iron with titanium 0.984, and cobalt with iron is 0.975.

A hierarchical cluster analysis was conducted for the main elements in the study area. Cluster analysis is one of the multivariate methods aimed at achieving a criterion for classifying the most suitable variables or samples based on more internal similarity and more discrepancy between groups [1]. In this study, the criterion of the correlation coefficient and clustering algorithm is the Ward method and Pearson Product (r). The results are dendrogram in Fig. 7. As shown in the figure, the elements are divided into three separate clusters. The first cluster contains the elements Fe, Ti, Cr, Co, Mn. These elements are hydrophilic and are often placed on the margin of mineralization. The second cluster consists of Mo, Zn, Ni elements. In the third cluster, the elements of As, Sr, Sn, Sb, Pb, Cu, Ag are included. The first cluster is not related to mineralization because they are hydrophilic and are often placed on the margin of mineralization. The third cluster is associated with mineralization in post-magmatic phases or hydrothermal processes. Hydrothermal solutions can be the cause for mineralization. Hydrothermal solutions by impregnating the embedded rocks can cause mineralization. In total, it appears that the third cluster represents a base-metal mineralization center, and other clusters are also associated with mineralization, including porphyry Cu-Ag related systems possibly located around mineralized systems [27, 2].

To determine the accuracy and confirmation of factor analysis, the KMO coefficient was calculated. The large quantities of this coefficient signify confirmation of factor analysis and its small values imply that the factor analysis is not approved. KMO was 0.74 (> 0.50) which was acceptable. By applying factor analysis on the values of variables, special values, percentage variance, and cumulative percent of variance of each factor are calculated separately. The number of significant factors revealed that according to the scree plot (Fig. 8) and the table of data variances obtained from factor analysis (Table 3), the number of factors is 6. These six factors justify a total of 76.353 percent of environmental change.

The first factor, in which the elements Cr, Mn, Co, Fe, and Ti have the highest eigenvalues, but is unrelated to mineralization and is a function of the rock composition. The elements of this group are almost identical to those of the first cluster of the cluster analysis. This factor justifies around 30% of the environmental change. The second factor includes Ni, Zn, and Mo with high eigenvalues, which can justify lithological and mineralogical changes in the region. This factor justifies 16% of the environmental change and corresponds to the second cluster of cluster analysis. The largest eigenvalues in the third, fourth, and fifth factors belong to the mineralization trace elements. These trace elements include As, Sb, Cs, and Sr. In factor six, Cu and Ag have the highest weight (copper has the highest positive weight, and silver with the highest negative weight), which can justify copper mineralization and silver dilution. Fig. 9 shows the 6th-factor score map in the Maleksiahkuh area. This map was generated with IDS (Inverse Distance Squared) method using RockWorks™ v. 2006 software package. As shown in the figure, copper mineralization in the southwest of the region is maximum and dilution is also observed in the north-east of the region.

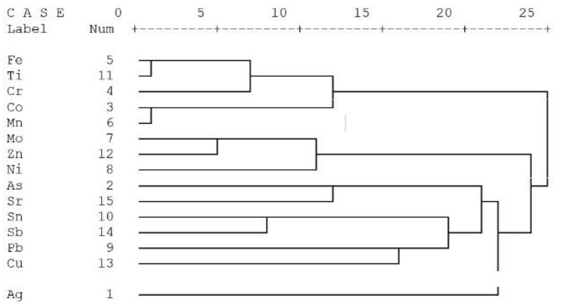

Fig. 7. Dendrogram obtained from the hierarchical cluster analysis method in the Maleksiahkuh area.

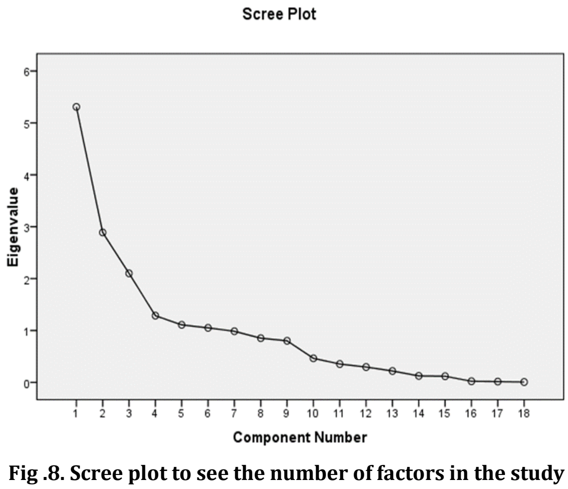

Fig .8. Scree plot to see the number of factors in the study area

Table 3. Level of variance obtained from factor analysis

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.310	29.498	29.498	5.310	29.498	29.498	4.969	27.608	27.608
2	2.888	16.045	45.543	2.888	16.045	45.543	2.515	13.970	41.578
3	2.101	11.674	57.217	2.101	11.674	57.217	2.017	11.205	52.783
4	1.285	7.141	64.358	1.285	7.141	64.358	1.617	8.981	61.764
5	1.109	6.160	70.518	1.109	6.160	70.518	1.479	8.217	69.981
6	1.050	5.836	76.353	1.050	5.836	76.353	1.147	6.373	76.353
7	.985	5.471	81.824	-	-	-	-	-	-
8	.852	4.732	86.556	-	-	-	-	-	-
9	.801	4.453	91.008	-	-	-	-	-	-
10	.463	2.574	93.582	-	-	-	-	-	-
11	.354	1.967	95.549	-	-	-	-	-	-
12	.295	1.641	97.190	-	-	-	-	-	-
13	.219	1.218	98.409	-	-	-	-	-	-
14	.125	.693	99.102	-	-	-	-	-	-
15	.118	.658	99.760	-	-	-	-	-	-
16	.021	.119	99.879	-	-	-	-	-	-
17	.015	.082	99.961	-	-	-	-	-	-
18	.007	.039	100.000	-	-	-	-	-	-

Extraction Method: Principal Component Analysis.

Number-size (N-S) graphs were drawn for arsenic, copper, silver, lead, zinc, and chromium (Fig. 10). The values of these elements were more of their Clark. For this reason, only these six elements were examined. As seen in these figures, there are different populations for different elements. There are five populations for arsenic, three for copper, three for molybdenum, six for lead, four for zinc, and five for chromium in the community.

There are four enrichment phases for Cu. The first and second phases are background. The third and fourth populations are Cu anomalies. Copper shows multifractal nature in the region. The condition of Mo is a little different from copper. As cab be seen in the Fig. 10, there are three population for Mo. The first and second phases are background and the last phases is enrichment phases i.e. anomaly. The anomaly maps of these elements are depicted in Fig. 11. Extreme concentrations of copper in the southwest of the region (Fig. 11) are well matched by increasing the score of the sixth factor (probable copper mineralization) (Fig. 9). This means that the factor analysis is valid in the area. Comparing the location of this anomaly with the geological map, the copper anomaly seems associated with intermediate andesite and trachyandesite rocks; given that most of the copper mineralization is associated with the intermediate masses, this is possibly related to PCD.

Lead, Cr, Cu, and As have a strong anomaly in the southeast of the study area. By studying the geological map of the study area, it can be said that this anomaly is correlated to the sandstone, schist, shale, and green siltstones. The greenschist arches and belts have always been associated with mineralization, and in this area, it can be concluded that the host of this mineralization is also the same type of greenschist belts. Arsenic has scattered anomalies, which is due to its traceability. In addition, in some cases, there is a good correlation between arsenic anomalies with zinc and lead anomalies (Ghorbani 2013; Daya 2105a).

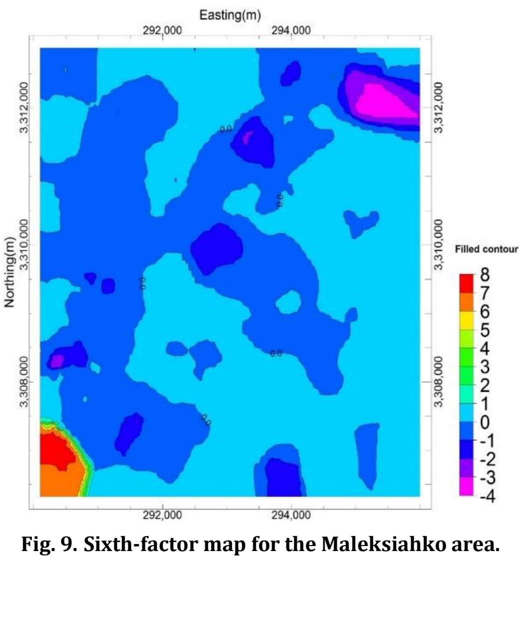

Fig. 9. Sixth-factor map for the Maleksiahko area.

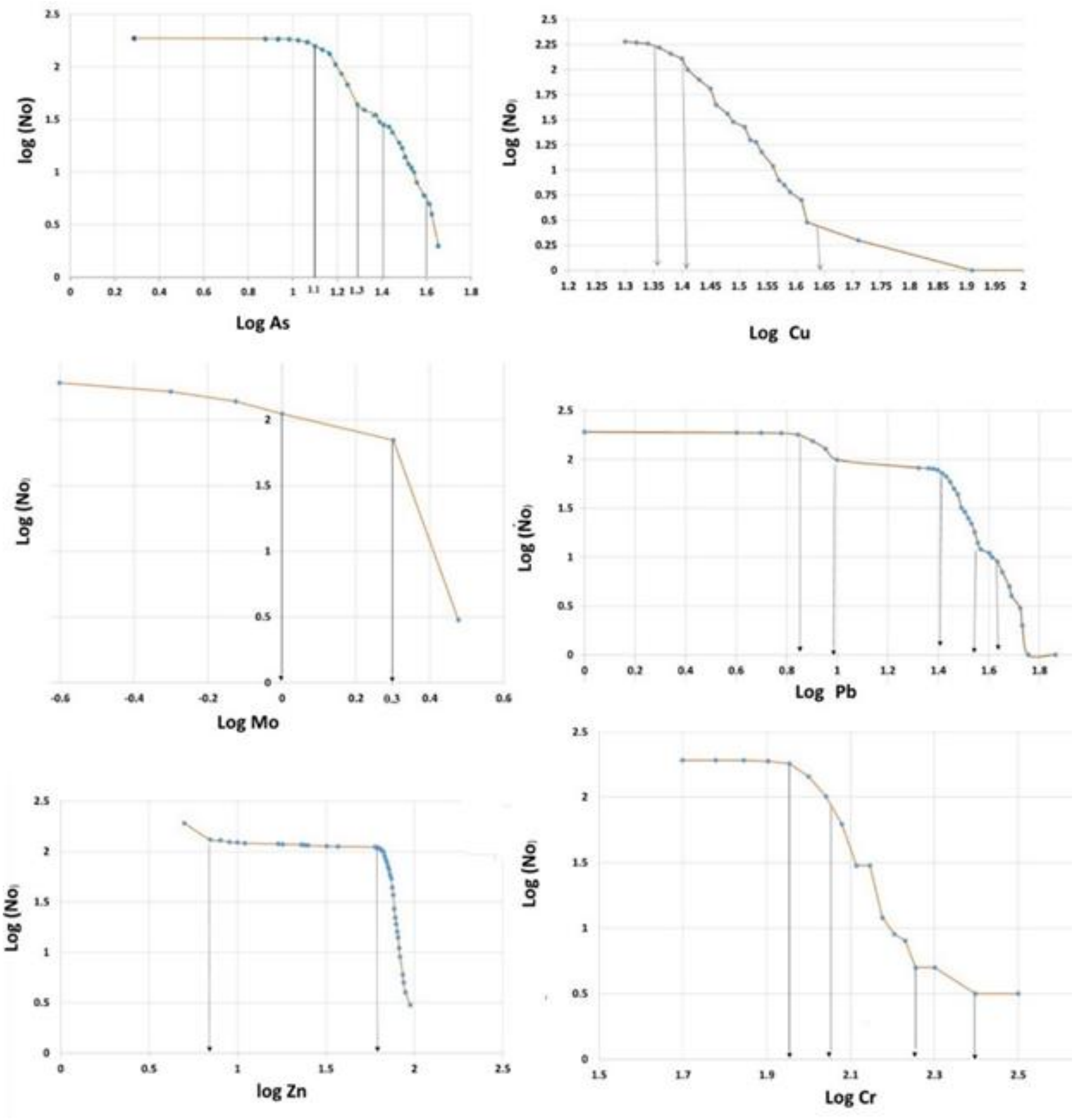

Fig. 10. Number-size (N-S) graphs for arsenic, copper, molybdenum, lead, zinc, and chromium (ppm – g/t).

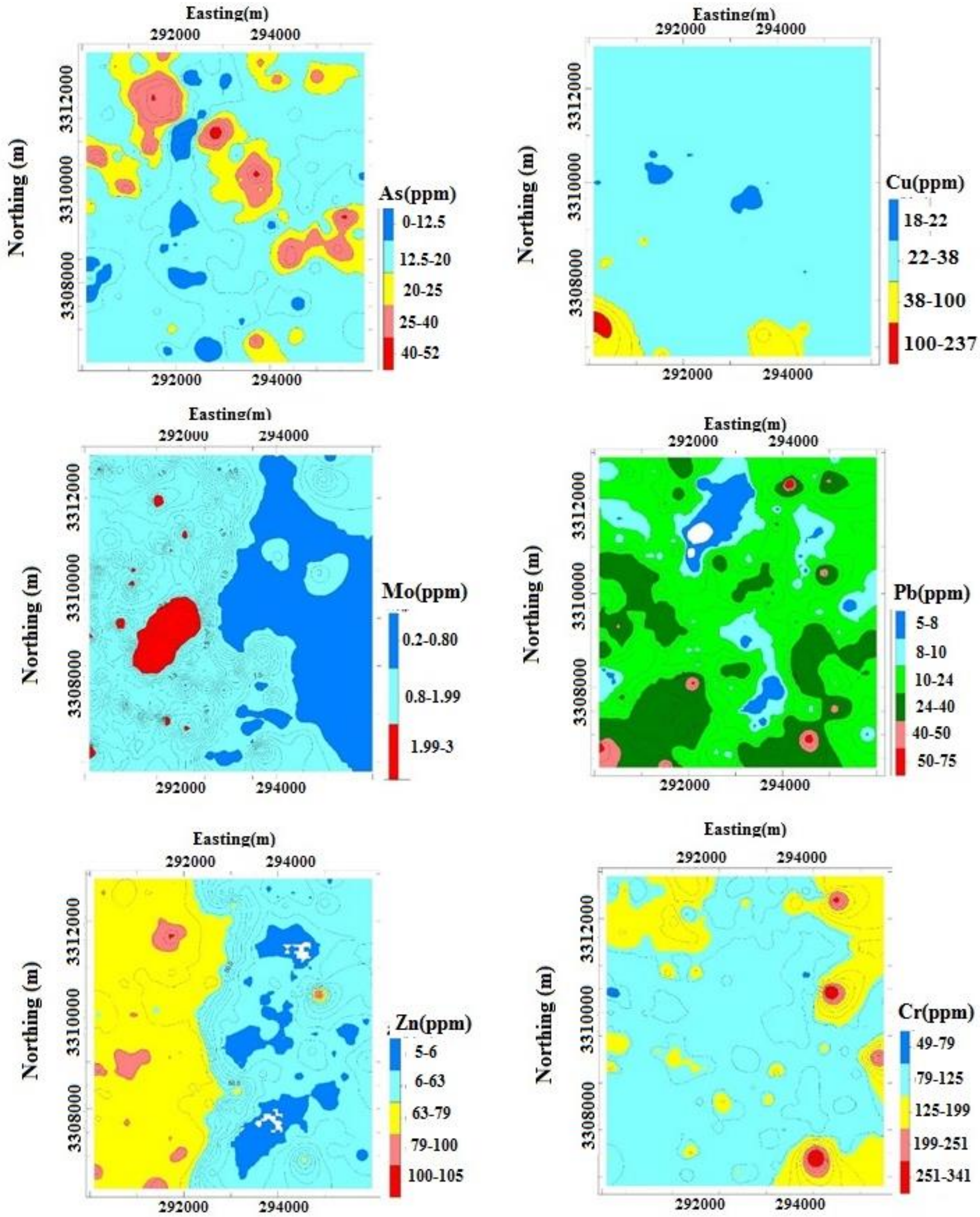

Fig. 11. Map of anomalies of elements based on the Fractal number-size (N-S) model in the Maleksiahkuh area.

6. CONCLUSIONS

Geological surveys conducted in the area showed that the geological units consist of flysch-like rocks, including shale, sandstone, mudstone, and various types of igneous rocks. The sedimentary rocks experienced localized changes when they came into contact with intrusive rocks. The igneous rocks found in the research site comprise andesite, alkaline basalts, and diorite. A set of statistical surveys was conducted in the Maleksiahkuh area. The findings revealed that the concentrations of arsenic, copper, molybdenum, zinc, lead, and chromium in this region are higher compared to their usual background concentrations. Particularly, the concentration of chromium in the area was found to be notably high, which is possibly attributed to the presence of mafic rocks. Furthermore, a Q-Q plot was generated to analyze the distribution of these elements. The plot indicated that molybdenum, chromium, and arsenic followed a normal distribution pattern, while lead, copper, and zinc displayed a distribution pattern that deviated from normality. Multivariate analysis revealed that Maleksiahkuh's manganese and cobalt exhibited the highest correlation at approximately 0.979, followed by iron and titanium at 0.984, and cobalt and iron at 0.975. Cluster analysis was carried out in the study area to identify the main groups, resulting in three separate clusters. The third cluster, consisting of As, Sr, Sn, Sb, Pb, Cu, and Ag, was associated with mineralization. The variables were subjected to factor analysis, and out of the six factors available, the sixth factor with Cu and Ag elements had the highest eigenvalues. Copper had the highest positive weight, while silver had the highest negative weight, indicating their importance as mineralization factors. The Sixth Factor Score map shows a potential area for copper mineralization in the southwest of Maleksiahkuh. By using the N-S fractal model, Cu anomalies were detected. These copper anomalies in the southwest region correspond well with the sixth-factor scoring map, indicating probable copper mineralization. Therefore, it is recommended to conduct more detailed studies and collect lithological samples in the northwest region. The fractal method and factor analysis method showed a strong correlation. The copper anomaly aligns with the presence of greenschist rocks, which have always been associated with mineralization in greenschist belts and arcs.

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