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Research Paper

Regional Geochemical Exploration for Cu-Au Deposit Based on Self-Organizing Map (SOM) in Valezir Area, Meshginshahr, NW of Iran

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Abstract

Since most of the geochemical data analysis procedures require preliminary assumptions that lead to constraint and errors in the true nature of the data causing reduction in the effectiveness of the adopted methods. Therefore, a model-based clustering method as self-organizing map (SOM) were employed with the aim of recognizing Cu-Au mineralized zones by establishing an optimized exploration tool in Valezir area, NW of Iran. SOM as a dimension reduction method was introduced to recognize geochemical distribution patterns of Cu-Au with higher certainty while preserving the originality of the data. Subsequent to data preprocessing and testing different SOM architectures, an appropriate structure with a pattern containing six clusters was selected. Accordingly, the related elements distribution model was extracted and interpretation of the geochemical system represents two significant sets of elements in clusters (i.e. 1st, 2nd and 6th clusters) to anticipate the mechanism of distribution: 1- Copper and pertaining trace elements formation from intermediate to acidic hydrothermal solutions, which are localized in the northern part of the area and emplaced in the quartz monzo-dioritd intrusive body. 2- Au Anomalies and its associated elements As, Hg and Bi depicted in 2nd cluster. The Au anomalies follow geochemical pattern with Bi, Sb, As, and W that are mostly elongated from NW to SW of the area. It seems relatively the low enrichment of gold has occurred during the intrusion of the igneous body into older volcanic units that caused extensive alterations, remobilization and localization of Au and related elements. To assess the SOM results, a comparative study was carried out with the results obtained from hierarchical clustering analysis (HCA). The results illustrated higher performance by SOM approach in characterizing geochemical system and detecting the elements paragenetic sequence in the area for locating the exploration targets.

Keywords

Geochemical system modeling, Pattern recognition, Self-Organizing Maps (SOMs), Valezir area, NW of Iran.

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1- INTRODUCTION

Recognition of geochemical distribution patterns of ore-related elements, their paragenetic interrelationship and more accurate discrimination of population can be effective in better identification of anomalies in the geochemical environments. The proper mapping of the genetic accumulation of the elements and associated minerals is an important aspect in the prospecting of metals in an area. In most cases, due to the large scale of data and their empirical analysis, the lack of proper models for describing the source, how the migration, magmatic differentiation, deposition, and the concentration of different elements in rocks leads to conceal prone areas and influence the factors associated with mineralization components in the area. Therefore, it is essential to have a geochemical model that illustrates the nature and origin of the surface expression of mineralization. Such models attempt to express the spatial and genetical relationship between geochemical distribution process and the formation, and to apply them to the optimization of exploration procedures [1]. Thus, this paper aims to optimize the recognition of geochemical patterns while constraining the prospecting uncertainty in order to map the mineral potentials in the Valehzir Area, Meshginshahr, Ardebil, NW of Iran. Integrating and analyzing different spatial data using various modeling techniques for mineral exploration programs have been attempted by various authors [2,3]. Among them, the techniques associated with the elemental pattern recognition are of great importance such as the Bayesian decision-making theory [4,5], Clustering based methods [6-8], Decision-Tree method [9], non-linear Kernel methods [10,11], Neural networks based methods 5]] and Multivariate statistical methods [12-16]. Meanwhile, different methods have developed for identifying patterns and clustering variables to reduce the dimensions of the data matrix. It is essential to note that some aforementioned methods, despite their desirability, adhere to the statistical assumptions about data distribution, which affects the nature of the exploration data and the final results. Therefore, in order to overcome this problem, a self-organizing map neural network (SOM) [17,18] was proposed for recognizing geochemical patterns in the area. In addition, the application of this method is important in overcoming the limitations of neural network input variables, for improving the accuracy of predictions in exploratory environments by recognizing & analyzing the nonlinear multi-dimensional spaces in order to propose an optimal hybrid method for mapping the geochemical anomalies. Hence, the assessment of the elements distribution, enrichment, and trend of their linear and nonlinear regional variations in the area, was utilized by using the proposed method.

The Self-Organizing Map (SOM) is a fairly well-known neural network and indeed one of the most popular unsupervised learning algorithms which has been introduced by Finnish Professor Teuvo Kohonen in the early 1980s. The method performs a non-linear projection of multi-dimensional data onto a two-dimensional map. The mapping is topology-preserving from an input space onto the 2-D grid of map units. It means that the more alike two data samples are in the input space, the closer they will appear together on the final map. The resulting maps comprehensively visualize natural groupings and relationships in the data. The method as a remarkable tool in information visualization has a simple basic implementation, capability in data structure maintaining, reliable results and the algorithm scales exceptionally well [19].

From the SOM training point of view, it can express that the SOM consists of a regular, usually two-dimensional grid of map units. Each unit i is presented by a prototype vector $m_i = [m_{i1},...,m_{id}]$, where d is the input vector dimension. The units are connected to adjacent ones by a neighborhood relation. The SOM is trained iteratively and at each training step, a sample vector x is randomly selected from the input data set. Distances between x and all the prototype vectors are computed. The best matching unit (BMU), which is denoted here by b, is the map unit with prototype closest to x (Equation 1):

$$\|x - m_b\| = \min\{\|x - m_i\|\} \tag{1}$$

Then, the prototype vectors are updated. The BMU and its topological neighbors are moved closer to the input vector in the input space. The updated rule for the prototype vector of unit i is (Equation 2):

$$m_i(t+1) = m_i(t) + \alpha(t) h_{bi}(t)\left[x - m_i(t)\right] \quad ,$$
$$h_{bi}(t) = \exp\left(-\frac{\|\tau_b - \tau_i\|^2}{2\sigma^2(t)}\right) \qquad (2)$$

Where:
t: time,
$\alpha(t)$: adoption coffecient,
h_{bi}: neighborhood kernel centered on the winner unit,
τ_b, τ_i: positiones of neurons b and i on the SOM grid.

For a discrete dataset and fixed neighborhood kernel, the error function of SOM can be shown to be (Equation 3):

$$E = \sum_{i=1}^{N} \sum_{j=1}^{M} h_{bj} \left\| x_i - m_j \right\|^2 \qquad (3)$$

Where:
N: number of training sample,
M: number of map units.

Neighborhood kernel h_{bi} is centered at unit b, which is the BMU of vector x_i, and evaluated for unit j .If neighborhood kernel value is one for the BMU and zero elsewhere, this leads to minimization of the error function [20].

SOM has been successfully applied in a broad spectrum of research areas ranging from speech recognition to financial analysis and mineral exploration. For instance, it has been used to solve the prediction problems in neural networks [21,22]. It also as an effective clustering method in spatial data analysis has widely been applied in various fields such as image processing [23], precipitation estimation [24-28], biology and ecology [29,30], underground water investigation [31,32], in seismic attributes assessment and interpretation [33], well logging [34,35], hydrology [24,28,36], catchment basin classification [37,38], remote sensing hyperspectral image processing [32,14,39-46], mineral exploration[47-53] and most other fields. Despite of SOM multiple privileges, only limited implementation has been undertaken in earth sciences. Therefore, this study tends to address the shortcomings of the research history in applying of the SOM method in mineral exploration and highlights its practical application in the field of geochemical exploration for predicting promising areas of copper mineralization in the northwestern part of Iran.

1-1- Location and Geology of the Study Area

The study area is situated in the Meshginshahr region in NW of Iran (Figure 1). The area is located in the western part of the Ardebil province about 12 km southwest of Mesginshahr city and 1.5 km southwest of Aghbolagh town. According to [54], the province is located in the northwest of Alborz-Azerbaijan zone. Since the lithological similarity exist between the higher potential mineralized areas in the vicinity such as (Arasbaran-Garadagh area) with similar indices and mineralization, it is essential to recognize optimal exploration patterns more accurately for targeting mineral potentials based on elemental association in the Meshginshahr.

The major rock units that are involved in the evolution of the area are igneous, pyroclastic and Cenozoic sediments cover more than 95% of exposed rocks [55,56]. Eocene volcanic rocks, pyroclastic and sedimentary rocks are expanding in the northeastern and western parts of the study area and their composition varies from trachybasalt through trachyandesite to trachyte. These rocks contain SiO_2 = 48.8%, K_2O = 5.0.09%, Na_2O = 6.11%, Al_2O_3 = 16.6%. The E^{pa} unit often has been epidotized and carbonatized in the vicinity of the granitoidic intrusive mass which partly can be called meta-volcanic. The E^{tat} unit includes trachyandesite- trachy basalt and tuffites [57]. The rocks of this unit in vicinity of the intrusive mass O^m have been intensively altered due to hydrothermal solutions where Plagioclase have been sericitic and chloritic due to alteration [58]. The presence of Shale and tuffite sediments suggests a marine environment for these sediments. The Oligocene (O^m) intrusive body is characterized by yellow color comprising monzonite, quartz monzonite and in some cases granodiorite which is the host to sulphide mineralization in the area. The northern and northwestern parts of the mass are strongly altered due to hydrothermal solutions and their feldspars are kaolinitized, Sericitizatized and mafic minerals have been converted to metal oxides.

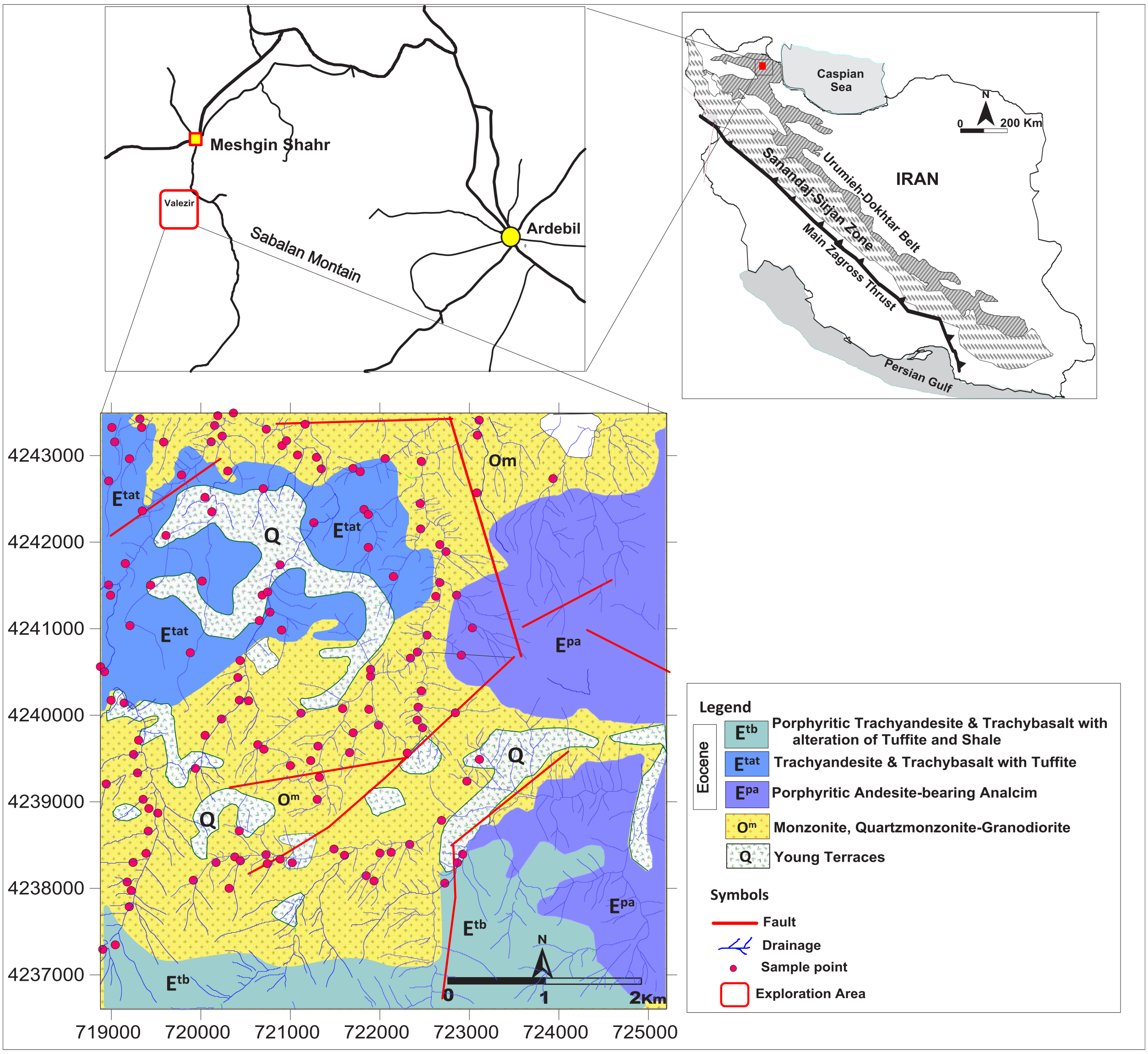


Figure 1. Simplified geological map and sample points of the studied area

1-2-Sampling

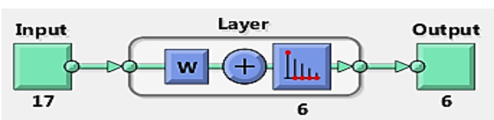
The sampling points are shown on the geological map in Figure 1. Choosing the sampling environment and appropriate parts of the stream sediment for analyzing is a crucial problem in achieving the best possible contrast. The main objective is to increase the contrast and reduce the natural variation within the communities of background and anomalies with a better level of confidence. In order to determine the optimal size of sampling for enhancing the geochemical signatures in the area, an orientation sampling was carried out. These samples were mostly taken from the stream branches corresponding to the igneous intrusive mass and some also from the branches pertinent to volcanic rocks with a sampling density of 6 samples per 1km^2. The appropriate precautions such as the intersections of the stream branches, distribution and number of samples with respect to stream basin were also considered. In total, 144 stream sediment samples especially from silica and clay components were collected and sieved up to -120 mesh for the analysis of As, Au, Ba, Bi, Cd, Ce, Co, Cr, Cu, Hg, Mo, Pb, Sb, Sn and W. The Au, Pb, Ag, Sn analyzed using the emission spectrograph (Es) and Hg, Bi, Sb, As by

Atomic fluorescence (AF) where as polarography (POL) adopted for Mo, W; atomic absorption (AA) for Cd and other elements and oxides analyzed by ICP-OES method in Karaj applied research center.

2- MATERIALS & METHODS

2-1- Application of SOM in Geochemical Pattern Recognition

In order to evaluate the performance of the proposed method for pattern recognition of geochemical data in the area, the spatial variables and geochemical elements were considered as input neurons, whereas the partition of input vectors into clusters were presented as output neurons in the mapping space. Every input neuron is connected to every output neuron with weighted links. For assessing the geochemical distribution patterns and vectoring exploration targets in the area, five steps were undertaken. At first, all variables were standardized between (0-1) based on the Z-score. Considering that, the optimal number of clusters is not known from the beginning of data analysis, therefore, clustering based on SOM was carried out independently and each time by taking a number of different classes. In the second stage, the data was divided into training and testing data. Then, organizing of the nonlinear relation between geochemical data in patterns was made based on Self- Organizing Maps (SOMs) (Figure 2). Accordingly, K-means clustering technique [59] was employed to classify the SOM topography into related conceptual models. Finally, the geochemical distribution model was constructed to illustrate the nature and origin of the surface expression of mineralization in the area. The topology of the employed SOM network is presented in Figure 2, which was designed in MATLAB R2013a software. According to [17], during the process, the algorithm provides a projection of the multi-dimensional data into a two-dimentional map and preserves the topology of this input data space. The presented SOM was trained with different numbers of map units and the optimum map size was selected based on the R-Squared(RS) index (Figure 3). The RS index measures the dissimilarity of clusters and has the values from 0 to 1 where 0 shows there are no differences among the clusters and 1 indicates significant differences among them [7]. Noted that, if the resulting map size is small, it might not explain some important differences in the data that should be detected. In contrast, if the map size is too big, the differences are too small [59]. Considering the above mentioned context, the results of SOM performance on the data are presented in Figures (4 to 8) and the optimal distribution pattern of each element was shown in six main clusters.



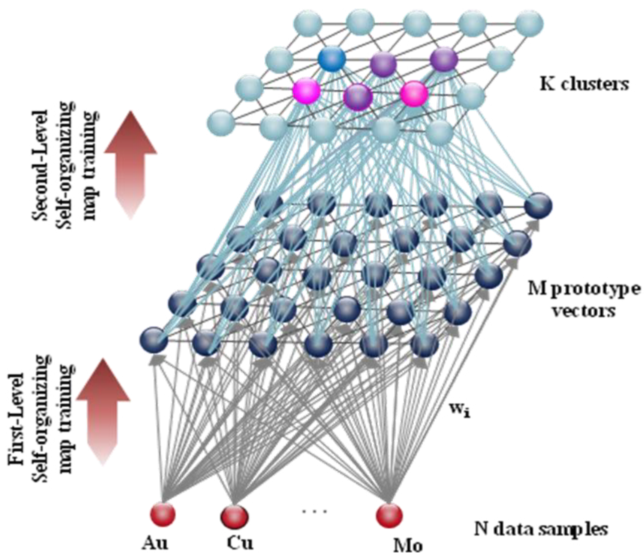


Figure 2. Topology of SOM network for geochemical pattern recognition in the studied area

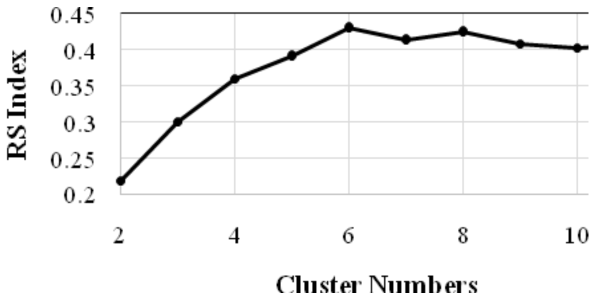


Figure 3. RS Index variations based on the number of clusters in the data

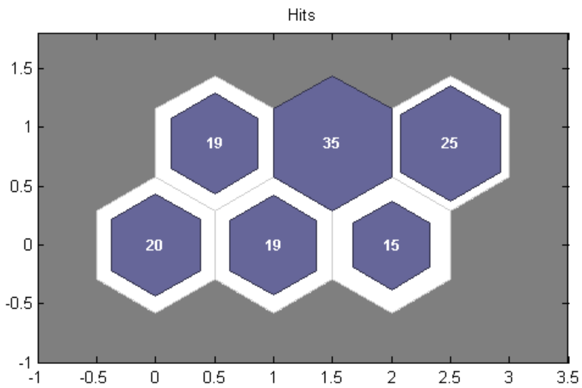


Figure 4. U-matrix representation with white hexagons sized proportional to the number of input samples falling on the each node

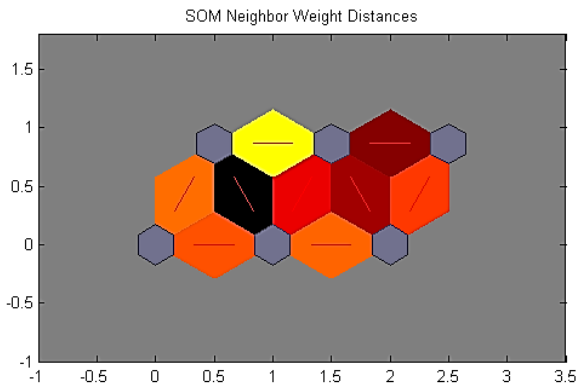


Figure 5. The color-coding of the nodes

Ultimately, the model-based clustering and Hierarchical Cluster Analysis (HCA) results were compared. Based on clustering accuracy and capability of the implemented methods in discriminating optimal geochemical pattern, the best option was proposed.

HCA is one of the most popular techniques of multivariate statistics. Its purpose is to classify a dataset into groups that are internally homogeneous and externally isolated on the base of measuring the similarity or dissimilarity between groups. It first computes the distance (similarity) between all pairs of objects, then ranks the groups by their similarity and finally creates a hierarchical tree visualized as a dendrogram [60]. There are numerous algorithms for calculating the distance between data vectors that here, the Pearson algorithm was considered in this study (Figure 8). In order to implement the R-mode HCA on the data, all geochemical stream sediments samples that control the lithology and environments was undertaken. Normally, the area geological anisotropy controls the optimal number of groups, which are to be generated. The greater the geological anisotropy, the higher the number of clusters.

3- RESULTS AND DISCUSSIONS

In order to demonstrate the effectiveness of the proposed model-based clustering method, the performance of the SOM algorithm on discriminating geochemical distribution patterns was tested the relevant results are presented in Figures. (2-7). Based on the SOM visualization (Figures 4-5), the data were classified into six clusters associated with the specific geochemical behavior. Figure 4 presents “unified distance matrix” U-matrix [61] which indicates the closeness between adjacent nodes on the map and Figure 5 shows a color-temperature scale where the cooler colors separate adjacent nodes that are closer (similarity) and the hotter colors indicate larger Euclidean separations (difference).

Concerning the optimal number of clusters, it is essential to express that the number of clusters depends on the precision, interpretation overview and the discrimination quality of clusters. Generally, with an increasing cluster number,

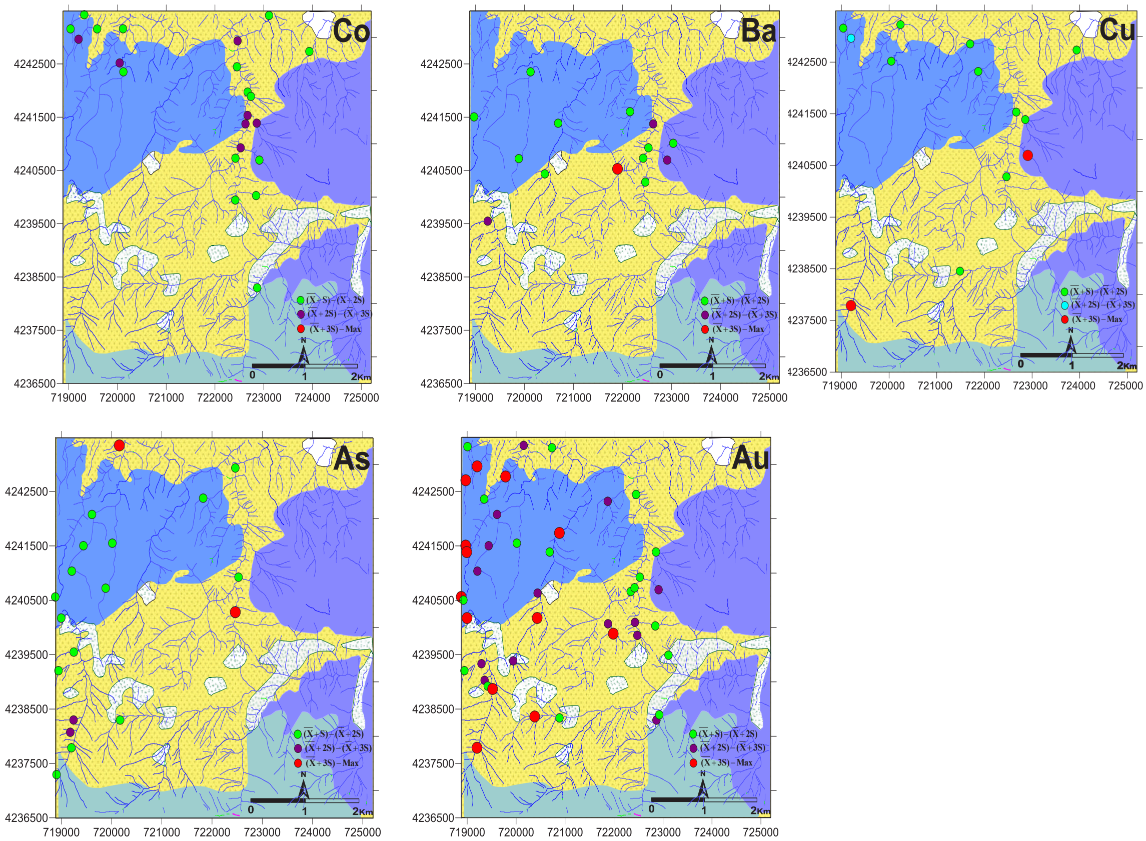


Figure 6. Geochemical distribution pattern of elements in the first cluster (Cu, Co, Ba) and second cluster (Au, As) based on the SOM method

Table 1. The statistics of elements in different clusters derived from SOM

	Au	Pb	Ag	Sn	Hg	As	Sb	Bi	W	Mo	Ba	Ce	Co	Cr	Cu
Class 1	0.0035	12.8	0.12	3.0	0.050	7.4	0.55	0.18	1.93	3.10	711.87	143.07	30.55	97.79	90.31
Class 2	0.0113	18.3	0.12	2.9	0.085	13.3	0.84	0.28	2.32	3.00	687.25	96.52	19.62	71.41	58.79
Class 3	0.0025	22.3	0.13	3.2	0.081	11.8	1.51	0.58	4.55	3.36	548.22	139.26	19.03	104.81	57.46
Class 4	0.0019	13.9	0.10	2.4	0.058	8.0	0.52	0.20	2.51	4.21	475.69	268.70	21.64	132.75	62.41
Class 5	0.0027	17.7	0.13	3.2	0.053	6.7	0.61	0.22	3.24	3.82	615.57	222.12	17.78	79.65	56.09
Class 6	0.0066	27.2	0.14	3.7	0.051	8.3	0.93	0.51	7.11	5.03	453.39	188.28	13.31	75.60	58.41

the precision and the separation quality increase, whereas the overview decreases. Also, when the cluster numbers become too large, the overview of them gets lost [62]. In this respect, the separation quality is controlled by the RS index (Figure 4). Accordingly, the next interpretations were performed assuming an optimal pattern with six clusters on the data. Table 1 illustrates the average concentration of different elements in clusters where the important concentrations of elements among the six clusters have been marked by gray color. Therefore, it can be said that, the enrichment of which elements are significant in each of the clusters.

Subsequently, Figures 6-7 show the elements distribution pattern, which provides a proper context for interpreting the geochemical expression of mineralization by characterizing the principal factors influencing elements distribution in the area. The associated elements with cluster 1 are extended from N to NW of the region and to some extent located in the central part of the studied area marked by enrichment of Ba, Co and Cu elements (Figure 1). This part is mostly associated with igneous intrusive mass varying from quartz monzonite, granodiorite.

The 2nd cluster has been located in the center and northwestern part of the studied area (Figure 6) and contains the anomalies of Au, As, Hg and Ba elements. This part includes mostly trachyandesite and trachybasalt along with tuffite. There is a relatively good compliance between the anomalies and the position of points in the second and sixth clusters. In addition, the 6th cluster has expanded in the south and southwest of the studied area (Figure 7) consisting of monzonite, quartz-monzonite and granodiorite rocks. According to Table 2 and Figure 7, W, Sn, Pb, Mo, Ag elements show significant anomalies in this cluster. The geochemical distribution pattern of Ag in the cluster is related to its higher mobility in the absence of Cl and then the creation of its extensive halo in secondary environments.

It seems a small locally enrichment of Au has occurred during the igneous intrusive mass into the volcanic units of the area causing huge amounts of heat for reactivation and remobilization of volcanic associated elements to re-localize and re-concentrate the Au.

The distribution pattern of Pb, Sn, Ag, Mo, Au, Bi, Sb, and W in the 6th cluster is shown in Figure 7. The enhancement of their anomalies, except for Sn, is strong in the sixth cluster and has a south-southwest trend.

Paragenetic sequence of elements, which were explained in different clusters, has been presented in Table 2. Accordingly, in the first cluster, the group of Ba, Co and Cu reflect ore-forming elements associated with the base metals. The distribution pattern of Cu is controlled by the average effect of its concentration in the secondary environment dominated by presence of Ba in the surface indicating lack of weathering and erosion level and most probably the mineralization at depth. In this group, Ba is an element with higher chemical activity, higher mobility and low mobility and low temperature with hydrothermal supra ore behavior. This element indicates the activity of hydrothermal solutions in the area and it is entered into aqueous environment during the reaction between water and rock. A mentioned, the presence of Ba indicates a lack of higher erosion in the area.

The explained elements in the second cluster comprises of As, Hg, Ba, Au elements which expressing the relative enrichment of Au and the relevant trace elements. No significant dispersion characteristics of Cr, Ce and Co elements were observed in the fourth cluster possibly due to their relevance to syngenetic effects of lithology. The enrichment of the oriented elements in the sixth cluster indicates the geochemical system of Ag, Mo, Pb, Sn, W, Au, Bi, Sb that are associated with the acidic solutions resulting from the penetration of igneous masses into the acidic volcanic rocks of the area.

In order to evaluate and confirm the results of SOM in geochemical pattern recognition, it was attempted to compare its performance with the results of hierarchical clustering Analysis (HCA) in the area (Figure 8).

3-1- Identifying Distribution Pattern of Geochemical Samples in Valezir Area of Meshginshahr using Hierarchical Clustering Analysis (HCA)

Multivariate statistical methods can be responsive to issues such as genetic relationships

Table 2. SOM based clusters and their pertinent elements

SOM -based clustering	SOM -based clustering
Cluster 1: Ba, Co, Cu	Cluster 4:Ce, Cr, Co
Cluster 2: As, Au, Hg, Ba	Cluster 6: Ag, Mo, Pb, Sn, W, Au, Bi, Sb
Cluster 3: Bi, Sb, As, Cr, Hg	-

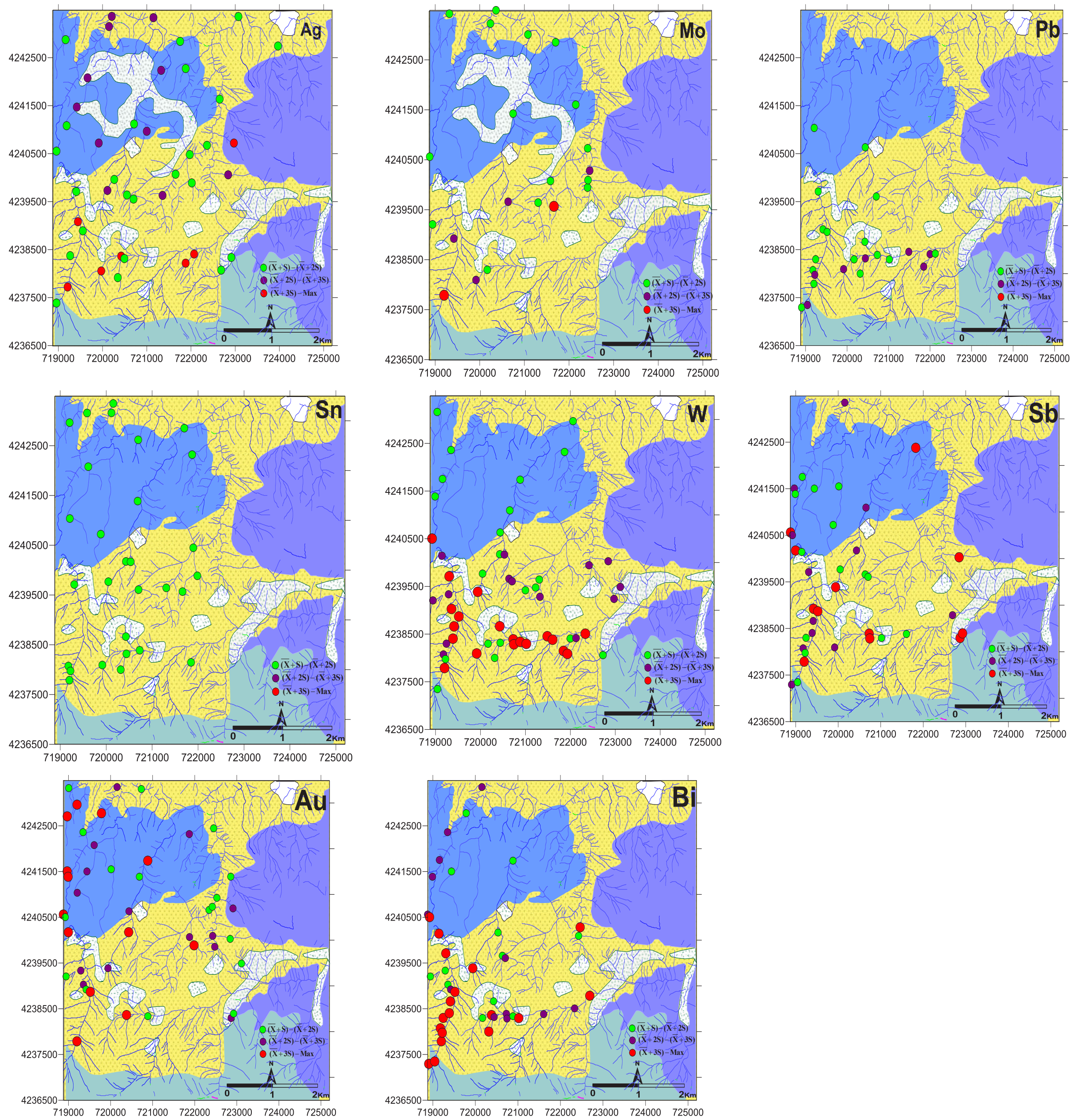


Figure 7. Geochemical distribution pattern of the elements justified in the sixth cluster based on the SOM method

between elements and the more accurate knowledge of changes in geochemical environments. In these statistical methods, due to the fact that the random errors of a variable can be controlled to some extent by other variables and this can be effective and useful, especially in reducing abnormal errors in data analysis and lead to more realistic inferences. Therefore, multivariate statistical inferences are more reliable [2,6,63,64]. Researches have also shown that if a combination of values of a group related to indicator elements is used instead of the value of a special element, in this case, favorable areas and geochemical halos around the ore deposits are more intensely enhanced. In addition, the effects of their random errors are also minimized and the uncertainty related to the location of exploration targets will be constrained. So, in this study, it was attempted to apply

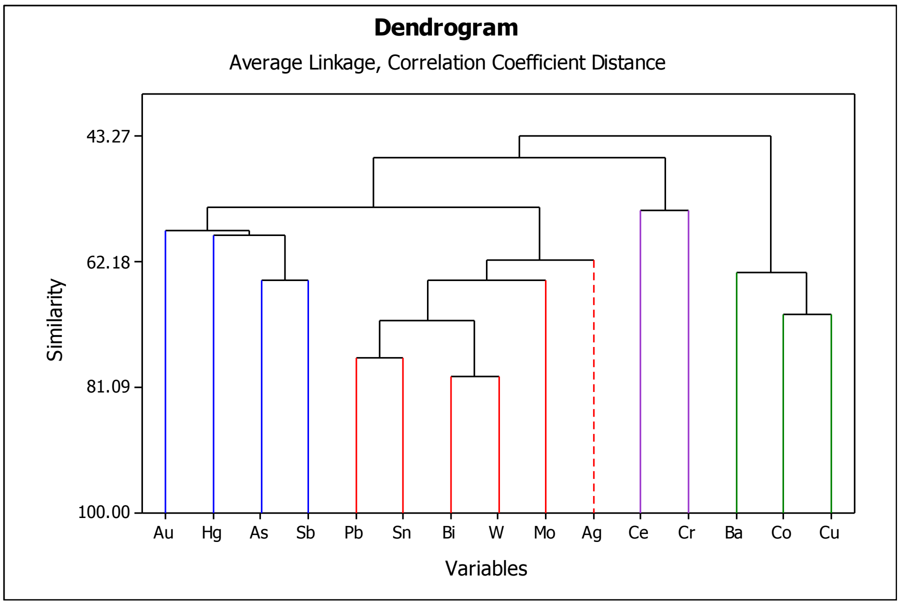


Figure 8. Dendrogram obtained from the Hierarchical Clustering of elements in the studied area

Hierarchy Clustering Analysis (HCA) as a most common multivariate statistical method which has remarkable ability in recognizing elements distribution pattern and identify the epigenetic components [6,8,65,66]. In this respect, the most reliable cluster structure, which was compatible with geology, geochemical characteristics and paragenesis of minerals in the study area, was extracted. The resulting dendrogram is depicted in Figure 8 that displays some of the important sets of clusters.

1. The geochemical system of Bi, W, Pb, Sn, and Mo that are associated with acidic rocks and it seems that in both of the clustering methods, Mo is not only distinct from Cu, but also its accumulation has been mostly affected by acidic solutions.
2. The group of As, Au, and Sb are related to Au local enrichment.
3. The group of Ba, Co, and Cu are affected by hydrothermal solutions and are mostly concentrated in the north of the area.
4. Cr and Ce elements distribution were influenced by lithology and syngenetic effects.

Comparing the results of two above mentioned clustering methods reveal the appropriate compliance of them but the higher capability of the SOM method in geochemical pattern recognition (Tables 3 and 4). Given that, this method does not require initial assumptions about the number of samples and variables, the distribution of data and their normalization, or the linear relationship between elements [49]. Therefore, this would simplify the problem and constrain the uncertainty in detecting appropriate patterns and save time. Furthermore, the identification of major alteration minerals in the area was carried out using remote sensing. Given that, ASTER images of the Valezir area were cloudy, so that, ETM^+ images were employed for this purpose (Figure 9).

Well correlation of the ore-related elements patterns resulted from SOM with the major alteration zones containing Fe-bearing and clay minerals in the area shows that most of the major anomalies trend correspond to iron minerals in the northwest-southwest direction (Figure 10).

4- CONCLUSIONS

In this paper characterizing the distribution pattern of elements for a large volume of geochemical data have undertaken by the SOM method. The method could preserve the inherent

Table 3. SOM and HCA performance evaluation based on external indexes

Algorithm	Rand index	Jaccard coefficient	Fowlkes-mallows index	Adjusted rand index
SOM	0.59	0.53	0.63	0.13
HCA	0.56	0.54	0.65	0.04

Table 4. SOM and HCA performance evaluation based on internal indexes

Algorithm	Davies-bouldin index	Silhouette index	Dunn index	R-squared index
SOM	0.57	0.95	0.6	0.39
HCA	0.65	0.96	0.5	0.45

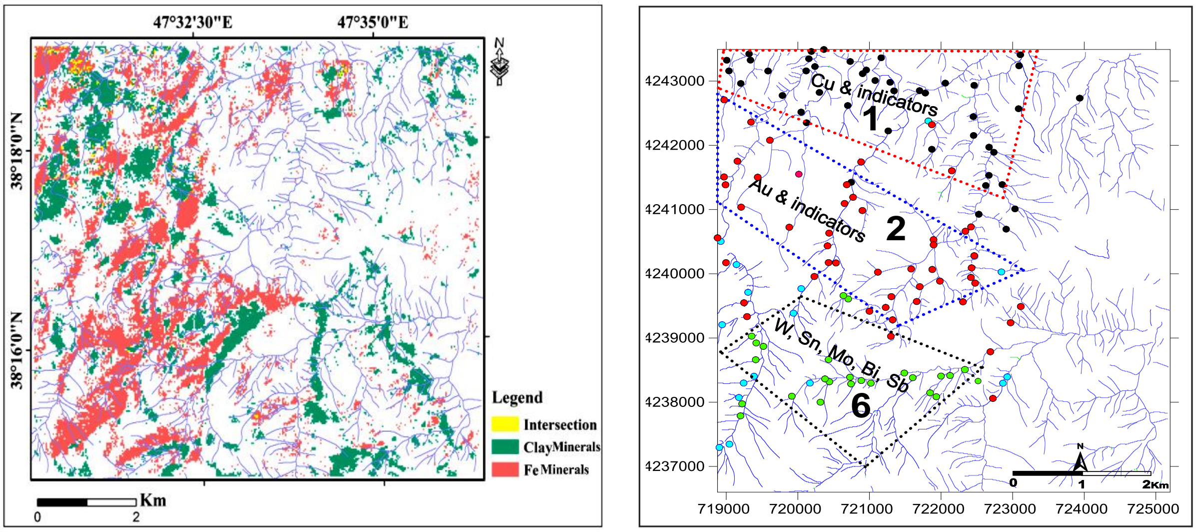


Figure 9. The affiliation of elements to specific clusters (1,2 and 6 of the Table 2) discriminated by SOM method and their compliance with the alteration of the area resulted from remote sensing

nature of the data and discriminate them in three distinct geochemical patterns. The clustering of the data was carried out by different architectures, which lead to identify an appropriate structure based on RS index. Overall, six clusters were selected as the optimal pattern. Out of which two important clusters emerged to be ore-related. These series include the Cu and its related pathfinders and the Au series along with associated elements. The summary of the clusters derived from SOM illustrate that the 1, 2 and 6th clusters are important mineralization trends. The first cluster comprises of Cu mineralization along with Ba and Co. The presence of Ba may suggest lack of higher level of erosion in the area and reveals the potential Cu mineralization at depth. Cu concentrations are confined to the northern part of the area in compliance with the quartz-monzodiorite intrusion. The significant concentration of 90ppm Cu in the first cluster is noticeable in spite of the higher average effect of the second environment. The lower concentration of Au and relevant pathfinders are manifested by second cluster. This strongly recommends at least two distinct phases of mineralization for (Cu & Au) in the area. The Au anomalies and its pathfinders (Bi, Sb, As, W) are rarely associated with intrusive but mostly accompanying with volcanic rocks. The Au concentration seems to have occurred during the intrusion of igneous body into tracky-andesites of

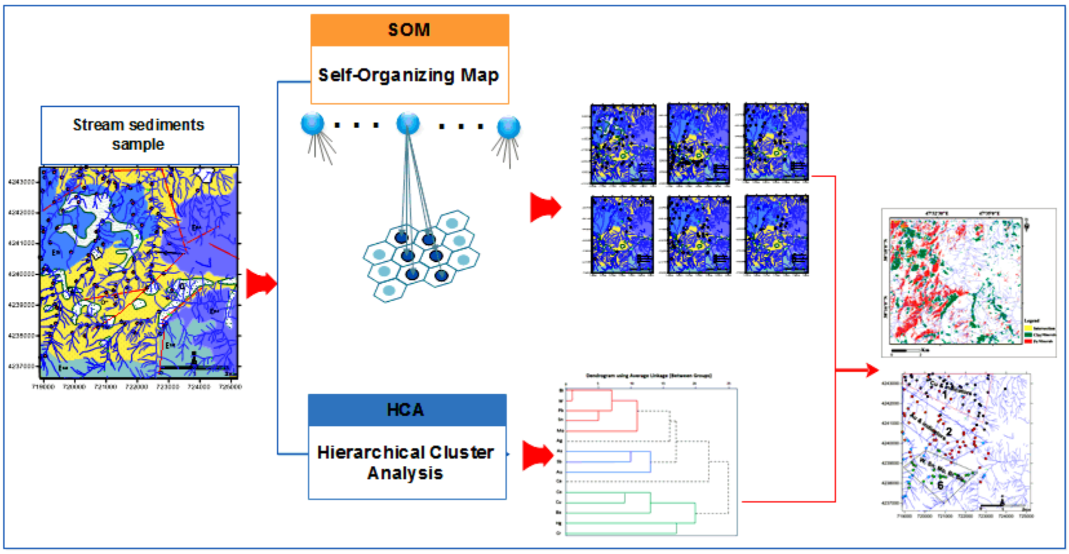


Figure10. Stepwise optimization of geochemical pattern recognition in the Valezir area, based on SOM and HCA methods

the area that caused the alteration, remobilization and relative enrichment of Au and pertinent indicator elements.

In order to assess the results of the SOM-based clustering, comparison was made with the results of the hierarchical clustering analysis (HCA) that revealed well correlation among the results of the methods and favorability of the area for Cu mineralization.

This study suggests the higher capability of SOM method in identifying elements association and its competence for optimal discriminating of paragenetic sequence. The method preferably could divide the area into zones with elements of similar behaviors. The clean ore-related clusters based on SOM enable the exploratory planning for various purposes and reduce uncertainty, leading prospecting programs to more reliable promising areas with higher accuracy and precision.

5- ACKNOWLEDGEMENT

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