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Using the innovative method of Cellar Weight Base Association to identify potential areas for gold exploration in Mahallat, Iran

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ABSTRACT Mineral potential modelling and identifying promising areas are among the most important stages of preliminary exploration. Cell-Based Associations (CBA) is one of the recent and innovative mining processes in this regard. Designing the new method of Cellular Weight Based Association (CWBA) was initially based on the weight-cell weighting of maps. In this study, implementing CWBA on the 1:100,000 geological maps of Mahallat resulted in identifying and introducing promising points for gold mineralisation. For this purpose, we integrated three information layers of tectonic, geological data and remote sensing related to the pre-exploration of the Akhtarchi gold mine and considering Akhtarchi mine as the control. According to the results of the CWBA method, although all data in the present study are related to 2002-2005 when no mines were discovered as an anomaly, the anomalies overlap with the existing mines.

Key words: gold mineral potential map, CBA, CWBA, remote sensing, Iran.

1. Introduction

Combining information entails putting together the results of several different methods to reduce errors and increase the accuracy. Since various mineral exploration methods are constantly evolving, and given the increasing volume of data owing to the introduction of new technologies compared to the past, the requirement to combine information is further desired to increase the level of trust in exploratory data. Moreover, considering the high costs of the mining sector, the more accurate and complete interpretation of different data from several sensors will lower exploration costs (Tokhmchi *et al.*, 2016).

One of the uses of information combination is preparing mineral potential maps to identify the potential areas for detailed exploration operations. Today, different methods are utilised to prepare mineral potential maps that are generally developed in three types of knowledge-driven, data-driven (Mortier *et al.*, 2017), and hybrid methods (Bonham-Carter *et al.*, 1989; Carranza, 2008). In addition to data-driven, knowledge-driven and hybrid methods, various others have been utilised in mineral potential detection, such as Hierarchy Analysis (AHP), AHP-Fuzzy, and TOPSIS, as well as their combination (Pazand *et al.*, 2011, 2012; Abedi *et al.*, 2013).

The Cell-Based Associations (CBA) method has recently been introduced as a new concept for mineral potential detection. In this method, along with the information in each place, the adjacent information is also considered for the potential search. In this technique, the areas are considered with the mineralisation potential where a set of lithology units (for example) or alteration are placed next to each other and the presence of one unit alone is not sufficient to be considered as the exploratory target (Pakyuz-Charrier, 2013).

The Cellular Weight Based Association (CWBA) ranking as an innovative method, can be developed in different areas of mineral exploration with simplicity and understandability. Among the objectives of developing the CWBA are to apply it over a regional scale, produce predictive maps on the same scale, and ultimately integrate the maps to identify the potential points for detailed exploration. Moreover, by altering the details of the method and utilising new hypotheses about different geological, geochemical and geophysical data, new dimensions can be developed to prove the efficiency of this technique as a comprehensive method in different parts of exploration.

In the present paper, while reviewing this method, the innovative CWBA method is introduced and its utilisation is considered for geological and remote sensing of the area in the 1:100,000 sheets of Mahallat; ultimately, potential and high potential areas are identified.

The study area is limited by the coordinates 33°30’ to 34°00’N and 50°00’ to 50°30’E in the south of the Markazi province in Iran (Fig. 1).

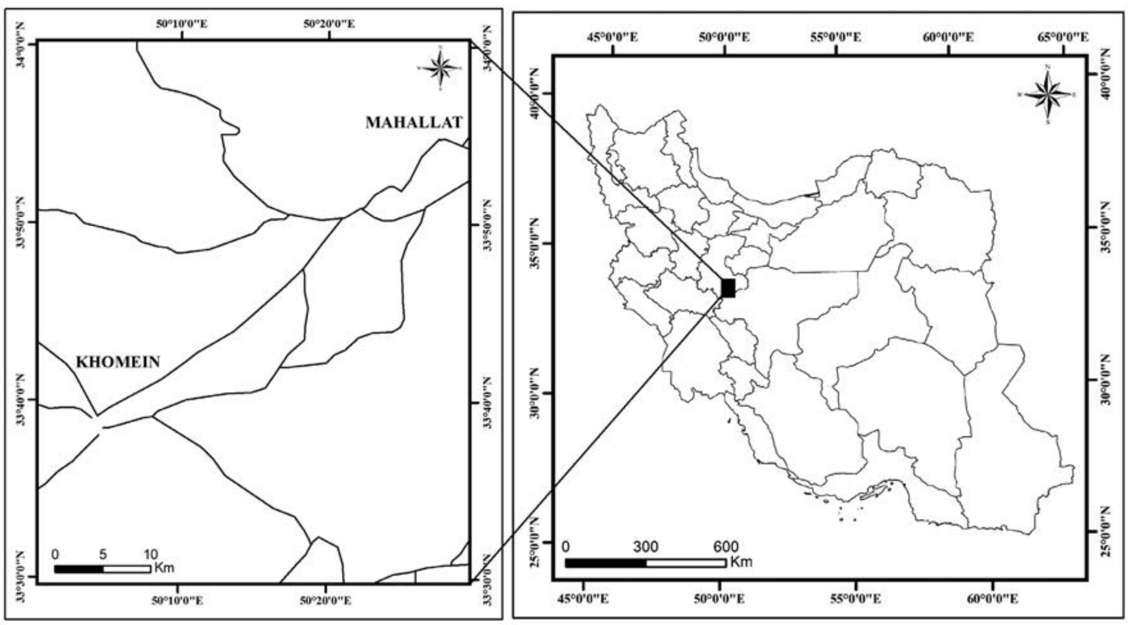

Fig. 1 - Location of the study area.

2. Fundamentals of the CBA and CWBA methods

In this research, the information of each of the three geology and remote sensing layers is first prepared separately. Next, all three layers are gridded in ArcGIS 10.5, and then modelled in the MATLAB environment based on the CWBA.

The CBA method is principally based on mapping the desirable mineral areas where the points represent the minerals occurrence and the polygon shows the geological units (lithology). The relationship between intracellular changes of the network and its size in the data set was studied to determine the optimal size for a cell. The variable is estimated using two parameters:

1. the average number of geological units per cell;
2. the number of lithographic spectra created by 'cutting' the maps with networks of different cell sizes (Tourlière *et al.*, 2015).

One of the objectives of developing the CBA is to use it on a regional scale, produce predictive maps on the same scale, and, finally, integrate the maps to identify potential points for detailed exploration. By changing the details and using new hypotheses about different geological, geochemical and geophysical data, it is also possible to develop new dimensions in using this technique as a novel CWBA method and prove its efficiency as a comprehensive technique in different exploration sections.

The calculations rely on the non-correlation index based on 'percentage difference' (Eq. 1) and a cumulative function in terms of the Cross Neighborhood Community Network (de Rham, 1980), after centring and reducing the data (Tourlière *et al.*, 2015):

$$dP(I_i, I_j) = \frac{number\ of\ (x_{ik} \neq x_{jk})}{k} \tag{1}$$

where *i* and *j* are the indexes of the compared elements of *I*, *k* denotes the variable (geological unit) index identifier, *x* represents the value of the variable and *K* is the number of variables (number of units).

Such an asymmetric function is utilised for discrete type variables and estimating the distance between elements. However, the usual Euclidean distance (Eqs. 2.1, 2.2, and 3) can be used in special cases:

$$dE(I_i, I_j) = \sqrt{\sum_k (X_{ik} - X_{jk})^2} = number\ of (x_{iK}) \neq (x_{jK}) \quad \forall x = \{0,1\} \tag{2.1}$$

$$dE(I_i, I_j) = \sqrt{\sum_k (Y_{ik} - Y_{jk})^2} = number\ of (y_{iK}) \neq (y_{jK}) \quad \forall y = \{0,1\} \tag{2.2}$$

$$dE(I_i, I_j) = dp(I_i, I_j) * K \quad \forall X = \{0,1\} \tag{3}$$

where *i* and *j* are the indexes of the compared elements *I* (cell), *k* is the identifier of the variable (unit), *x* represents the variable, and *K* is the number of variables (units).

As previously stated, in the CBA, only the presence or absence of a formation in the cell is determinant; however, in the CWBA, the importance of the unit, the amount of the unit, and the length of the faults in each cell affect the cell value. Thus, the following changes were made in the above equation.

X and *Y* in Eqs. 2 and 3 can be calculated as follows:

$$X = F(x) = \frac{\sum(x_i * A_i)}{a \times b} \tag{4}$$

and

$$Y = F(y) = \frac{\sum(y_i * L_i)}{\sqrt{a^2 + b^2}} \tag{5}$$

where *a* and *b* are the length and width of the cell and x_i is the geological unit in the cell and y_i represents the fault in the cell, A_i shows the area of each geological unit in the cell and L_i is the related fault in each cell.

Since the selection of Euclidean distance is optional, it can also be calculated in other ways (for instance, from the Manhattan distance). The cumulative factor for classes is the class with the least variance.

The process produces a binary hierarchical grouping of the features of each element in a class. The quality of such grouping is constantly decreasing by reducing the number of classes.

Moreover, the CBA is currently used only to prepare a geological potential map. However, attempts have been made to prepare the CWBA for other stages of exploration such as geochemical data, remote sensing, and then combine the data to represent the potential areas.

3. Application to the Mahallat study area

3.1. Gridding and preparing the information layers

First, the entire study area was gridded through Arc Map software. The design of the dimensions of the network is based on the accuracy needed for the exploratory activity and the considered geological map's scale. The larger the network, then, the higher number of units in each cell, the more difficult calculations, and, thus, the lower reliability of the results. On the other hand, the very small dimensions of the network practically eliminate the concept of cellular communication, by making zero lithological diversity. Since the CWBA was designed for the first time, it has major differences with the CBA, the size of the network depends on the number of cells and the average number of geological units in the cell (Fig. 2).

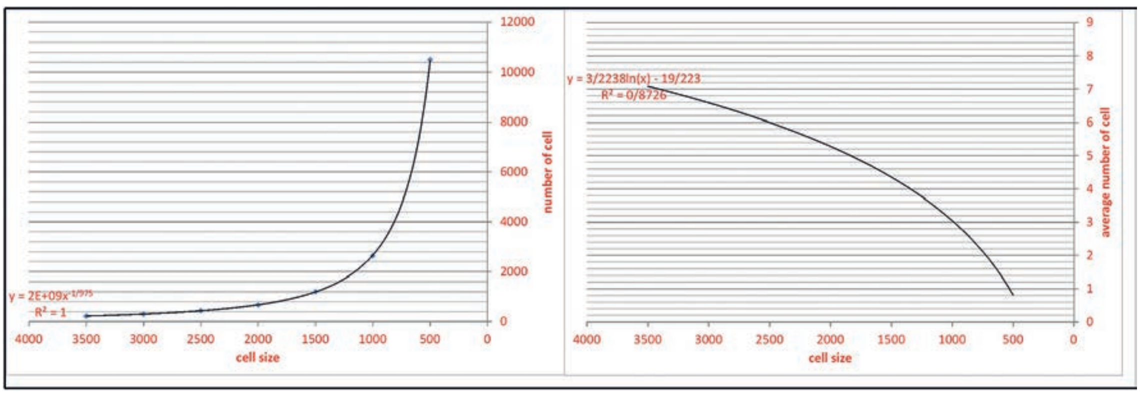

Fig. 2 -Select the dimensions of the cells used. **Title not clear, please specify.**

Thus, the dimensions of the network were selected as 2000 m through trial and error to maintain the necessary lithological diversity within the network. Then, the centre of each cell was selected as the centre of gravity of that cell by gridding. The next scoring steps, in each layer, were focused on the point of gravity, based on which an identification code was assigned to each cell attributed.

3.2. Geological information layer

The study area includes parts of the volcanic-metallogenic province of Urmia-Dokhtar in the north, and the metamorphic strip of Sanandaj Sirjan in the southern half, in terms of the structural divisions of geological zones of Iran. The rock units of the region comprise a sequence of Cambrian to Tertiary rocks with Quaternary sediments, including a significant volume of plutonic and volcanic rocks related to the Tertiary period (Sheikh Al Zamani *et al.*, 2007) that penetrated the generally sedimentary and older volcanic rock units. Under the various plutonic masses with a combination of often granite to granodiorite and quartz monzonite in older units, the occurrence of scattered mineralisation is observed in this area, some of which are currently being exploited as active mines (Sarcheshmeh copper, Chadormalu iron, Mouteh gold). Metamorphic rock units were also identified in the area (Fig. 3), which has been metamorphosed under the early Cimmerian phase to the amphibolite facies (Rashidnejad-Omran *et al.*, 2002).

The shapefile related to the 1:100,000 geology sheet of Mahallat prepared by the Geological Survey of Iran was utilised. The type of rock units has been entirely determined on this scale. Gridding was then prepared for the scoring step (Fig. 3) in the software. This gridding resulted in the creation of 672 squares containing lithological information of rock units.

3.3. Scoring

As mentioned, in the CBA, the presence or absence of geological formations related to the mineralisation is indicated with 1 and 0 (Tourlière *et al.*, 2015). However, in the CWBA method, since the type of geological formations is specified in each cell, each formation with the possibility of mineralisation can be scored. The scoring status is represented in Table 1.

Table 1 - Scoring status of the units.

Scoring	
No mineralisation	0
Very low mineralisation	1
low mineralisation	2
Moderate mineralisation	3
High mineralisation	4
Very high mineralisation	5

Furthermore, in CBA, the area of the formation in each cell does not affect the cell's value, while the area of the considered unit in the cell is also an effective factor in the possibility of mineralisation. Therefore, the area of each formation was included in the calculations in the CWBA method. In addition to the type of formation, the mineralisation can also be affected by the presence of faults. Thus, in the CWBA method, the faults in the area were also assessed considering the effect of the fault's length on the final value of the cell. The status of faults in the area based on geological maps and information obtained from remote sensing is represented in Fig. 4.

A new scoring was performed based on the length of the faults and the type of formation in which the fault is located. The final score was calculated and applied from the sum of geological and technical scores and provided in Fig. 5.

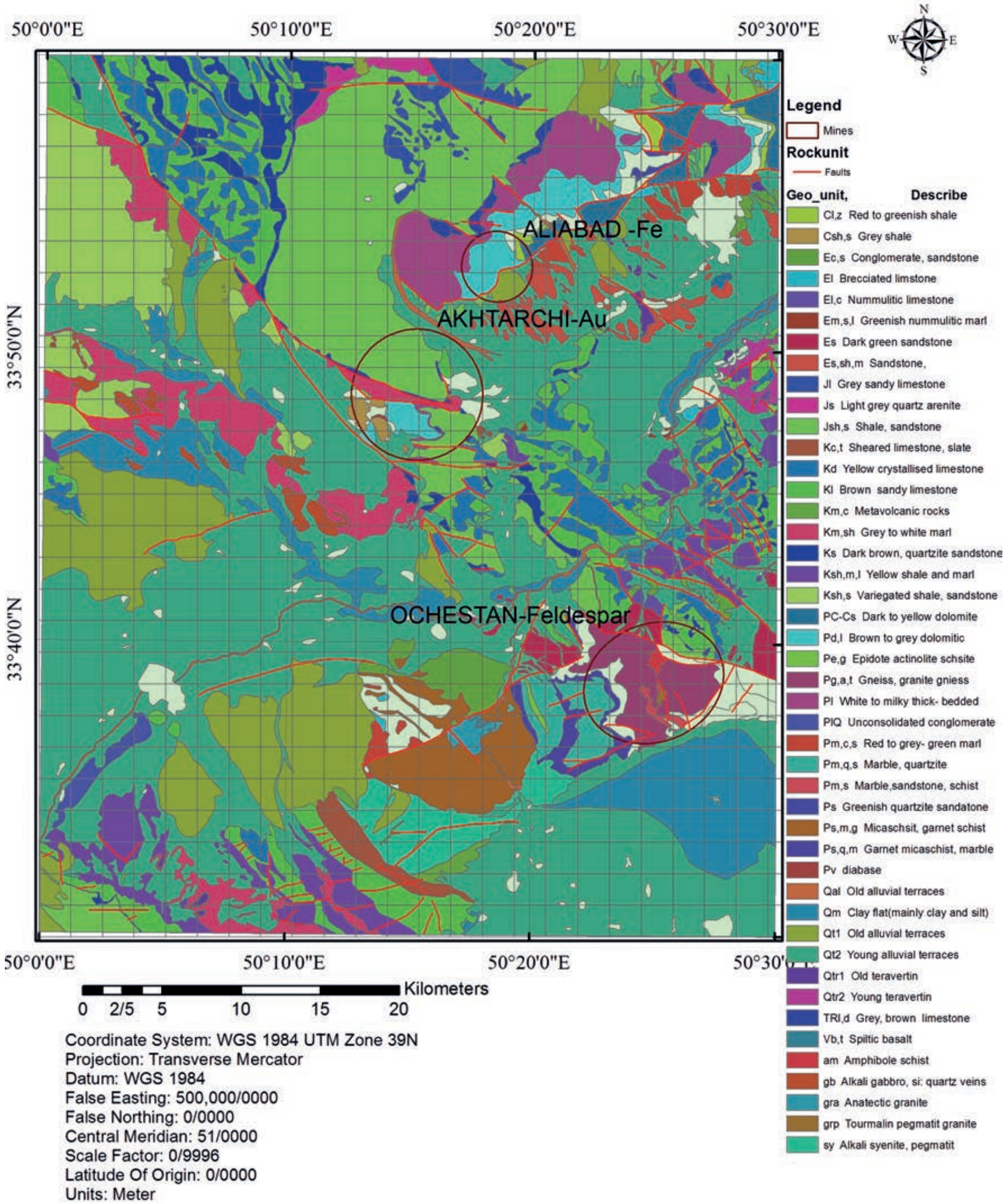

Fig. 3 - Gridded geological map of Mahallat (scale 1:100,000) representing the position and the relationship of different rock units and their position in each square of the network.

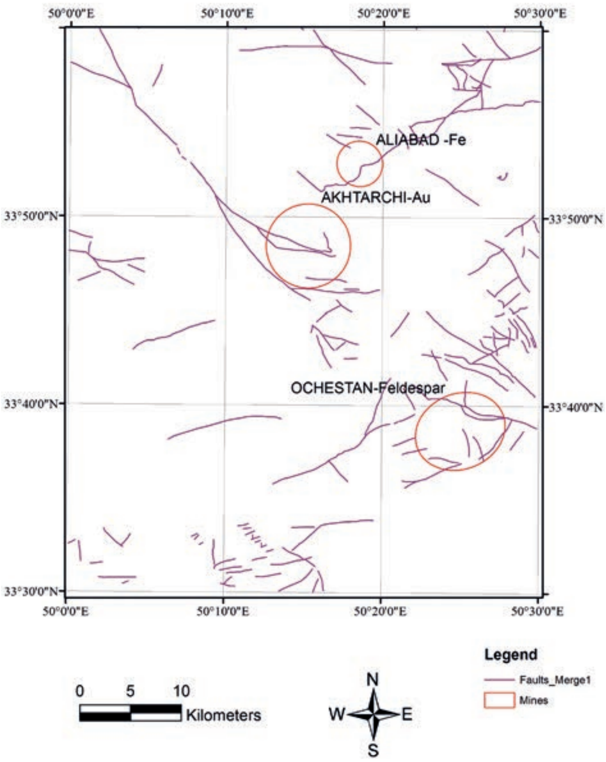

Fig. 4 - Status of faults in the area.

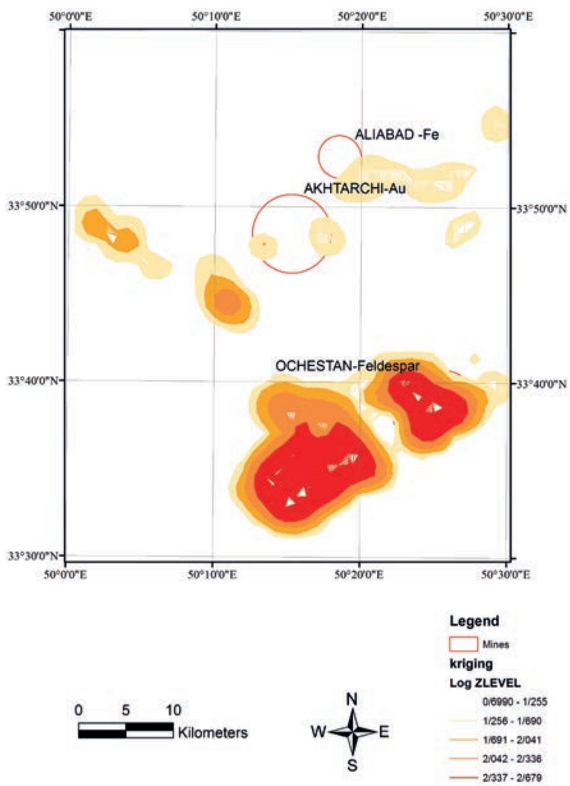

Fig. 5 - The anomalies obtained in the study area.

lithological contours and the identification of the majority of the tectonic accidents derived from the analysis of Landsat satellite data (Nemmour-Zekiri and Oulebsir, 2020).

The application of remote sensing has significant time- and cost-saving benefits as a technological tool for the delineation of iron prospects (Ahmadi and Uygucgil, 2021). Investigation proves that remote sensing can be a cost-efficient and time-saving technique for mineral exploration, and its application in new areas can accurately map hydrothermal alteration and outline potential new exploration targets (Frutuoso *et al.*, 2021).

The image obtained from the RGB468 false-colour combination method is represented in Fig. 6.

In Fig. 6, the areas with propylitic alteration are shown in green, with sericitic alteration in pink, and the areas with argillic alteration are shown in yellow. This is caused by the high reflectivity of alunite, kaolinite, and muscovite minerals in band 4 compared to bands 6 and 8.

4.2. Spectral Information Divergence classification and comparison of different methods

Spectral Information Divergence (SID) is a spectral classification method that uses divergence measurements to match pixels to reference spectra. The lower the divergence, the greater will

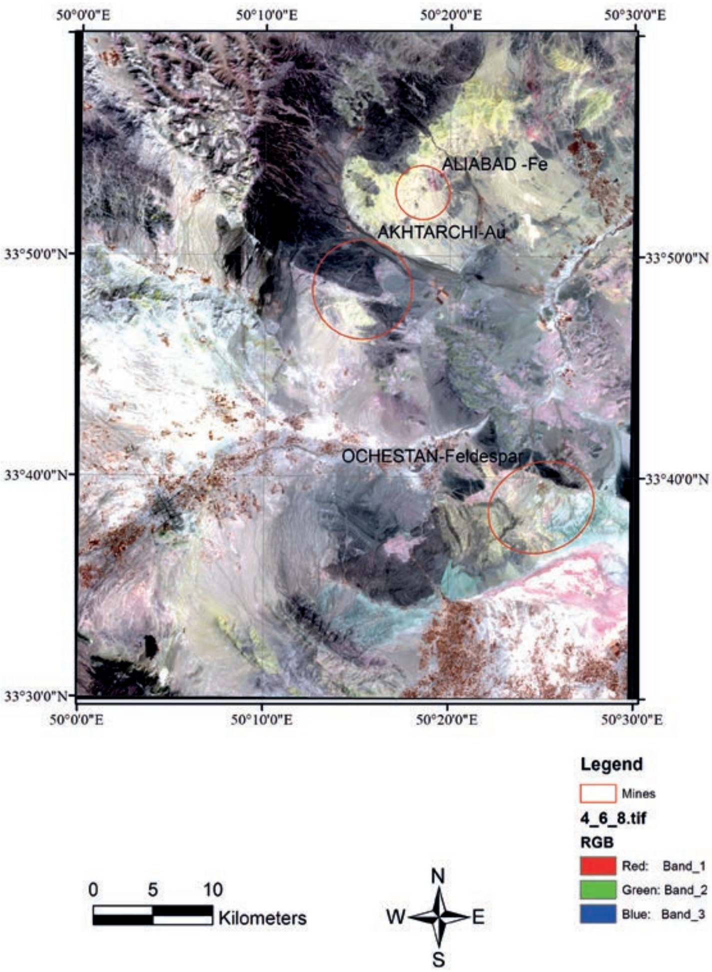

Fig. 6 - Image obtained from the RGB468.

be the similarity of the pixels. The pixels larger than the visual threshold are not classified. The spectrum used by the SID can be obtained from ASCII files or spectral libraries, or extracted directly from an image (Manual of ENVI 5).

To check the status of the results, the important mines related to gold orebodies in the region were identified (Fig. 7) and the current status of the mines was used to verify the results since the satellite data were related to 2001.

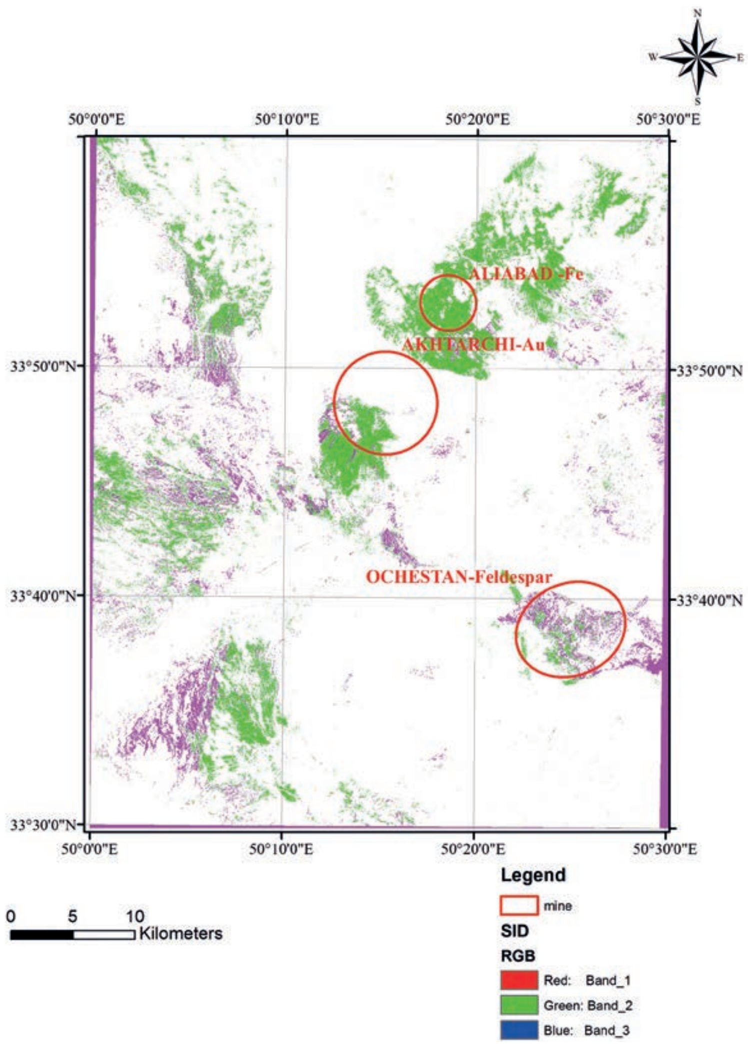

Fig. 7 - Colour image of SID (the green area is propylitic zone and the purple one shows argillic and phyllic zones).

Comparing the maps obtained from various methods used in this research revealed that the accuracy of the SID, Spectral Angle Mapper [SAM: Malekzadeh *et al.* (2009)], Principal Components Analysis (PCA) methods (Crosta *et al.*, 2003), and the combination of SAM and PCA methods is higher compared to other methods (Payamani *et al.*, 2020).

The results of combining SAM and PCA in CWBA methods are presented in Fig. 8 (Payamani *et al.*, 2020).

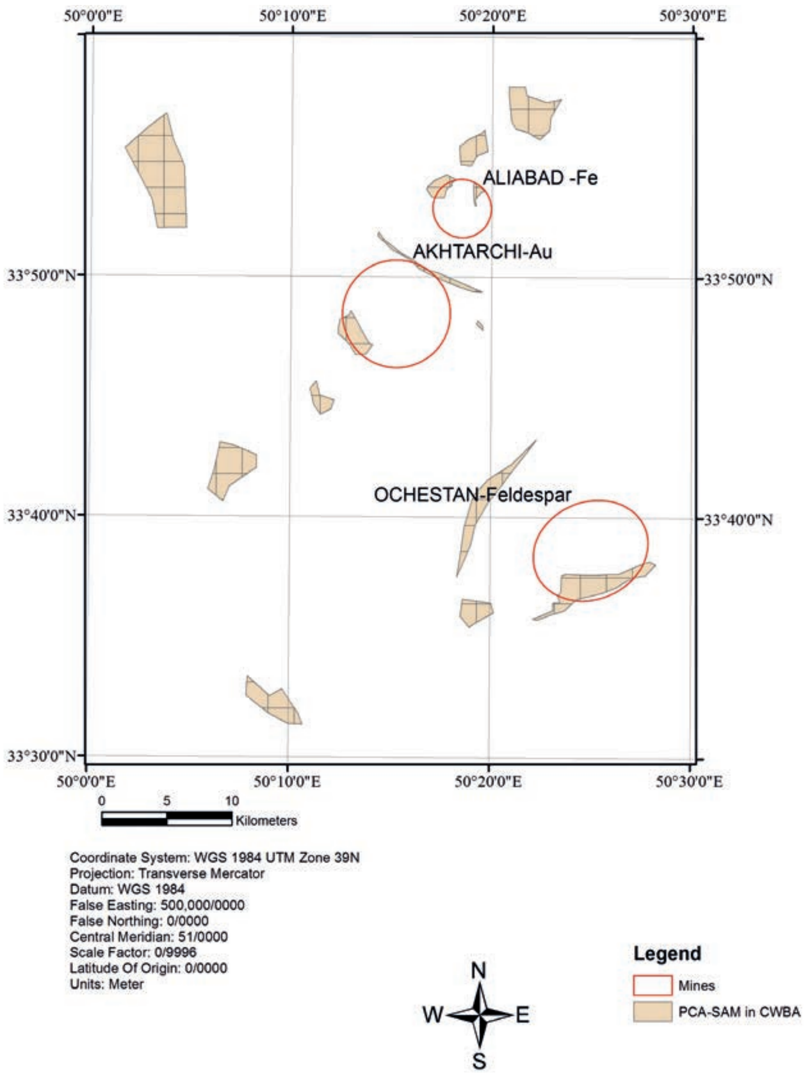

Fig. 8 - Results of combining SAM and PCA in CWBA.

5. Conclusions

The main conclusions of the present study can be summarised as follows:

1. the CWBA method, as an innovative procedure, can be developed in different parts of mineral exploration while being simple and understandable;
2. CBA was used only for geological layers; nonetheless, in the innovative CWBA method, information layers can also be combined in addition to other information layers such as remote sensing information layer and geochemistry;
3. in the CBA method, geological structures do not affect the results; however, a tectonic layer can be formed and combined with other information in CWBA;
4. comparing the maps obtained from various methods utilised in the present research, higher accuracy was found for SDI, SAM, and PCA methods, and the combination of SAM, and PCA methods compared to the other methods;

5. the results of CWBA in the study area indicated that the anomalies overlap with the existing mines, although all our data in this article were related to 2002-2005 when no mines were explored representing, then, an anomaly in this method;
6. the CWBA method was used on a regional scale in the present work, however, it is recommended to use it on a small regional scale.

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