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Research Paper

Clustering of Areas Prone to Iron Mineralization in Esfordi Range based on a Hybrid Method of Knowledge- and Data-Driven Approaches

Agha Seyyed Mirzabozorg S.A.[1], Abedi M.[2*], Ahmadi F.[3]

1- M.Sc Student, School of Mining Engineering, College of Engineering, University of Tehran, Tehran, Iran
2- Assistant Professor, School of Mining Engineering, College of Engineering, University of Tehran, Tehran, Iran
3- Ph.D, Faculty of Mining, Petroleum and Geophysics, Shahrood University of Technology, Shahrood, Iran

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Abstract: In this study, a hybrid approach is established for clustering the most favorable regions in association with magnetite-apatite mineralization at the Esfordi district in the central Iran. An optimum number of clusters is derived from a data-driven methodology through a concentration-area (C-A) fractal model of a synthesized geospatial data set. According to the metallogenic characteristics of the sought deposits, nine evidential layers deriving from geological, geochemical, geophysical, and remote sensing data were extracted. Prediction-area curve (P-A) was used as a data-driven method to determine the weight and importance of those evidences; then an index overlay method integrated them into a single propsectivity map. The number of clusters significantly affects the mineral potential modeling results in clustering algorithms. To determine an optimum number of clusters, the C-A fractal curve of the overlaid map indicated the correct population within this district, and then used as the optimal number to run the unsupervised clustering algorithms. Assuming five clusters, three clustering algorithms, including K-means, fuzzy C-means, and self-organizing map (SOM), were used to identify and localize iron-bearing favourable areas. The K-means algorithm had the highest accuracy in identifying those potential areas, by which 8% of the whole area could predict 65% of known deposits in the main favorable region.

Keywords: Clustering, Esfordi, Hybrid methods, Magnetite-apatite deposits, Mineral potential mapping.

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*Corresponding Author Email: *maysamabedi@ut.ac.ir*

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INTRODUCTION

Prospecting for deep and hidden mineral deposits is still one of the most important and somewhat challenging issues in the exploration and evaluation of mineral resources. The exploration of these deposits always faces many challenges, when geospatial data set (i.e. geological, geochemical, and geophysical indicators) have sophisticated exploratory signitures and even discordance with each other. Considering that, new methods and techniques are needed to map, interpret and integrate diverse geological information in order to increase the success rate and reduce the cost of mineral exploration [1,2].

The purpose of mineral potential map "MPM" is to quantitatively determine the probability of mineral deposits in a given area to facilitate mineral exploration [3]. In other words, mineral potential mapping is pursued with the aim of modelling and prioritizing promising ore-bearing areas for further exploration of undiscovered mineral reserves [4]. To achieve this goal, one of the important steps is to access high-quality and multidisciplinary geospatial data sets, in which a powerful signature of the mineral target is sought [5]. According to the type of the target mineralization, various exploration criteria are considered, including geological, remote sensing, geochemical and geophysical evidence. Therefore, if the evidential layers extracted from the exploratory criteria are properly quantified, the mineral potential map would provide reliable favourable zones [6].

Over the past decade, machine learning methods, which have been implemented to solve classification and pattern recognition problems, have been emerged as promising tools for mineral potential modeling. In recent years, clustering algorithms, which are a prominent class of unsupervised machine learning techniques, have gained attention in mineral potential mapping [7-9]. One of the major advantages of these algorithms is the ability of finding natural and hidden patterns in data to classify them without using labeled training data and to use all the training data without the requisition of validation [10].

In this research, clustering methods such as K-means, fuzzy C-means and self-organizing map (SOM) have been utilized to map the mineral potential at the Esfordi district in the Bafq, central of Iran. The most important step on every clustering algorithm is accurate determination of the number of clusters. The number of clusters has also a significant impact on the final mineral potential model. A data-driven multi-class index overlay method has been used to determine the optimal number of clusters.

MATERIAL AND METHODS

Based on previous geological studies and the conceptual model of deposits related to Kairona type iron, nine evidence layers, which include phyllic, iron oxide and gossan alterations, host rock, lineaments, airborne magnetic and concentration of three geochemical elements (iron oxide, titanium oxide and vanadium), have been extracted from the geospatial data set and used as the most appropriate evidence layers. In this research, knowledge and data-driven MPM methods have been applied in two consecutive phases as a hybrid approach for modeling iron-bearing potential in the Esfordi area.

In the first phase, a combination of fractal-based concentration-area (C-A) [11] and prediction-area (P-A) [12] curves was established to estimate the weight of each evidence layer. Data-driven multi-class index overlay [13] was used to integrate these weighted layers. The different populations of the generated mineral potential map have been separated through the C-A fractal technique. The number of populations obtained corresponds to the number of clusters feeded in the second phase. In this phase, K-means, fuzzy C-means and SOM clustering algorithms have been implemented for mineral potential modeling.

Finally, the success-rate curve [14] has been used to evaluate and to compare the overall performance of synthesized models obtained from clustering and index overlay algorithms.

FINDINGS AND ARGUMENTS

Based on the results of the first phase of the study, the optimal number of clusters was set to five and clustering algorithms were implemented to map all evidence layers into five clusters. In order to depict the performance of each cluster in terms of iron deposits identification, the prediction rates and occupied areas of all clusters were calculated. The normalized density was calculated by dividing the value of the ore prediction rate by the included area, and then, by taking its logarithm, the weight of each cluster was calculated. In the following, the most suitable cluster in each algorithm is determined based on the weight obtained for each cluster.

The K-means algorithm has performed better than other algorithms due to the high weight of cluster number 5. The fifth cluster of this algorithm has high compatibility with geological units of granite, dolomite, and rhyolite (generally with volcano-sedimentary units, and volcanic and intrusive masses) as areas prone to mineralization. These geological units are one of the important indicators of iron mineralization in Esfordi area.

The success rate curve is used to depict the general performance of clustering and index overlay models and their quantitative comparison (Figure 1). By considering the location of the known active mines, this curve shows how successful the mineral potential map has been in prioritizing promising areas. The obtained value of the area under the success rate curve of the data-driven multi-class index overlay model, with the value of 0.88, is higher than the clustering algorithms, which shows the superiority of this method over them. This value equals 0.85, 0.80, and 0.82 for 3 K-means, fuzzy C-Means, and SOM algorithms, respectively. Although this shows the overall superiority of data-driven methods in well-explored areas [13,15], a comparison of the initial part of the success rate curves shows that the unsupervised K-means algorithm has been able to identify more reserves with a smaller area compared to the index overlay method. The K-means algorithm (cluster 5) and the index overlay method have identified 65% and 56% of known Iron and phosphate reserves by 8% of the area, respectively (Figure 1). The mineral potential map extracted from the K-means algorithm is shown in binary form in Figure 2, whose class two corresponds to cluster 5 of this algorithm.

CONCLUSIONS

In this research, a combination of data-driven index overlay and clustering algorithms was used as a hybrid method for modeling the mineral potential map of iron deposits at the Esfordi district. A quantitative comparison using the success rate curve shows the overall superiority of the index overlay method, but the prone areas obtained from the K-means clustering algorithm (cluster 5) have more spatial correlation with iron mineralization, which indicates the superiority of the method compared to other conventional methods. Most occupied areas by cluster 5 of the K-means algorithm are located in the areas where lineaments intersect with iron mineralization host rock and high lineament density. Therefore, it is possible to determine the optimal number of clusters for the implementation of unsupervised clustering algorithms by classifying and identifying the populations of the generated maps.

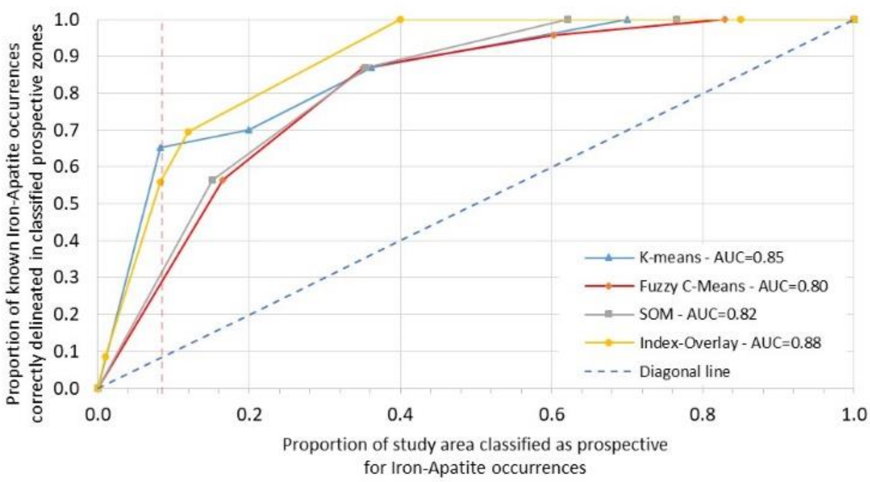

Figure 1. Success rate curves of index-overlay, K-means, Fuzzy C-Means, and SOM models

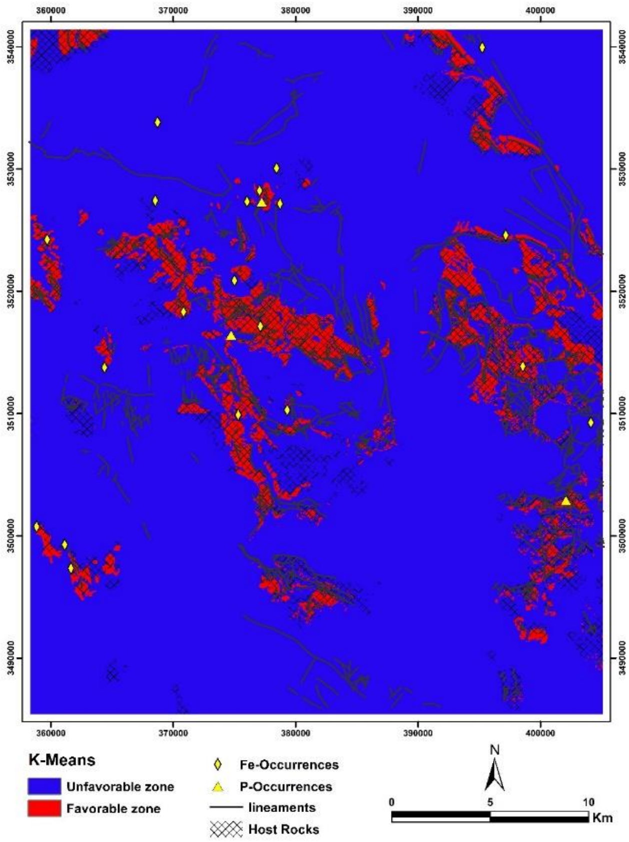

Figure 2. Iron potential map based on the proposed hybrid method

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