



Research article

Mineral potential mapping of porphyry copper using a fuzzy inference system in the Kerman belt

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Keywords

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English Extended Abstract

Summary

The implementation of mineral exploration operations is inherently expensive and time-consuming, often requiring extensive fieldwork, laboratory analysis, and the integration of diverse datasets. One effective strategy for optimizing resources and reducing costs is the application of mineral potential modeling (MPM), which aims to predict areas with higher probabilities of mineralization. MPM can be categorized as an information-driven decision-making process that synthesizes various geoscientific datasets—such as geological, geochemical, geophysical, remote sensing, and alteration data—each offering complementary insights into subsurface conditions. In the present study, a fuzzy-based approach is proposed to model the mineral potential for the exploration of porphyry copper deposits. The method integrates multiple exploration datasets, including geophysical, geochemical, geological, and remote sensing layers. Initially, each thematic map was transformed through a fuzzification process using linguistic variables and trapezoidal membership functions to model the inherent uncertainty and ambiguity in boundary definitions between spatial features. These fuzzified layers were then integrated using a Mamdani-type fuzzy inference system (FIS), which enables the translation of expert knowledge into a rule-based system for predictive mapping. To evaluate and validate the performance of the proposed fuzzy approach, a comparative analysis was conducted using the modified TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, a multi-criteria decision-making technique. Both models were assessed using Prediction-Area (P-A) plots and Normalized Density metrics. The Normalized Density value for the modified TOPSIS approach was calculated as 4, while the proposed fuzzy logic approach yielded a significantly higher Normalized Density value of 6.14, indicating its superior predictive capability. This enhanced performance suggests that the fuzzy-based model not only improves the accuracy of mineral potential maps but also offers greater flexibility for application under various geological scenarios. The ability to incorporate expert knowledge and handle data uncertainty makes the proposed method a robust and interpretable tool for mineral exploration targeting.

Introduction

Most of the surface mineral resources are being depleted as a result of exploring and exploiting mines that have revealed more evidence. Due to the increasing consumption of surface mineral resources over time, which could be identified by simple exploration techniques, more novel exploration technologies should be developed to identify deep and hidden resources that have not left noticeable traces on the Earth's surface

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and, accordingly, respond to human needs in the future.

Mineral potential modeling is among the mining exploration methods that have been increasingly used in recent years. This method involves the process of analyzing, extracting prospectivity patterns, and integrating spatial datasets from different sources in order to identify and rank target areas for exploring unknown mineralization. In mineral potential modeling, target areas are identified by collecting, analyzing, and integrating relevant and appropriate data. These steps are performed to extract spatial data of mineralization evidence (geological patterns, geochemical or geophysical anomalies along with prospected resources, etc.) [1, 2]. The mineral potential model output turns into a map, in which the potential location of unknown resources is predicted. Therefore, the presence/absence of mineralization in a place could be evaluated by developing the mineral potential model. This evaluation could be indirectly performed by finding the relationship between mineralization and evidential patterns and measurable features of the exploratory predictive variables [2].

These steps are performed using data- and knowledge-driven and hybrid techniques.[2] Data-driven techniques are mainly used for regions where necessary, and sufficient exploratory operations have been carried out (brown fields). These regions include a significant number of points with mineral potential or deposits, which are utilized as training points to create spatial associations with specific geophysical, geochemical, and geological features[3].

Data-driven techniques that have been recently used to develop mineral potential maps include weights of evidence[4, 5], logistic regression [6, 7], neural network [8-10], support vector machine [11, 12], random forest [13, 14], and Bayesian network[15]. Knowledge-driven techniques are based upon expert views regarding the significance of factor maps in developing mineral potential maps and are mostly used in modeling regions where few exploratory studies have been conducted (green fields) [16].

The most famous and widely used knowledge-driven techniques include index overlay [17, 18], fuzzy logic [19, 20], multi-criteria decision making [17, 18], Dempster-Shafer theory [21], prioritization methods such as TOPSIS [22], and PROMETHEE [23].

In addition to data- and knowledge-driven methods, there is another group of mineral potential modeling methods integrating data- and knowledge-driven techniques. Fuzzy-weighted evidence[24] and fuzzy-neural network [25] are among the hybrid methods used for developing mineral potential maps. All the mentioned methods have advantages and disadvantages, and are used considering the study area and available data.

This study primarily aims to present a fuzzy inference system-based approach in order to model the mineral potential, improve the results leading to more accurate identification of promising areas, and reduce uncertainty, risks, and exploration operation costs. For this purpose, the existing literature on developing mineral potential maps is first reviewed. Then, the methods and materials, including geological, geophysical, and geochemical features of the study area as well as the basics of fuzzy inference systems, are provided. After proposing the approach, its implementation and mineral potential map development stages are described. In the results section, consistency of the obtained mineral potential map with the real world is assessed by utilizing the study area's known mineral index locations. The used method and obtained results are discussed, and then, a comparison is made with the results obtained from other methods. Finally, the research conclusion is presented, and recommendations are provided for conducting further research.

Methodology and Approaches

Mineral potential modeling includes creating evidential layers, weighting these layers and generating weighted evidential maps, integrating evidential maps and, finally, ranking areas of exploration targets for further investigations in the subsequent exploration stages[26]. The first step to generate a mineral potential map in the studied area is to define and present an exploratory model of the potential deposit, known as a conceptual model, in the area. Defining a conceptual model for mineral deposits explored in the studied area requires data of various types of geological processes associated with mineral deposit formation, along with



the types of deposits being explored[27]. In this research, geological, geophysical, and geochemical evidential maps were integrated to generate MPM of the study area using different methods. For this purpose, MPM of the study area was obtained using 16 different layers as well as modified TOPSIS and fuzzy inference system. The study area, situated in the Urumieh-Dokhtar (Sahand-Bazman) magmatic assemblage (UDMA) arc in central Iran, is part of tertiary and Plio-Quaternary intrusive units extended from the northwest to the southeast. The data related to active mineral indices in the study area were gathered by examining different sources in order to evaluate the research results. In this paper, a fuzzy inference system was used to generate MPM of the study area. The normalized density and P-A methods were used to assess and compare the prepared models. In P-A plot, two curves are drawn against different mineral potential model classes. One curve is related to the prediction of known indices corresponding to the classes of the mineral potential model. The other curve shows the area occupied by each class of the mineral prospectivity model related to the total area of the study area.

Results and Conclusions

In this paper, a fuzzy inference system was used to generate MPM of the study area (as shown in Figure 1). The normalized density and P-A methods were used to assess and compare the prepared models. A normalized density of greater than 1 indicates acceptability of the generated MPM. This parameter is obtained from the ratio of the known indices to the occupied area at the intersection point of P-A plot. The higher the intersection point, the larger the normalized density will be and the better the used method will perform. This value was obtained as, 4 and 6.14 for the mineral potential model generated using modified TOPSIS and the proposed approach, respectively. Considering that these values were greater than 1, these two methods showed an acceptable performance for mineral potential modeling of the study area. The normalized density of the methods used for generating MPM in this research indicated that the proposed approach performed significantly better than modified TOPSIS (as shown in Figure 2). Therefore, this method could significantly reduce exploration costs and risks. It is recommended to examine the effect of assigning different weights to fuzzy rules in future studies in order to integrate evidential layers on MPM.

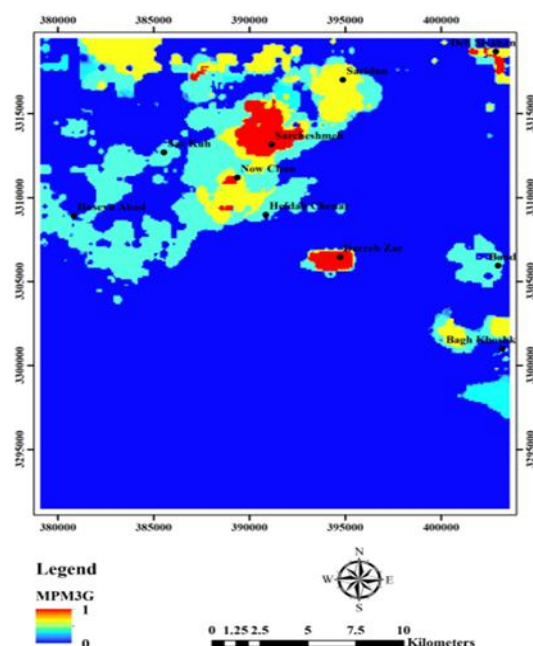


Fig. 1. Generated mineral potential map using fuzzy inference system considering geological, geophysical and geochemical evidential layers by three trapezoidal membership functions.

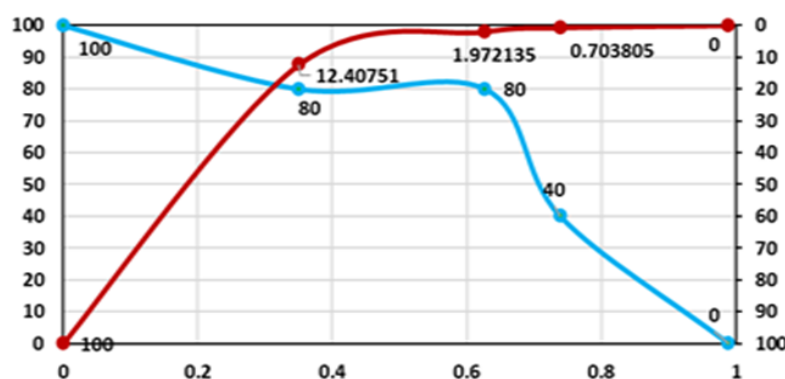


Fig. 2. P-A plot of the mineral potential map obtained using FIS.

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