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Mineral Potential Modeling of Porphyry Copper Deposits using Continuously-Weighted Spatial Evidence Layers and Union Score Integration Method

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Abstract

There are different exploration methods, each of which may introduce a number of promising exploration targets. However, due to the financial and time constraints, only a few of them are selected as the exploration priorities. Instead of the individual use of any exploration method, it is common to integrate the results of different methods in an interdependent framework in order to recognize the best targets for further exploration programs. In this work, the continuously-weighted evidence maps of proximity to intrusive contacts, faults density, and stream sediment geochemical anomalies of a set of porphyry copper deposits in the Jiroft region of the Kerman Province in Iran are first generated using the logistic functions. The weighted evidence maps are then integrated using the union score integration function in order to model the deposit type in the studied area. The weighting and integration approaches applied avoid the disadvantages of the traditional methods in terms of carrying the bias and error resulting from the weighting procedure. Evaluation of the ensuing prospectivity model generated demonstrate that the prediction rate of the model is acceptable, and the targets generated are reliable to follow up the exploration program in the studied area.

1. Introduction

Due to the fact that most of the outcropping mineralizations have been explored, it is necessary to explore deep targets. For this, some techniques have been developed according to the diversity of mineral resources and their characteristics, and the diversity of natural conditions prevailing in complex geological environments. They include geology, geochemical exploration, geophysical exploration, and remote sensing, in general. According to the high cost of exploration, efforts have always been made to develop the methods that minimize the error of detecting the promising areas. Since the late 20th century, attempts have been made to compare and integrate the results of various exploration methods, under the heading of mineral potential modeling, in order to identify the areas that are required to be further explored [1]. Mineral potential modeling is a step-by-step process in which the conceptual model of the prospected reserve is studied and examined, and the criteria for identifying the reserve are determined. After that and based on these criteria, the control maps that predict the mineralization are made from various exploratory methods [1, 2]. After defining the control maps, the most important step of the mineral potential modeling process is to weight these control maps using different knowledge-based, data-driven, combined methods, and experimental, continuous, and logistic functions. The knowledge-based methods can be used in the areas that are geologically suitable but where there are no known reserves or their numbers are very small (green areas). Since in these methods, the weighting of the control classes and maps is carried out by an expert based on the expertise, the results obtained have the uncertainty

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and random errors. The data-driven methods are suitable for the areas with moderate-to-good exploration operations (brown areas). Since the weighting is carried out based on the existing data and in a quantitative way in these methods, weighting is given a high score to the places where the data exists and a low score to the places where the data is not there. In other words, these methods have a systematic error and some uncertainty in the results [3-5]. In combined methods, which are, in fact, a combination of the data-driven and knowledge-based methods, the generally assigned weights and the studied results in the data-driven method are used in order to allocate weight in the knowledge-based method or vice versa, which has both above the mentioned systematic and random errors [1, 2]. In the method of using the experimental functions, different functions are used in order to assign weight to the classes (patterns) of control maps in which the numerical values of the two parameters of turning point and slope of the function are determined by trial-and-error by an expert. Therefore, these methods have the uncertainty and random errors in determining the values of the slope and the turning point parameters of the function [4]. In the continuous method, using the logistic functions, similar to the method before, the sigmoid (S-shaped) logistic function is used in order to weight the fuzzy control map classes (between 0 and 1). The difference is that the values of the slope and the turning point parameters of the function are obtained without the intervention of an expert by solving the mathematical equations and calculation, and do not have any of the disadvantages mentioned in the previous methods as a new and efficient method for weighting the classes and control maps. Thus the results obtained have a very high certainty [5]. Therefore, in the present work, this method was used to weight the control maps. In this work, the aim was to produce a model of mineral potential of porphyry copper deposits in the Jiroft region of the Kerman Province in Iran using the continuous and fuzzy gamma methods in the stages of weighting and integration of the control maps. In order to build a model of mineral potential of metal deposits including the porphyry copper deposits, some research works have been carried out by various researchers using the methods mentioned above: At first, the knowledge-based methods have been used in the weighting stage and integration of the control maps [6, 7]. Then in order to eliminate the uncertainty caused by the random error of the knowledge-based methods, the data-driven methods have been used to generate the mineral potential model [1, 8, 9]. Later, the combined methods have been used to construct the mineral potential model of the porphyry copper deposits [10]. Recently, some research works have been conducted using the method of experimental functions to build the models [4, 11]. Finally, the logistic functions have been used for the continuous weighting of control maps as a new and efficient method in order to build the mineral potential model of the reserves [5, 12, 13, 14, 15, and 16]. In this work, using the logistic functions, the control maps obtained from various data and exploratory methods were continuously weighted to reduce the uncertainties resulting from the other weighting methods in the previous research works. Then the mineral potential model of the porphyry copper deposits in the studied area was constructed to use in the next stages of exploration by combining the weighted control maps using the union score function. It should be noted that in the present study, all the steps of weighting and combining information layers and production of mineral potential model were performed in the GIS environment with a cell size of 100 × 100.

2. Geology of studied area

The Jiroft area is located in SE of Iran in the Kerman Province. This area is a part of the Urumieh-Dokhtar magmatic arc that forms the Zagros Mountains in Iran. The Urumieh-Dokhtar magmatic arc forms an elongated volcano-plutonic belt, and is a subduction-related zone [11]. The rocks and structural features of the area indicate the operation of the Late Precambrian tectonic activities. One of the important geological features of this region is the existence of a huge volume of the magmatic and metamorphic rocks with Paleozoic and especially Mesozoic age. The Paleozoic metamorphic rocks are the most exposed and the oldest rock units in the studied area. Based on the available fossils, the age of the Paleozoic metamorphic assemblages is attributed to the Late Devonian to the Early Carboniferous. These rocks have an extension along the NE-SW and their slope is to NW. The main outcrops of these units are in the southeastern and southwestern parts of the studied area [18]. Figure 1 shows the geological map of the Jiroft region studied.

3. Deposit model and data used

The first step in the process of constructing a mineral potential model is to define a conceptual or descriptive model of the reserve or more precisely, to define the conceptual genetic model of the prospected reserve. Prediction of the mineral location is mostly based on the experimental relationships obtained from the descriptive models of the known reserves. A descriptive model of a type of mineral resource based on the characteristics of a number of similarly known reserves is a guide to find new reserves of the same type [3]. Defining a conceptual model for a type of prospected reserve requires information and data from different types of geological processes related to the mineral deposits similar to the reserve being explored. Therefore, it is very important to study and review the discovered reservoir models, the same type of reserves to be explored, in the studied area and the related geological environments [13, 14]. According to the above explanations and studies, the conceptual model of porphyry copper deposits is defined as follows:

- The porphyry copper deposits are composed of post-magmatic hydrothermal fluids associated with the granitic porphyry intrusive rocks. Therefore, in the porphyry copper deposits, the primary mineral is under the structural control, and is spatially and genetically related to the felsic to intermediate porphyries. Thus a wide range of intrusive rocks with granitic to diuretic composition including quartz diorite, monzonite, granodiorite, quartzmonzonite, and diorite are spatially and genetically related to the porphyry copper deposits or their host rock [15-17].
- The porphyry copper deposits can be recognized from other granite-related deposits according to their large size and structural controls, which primarily include stockworks, porphyry stocks, veins, vein assemblies, fractures, and breccia. In the formation of the porphyry copper deposits, when the magma stabilizes, liquids with a high temperature are released and surrounded by the host rock in the stabilized porphyry. The rich-mineral fluids take the least resistant path and move within the cracks and fractures that expedite the passage of magma and the hydrothermal fluid circulation. Generally, the fault zones act as a major transit path for deep melt sources and hydrothermal fluids. Therefore, the faults are used to detect the porphyry systems around the world [18, 19] and also in Iran [20, 21].
- The porphyry copper deposits are associated with the trace elements or mineralizing agents Sb, As, Pb, Zn, Ag, Au, Mo, and Cu or their halos in rocks, sediments, and soils [4].

Therefore, according to the conceptual model of the porphyry copper deposits and their investigations, the data required for the research work was collected as follows:

- Location of the known copper mines in the studied area.
- 1:100000 geological map of the studied area, which was investigated, and the upper half of the area was selected for modelling according the presence of intrusive masses and known copper mines in this part. From this map, the faults and intrusive masses' maps were extracted.
- 485 geochemical samples of stream sediments from the trace elements and reagents of porphyry copper mineralization in the studied area.

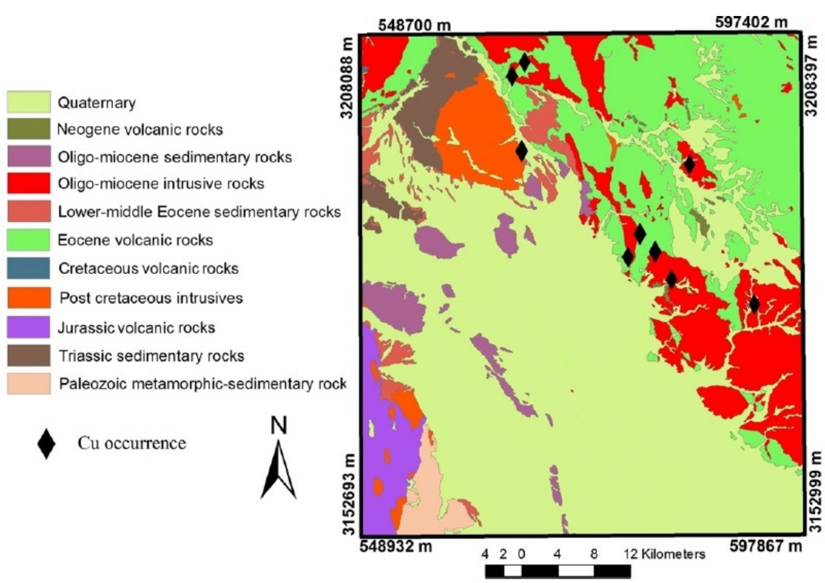

Figure 1. Geological map of studied area along with location of the known copper mines.

4. Control map preparation

Using the geological map, the maps of the faults and the intrusive masses of the region were obtained, and the control maps of the density of the faults and the proximity to the intrusive masses were made in the GIS environment. For the analysis and processing of the geochemical data of stream sediments to construct a geochemical control layer, the step factor analysis method was used, which was a statistical method for analyzing the information in the dataset. This method was first proposed by Carl Pearson (1901) and Charles Spearman (1904) when measuring the intelligence, and was used to determine the most influential variables when the number of variables under study were large and the relationships between them were unknown. In this method, the variables should be placed in factors so that the variance is reduced from the first factor to the next factors. Hence, the variables that are placed in the first factors are the most influential [22] that by using this method and also using the geochemical mineralization probability index (GMPI), which is a new approach to map geochemical anomalies of stream sediments by step factor analysis and probability theory, the weighted geochemical control map is made according to Figure 2.

The GMPI value is obtained from Equation 1 [7].

$$GMPI = \frac{e^{Fs}}{1 + e^{Fs}} \tag{1}$$

5. Weighing control maps

Control maps of fault density and proximity to intrusive masses were continuously weighted using Equation 2 [14].

$$FEV = \frac{1}{1 + e^{-s(EV-i)}} \tag{2}$$

where F_{EV} is a point between 0 and 1, EV is the value of each cell of the control map, and i and s are the inflection point and slope parameters of the function, respectively. In order to find the values of i and s, we used the following equation system (3) [14]:

$$\begin{cases} FEV(min) = \dfrac{1}{1 + e^{-s(EVmin-i)}} \\ FEV(max) = \dfrac{1}{1 + e^{-s(EVmax-i)}} \end{cases} \tag{3}$$

where F_{EV} (min) and F_{EV} (max) are the lowest and highest fuzzy scores in the range between 0 and 1, and EV (min) and EV (max) are the highest and lowest scores of the control map, respectively.

Solving the above system of the equations, the values of i and s are obtained using Equations 4 and 5 [14].

$$S = \frac{9.2}{EVmax - EVmin} \tag{4}$$

$$i = \frac{EVmax + EVmin}{2} \tag{5}$$

In this method, as stated earlier, the values of i and s are calculated through the function, and there is no uncertainty due to the application of the expert's opinion in the selection of i and s. The weighted control maps of fault density and proximity to the intrusive contacts are shown in Figures 3 and 4.

6. Integrating weighted control maps

The weighted control maps were combined integrated using the union score method and using Equation 6 [5].

$$US = \sum_{i=1}^{n} Fxi \tag{6}$$

where US is the score of each cell of the final map, Fx is the weight of each cell of the control map (obtained from the logistic function), and n is the number of weighted control maps.

The final model of mineral potential of porphyry copper deposits in the studied area is shown in Figure 4.

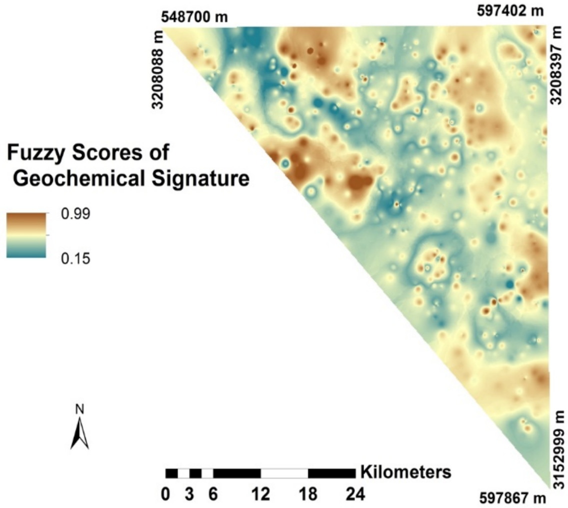

Figure 2. Weighted geochemical control map.

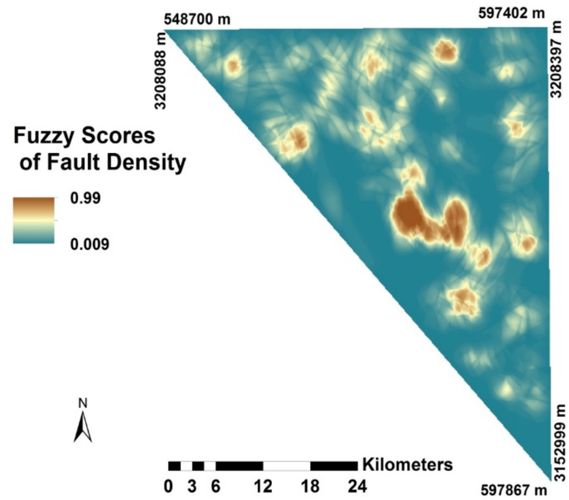

Figure 3. Weighted control map of fault density.

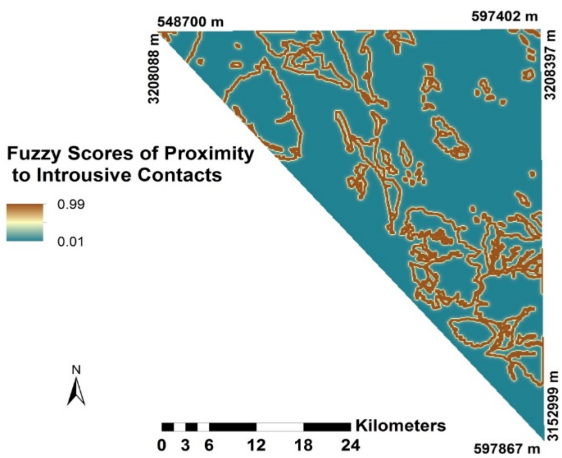

Figure 4. Weighted control map of proximity to intrusive masses.

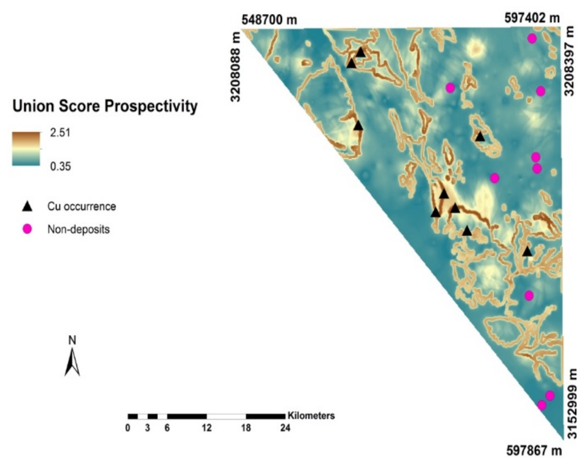

Figure 5. Final model produced along with the known copper indices in studied area.

7. Model evaluation

The mineral potential models made by different methods should be evaluated in order to assess their efficiency and accuracy of estimation. In the mineral potential modeling, the weights assigned to the evidence and spatial patterns should reflect the actual spatial relationships between them and the mineral deposits of the type sought. Therefore, the known mineral deposits can be used in order to evaluate the accuracy and realism of the weights assigned to the evidence and spatial patterns, which indicate their spatial relationship with mineralization in the studied area. This is achieved by overlapping the location of the known mineral resources and a classified mineral potential map [7, 23]. We can use the weight division ratio of different classes to the area occupied by that class in order to determine the probability of the presence of mineral reserves [24]. In this regard, in 2015, Yousefi and Caranza used both of the above criteria to evaluate the models simultaneously, and proposed the prediction-area (P-A) rate chart to evaluate the models; the point of intersection of the two curves is the evaluation criterion of the models [4]. In evaluating the mineral potential models, another criterion that should be considered is the share of locations without any reserve in the evaluation of models. Accordingly, the areas identified as the mineral potential zones in the models should have the least overlap with the non-reserve sites, where there is no geological evidence and desirable exploration criteria [3]. Therefore, in order to consider all the above criteria in the form of a single method for evaluating the mineral potential models, a modified PA rate diagram with the following three curves was used [25-28]:

A) The prediction rate of the known mineral reserves in each class of the final model;

B) The prediction rate of the unreserved locations in each class of the final model;

C) The area occupied by each class of the final model.

Therefore, this diagram has two intersection points, as follow:

A) The intersection point of the known mineral reserve prediction rate curve with the percentage area of the occupied curve, the values of which are displayed on the left and right of the Y axis, called Pm and Om, respectively.

B) The intersection point of the prediction rate curve of unreserved locations with the percentage area of the occupied curve, the values of which are displayed on the left and right of the Y axis, called Pn and On, respectively.

The overall network performance (Oe) is obtained from Equation 7 [28]:

$$O_e = P_m - P_n \quad (7)$$

where Pm and Pn are the values of the known reserve prediction rate curves and the prediction rate of unreserved locations at the intersection with the area occupied curve, expressed as a percentage, respectively. The result of the above relation will be a number in the range of -1 to 1; the larger this number, the higher is the efficiency and performance of the evaluated model. Also the positive and negative values indicate the efficiency and inefficiency of the evaluated model, respectively, for use in the next stages of exploration of the searched reserve in the studied area. Finally, in order to evaluate the mineral potential model of the porphyry copper deposits, the prepared model was classified discretely by the equal distance method, and then the model was evaluated using the –P-A rate plot [29]. The results of this evaluation are shown in Figures 6 and 7.

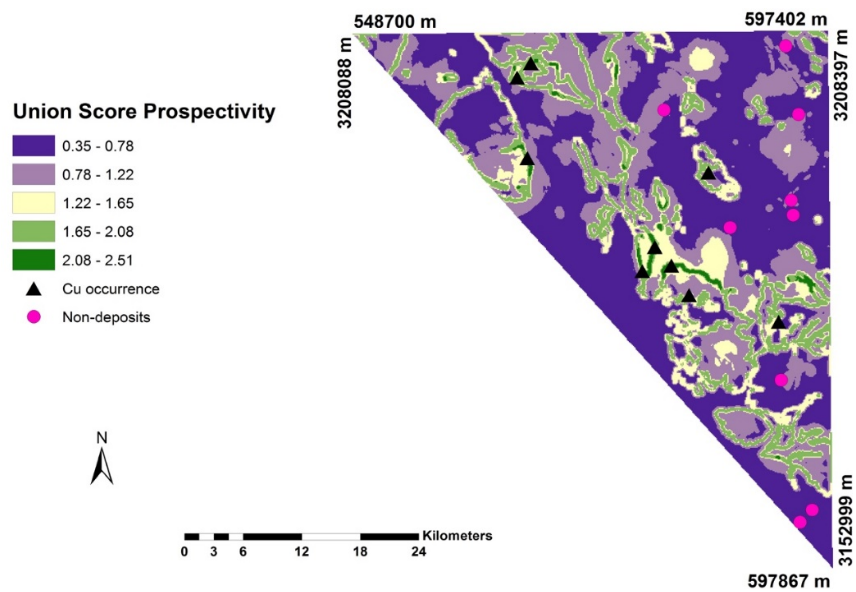

Figure 6. Final classified model.

Examining the PA plot, it is observed that the prediction rate of the known mineral reserves (Pm) as a criterion for showing the degree of overlap of high-grade mineral potential reserves in the model with the location of mineral indices is 0.78 in the final model. The larger this value, the more desirable it is. This means that the performance of this model in estimating the location of mineral reserves and points with a high mineralization potential is 78% correct and true. Also by examining the P-A of unreserved locations (Pn), which is, in fact, a criterion for showing the degree of overlap of high-grade mineral potential reserves in the model, with unreserved locations in the studied area, the number 0.4 was obtained. The smaller the number, the more desirable it is; here, it means that the performance of this model is correct in not estimating the places without reserve as the points with a high potential for mineralization of the reserve to the extent of 60% (100-60). Finally, by examining the overall performance (Oe) of the model, it can be concluded that the model with a total performance of 38% is a strong and efficient model and reliable for use in the stage of detailed exploration in the studied area.

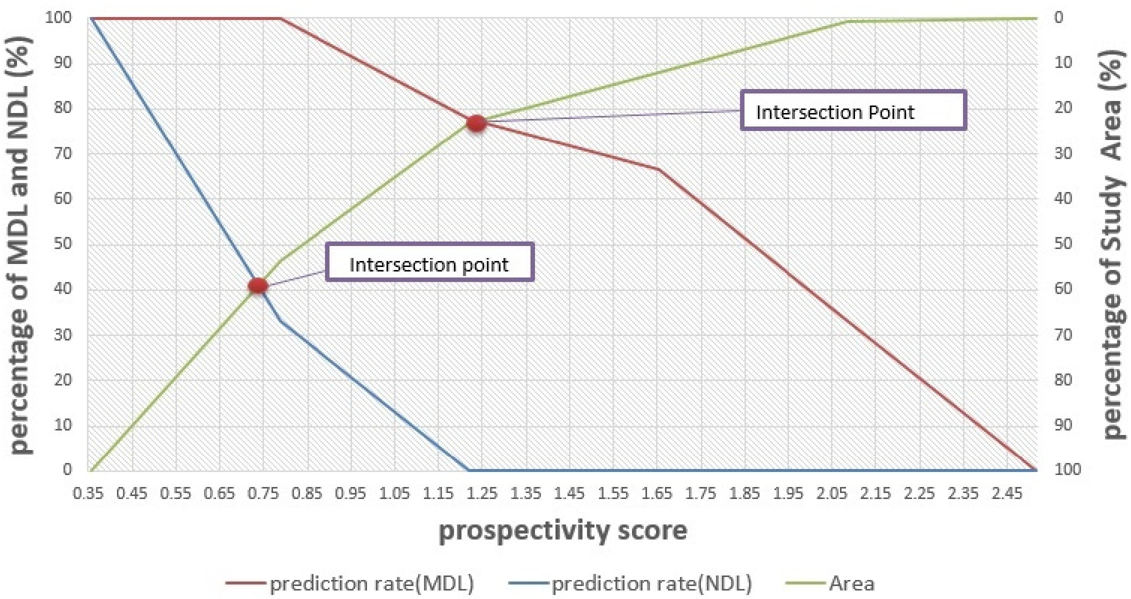

Figure 7. P-A diagram of the fuzzy gamma model.

8. Conclusions

- Application of logistic functions to create the weighted evidence layer modulates of the exploration bias associated using the training point for data-driven prospectivity analysis and avoiding the systemic errors associated with the expert judgments for prospectivity analysis.
- By creation of the continuous weighted evidential layers instead of assigning the discrete weights, using a logistic function, the bias caused by simplification and classification of the exploration data is avoided.
- Combining the continuous weighted evidence maps using the union score function results in the reliable exploration targeting models.

References

[1]. Yousefi, M., Kreuzer, O.P., Nykänen, V., and Hronsky, J.M.A. (2019). Exploration information systems—a proposal for the future use of GIS in mineral exploration targeting. Geology Reviews 111, 103005.

[2]. Afzal, P., Yousefi, M., Mirzaei, M., Ghadiri-Sufi, E., Ghasemzadeh, S. and Daneshvar Saein, L. (2019). Delineation of podiform-type chromite mineralization using Geochemical Mineralization Prospectivity Index (GMPI) and staged factor analysis in Balvard area (southern Iran). Journal of Mining and Environment 10: 705-715.

[3]. Carranza, E.J.M. (2008). Geochemical Anomaly and Mineral Prospectivity Mapping in GIS. Handbook of Exploration and Environmental Geochemistry. Vol. 11, Elsevier, Amesterdam.

[4]. Yousefi, M. and Carranza, M.J.M. (2015). Fuzzification of Continuous-value spatial evidence for mineral prosprctivity mapping. Computers & Geosciences 74: 97-109.

[5]. Yousefi, M., Carranza, M.J.M. (2017). Union score and fuzzy logic mineral prospectivity mapping using discretized and continuous spatial evidence values. Journal of African Earth Sciences 128: 47-60.

[6]. Ghaeminejad, H., Abedi, M., Afzal, P., Zaynali, F., and Yousefi, M. (2020). A fractal-based outranking approach for mineral prospectivity analysis. Bollettino di Geofisica Teorica e Applicata. 61 (4): 555-588.

[7]. Yousefi, M., Kamkar-Rouhani, A., and Carranza, M.J.M. (2012). Geochemical mineralization probability index (GMPI): A new approach to generate enhanced stream sediment geochemical evidential map for increasing probability of success in mineral potential mapping. Journal of Geochemical Exploration 115: 24–35.

[8]. Yousefi, M. and Khaloo Kakaei, R. (2004). Mineral Potential Modeling of Gold in Mahneshan Area using GIS. Mining Engineering Conference, Tarbiat Moddares University.

[9]. Saadati, H., Afzal, P., Torshian, H., and Solgi, A. (2020). Geochemical exploration for Li using Geochemical Mapping Prospectivity Index (GMPI), fractal and Stage Factor Analysis (SFA) in NE Iran. Geochemistry: Exploration, Environment, Analysis 20: 461-472.

[10]. Kianpoorian, S., Farahmandian, M., Karimi, M., and Bahroodi, A. (2014). Mineral Potential Modeling of copper using Neuro-Fuzzy Model in Chargonbad, Kerman. Earth Science Journal, 94: GSI.

[11]. Berberian, F., Muir, I.D., Pankhurst, R.J., and Berberian, M. (1982). Late cretaceous and early miocene andean-type plutonic activity in northern Makran and central Iran. J. Geol. Soc. Lond. 139, 605e614.

[12]. Badrzadeh, Z. and Aghazadeh, M. (2014). Geochemistry and Structural Geology of Intrusive Masses of South-Western Part of Jiroft. Geochemistry Journal, 2, Payame Noor University

[13]. Roberts, R.G., Sheahan, P., and Cherry, M.E. (1998). Ore Deposit Models. Geoscience Canada Reprint Series 3, Geological Association of Canada, Newfoundland.

[14]. Berger, B. R. and Drew, L.J. (2002). Mineral–deposit models: new developments in: A.G. Fabbri, Gaal, G., Mccammon, R.B. (Eds.), Deposit and Geoenviromental models for Rsource Exploration and Enviromental Security. NATO Science Series 2, 80: 121-134.

[15]. Arribas, A.J. (1995). Contemporaneous formation of adjacentporphyry and epithermal Cu-Au deposits over 300 ka innorthern Luzon, Philippines. Geology, 23: 337–340.

[16]. Singer, D.A., Berger, V.I., and Moring, B.C. (2005). Porphyry copper deposits of the world: database, map, grade, and tonnage models. U.S. Geological Survey. Open-File Report: 1005–1060.

[17]. Hezarkhani, A. (2006). Mineralogy and fluid inclusion investigations in the Reagan Porphyry System, Iran, the path to an uneconomic porphyry copper deposit. Journal of Asian Earth Sciences 27: 598–612.

[18]. Guillou-Frottier, L., and Burov, E. (2003). The development and fracturing of plutonic apexes: Implications for porphyry ore deposits. Earth and Planetary Science Letters 214: 341–356.

[19]. Qu, X., Hou, Z., Zaw, K., and Youguo, L. (2007). Characteristics and genesis of Gangdese porphyry copper deposits in the southern Tibetan Plateau: Preliminary geochemical and geochronological results. Ore Geology Reviews 31: 205–223.

[20]. Ghasemi, A. and Talbot, C.J. (2006). A new tectonic scenario for the Sanandaj–Sirjan Zone (Iran). Journal of Asian Earth Sciences 26: 683–693.

[21]. Meshkani, S.A., Mehrabi, B., Yaghubpur, A. and Sadeghi, M. (2013). Recognition of the regional lineaments of Iran: using geospatial data and the implications for exploration of metallic ore deposits. Ore Geology Reviews 55: 48–63.

[22]. Zare Chahooki, M.A. (2010). Moltivariate Analysis in SPSS. University of Tehran.

[23]. Carranza, E.J.M., Woladi, T., and Chikambwe, E.M. (2005). Application of data-driven evidential belief functions to prospectivity mapping for aquamarine-bearing pegmaties, Lundazi District, Zambia. Natural Resource Reserves 14: 47-63.

[24]. Bonham-Carter, G.F., Agterberg, F.P., and Wright, D.F. (1989). Weight of evidence modeling: a new approach to mapping mineral potential In: Agterberg, F.P., Bonham-Carter, G.F. (Eds.), Statistical Applications in the Earth Science. Geological Survey of Canada 89: 171-183.

[25]. Nezhad, S.G., Mokhtari, A.R. and Rodsari, P.R. (2017). The true sample catchment basin approach in the analysis of stream sediment geochemical data. Ore Geology Reviews. 83: 127–134.

[26]. Zhang, N., Zhou, K., and Du, X. (2017). Application of fuzzy logic and fuzzy AHP to mineral prospectivity mapping of porphyry and hydrothermal vein copper deposits in the Dananhu- Tousuquan island arc, Xinjiang, NW China. Journal of African Earth Sciences 128: 84–96.

[27]. Du, X., Zhou, K., Cui, Y., Wang, J., Zhang, N. and Sun, W. (2016). Application of fuzzy Analytical Hierarchy Process (AHP) and Prediction-Area (PA) plot for mineral prospectivity mapping: A case study from the Dananhu metallogenic belt, Xinjiang, NW China. Arabian Journal of Geosciences 9: 298.

[28]. Roshanravan, B., Aghajani, H., Yousefi, M. and Kreuzer, O. (2018). An Improved Prediction-Area Plot for Prospectivity Analysis of Mineral Deposits. Natural Resources Research.

مدلسازی پتانسیل معدنی ذخایر مس پورفیری به روش امتیاز همبودی با استفاده از لایه‌های شاهد وزن‌دار پیوست

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چکیده:

روش‌های مختلف اکتشافی وجود دارند که هر روش ممکن است تعدادی نواحی امید بخش اکتشافی را معرفی کند ولی به دلیل محدودیت مالی و زمانی فقط تعداد کمی از آنها به عنوان اولویت اکتشافی انتخاب می‌شوند. پس اگر به جای بررسی جداگانه هر روش اکتشافی، نتایج روش‌های مختلف در یک چارچوب وابسته به هم مورد بررسی قرار گیرند، انتخاب بهترین نواحی برای تمرکز عملیات اکتشافی با دقت بیش تر و عدم قطعیت کمتر صورت خواهد پذیرفت. در مقاله حاضر نقشه‌های شاهد وزن‌دار پیوسته: مجاورت با توده‌های نفوذی، چگالی گسل‌ها و آنومالی‌های ژئوشیمیایی رسوبات آبراهه‌ای مربوط به مجموعه‌ای از ذخایر مس پورفیری در منطقه جیرفت کرمان در ابتدا با به کارگیری توابع لجستیکی ساخته شدند. سپس نقشه‌های شاهد وزن‌دار شده جهت مدلسازی پتانسیل معدنی ذخایر مس پورفیری در منطقه مورد مطالعه با استفاده از تابع تلفیق امتیاز همبودی با یکدیگر تلفیق شدند. ارزیابی مدل تولید شده در این مطالعه نشان داد که نرخ پیش بینی مدل قابل قبول بوده وهمچنین اهداف اکتشافی مشخص شده توسط آن جهت انجام اکتشافات تفصیلی تر در منطقه مورد مطالعه قابل اعتماد است.

کلمات کلیدی: مدلسازی، تلفیق، اهداف اکتشافی، مس پورفیری، جیرفت.