PROMETHEE II: A knowledge-driven method for copper exploration

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1. Introduction

Mineral exploration is a sophisticated process in which the main purpose is to discover a new mineral deposit in the region of interest. One of the main steps in mineral exploration is to discriminate prospective areas within the region. Various thematic geo-datasets (e.g., geological, geophysical and geochemical datasets) should be collected, analyzed and integrated for mineral prospectivity mapping (MPM) to discriminate prospective areas. The MPM process is a multiple criteria decision making (MCDM) task and produces a predictive model for outlining prospective areas. Several approaches may be used for MPM that can be categorized as either data-driven or knowledge-driven methods (Bonham-Carter, 1994; Pan and Harris, 2000; Carranza, 2008). In data-driven techniques, the known mineral deposits in a region of interest are used as 'training points' for establishing spatial relationships between particular geological, geochemical and geophysical features. The spatial relationships between the input data and the training points are quantified and used to establish the importance of each evidence map and are then integrated into a single mineral prospectivity map (Nykänen and Salminen, 2007; Carranza, 2009). Examples of data-driven methods include the weights of evidence (Bonham-Carter et al., 1989), logistic regression (Agterberg and Bonham-Carter, 1999), neural networking (Singer and Kouda, 1996; Porwal et al., 2003; 2004), and evidential belief function approaches (Carranza and Hale, 2002; Carranza et al., 2008).

Knowledge-driven methods, in which the expertise of a geoscientist (i.e., a judgmental opinion) is applied, include the use of Boolean logic (Bonham-Carter, 1994), index overlay (Bonham-Carter, 1994), Dempster-Shafer belief theory (Moon, 1990), and fuzzy logic overlay techniques (Chung and Moon, 1990; An et al., 1991).

Currently, the use of MCDM tools for improving the results of mining projects is growing (Prol-Ledesma, 2000; De Araújo and Macedo, 2002; Moreira et al., 2003; Bitarafan and Ataei, 2004; Hosseiniali and Alesheikh, 2008; Carranza, 2008). The use of MPM as a MCDM technique is a complicated process that requires the simultaneous consideration of several types of indicators, such as geological, geochemical and geophysical data. Each of these indicators is presented in the form of geospatial information system (GIS) layers. Areas in the region of interest are prioritized according to the considered criteria of mineral prospectivity. This prioritization allows for the exploration of high-potential areas that are delimited for detailed prospecting to reduce drilling costs and minimize the number of boreholes in the study area.

In this study, after a brief introduction of PROMETHEE II, thirteen layers of various raster-based evidential layers, involving geological, geophysical and geochemical geo-datasets, are integrated for MPM.
To this end, real data pertaining to the Now Chun porphyry copper deposit located in Kerman, central Iran, are applied. The main motivation of this study is to determine whether additional drilling is needed in the study area. A comparison with twenty-one boreholes drilled in the Now Chun prospect is also provided.

2. PROMETHEE II

PROMETHEE is a comprehensive MCDM method that was developed by Brans (1982) and further extended by Vincke and Brans (1985). There are a considerable number of PROMETHEE applications currently available for various fields because despite its comprehensive features, it is easily implementable (Brans et al., 1986; Goumas and Lygerou, 2000; Macharis et al., 2004; Dağdeviren, 2008). PROMETHEE is a superior method for ranking and selecting from among a finite set of alternative actions while considering a number of conflicting criteria. PROMETHEE is also a rather simple ranking method in concept and in practice when compared with the other MCDM methods (Brans et al., 1986).

The basic principle of PROMETHEE II is based on the pair-wise comparison of alternatives along each selected criterion. Therefore, the number of practitioners who are applying the PROMETHEE method to practical MCDM problems, and researchers who are interested in the sensitivity aspects of the PROMETHEE method, has increased in recent years, as evidenced by increased number of scholarly papers and conference presentations that have used PROMETHEE. PROMETHEE has been applied in various areas including environment management, hydrology and water management, business and financial management, chemistry, logistics and transportation, manufacturing and assembly, energy management, social, and other fields (Behzadian et al., 2010). Different versions of the PROMETHEE method have been developed including PROMETHEE II, which is the most frequently applied version because it enables a decision maker (DM) to find a full-ranked vector of alternatives (i.e., complete ranking). A brief explanation of PROMETHEE II is provided here. However, interested readers are referred to Figueira et al. (2005) for additional details.

The basic principle of PROMETHEE II is based on the pair-wise comparison of alternatives along each selected criterion. PROMETHEE II requires two additional types of information: (1) information on the weights of the criteria and (2) decision-maker’s preference functions, which were used for comparing the alternatives (Dağdeviren, 2008). In this study, the criteria weights are determined using the Delphi method (Rowe and Wright, 2001). The PROMETHEE II method involves six steps (Figueira et al., 2005; Behzadian et al., 2010):

Step 1. Construction of an evaluation matrix: the basic data must be prepared in the evaluation matrix \( G_{ij} \) table in which the performance of each alternative with respect to each criterion is provided.

Step 2. Determination of performance differences: the performance difference between each pair of alternatives with respect to each criterion is calculated as follows:

\[
d_{j}(a,b) = g_{j}(a) - g_{j}(b)
\]

where \( g_{j}(a) \) and \( g_{j}(b) \) show the performance of alternatives \( a \) and \( b \), respectively, with regard to criterion \( j \), and \( d_{j}(a,b) \) denotes the difference between these performances.

Step 3. Constructing the preference functions: after determining the values \( d_{j}(a,b) \), the decision-maker (DM) may give a small preference to one of the compared alternatives and even possibly no preference if the DM considers this difference to be negligible. A larger difference is given a larger preference. There is no objection to considering that these preferences are real numbers varying between 0 and 1. Thus, for each criterion, the DM has a preference function as follows:

\[
P_{j}(a,b) = F_{j}[d_{j}(a,b)] \quad j = 1, \ldots, k \quad \forall a, b \in A
\]

where \( P_{j}(a,b) \) denotes the preference of alternative \( a \) over alternative \( b \) with respect to criterion \( j \) as a function of \( d_{j}(a,b) \). Notably, the preference function should be reversed for criterion that are to be minimized as follows:

\[
P_{j}(a,b) = F_{j}[-d_{j}(a,b)] \quad \forall a, b \in A
\]

Six types of preference functions that are commonly used in practice have been proposed by Vincke and Brans (1985):

1. usual criterion,
2. U-shape criterion,
3. V-shape criterion,
4. level criterion,
5. V-shape with indifference criterion and

Furthermore, for each preference function, at most two out of three parameters \( q \), \( p \), and \( s \) must be determined by the DM. Parameters \( q \), \( p \), and \( s \) indicate the indifference, preference and Gaussian threshold, respectively. Two common preference functions are indicated in Fig. 1.

Step 4. Calculation of aggregated preference indices: for each pair of alternatives, an aggregated preference index is calculated as follows:

\[
\pi(a,b) = \sum_{j=1}^{k} P_{j}(a,b)w_{j} \quad \forall a, b \in A
\]

where \( \pi(a,b) \) denotes the overall preference of \( a \) over \( b \), and \( w_{j} \) is the weight associated with the \( j \)th criterion.

Step 5. Calculation of outranking flows: for each alternative \( a \) when compared with \( (n-1) \) other alternatives in \( A \), a positive
and negative outranking flow is calculated as follows:

\[ \phi^+(a) = \frac{1}{n-1} \sum_{x \in A} \pi(a,x) \] for each \( a \) \hfill (5)

\[ \phi^-(a) = \frac{1}{n-1} \sum_{x \in A} \pi(x,a) \] for each \( a \) \hfill (6)

where \( \phi^+(a) \) and \( \phi^-(a) \) denote the positive and negative outranking flow, respectively, for alternative \( a \). A positive outranking flow of alternative \( a \) indicates the overall outranking degree of this alternative, which indicates the extent to which this alternative dominates all other alternatives. Similarly, a negative outranking flow of alternative \( a \) indicates the extent to which this alternative is dominated by all other alternatives.

**Step 6. Calculation of net outranking flows**: the net outranking flow of alternative \( a \) can be calculated as follows:

\[ \phi(a) = \phi^+(a) - \phi^-(a) \] for each \( a \) \hfill (7)

Using these net outranking flows, PROMETHEE II can provide a complete ranking of the alternatives from best to worst (Macharis et al., 2004).

3. **Geology of the study area**

The study area of interest is located in the Kerman province within the Central zone of Iran. This area includes the Now Chun copper prospect. In general, the main lithological units exposed in this area consist of a volcanic–subvolcanic complex and intrusive bodies (Fig. 2). Volcanic rocks cover most of the studied area and consist of Eocene andesitic-, dacitic- to rhyo-dacitic lavas and associated breccia tuffs. The intrusive bodies consist of granite- to diorite-porphyrite distributed in the south to southwestern regions of the study area.

Most of the geological units in the study area have been hydrothermally altered, and the most intensive alteration occurred in the subvolcanic rhyo-dacitic bodies. The altered rhyo-dacitic unit and hydrothermal dissemination follow a general northeast-southwest trend. Because there is a comprehensive correlation between the hydrothermal zone and the faults, we assume that the alteration zones were probably controlled by major faults and fractures. However, the Cu-bearing mineralization zones are mainly associated with azurite and malachite stockwork with minor chalcopyrite inclusions in quartz. Specific copper-bearing mineralized outcrops are shown on the geological map.
4. Application of PROMETHEE II to the Nax Chun copper deposit

4.1. Criteria for the mineral prospectivity map

Magnetic and electrical surveys are two common geophysical methods for prospecting porphyry copper deposits. Magnetic methods are used worldwide in the exploration and characterization of porphyry copper deposits. The primary control on the bulk magnetic properties of host rock and magnetic intrusions is the partitioning of iron between oxides and silicates (Clark, 1999), although sulfide minerals associated with hydrothermal alteration also provide fundamental, localized geophysical targets (John et al., 2010). Simple models for porphyry copper deposits involve contrasting zones of alteration centered on the deposit. Magnetic anomalies, at least in principle, reflect the location of these zones: weak local magnetic highs occur over the potassic zone, low magnetic intensity occurs over sericitic zones, and magnetic intensities increase gradually over the propylitic zone (Thoman et al., 2000). For example, Fig. 3 shows a magnetic anomaly over a hypothetical, but geologically plausible, porphyry copper deposit (John et al., 2010).

The resistivity method is one of the oldest techniques used in geophysical exploration. Resistivity is a measure of the ability of an electrical charge to form currents that move through a geological section. Minerals and rocks associated with hydrothermal alteration often have anomalous electrical properties, and thus, geophysical methods that detect and model such properties are mainstays in the exploration for, and characterization of, porphyry copper deposits. Like the distribution of magnetic minerals, electrical properties reflect the type and degree of hydrothermal alteration. Hydrothermal minerals relevant to geophysical exploration include pyrite, chalcopyrite, chalcocite, biotite, and sericite. As with magnetic anomalies, we would expect to see the intensity and type of alteration reflected in resistivity anomalies, with the lowest resistivity centered on sericitic alterations that develop in zones with the greatest extent of fracturing and fluid flow (Thoman et al., 2000; John et al., 2010). The dispersed nature of sulfide minerals in porphyry systems is particularly suitable for induced polarization (IP) methods (Sinclair, 2007). The IP method was originally developed for the exploration of porphyry copper deposits (Brant, 1966) and is still commonly used. Induced polarization is a complex phenomenon.

In the simplest terms, IP anomalies reflect the ability of a mineral, rock, or lithology to act as an electrical capacitor. In porphyry copper deposits, the strongest IP responses correlate with quartz-sericite-pyrite alterations (Thoman et al., 2000; John et al., 2010). Typically, the zone of potassic alteration in the core of the deposit is depleted in total sulfide minerals, the surrounding zone of sericitic alteration has high sulfide content, including pyrite, and the distal zone of propylitic alteration has low amounts of pyrite. Thus, the sericitic zone of alteration is an important IP target (John et al., 2010). Therefore, various layers of information are derived from magnetic and electrical surveys for the MPM process.

4.2. Data processing for the representation of prospectivity criteria

In this study, thirteen layers of information are used to prepare a prospectivity map (Table 1).

According to the geology of the study area, rhyodacite is the known host of the porphyry copper deposit. Four buffers with a 25-m interval around the rhyodacite units are considered to represent the presence of mineralization in the adjacent rocks (tuff-andesite and alluvial deposits). Then, the host rock map is reclassified as fuzzy scores by some geologists. A fuzzy membership function for each layer was previously obtained from a group of geoscientist experts at the National Iranian Copper Industries Company (NICIC), who considered the statistics of the data in comparison with their knowledge about each layer to be evidence that:

Table 1

<table>
<thead>
<tr>
<th>Geological map</th>
<th>Geochemical map</th>
<th>Geophysical map</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Alteration zone</td>
<td>1. Copper anomaly (Cu)</td>
<td>1. Induce polarization (IP) “Chargeability map”</td>
</tr>
<tr>
<td>2. Fault area</td>
<td>2. Molybdenum anomaly (Mo)</td>
<td>2. Resistivity map (RS)</td>
</tr>
<tr>
<td>3. Mineralization indicators</td>
<td>3. Additive map (Cu + Mo)</td>
<td>3. Metal factor (MF)</td>
</tr>
<tr>
<td>4. Host rock</td>
<td>4. Residual magnetic that 10 m upwarded (UP10)</td>
<td>4. Residual magnetic that 10 m upwarded (UP10)</td>
</tr>
<tr>
<td></td>
<td>5. Reduced to pole magnetic data (RTP)</td>
<td>5. Reduced to pole magnetic data (RTP)</td>
</tr>
<tr>
<td></td>
<td>6. Analytic signal of the magnetic data (AS)</td>
<td>6. Analytic signal of the magnetic data (AS)</td>
</tr>
</tbody>
</table>

Fig. 3. Magnetic anomaly caused by a hypothetical porphyry copper deposit. The following magnetic field parameters are assumed: inclination of 58.3° and declination of 11.6°. M indicates magnetizations in amperes per meter (A/m) (John et al., 2010).
for porphyry copper deposit occurrence (Elyasi, 2009). Other types of rocks (granite and diorite porphyrite) do not have role in the mineralization, and thus, their scores are considered minimal (Fig. 4(a)). Because no hydrothermal alterations are indicated in the geological map (Fig. 2), hydrothermal alterations in the study area are delineated based on ore guides and subsequently classified (Fig. 4(b)). Rocks adjacent to NE–SW faults are crushed and altered, and therefore, these areas have maximum scores in contrast to non-fault zones (Fig. 4(c)). Four 25-m interval buffers were considered to represent parts of the study area adjacent to the observed mineralized outcrops (Fig. 4(d)).

Soil geochemical data for copper and molybdenum are interpolated using an inverse distance weighted method to map their anomalies (Fig. 5(a, b)). After the transformation of Cu and Mo data into standard normalized distributions ($Z_i$), an additive map was produced as a summation of the Cu and Mo concentrations, as shown in Fig. 5(c). This transformation can be implemented using the following formula for data $x$:

$$Z_i = \frac{\ln(x) - \bar{x}\ln(\bar{x})}{\sigma(\ln(x))}$$

where $\bar{x}$ and $\sigma$ denote the mean and standard deviation, respectively, of the element concentration data. A logarithmic conversion is used to obtain a normalized distribution of the data.

A ground-based magnetic survey was performed previously in the study area whereby distances between profiles and stations were 50 and 20 m, respectively. The study was conducted by a group of geoscientist experts at the NICIC. The geomagnetic field was 46,000 nT (inclination=46°, declination=2.5°). Analytical upward continuation was used because it was suspected that a copper deposit exists at depth. This method calculates the magnetic field farther to the source and consequently results in a better map of deeper deposits and reduces the effect of shallow structures with a high magnetic frequency. Residual magnetic data continued upward by 10 m (UP10) are shown in Fig. 6(a).

A general filter operation applied to the magnetic data is reduced to the pole (RTP), which is a technique that converts a magnetic anomaly to a symmetrical pattern that would have been observed with vertical magnetization. The RTP technique eliminates the dipolar nature of magnetic anomalies and converts its asymmetric shape to a symmetric shape (Ansari and Alamdar, 2009). An RTP map of the Now Chun deposit is shown in Fig. 6(b).

Many filters are available to enhance magnetic field data, such as downward continuation, horizontal and vertical derivatives, and other forms of high-pass filters. One of these techniques is the analytic signal method. The basic concept of using the analytic signal method for magnetic data is discussed extensively by Nabighian (1972, 1974, 1984). Fig. 6(c) shows the analytic signal.

Electrical techniques are the most commonly used geophysical methods for sulfide deposit exploration. In this study, resistivity (RS), an induced polarization (IP) "chargeability map", and a metal factor map (as the ratio of chargeability to resistivity) are used. A rectangular array with 1600 m of space was used as the current electrode in

Fig. 4. Geological information layers, (a) Host rock, (b) Alteration zone, (c) Fault, (d) Mineralization indicators.
the area; the distances between profiles and stations were 100 and 20 m, respectively. These maps are shown in Fig. 6(d–f).

It is a common practice to determine the weights of attributes (i.e., feature data including geological, geophysical and geochemical layers) using knowledge-driven methods, such as the Delphi method, in MPM. Therefore, the Delphi method was applied to determine the weights of each of the thirteen layers by asking proposing question to a group of experts at the NICIC. The Delphi method is based interviewing a group of experts using a series of questionnaires. Judgments derived from several experts are generally more accurate than results from only one expert. However, group processes often lead to sub-optimal judgments. Between 5 and 20 experts with appropriate expertise in a particular field of knowledge must be employed to acquire a reasonable answer. Final weights of evidence layers for MPM can be obtained by this method (Rowe and Wright, 2001). Normalized weights of the evidential layers are shown in Table 2.

4.3. Application to real data

To use the PROMETHE II method, an evaluation matrix is first constructed. The thirteen layers are considered to be key criteria, as illustrated in Table (1). Cell values of raster datasets associated with these criteria are extracted and stored in 13 separate columns and 1812 rows in a table of database. The number of alternatives can be correlated to the locations of geochemical samples or geophysical surveys. Fuzzy scores of four geological layers and real values of other layers are applied to construct the respective $G_{1812 \times 13}$ matrix. The performance value of each alternative with regard to each criterion is extracted to generate the evaluation matrix in the first step of applying the PROMETHE II technique. Differences between the performance values of alternatives regarding each criterion (evidential layer) are calculated and stored to be used as inputs for constructing the preference functions in the second step. There is no optimal method for choosing the most appropriate preference functions and their respective parameters at the third step; these are generally selected according to the preferences of the DM. Nevertheless, the V-shape indifference and Gaussian functions are chosen as preference functions in this study. The V-shape function is selected for geological layers. In this way, preferences between alternatives for each geological criterion increase linearly over an interval distance of 0 to $(x_{max} - x_{min})$. This preference function is recommended when there is no rule to apply in step 3.

For other layers, the Gaussian function is used for which the respective $q, p$ and $s$ parameters are determined by considering a statistical approach (Fig. 1). Because it is known in MPM, a membership value reflects the favorability degree of occurrence for the mineral deposit of interest. Thus, the expert geoscientists can divide each layer of criterion into the four zones, i.e., the non-anomalous, possible, probable, and anomalous zones. Assuming a normal or log-normal data distribution, any numerical data layer can be reclassified into the $\bar{x} + \sigma$, $\bar{x} + 2\sigma$ and $\bar{x} + 3\sigma$ classes according to its standard deviation ($\sigma$) and mean ($\bar{x}$). Values less than $(\bar{x} + \sigma)$ are associated with non-anomalous zones, and those values greater than $(\bar{x} + 3\sigma)$ are considered anomalous. The values

![Fig. 5. Geochemical information layers, (a) Copper, (b) Molybdenum, (c) Additive concentration.](image-url)
\( x + 2\sigma \) and \( x + 3\sigma \) are thresholds for defining possible and probable zones, respectively. By considering the statistical distributions of the data, the parameters \( q, s \) and \( p \) are determined to be equal to the thresholds \( x - x_{\min}, x - x_{\min} + 2\sigma \) and \( x - x_{\min} + 3\sigma \), respectively. It is important to note that the domain of each alternative is between \([x_{\min}, x_{\max}]\), and thus, the interval \([x_{\min} - x_{\max}]\) must be considered when choosing suitable thresholds. The selection of these thresholds is based on experts' opinions. By considering Eqs. (2) and (3), the program must maximize the effect of all criterion layers with the exception of the resistivity, which can be minimized in most porphyry copper prospects.

The Delphi method was previously applied by DMs of the NICIC to determine the weights of each criterion (Elyasi, 2009). Normalized weights are indicated in Table (2), and the aggregated preference indices are calculated using Eq. (4) at step 4. At step 5, the positive and negative outranking flows of each alternative are calculated using Eqs. (5) and (6), respectively. Finally, the net outranking flows of the alternatives are determined during step six that, in turn, are used to provide a complete ranking of the alternatives from the best to worst.

The economically viable concentration of copper along each of 21 boreholes, which were drilled previously, are considered by...
the experts to classify the concentrations into the five classes (Table 3). In this manner, the best class to indicate continued exploratory drilling operations corresponds to class 5, i.e., an extremely good-quality class. If the study area belongs to class 1, 2 or 3, additional drilling will not be recommended. Drilling in an area belonging to class 4 is subject to an expert's opinion. Consequently, for providing the final prospectivity map, the net outranking flows of PROMETHE II are divided into five equal-sized intervals. Higher-class labels are related to both higher values of net outranking flows and high potential zones for additional drilling, and vice versa. Final results are shown in Fig. 7 and Table 3.

4.4. Validation of the results

The multiple classifications of mineral prospectivity areas can be used to prioritize high potential zones for additional exploratory drilling. In the case study, 21 boreholes were classified by a group of experts at the NICIC after analyzing the economically viable concentration of copper along them. As shown in Table 3, those areas that belong to classes 4 and 5 can be considered suitable candidate zones for detailed studies, and the remaining areas are excluded from further studies because they do not have a sufficient value to justify the drilling of additional boreholes. The weight of the misclassification error for each borehole is highly dependent on the corresponding misclassified classes. For example, the amount of error will be higher if a borehole has a class of 5 when the actual class is 1, and the error is lower if a borehole is classified as class 2 when the actual class is 1. If an area is classified as class 2, the managers of a prospecting project would likely refuse to perform additional drilling, although they may continue the project and suggest additional borehole drilling in the same zone if it is designated as class 5.

To evaluate the capability of the PROMETHE II method in the context of MPM, the correct classification rate (CCR) is calculated by comparing real and estimated classes. The CCR as a criterion is obtained from the confusion matrix. This matrix allows for the comparison of the afore mentioned five borehole classes. The estimated and real classes of boreholes, in which the elements are the number of classified boreholes, are shown in Table 3. A more diagonal matrix indicates a better classification. The CCR can be obtained from the confusion matrix by dividing the summation of the diagonal elements by the total number of boreholes. Table 4 shows the confusion matrix, in which the CCR is equal to 0.4286, for the 21 boreholes. The CCR will be equal to 1 if the estimated classes of all boreholes are correct. An important aspect to the MPM process is that the CCR value decreases when the number of classes increases. This rate could be increased if only two classes, i.e., the prospect-deposit and non-deposit class labels, were considered in our study.

The method based on PROMETHE II can be a useful geospatial tool for integrating multiple features/attributes that affect the mineral prospectivity mapping process. The results obtained by applying the proposed PROMETHE II technique in our case study demonstrate that a suitable zone in the prospective area for copper deposits is located mainly among the existing boreholes and that there is a low potential outside of this region. Because this is considered a high potential area, with the exception of areas with class labels four or five, additional drilling is not suggested. These results indicate that the PROMETHE II technique is a promising tool for integrating multiple raster-based evidence layers for copper prospectivity mapping.

Table 2
Weights extracted using the Delphi method.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Weight</th>
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<tbody>
<tr>
<td>Alteration zone</td>
<td>0.1138</td>
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<tr>
<td>Fault area</td>
<td>0.0506</td>
</tr>
<tr>
<td>Mineralization indicators</td>
<td>0.1013</td>
</tr>
<tr>
<td>Host rock</td>
<td>0.1013</td>
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<tr>
<td>Copper anomaly (Cu)</td>
<td>0.0868</td>
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<tr>
<td>Molybdenum anomaly (Mo)</td>
<td>0.0767</td>
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<tr>
<td>Additive map (Cu + Mo)</td>
<td>0.1635</td>
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<tr>
<td>Induce polarization (IP) “Chargeability map”</td>
<td>0.06885</td>
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<td>Resistivity map (RS)</td>
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<td>Metal factor (MF)</td>
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<tr>
<td>Analytic signal of magnetic data (AS)</td>
<td>0.04284</td>
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Table 3
Borehole classifications.

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<th>Estimated class</th>
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<td>Extremely weak</td>
<td>4</td>
</tr>
<tr>
<td>19</td>
<td>2</td>
<td>Weak</td>
<td>1</td>
</tr>
<tr>
<td>20</td>
<td>1</td>
<td>Extremely weak</td>
<td>2</td>
</tr>
<tr>
<td>21</td>
<td>1</td>
<td>Extremely weak</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 4
Confusion matrix obtained using the PROMETHE II Method.

<table>
<thead>
<tr>
<th>Estimated class</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real class</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

Fig. 7. Prospectivity map generated using the PROMETHE II method.
5. Conclusion

In this study, a new knowledge-based method using the PROMETHE II technique was proposed for copper prospectivity mapping and applied for an area comprising the Now Chon copper deposit in Iran. A comparative evaluation was also employed using 21 existing boreholes in the region of interest. The results of the case study indicate that the PROMETHE II method can prioritize the prospect area effectively. The main motivations for applying the PROMETHE II method were as follows:

- It could be applied readily in the context of MPM
- Different decision criteria with diverse dimensions and scales can be taken into account
- All collected information in the decision matrix can be fully and efficiently considered when making the final decision

The final result of the PROMETHE II based method showed a CCR equal to 0.4286 with 21 boreholes drilled in the study area. The proposed method can be applied as a reliable and powerful knowledge-based tool to prepare prospectivity maps in other application areas.

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References


