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Prospectivity modeling of porphyry-Cu deposits by identification and integration of efficient mono-elemental geochemical signatures

Mohammad Parsa [a], Abbas Maghsoudi [a, *], Mahyar Yousefi [b], Martiya Sadeghi [c]

[a] Department of Mining and Metallurgical Engineering, Amirkabir University of Technology, Tehran, Iran
[b] Faculty of Engineering, Malayer University, Malayer, Iran
[c] Mineral Resource Department, Geological Survey of Sweden, Uppsala, Sweden

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ABSTRACT

Dispersion pattern of geochemical elements in stream sediment data of a study area is affected by several factors, e.g., geological and geomorphological characteristics of the area. In this paper, we demonstrated recognition of efficient and inefficient mono-elemental geochemical signatures in a study area and exclusion of inefficient elements is worthwhile for increasing the probability of exploration success. For this, we adapted prediction-area (P-A) plot, normalized density and success-rate curve as tools that evaluate the ability of geochemical signatures in prediction of undiscovered mineral deposits and in delimiting exploration targets. After identification of efficient and inefficient elements, we combined efficient indicator elements to generate an effective prospectivity model. To illustrate the procedure we used a stream sediment data set for prospecting porphyry-Cu deposits in the Noghdouz area, Iran.

1. Introduction

In preliminary exploration stages, stream sediment geochemical data have been used to delineate target areas for further exploration of mineral deposits (e.g., Carranza and Hale, 1997; Cheng, 2007; Zuo et al., 2009; Bai et al., 2010; Carranza, 2011; Zuo, 2011; Afzal et al., 2014; Zheng et al., 2014; Wang et al., 2014, 2015; Shamseddin Meigoony et al., 2014; Hosseini et al., 2015). The material of each stream sediment sample comes from the whole area of its upstream (e.g., Bonham-Carter, 1994; Bonham-Carter and Goodfellow, 1984, 1986; Carranza and Hale, 1997; Moon, 1999; Spadoni et al., 2004, 2005; Spadoni, 2006; Carranza, 2008, 2010; Yilmaz, 2003, 2007; Yilmaz et al., 2015; Yousefi et al., 2013). In this regard, due to complex erosion processes, influence of pollutants (Bogen et al., 1992; Macklin et al., 1994; Spadoni et al., 2005; Spadoni, 2006) and influence of composition and distribution of regolith and bedrock, details of processes controlling downstream variations of stream sediment compositions are poorly understood or unknown. Some of the most important known generic factors affecting downstream variations in stream sediment composition and downslope variations in the intensity of erosion processes are climatic, topographic, geomorphologic, geologic and anthropogenic factors (Maclin et al., 1994; Spadoni, 2006). Therefore, complex anomaly patterns exist as a function of topographic, geomorphologic, and geologic factors (Yilmaz, 2003; Cheng, 2007; Zuo et al., 2009; Xie et al., 2010; Yousefi et al., 2013). It means, due to differences in physical and chemical characteristics of geochemical elements (e.g., mobility), stream sediment samples with anomalous concentrations of different indicator elements can be located differently downstream from an anomaly source (c.f., Yilmaz, 2003; Cheng, 2007; Zuo et al., 2009; Xie et al., 2010; Yousefi et al., 2013). In this regard, surficial geochemical patterns of indicator elements even for a certain type of ore deposition vary in different areas (c.f., Solovov, 1987; Grigorian, 1992; Silitoe, 1973). In many cases, stream sediments downstream of mineral deposits exhibit non-anomalous contents for some indicator elements (c.f., Yilmaz, 2003; Cheng, 2007; Zuo et al., 2009; Xie et al., 2010; Yousefi et al., 2013) due to different characteristics (i.e., topographic, geomorphologic, and geologic factors), controlling anomaly dispersion in different areas (Yousefi and Carranza, 2015a,b; Spadoni et al., 2004; Spadoni, 2006). Therefore, respecting the characteristics of a study area, among several surficial mono-element geochemical signatures,

* Corresponding author.
E-mail address: a.maghsoudi@aut.ac.ir (A. Maghsoudi).

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which are genetically associated with ore deposit-type, some of the elements are efficient indicators vectoring into mineralized zones (Sillitoe, 1973; Hedenquist et al., 1998; Jones, 1992; Seedorff et al., 2005; Sinclair, 2007; Ziaii et al., 2011; Yousefi et al., 2014). In this regard, recognizing efficient and inefficient geochemical indicators for prospecting a certain deposit-type sought in a study area and excluding inefficient indicators from analyses allows for better discrimination of target areas for further exploration (c.f., de Palomera et al., 2014; Nykänen et al., 2014; Yousefi et al., 2014; Yousefi and Carranza, 2015b).

The aim of this paper is integration of different geochemical signatures of porphyry-Cu deposits to generate target areas for further explorations using stream sediment mono-element data of Noghdouz area, NW Iran. In this regard, only geochemical evidence layers were integrated for mineral prospectivity modeling. We generated two prospectivity models for comparison purposes, a model by integration of all the geochemical signatures of the deposit-type sought (efficient and inefficient) and a model by integration of only the efficient geochemical signatures of the deposit. For purification of geochemical signatures, we analyzed different indicator elements of the deposit to discriminate efficient and inefficient geochemical signatures. In this regard, we used a criterion termed normalized density, N_d, and proposed by Mihalasky and Bonham-Carter (2001) for evaluation of classes of evidential maps in mineral prospectivity modeling. This criterion was adapted in prediction-area (P-A) plot (Yousefi and Carranza, 2015b) and success-rate curves (Chung and Fabbri, 2003; Agterberg and Bonham-Carter, 2005; Carranza and Laborte, 2015) for evaluation and weighting individual evidence layers (e.g., geochemical evidence layers). This criterion considers the ability of a geochemical signature at the same time in both (a) prediction of mineral deposits and (b) delimiting the study area for further exploration.

2. Study area and the data set

The study area covers an area of 600 km ^{2} and is covered by the 1:50,000 scale quadrangle map of Noghdouz and is located in the Eastern Azarbayjan province, northwestern Iran. Geologically, the area belongs to the northern part of the Urumieh–Dokhtar magmatic arc (Fig. 1a). Three lithological units are recognized in the study area (Fig. 1b). Eocene volcanic rocks, including andesites, trachyandesites, basalts, basaltic andesites, and porphyritic andesites, constitute the oldest lithological units in the study area. Oligocene intrusive rocks include granodiorites and granodiorites to quart-monzonites, which intruded in the Eocene volcanic rocks, have made a fitting spot for porphyry copper deposits. Quaternary alluvial deposits are the youngest lithological units in the study area (Mahdavi and Amini Fazl, 1988).

In the study area, there are 10 known porphyry-Cu occurrences (Fig. 1b). These deposits were utilized as testing points for assessing the geochemical signatures in prediction of mineral deposits using the geochemical signatures.

The results of analyses of 174 stream sediment samples for eight elements (Cu, Mo, Pb, Zn, Au, Ag, As, Sb), collected by geological survey of Iran (GSI), were used in this study (Fig. 1c). These elements generally considered as good indicators for prospecting porphyry-Cu deposits (Cooke et al., 2005; Halter et al., 2004; Landtwing et al., 2005; Liu and Peng., 2003; Singer et al., 2005; Sotnikov et al., 2007; Weixuan et al., 2007; Xiaoming et al., 2007; Yang et al., 2009). Concentrations of elements in the collected samples were determined by inductively coupled plasma optical emission spectrometry (ICP-OES) method except Au that fire assay method was employed for its measurement.

3. Methods and results

3.1. Statistical parameters of elementals applied

Statistical parameters of the raw data are given in Table 1. The skewness of the raw data and Quintile – Quintile plots (Q–Q plots) (Fig. 2) illustrate that concentrations of elements do not follow normal distributions. Q–Q plot is commonly used to determine the nature of data distributions (normal or log-normal) and to recognize different geochemical populations (e.g., Cheng et al., 1994; Zuo, 2011; Xiao et al., 2012; Zhao et al., 2015). Aiming to assess whether the raw data follow log-normal distribution, the logarithmic transformation was applied on the raw data. The Q–Q plot of the log-transformed data (Fig. 3) exhibit that the log-transformed data contain some outliers and therefore they do not follow log-normal distribution (e.g., Zuo, 2011; Zhao et al., 2015). Instead, they revealed the presence of multiple populations in the individual data set, suggesting that the study area has been affected by several geological events or mineralization processes (Reimann et al., 2002; Zuo et al., 2009; Zuo, 2011).

3.2. Generation of mono-elemental geochemical signatures

Transformation of the values of stream sediment geochemical signatures into a logistic space, compared using original space (i.e., raw data), not only allows for better discrimination of geochemical anomalies but also improves the prediction rate of mineral occurrences (Yousefi et al., 2014; Yousefi and Carranza, 2015a,b). For generating mono-element geochemical signature layers we used logistically transformed-values of element concentrations instead of original raw data. We used Eq. (1), as a logistic function, to transform the values of concentrations from raw data space into logistic space, [0, 1] range (Yousefi and Carranza, 2015a):

$$\mu_x = \frac{1}{1 + e^{-s(x-i)}} \tag{1}$$

where μ_x and x are the transformed value and the raw value respectively. In the above mentioned equation, s and i are the slope and the inflection point of the logistic function respectively. These parameters are determined by the below equations (Yousefi and Nykänen, 2015):

$$i = \frac{2 \ln 99}{\max(x) - \min(x)} \tag{2}$$

$$s = \frac{\max(x) + \min(x)}{2} \tag{3}$$

After transformation of element concentrations, because each stream sediment sample is representative of its upstream composition (Bonham-Carter, 1994; Bonham-Carter and Goodfellow, 1984, 1986; Carranza and Hale, 1997; Moon, 1999; Spadoni et al., 2004; Spadoni, 2006; Carranza, 2008, 2010; Yousefi et al., 2013), Sample catchment basin (SCB) modeling method was employed to portray geochemical anomalies (e.g., Bonham-Carter, 1994; Carranza, 2008). Based on Bonham-Carter and Goodfellow (1984, 1986) and Spadoni et al. (2004), using the SCB mapping technique, the area of influence of each stream sediment sample is defined as the upstream area until the next sample location. The SCB models of transformed element concentrations have been shown in Fig. 5. Each map in Fig. 5 is a mono-element geochemical signature layer ranking different parts of the study area for further exploration of the deposit-type sought.