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Union score and fuzzy logic mineral prospectivity mapping using discretized and continuous spatial evidence values

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ABSTRACT

Two common problems affect integration of exploration criteria for mineral prospectivity mapping (MPM) in geographic information system (GIS): (a) stochastic error associated with sufficiency in number of known mineral occurrences (KMOs) used to estimate evidential weights and (b) systemic error associated with subjectivity of expert judgment applied to process, analyze, and assign weights to evidential data. In this paper we used logistic sigmoid (or S-shaped) function to transform continuous-value evidential data into logistic space without using KMOs as in data-driven MPM and without discretization of evidential data into classes by using arbitrary intervals based on expert judgment as in knowledge-driven MPM. We generated a prospectivity model using discretized evidential data as well. Then, we compared the prospectivity models generated using continuous- and discretized-value evidential data and demonstrated that the former is better model for selecting target areas for further exploration.

1. Introduction

There are data- and knowledge-driven methods to assign evidential weights and to combine various evidential maps for mineral prospectivity mapping (MPM) using geographical information system (GIS) (e.g., Bonham-Carter, 1994; Carranza, 2008b; Porwal and Kreuzer, 2010). The main problem in data-driven MPM methods, which are appropriate for brownfield or well-explored areas, is exploration bias, which results from accessibility factors and exploration criteria, because known mineral occurrences (KMOs) are used as training sites (Coolbaugh et al., 2007). That means data-driven models of mineral prospectivity are affected by locations of KMOs, such that these models predict KMOs well but predict undiscovered deposits poorly (Coolbaugh et al., 2007); this is, in fact, stochastic bias and error. In addition, there is generally no consensus on what is a sufficient number of KMOs to be used in data-driven MPM. With knowledge-driven methods for MPM, which are appropriate in greenfield (or poorly explored) areas (e.g., Carranza and Hale, 2001; Porwal et al., 2003, 2015; González-Álvarez et al., 2010; Lusty et al., 2012; Abedi et al., 2012; Abedi and Norouzi, 2012; Lisitsin et al., 2013), the challenge is how to assign weights to classes of features indicating the presence of the mineral deposit-type sought. For this, the theory of fuzzy sets and fuzzy logic (Zadeh, 1965) has been widely applied in knowledge-driven MPM. However, as Tsoukalas and Uhrig (1997) mentioned, discretization is not necessary in knowledge-driven MPM, but continuous spatial evidence values have been widely discretized into classes and then values in each class of evidential features have been assigned the same weight based on expert judgment (Bonham-Carter, 1994; Cheng and Agterberg, 1999; Carranza and Hale, 2001; Carranza, 2008b; Luo and Dimitrakopoulos, 2003; Porwal et al., 2003, 2004, 2006; McKay and Harris, 2015; Elliott et al., 2016; Ford et al., 2016). Therefore, these MPM methods are sensitive to the widths of classes of evidential values and the relative importance of evidential values in each class is not really evaluated because of the assignment of the same weight to all values in a class.

To address the foregoing issues in MPM, Nykänen et al. (2008), Yousefi et al. (2012, 2013, 2014), Yousefi and Carranza (2015a,b,c, 2016), and Yousefi and Nykänen (2016) applied logistic functions for the estimation and assignment of weights to evidential values without using the locations of KMOs and without discretization of continuous-value spatial data (e.g., geochemical data, distance to

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geological features). In this paper, we further demonstrate the efficiency of logistic-based weighting approach for the estimation and assignment of fuzzy weights to different types of continuous-value spatial data, over discretized spatial data, for fuzzy logic MPM in either greenfields or brownfields exploration. For this, the continuous weighted evidential maps were combined using two different functions to delineate target areas. Then, we compared the mineral prospectivity models generated using continuous weighted evidential maps with a prospectivity model generated using discretized evidential maps. For evaluating and comparing the mineral prospectivity models, we used the locations of 18 KMOs in the study area.

In this paper, we demonstrate and compare the methods applied in a case study using geochemical, geological, alteration, and faults distribution data to map prospectivity for porphyry-Cu mineralization in an area in the Kerman province in southeast Iran. We determined the appropriate cell or pixel size for the evidential maps based on the function of scale number recommended by Hengl (2006) and obtained a pixel size of 100 m × 100 m, which is used for all of the maps in this study.

2. The study area and regional geological background

The study area is a small part of the Urumieh-Dokhtar magmatic arc forming the Zagros Mountains in Iran. The Urumieh–Dokhtar magmatic arc, which is classified as a magmatic arc (Alavi, 1980; Berberian et al., 1982), forms an elongate volcano-plutonic belt running from eastern Turkey to southeast Iran and has been interpreted as subduction-related (Berberian et al., 1982). Magmatism in the Urumieh–Dokhtar magmatic arc occurred mainly during the Eocene but later resumed, after a quiescent period, during the Upper Miocene to Plio-Quaternary. The study area, with a surface of about 2600 km^2, is covered by the 1:100,000 scale Chahargonbad quadrangle map prepared by the Geological Survey of Iran (GSI) (Khan-Nazer et al., 1995). The lithostratigraphic units of the study area have been simplified here into nine classes (Fig. 1).

3. Deposit model and data used

Porphyry-Cu deposits consist of copper minerals as disseminations in host rocks or as open-space fillings in veins and breccias that are distributed in relatively large volumes, forming high tonnage but low to moderate grade ores. Most of porphyry-Cu deposits form in subduction-related magmatic arcs along convergent plate margins, both in continental and oceanic settings (Sillitoe, 1972, 1997, 2010). Porphyry-Cu deposits are mostly centered in high-level intrusive complexes. A wide variety of intrusive rocks with dioritic to granitic compositions, for instance quartz monzonite, diorite, granodiorite, quartz diorite, and monzonite, are spatially and genetically associated with, or host, porphyry-Cu deposits (Hezarkhani, 2006; Boomeri et al., 2009; Peytcheva et al., 2009). Host rocks are altered and genetically related granitoid porphyry intrusions and adjacent wall rocks. Several types of wall-rock alterations, which characterize porphyry-Cu mineralizations, may extend for few kilometers upward and outward from deposit centers. Major alteration types commonly present in porphyry-Cu deposits are potassic, sericitic, advanced argillic, intermediate argillic, propylitic, sodic-calcic and sodic, greisen, and skarn (Sillitoe, 2010). As geochemical characteristics of porphyry-Cu deposits, the spatial distributions of Cu, Mo, Au, Zn, Pb, Ag in rocks, soils, and sediments have also been routinely used in exploring for these deposits (e.g., Sillitoe, 2010). Fractures typically are present in porphyry-Cu deposits and they may host porphyry dikes and be hydrothermally altered and provide fluid pathways for entry of external non-magmatic fluids into the outer parts of the hydrothermal system that cause alterations (Sillitoe, 1972, 1997, 2010). Considering the foregoing general characteristics of porphyry-Cu deposits, mapping of alterations, fractures, host rocks, and geochemical signatures can be used as evidential layers for MPM. Thus, we generated five evidential layers of prospectivity, namely (i) proximity to intrusive contacts, (ii) fault density (FD), (iii) indicator factor score (FS) derived from geochemical data as a multi-element geochemical signature, (iv) proximity to iron-oxide alteration and (v) proximity to argillic alterations.

4. Methods and results

4.1. Generation of continuous weighted evidential maps

Based on the available evidential data sets of the study area, we generated five layers of evidence of prospectivity for porphyry-Cu deposits. The estimated values of proximity to intrusive contacts, FD, FS, and proximity to iron-oxide and argillic alterations are unbounded. Because these values are derived from different spatial data sets, their minimum and maximum values are not the same and their spaces are different as well. In this paper, we transformed the values of different evidential data sets into the same space by applying the following logistic function as a non-linear transformation (Yousefi and Carranza, 2015a):

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

where F_E is a fuzzy membership (fuzzy score), i and s are inflexion point and slope, respectively, of the logistic function, and E is an evidence value to be transformed in the [0,1] range. The values for i and s are defined by the analyst such that resulting fuzzy scores of evidential values lie in the [0, 1] range.

4.1.1. Heat source and host rock evidence map

The porphyry-Cu deposits in Urumieh-Dokhtar magmatic arc are genetically and spatially related to intrusive porphyries and igneous plutons (Hezarkhani, 2006; Boomeri et al., 2009), because the margins of intrusions are strongly fractured and, thus, enabled hydrothermal fluids to exchange heat and mass with the intruded rocks (Sillitoe, 1972, 1997, 2010). Hence, areas close to contacts of intrusive bodies have stronger likelihood of porphyry-Cu mineralization compared to areas farther away (Carranza and Hale, 2002a; Peytcheva et al., 2009).

To generate a weighted geological evidential map, we used distance to intrusive bodies (including granodiorites to granites and quartz-diorites) in the study area as proxy of heat source and, thus, indicator of prospectivity for porphyry-Cu deposits. Because proximity to intrusive contacts represents favorability for porphyry-Cu mineralization (cf. Carranza, 2004; Carranza and Hale, 2002a,b; Pazand et al., 2011), we used the inverse of distance to contacts of intrusive bodies. To assign weights to distances from intrusive contacts, we used Eq. (1) to transform the values in the map of inverse of distances into logistic space (Fig. 2). Intrusive contacts have a value of 0 in the distance map but 1/0 does not exist in the map of inverse of distances although it should have the highest fuzzy score. However, contacts to intrusive bodies were manually assigned the highest value obtained by using the logistic function.

4.1.2. Geochemical evidence map

A fundamental problem with regard to geochemistry for mineral exploration is to determine a significant multi-element anomalous signature of the deposit-type sought (Carranza and Hale, 1997). In this regard, factor analysis, as one of the methods