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# Fuzzification of continuous-value spatial evidence for mineral prospectivity mapping

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ABSTRACT

Complexities of geological processes portrayed as certain feature in a map (e.g., faults) are natural sources of uncertainties in decision-making for exploration of mineral deposits. Besides natural sources of uncertainties, knowledge-driven (e.g., fuzzy logic) mineral prospectivity mapping (MPM) is also plagued and incurs further uncertainty in subjective judgment of analyst when there is no reliable proven value of evidential scores corresponding to relative importance of geological features that can directly be measured. In this regard, analysts apply expert opinion to assess relative importance of spatial evidences as meaningful decision support. This paper aims for fuzzification of continuous spatial data used as proxy evidence to facilitate and to support fuzzy MPM to generate exploration target areas for further examination of undiscovered deposits. In addition, this paper proposes to adapt the concept of expected value to further improve fuzzy logic MPM because the analysis of uncertain variables can be presented in terms of their expected value. The proposed modified expected value approach to MPM is not only a multi-criteria approach but it also treats uncertainty of geological processes a depicted by maps or spatial data in term of biased weighting more realistically in comparison with classified evidential maps because fuzzy membership scores are defined continuously whereby, for example, there is no need to categorize distances from evidential features to proximity classes using arbitrary intervals. The proposed continuous weighting approach and then integrating the weighted evidence layers by using modified expected value function, described in this paper can be used efficiently in either greenfields or brownfields.



## Introduction

Knowledge- and data-driven are two major types of approaches to create and integrate weighted evidential layers for mineral prospectivity mapping (MPM) to delineate target areas for further exploration of a certain deposit-type (Bonham-Carter, 1994; Carranza, 2008). The theory of fuzzy sets and fuzzy logic (Zadeh, 1965) has been applied in knowledge-driven assignment of evidential scores that need expert judgments reflecting realistic spatial as well as genetic associations between spatial evidence and mineral deposits of the type sought (e.g., D'Ercole et al., 2000; Knox-Robinson, 2000; Carranza and Hale, 2001; Porwal et al., 2003; Tangestani and Moore, 2003; Rogge et al., 2006; Nykänen et al., 2008; Lusty et al., 2012).

The assignment of fuzzy membership values to evidential features in the [0,1] range, also called fuzzification of spatial evidence, is the most important stage in fuzzy MPM (Carranza, 2008) because evidential scores should adequately represent the relative importance of geological features (or data) in the process of mineralization, however evidence is vaguely-known or completely unknown (e.g., Ye, 2011; Xu, 2007a,b). However, knowledge-driven evidential scores are assigned based on the analyst's expert judgment, which is inherently subjective, but an analyst usually cannot make an exact choice because of fuzziness (i.e., when there is vague evidence and no reliable proven value of evidential scores for a proposition). Thus, in cases of fuzziness, certain fuzzy membership values in the [0,1] range can be preferred by an analyst as evidential scores of vague evidence. This practice has been used in fuzzy logic MPM to delineate target areas for further exploration (e.g., D'Ercole et al., 2000; Knox-Robinson, 2000; Carranza and Hale, 2001; Porwal et al., 2003; Tangestani and Moore, 2003; Rogge et al., 2006). However, because expert judgment is subjective, defining fuzzy membership values in the [0,1] range as quantitative scores of evidential features is a source of uncertainty in MPM.

Natural resource management and exploration targeting are plagued with uncertainties of various kinds (Runge et al., 2011;

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McCuaig et al., 2010). Vagueness, ambiguity, similarity, possibility, probability, fuzziness, randomness, and imprecision are different types or sources of uncertainty (Celikyilmaz and Burhan Türksen, 2009). Dissimilarities of geological settings are also natural sources of uncertainties in decision-making for assignment of evidential scores in MPM (McCuaig et al., 2010; Lisitsin et al., 2013), even in areas with simple geology (Van Loon, 2002). Geological modeling of mineral systems is complex because there are significant uncertainties in knowledge as well as data about such systems (McCuaig et al., 2010) and they are rarely accurately and precisely represented in existing geological datasets (Lisitsin et al., 2013). For example, data may indicate the presence of evidential features of a deposit-type sought (e.g., geochemical anomaly of indicator elements, favorable host rocks) but mineral occurrence is not observed in the field, and vice versa. Besides natural sources of uncertainties, knowledge-driven (e.g., fuzzy logic) MPM is also plagued and incurs further uncertainty arising from subjective judgment of analyst to fuzzify evidential data.

Recently, Lisitsin et al. (2013) applied Monte Carlo simulation to model uncertainty of geological interpretations resulting from subjective expert opinion in fuzzy logic MPM. They assigned several evidential scores to a certain feature to obtain a distribution function of evidential scores as input probability distribution to support Monte Carlo simulation. This is an effective method for modeling uncertainty where there are some primary reliable historical data for supporting the analyst to obtain a probability distribution of uncertain variables (e.g., Fairbrother et al., 2007; Sari et al., 2009; Mun, 2006). However, the result of Monte Carlo simulation is affected by the probability distribution of the input uncertain variables (e.g., Mun, 2006). In knowledge-driven MPM, there is no reliable proven evidential score corresponding to relative importance of geological features that can be measured directly. Therefore, if evidential scores are assigned based on judgment of several analysts, the probability distributions of such scores carry the uncertainties of expert judgments as well.

Furthermore, in fuzzy logic MPM, distances to geological features are generally categorized into some proximity classes using arbitrary intervals of distance and then the same score is assigned for all distances in each proximity class (e.g., Carranza and Hale, 2001; Porwal et al., 2003; Rogge et al., 2006; Lisitsin et al., 2013). Therefore, this existing practice in fuzzy logic MPM is sensitive to the widths of classes of distances and the relative importance of every distance to geological features is not really evaluated as proxy evidence of mineral prospectivity. However, it has been the traditional practice in MPM to discretize continuous values into categorized data to facilitate understanding of the relation between predictor variables and the target variable (e.g., Bonham-Carter, 1994; Cheng and Agterberg, 1999; D'Ercole et al., 2000; Knox-Robinson, 2000; Carranza and Hale, 2001; Luo and Dimitrakopoulos 2003; Porwal et al., 2003, 2004, 2006; Rogge et al., 2006; Carranza, 2008; González-Álvarez et al., 2010; Markwitz et al., 2010; Lisitsin et al., 2013). Nevertheless, as has been shown in MPM by Nykänen et al. (2008) and as has been shown in other knowledge fields by many researchers (e.g., Clenshaw and Olver, 1984; Sakawa and Yauchi, 1999; Benitez-Read et al., 2005; Narmatha Banu and Devaraj, 2012; Ray, 2012; Guillén-Flores et al., 2013; Silva et al., 2014; Xie et al., 2014), it must be pointed out that discretization of continuous values is not needed in the fuzzification of evidence for a particular proposition.

Considering the caveats (i.e., subjective nature) of fuzzification of spatial evidence for MPM, recent works on fuzzification of geochemical anomalies (Yousefi et al., 2012, 2013, 2014), proximity to intrusive contacts (Yousefi et al., 2013), and fault density (Yousefi et al., 2014) strive to assign continuous fuzzy evidential scores. Following Nykänen et al. (2008), Yousefi et al. (2012, 2013, 2014) and Lisitsin et al., (2013), this paper aims for fuzzification of continuous-value spatial data used as proxy evidence in MPM. In addition, this paper proposes to adapt the concept of expected value to further improve fuzzy logic MPM because the problem of modeling evidential attributes that are incompletely known or completely unknown (Xu, 2007a,b) and the relative importance and integration of fuzzy evidential values can be and has been addressed by using expected values (e.g., Heilpern, 1992, 1997; Rubinstein, 1981; Wang and Chin, 2011; Ye, 2011; Liu, 2013; Gupta et al., 2013). The expected value approach is based on the idea that event level interaction and probabilities, here evidential attributes and their corresponding evidential scores representing the probability of mineral deposit occurrence, can be averaged to produce unbiased estimates that properly account for potential future events in modeling (e.g., Mosher et al., 2010). The expected value method in conjunction with fuzzy models has been applied in ranking and decision-making problems (e.g., Heilpern, 1992; Guo and Tanaka, 2001; Wang and Zhang, 2009 a,b; Wang and Chin, 2011; Ye, 2011; Gupta et al., 2013). Besides using fuzzy logic MPM with continuous weighted evidential maps, this paper proposes a modified expected value integrating approach whereby geo-exploration data inputs are first fuzzified using continuous fuzzy membership values, and then their expected values are used to support decision-making in MPM.

To demonstrate the procedure of fuzzification of continuous-value spatial evidence for MPM using a modified expected value approach that is suitable in greenfield areas, we chose a case study area in the Kerman province in southeast Iran where there are only nine known occurrences of porphyry-Cu deposits. This number of mineral deposit occurrences is inadequate for data-driven MPM (c.f. Carranza, 2004). We used these few deposits only as a set of testing samples to evaluate efficiency of the methodology, developed in this paper, for mapping mineral prospectivity.

## Methods and results

In this study, we used a pixel size of 100 m × 100 m in all of the maps stored in a GIS. This cell size was obtained by using the function of scale number recommended by Hengl (2006).

For fuzzification of continuous-value spatial evidence data, we first analyzed (i) geochemical multi-element data to derive a map of multi-element signature of porphyry-Cu mineralization, and (ii) extracted relevant features from the geological map to create a map of distances to intrusive contacts and a map of density of faults to depict, respectively, heat-source and structural controls on porphyry-Cu mineralization. The continuous values in the derived maps (i.e., factor scores representing multi-element geochemical signature, fault density (FD), and distance to intrusive contacts) do not lie within the [0,1] range, and thus are not appropriate for fuzzy MPM. In MPM, the main goal is to classify a region into highly prospective areas as targets for further exploration, areas with very low priority for prospecting, and some classes between them. Thus, MPM is a classification problem, and prospectivity models can be portrayed as classified maps. Transformation of data (e.g., binarization, multi-class representation, and continuous-value fuzzification) provides a set of values with more discriminatory information and less redundancy for classification (Micheli-Tzanakou, 1999). Defining a suitable non-linear transformation into a new space could facilitate interpretation of a pattern (e.g., dispersion pattern of geochemical indicator elements) for a set of evidential values in MPM compared to their original space (Bishop, 2006; Yousefi et al., 2014). The transformation of continuous-value data using a logistic sigmoid (or S-shaped) function gains an optimal decision boundary for classification (Bishop, 2006). A logistic sigmoid transformation has