Ore Geology Reviews 75 (2016) 16–28

Contents lists available at ScienceDirect

Ore Geology Reviews

journal homepage: www.elsevier.com/locate/oregeorev

Mapping mineral prospectivity for Cu polymetallic mineralization in southwest Fujian Province, China

Yuan Gao [a], Zhenjie Zhang [b], Yihui Xiong [a], Renguang Zuo [a,*]

[a] State Key Laboratory of Geological Processes and Mineral Resources, China University of Geosciences, Wuhan 430074, China
[b] School of Earth Sciences and Resources, China University of Geosciences, Beijing 100083, China

ARTICLE INFO

Article history:
Received 30 August 2015
Received in revised form 1 December 2015
Accepted 8 December 2015
Available online 10 December 2015

Keywords:
Mineral prospectivity mapping
Porphyry–epithermal Cu
Fuzzy weights of evidence
Random forest
Prediction–area plot
Receiver operating characteristics

ABSTRACT

In this study, both the fuzzy weights of evidence (FWofE) and random forest (RF) methods were applied to map the mineral prospectivity for Cu polymetallic mineralization in southwestern Fujian Province, which is an important Cu polymetallic belt in China. Recent studies have revealed that the Zijinshan porphyry–epithermal Cu deposit is associated with Jurassic to Cretaceous (Yanshanian) intermediate to felsic intrusions and faulting tectonics. Evidence layers, which are key indicators of the formation of Zijinshan porphyry–epithermal Cu mineralization, include: (1) Jurassic to Cretaceous intermediate–felsic intrusions; (2) mineralization-related geochemical anomalies; (3) faults; and (4) Jurassic to Cretaceous volcanic rocks. These layers were determined using spatial analyses in support by GeoDAS and ArcGIS based on geological, geochemical, and geophysical data. The results demonstrated that most of the known Cu occurrences are in areas linked to high probability values. The target areas delineated by the FWofE occupy 10% of the study region and contain 60% of the total number of known Cu occurrences. In comparison with FWofE, the resulting RF areas occupy 15% of the study area, but contain 90% of the total number of known Cu occurrences. The normalized density value of 1.66 for RF is higher than the 1.15 value for FWofE, indicating that RF performs better than FWofE. Receiver operating characteristics (ROC) were used to validate the prospectivity model and check the effects of overfitting. The area under the ROC curve (AUC) was greater than 0.5, indicating that both prospectivity maps are useful in Cu polymetallic prospectivity mapping in southwestern Fujian Province.

1. Introduction

The origin of mineral prospectivity modeling (MPM) can be traced back to the works of mathematical geologists such as Harris (1965, 1969); Sinclair and Woodsworth (1970); Agterberg (1971, 1973, 1974), and Bonham-Carter (1994). Methods for GIS-based mineral prospectivity analysis and predictive modeling have been developed over the past 30 years. A number of mathematical methods and models have been introduced for MPM in an attempt to provide objective tools for the integration of multi-source data to narrow down target areas for ground exploration at different scales. The integration functions applied in MPM vary from simple arithmetic or logical operators to complex mathematical functions. These methods can be generally subdivided into knowledge- and data-driven categories, depending on whether the function's parameters are estimated heuristically using theoretical or empirically based knowledge on the statistical spatial relationships between known deposits of the targeted type and predictor maps. Knowledge-driven methods, such as fuzzy logic (An et al., 1991; Ford et al., 2015), Boolean logic (Bonham-Carter and Cox, 1995; Carranza et al., 1999), and evidential belief (An et al., 1994; Carranza et al., 2005; Carranza, 2009), use expert opinions to assign the weights for each evidence map. Data-driven approaches, such as weights of evidence (WofE: Bonham-Carter et al., 1990; Liu et al., 2014; Ford et al., 2015), Bayesian network classifiers (Porwal et al., 2006), neural networks (Singer and Kouda, 1996; Brown et al., 2000; Oh and Lee, 2010), and support vector machine (Zuo and Carranza, 2011; Geranian et al., 2015) are based on quantitative measures of spatial associations between known mineral occurrences and multiple prospecting datasets (Bonham-Carter, 1994; Carranza, 2011; Porwal and Carranza, 2015). Knowledge-driven approaches are commonly applied in greenfields, where no or very few mineral occurrences have been discovered. In contrast, data-driven mineral prospectivity models are suitable for "brownfields" (moderately or well-explored regions) where the goal is to define new exploration targets for mineral deposits of the desired type.

When using ordinary WofE, evidence maps should be converted into binary or ternary form so that maps of different types can be compared and integrated into a single index of favourability or probability (Agterberg, 1989; Agterberg et al., 1990; Bonham-Carter et al., 1990). Cheng and Agterberg (1999) proposed the fuzzy weights of evidence (FWofE) method, an extension of the ordinary WofE method, to

* Corresponding author.
E-mail address: zrguang@cug.edu.cn (R. Zuo).

http://dx.doi.org/10.1016/j.oregeorev.2015.12.005

quantify spatial associations between evidence layers (or geological factors) and known mineral occurrences based on fuzzy sets and fuzzy probabilities. The FWofE method integrates the prior probability of mineral occurrences with the conditional probability for each evidential layer to obtain posterior probabilities of mineral occurrence. Instead of separating evidence into binary or ternary forms, this method allows objective or subjective definitions of fuzzy membership by relatively objective definitions of fuzzy or conditional probabilities. This effectively minimizes the uncertainty caused by missing data and improves the prediction accuracy, providing a powerful tool for measuring spatial correlations between spatial features (Cheng and Agterberg, 1999; Cheng and Zhang, 2002; Cheng et al., 2007).

The random forest (RF) method, which is a machine learning method based on a decision tree classifier (Breiman et al., 1984), is increasingly being applied to data-driven predictive mapping of mineral prospectivity. It is an ensemble classification scheme that uses a majority vote for class association based on the results of multiple decision trees (Cracknell and Reading, 2013). Reddy and Bonham-Carter (1991) used a decision-tree method to map mineral prospectivity for base-metal deposits in the Snow Lake area of Manitoba (Canada). Rodriguez-Galiano et al. (2014, 2015) applied the RF method to map gold prospectivity in southern Spain. Carranza and Laborte (2015a, 2015b, 2015c) tested the efficacy of an RF algorithm. Harris et al. (2015) utilized the RF method to map prospectivity in Canada's northern Melville Peninsula area. Furthermore, Zhang et al. (2015) chose southwestern Fujian Province in China as a case study area to compare the FWofE and RF methods for mapping mineral prospectivity for skarn-type Fe deposits. Mckay and Harris (2015) applied the RF for mapping gold prospectivity in southern Nunavut (Canada).

In this paper, both the FWofE and RF methods are used to map mineral prospectivity for Cu polymetallic mineralization in southwest Fujian

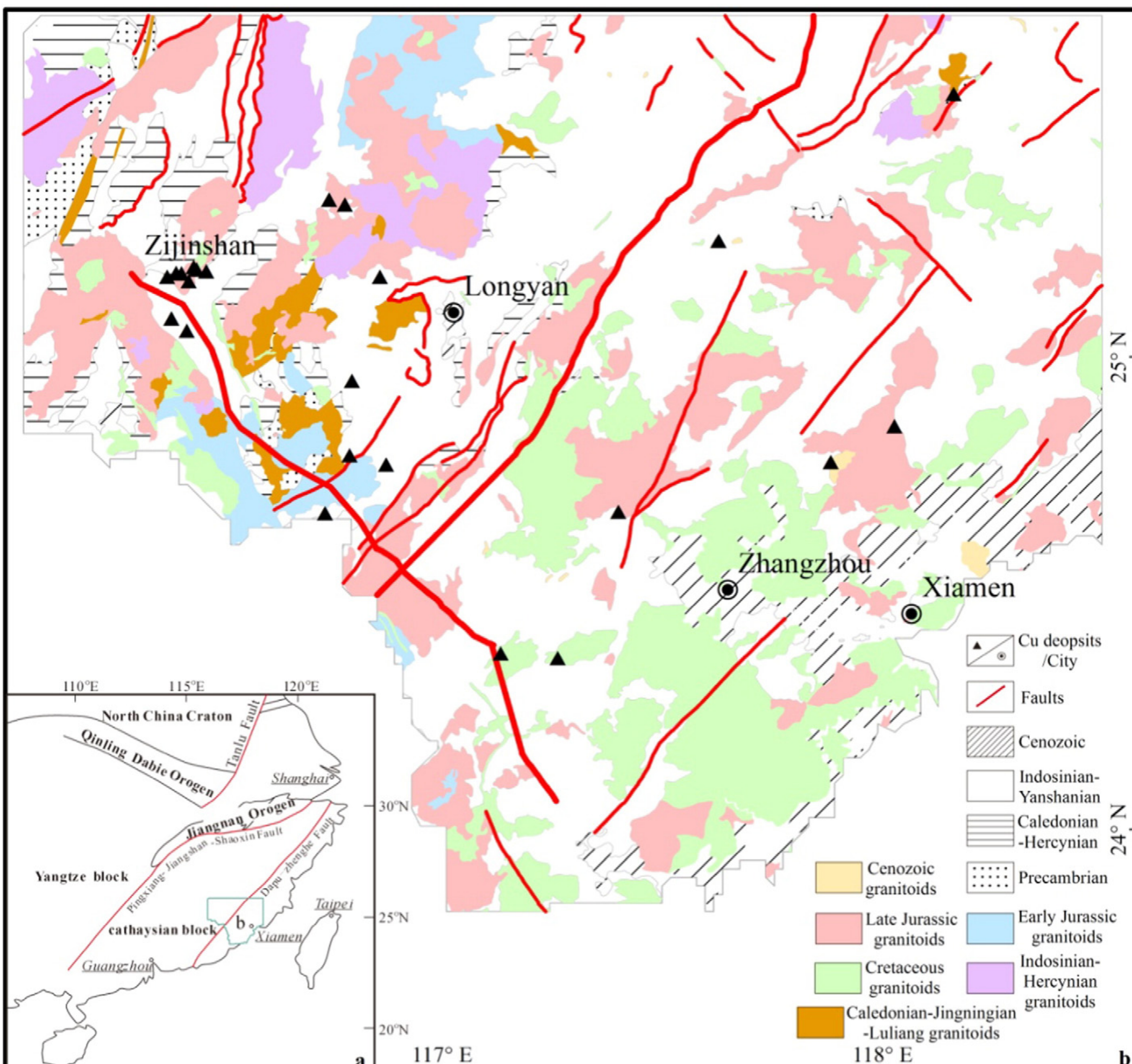

Fig. 1. Simplified geological map of southwestern Fujian Province (compiled from China Geological Survey, 2011).