Ore Geology Reviews 52 (2013) 100–112

Contents lists available at SciVerse ScienceDirect

Ore Geology Reviews

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

Regional prospectivity analysis for hydrothermal-remobilised nickel mineral systems in western Victoria, Australia

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ARTICLE INFO

Article history:
Received 27 December 2011
Received in revised form 10 April 2012
Accepted 15 April 2012
Available online 26 April 2012

Keywords:
Prospectivity analysis
Fuzzy logic
Uncertainty
Monte Carlo simulation
Hydrothermal nickel
Avebury

ABSTRACT

Fuzzy logic mineral prospectivity modelling was performed to identify camp-scale areas in western Victoria with an elevated potential for hydrothermal-remobilised nickel mineralisation. This prospectivity analysis was based on a conceptual mineral system model defined for a group of hydrothermal nickel deposits geologically similar to the Avebury deposit in Tasmania. The critical components of the conceptual model were translated into regional spatial predictor maps combined using a fuzzy inference system. Applying additional criteria of land use restrictions and depth of post-mineralisation cover, downgrading the exploration potential of the areas within national parks or with thick barren cover, allowed the identification of just a few potentially viable exploration targets, in the south of the Grampians-Stavely and Glenelg zones. Uncertainties of geological interpretations and parameters of the conceptual mineral system model were explicitly defined and propagated to the final prospectivity model by applying Monte Carlo simulations to the fuzzy inference system. Modelling uncertainty provides additional information which can assist in a further risk analysis for exploration decision making.

1. Introduction

Effective regional exploration targeting for major mineral deposits and camps in poorly explored areas is one of the most significant challenges for the mineral exploration industry. Defining and ranking regional targets are often done subjectively, on an intuitive level, which mainly draws from specific deposit models and past exploration experiences of the targeting geologist. This results in an introduction of systemic uncertainties (McCuaig et al., 2010; Porwal et al., 2003) in the form of bias resulting from the targeting geologist's subjective proclivity for the specific deposit model and/or past exploration experience. GIS-based prospectivity analysis has been developed in the last 30 years in an attempt to complement expertise of exploration geologists with objective tools more suitable for efficient and repeatable processing and integration of vast amounts of data from numerous information sources. However, these approaches generally do not explicitly deal with uncertainties resulting from inadequacies in the primary data (e.g., imprecision, inconsistent coverage) or from subsequent data processing (e.g., interpolation).

In recent years, prospectivity analyses have increasingly used the mineral systems approach (Czarnota et al., 2010; Hronsky and Groves, 2008; Knox-Robinson and Wyborn, 1997; McCuaig et al., 2010; Wyborn et al., 1994). This approach is based on breaking down the geological processes, which may lead to the formation of mineral deposits, into several groups of critical processes. While individual mineral system models vary in details of the break-down, common groups of critical processes include: 1) sources of metals and fluids; 2) geological features and processes responsible for transporting and focusing mineralising fluids; 3) metal deposition mechanisms.

The purpose of this study is to apply the mineral systems approach to perform a systematic regional prospectivity analysis for hydrothermal nickel deposits in western Victoria. On a broad regional scale, the region has been previously identified as having a potential for hydrothermal nickel deposits (Champion et al., 2009; Seymon, 2006). There has been only limited exploration for Avebury-style nickel mineralisation in recent years (Beaconsfield Gold, 2008; Evans and Cuffley, 2008; Weber and Guzel, 2009), with no deposits discovered to date. This study is based on the current understanding of the essential characteristics of the hydrothermal nickel mineral systems, specifically of the Avebury style (see Section 3) and of the presence of the critical mineral system components in the region. It utilises GIS-based fuzzy prospectivity modelling techniques to identify ore field/camp-scale areas with enhanced mineral prospectivity and exploration potential. It builds upon the previous prospectivity analysis of hydrothermal nickel deposits in Tasmania (González-Álvarez et al., 2010) and ongoing research into the genetic aspects of hydrothermal nickel mineral systems.

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doi:10.1016/j.oregeorev.2012.04.001

In addition, we attempt to quantify uncertainty in the resulting prospectivity maps using Monte Carlo techniques. The outputs are therefore not only potential exploration targets but also confidence in each target.

2. Methodology

2.1. Overall approach

On a high conceptual level, semi-automated GIS-based methods of prospectivity modelling can be subdivided into data-driven, knowledge-driven and hybrid categories (Bonham-Carter, 1994; Carranza, 2008; Porwal et al., 2003). Data-driven methods are based on empirical spatial statistical associations between known mineralisation and 'mappable' geological features. These methods are most suitable for mineral provinces with a reasonably large number of known deposits. Popular data-driven methods include weights of evidence, logistic regression and neural networks. Knowledge-driven and hybrid methods, on the other hand, rely on subjective expert opinions or more structured conceptual models defined by experts. These methods (including fuzzy logic, applications of probability and Dempster–Shafer belief theories and various structured expert systems) can be used in poorly explored terranes with few or no known deposits.

There are only a few minor nickel occurrences known in the study area. In addition, hydrothermal nickel deposits are relatively rare worldwide and remain poorly characterised and understood. This precludes an effective use of empirical data-driven prospectivity modelling techniques. We considered fuzzy logic modelling to be an appropriate knowledge-driven method of prospectivity analysis for this study. This technique is reasonably common in mineral prospectivity mapping. It has been recently used for a similar regional prospectivity assessment in Tasmania (González-Álvarez et al., 2010). Its additional advantage is that it can be modified and used to explicitly define, propagate and express uncertainty, which is important in the current study, as further discussed below.

The prospectivity analysis in this study involved the following steps:

- Review of hydrothermal nickel deposits worldwide. It was undertaken to identify essential geological characteristics of deposit groups with possible analogues in western Victoria.
- Definition of a conceptual model of hydrothermal Ni mineral systems applicable to western Victoria. A particular emphasis was made on the identification of likely critical components of the hydrothermal nickel mineral system(s) that operate at an ore field/camp scale and are essential for practical exploration targeting.
- Translation of the critical mineral system components into spatially defined regional prospectivity criteria in western Victoria.
- Definition of a fuzzy logic inference system reflecting likely interactions between the critical prospectivity criteria, consistent with the conceptual mineral system model.
- Prospectivity modelling, combining individual 'mineral system components' maps into a single mineral prospectivity map using the fuzzy logic inference system.

2.2. Fuzzy prospectivity modelling

A generalised fuzzy model for GIS-based mineral prospectivity mapping can be defined as follows. If X is a set of n predictor maps X_i (where $i=1$ to n) with r map classes, denoted as x_{ij} (where $j=1$ to r), then n fuzzy sets A_i in X, containing favourable indicators for the targeted mineral system, can be defined as:

$$\tilde{A}_i = \left(x_{ij}, \mu_{\tilde{A}_{ui}}\right) \Big| x_{ij} X_i \tag{1}$$

where $\mu_{\tilde{A}i}$ is the membership function for estimating the fuzzy membership value of x_{ij} in the fuzzy set $\tilde{A}_i$. The fuzzy membership function $\mu_{\tilde{A}i}$ can be linear, Gaussian or any other appropriate function (Bonham-Carter, 1994; Carranza, 2008; Porwal et al., 2003; Zimmerman, 1991).

A typical fuzzy model is implemented in two steps: defining fuzzy membership values for all map classes of the input predictor maps and combining the predictor maps to produce a prospectivity map.

2.2.1. Estimation of fuzzy membership values of predictor classes

The following linear function has often been used to estimate fuzzy membership values (e.g., González-Álvarez et al., 2010; Porwal et al., 2003):

$$\mu_{\tilde{A}_i} = \frac{m_i \times w_j \times cf_i}{D} \tag{2}$$

where m_i is the map weight, w_j is the class weight, cf_i is the confidence factor and D is a denominator set to constrain $\mu_{\tilde{A}i}$ to the range [0,1]:

$$D = \max\{m_i\} \times \max\{w_j\} \times \max\{cf_i\}. \tag{3}$$

Map weights and confidence factor are often subjectively assigned a value between 1 and 10 based on expert knowledge. Class weights are also assigned values between 1 and 10. Map weight and class weight, respectively, indicate the perceived importance of a predictor map and a class on the predictor map. The confidence factor is assigned to a predictor map based on the degree of directness, that is, how closely it represents an exploration criterion. The predictor map gets a higher confidence factor if it directly maps the exploration criteria and a lower confidence factor if it is based on mapping the indirect response of the exploration criterion. Confidence factor is also used to account for the uncertainties in the primary dataset that was used to create a particular predictor map.

2.2.2. Combining predictor maps and evaluating uncertainty

In fuzzy modelling, predictor maps are combined using a fuzzy inference engine. It constitutes a number of parallel and/or serial networks that sequentially combine predictor maps through fuzzy set operators (see Bonham-Carter, 1994, p. 301; Carranza and Hale, 2001; Porwal et al., 2003 for details). The design of an inference engine should be consistent with the mineral system model under consideration. The output of an inference engine is a fuzzy prospectivity map for the targeted mineral system.

Geological understanding of the hydrothermal nickel mineral system is still evolving and there are significant uncertainties on the critical components of the mineral system, their relative importance and details of their possible relationships. There are also major uncertainties involved in the translation of the inferred critical components of the mineral system into 'mappable' prospectivity criteria (McCuaig et al., 2010). For example, likely critical processes of a mineral system are rarely accurately and precisely represented in existing geological datasets. Even in the best-case scenario, when there is a direct correspondence between a critical process and a mappable criterion (e.g., a particular rock type), the spatial distribution of that criterion is mostly interpretative by nature — e.g., interpolation between, or extrapolation beyond, the observation points, or non-unique interpretations of geophysical datasets. When critical processes can only be recognised indirectly by proxy, there is an additional uncertainty of the representativeness of the proxies.

These numerous uncertainties are often made implicit, by making a series of 'best-guess' decisions, on the basis of information available to prospectivity modelling analysts at the time of analysis. Information on uncertainty of the individual decisions is usually ignored, leading to final prospectivity models and maps which may indicate an inappropriately high level of confidence. In effect, typical applications of knowledge-based prospectivity modelling techniques (including fuzzy