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Spatial data analysis of mineral deposit point patterns: Applications to exploration targeting

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A B S T R A C T

Systematic spatial analysis of mineral deposit point patterns can reveal significant spatial properties of mineral systems, with major implications for regional mineral prospectivity modelling. For valid results, a study area needs to be clearly defined, taking into account permissiveness of the geological units for a particular mineral system and effects of cover. Standard statistical tests assuming an isometric contiguous study area with regionally homogeneous distribution of deposits are likely to produce invalid results. Analysis of regional uniformity of spatial deposit density is required for adequate design and interpretation of tests for clustering. Spatial distribution of orogenic gold deposits in the Hodgkinson Province in Queensland and the Western Lachlan Orogen in Victoria (Australia) indicates the presence of significant regional linear metallogenic zones, probably controlled by deep crustal domain boundaries oblique and not related to any recognised major faults. Within the metallogenic zones in both regions, individual gold occurrences are strongly clustered into ore fields, but the distribution of ore fields is random.

1. Introduction

Predictive mineral potential modelling (both in forms of prospectivity mapping and quantitative mineral resource assessments) typically uses a combination of knowledge of essential natural processes leading to the formation and preservation of mineral deposits (mineral systems), on the one hand, and empirical evidence of spatial association between mineral deposits and other geological objects or their properties, on the other. However, any predictive modelling is invariably impeded by limited knowledge of mineral systems and frequently obscure manifestations of major metallogenic factors. Consequently, there is a significant risk of not recognising some essential mineralisation controls, potentially leading to grossly biased modelling results.

In an area with a relatively large number of known mineral deposits, their spatial distribution can provide critical information on metallogenic processes operating at different scales. For example, significant metallogenic controls may have only cryptic expressions in traditional geological datasets, initially revealing themselves only in the spatial distribution of mineralisation. The latter could also help to validate a common assumption of deposit clustering. Recognising cryptic regional metallogenic controls and establishing whether deposits (particularly large ones) tend to be close or distal from each other have major implications for exploration targeting. For example, major deposits within a province could occur in a relatively narrow richly endowed metallogenic zone (discordant to regional geological structures recognised at surface), surrounded by large geologically similar areas containing only sparse and mostly economically insignificant mineralisation. It is then critical to focus exploration for major deposits on that zone. Similarly, if major deposits tend to be spatially separated from each other by a relatively large distance, then extensive exploration in a close vicinity to a known major deposit may be a flawed exploration strategy if a desired target is another major deposit. Such information can be particularly important at scales of tens to hundreds of kilometres — intermediate between those of a broad regional scale (focusing on regional geodynamic and associated metallogenic factors) and detailed camp to deposit-scale studies (focusing on direct observations over relatively small areas).

Methods of spatial statistical analysis of point patterns are well developed and widely used in social and physical sciences, including applications in geology (Getis and Boots, 1978; Cressie, 1991; Diggle, 2003; Illian et al., 2008). They are appropriate for investigating stochastic processes, manifestations of which can be represented, at the scale of analysis, by a finite set of points. In a regional-scale prospectivity analysis (covering thousands of km^2), mineral deposits can be adequately

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represented by points, which has been almost universally accepted in previous spatial and mineral prospectivity analyses (Bonham-Carter, 1994; Porwal et al., 2003; Carranza, 2008, 2009).

Various techniques of spatial statistical data analysis have been applied to investigate distribution of mineral deposits, mostly involving methods of point pattern and fractal analysis (De Geoffroy and Wignall, 1971; Agterberg, 1984; Harris, 1984; Carlson, 1991; Kreuzer et al., 2007; Raines, 2008; Ford and Blenkinsop, 2008; Carranza, 2008, 2009; Mamuse et al., 2009, 2010; Singer, 2008; Singer and Menzie, 2010; Singer and Kouda, 2011; Dirks et al., 2013). However, different spatial statistical methods have been mostly used in isolation. As each specific method only characterises a particular aspect of a point pattern, outputs of any individual test could be insufficient to make reasonable inferences about spatial distribution of deposits, potentially leading to erroneous interpretations. Importantly, most traditional spatial statistical tests imply some underlying assumptions (similar to the assumption of the normal distribution in many classical statistical tests). In practice, these assumptions are rarely explicitly stated, analysed and validated, even though they are frequently violated. Formal confirmatory statistical analyses may not adequately characterise spatial distribution of mineral deposits, which in many situations would be more amenable to a suite of complementary methods for exploratory spatial data analysis.

Suitability of specific methods to study patterns of mineral deposits depends on ultimate goals of an analysis. The focus may be on the spatial distribution of the intensity of a metallogenic process (e.g., mapping zones of high or low spatial deposit density), interaction of points with each other (e.g., clustering or dispersion), spatial association between deposits and other features (spatial covariance with one or more explanatory variables), or a combination of the above. This paper describes a joint application of several complementary methods of spatial data analysis, many of which are not commonly used in mineral prospectivity modelling but can provide important insights into the spatial distribution of mineral deposits and underlying regional metallogenic controls. The selected set of methods is far from exhaustive and more powerful alternatives and comprehensive modelling strategies have been developed for some of them in recent years (Diggle, 2003; Illian et al., 2008; Gelfand et al., 2010). The method selection was deliberately biased towards traditional methods which are relatively easy to implement using standard readily available software and outputs of which are amenable to a reasonably straightforward intuitive interpretation. A major goal of this paper is to discuss pitfalls of many traditional spatial statistical methods applied to investigate the spatial distribution of mineral deposits and to illustrate their tentative use as part of comprehensive exploratory spatial data analysis. The reviewed methods include analyses of: centrography and directional distribution, Fry plots, nearest neighbour distances, spatial density and Ripley's K function. A systematic spatial data analysis, focusing on an effective combination of individual methods, was applied to investigate regional spatial patterns of orogenic gold deposits in the Hodgkinson Province in north Queensland and the Western Lachlan Orogen in central Victoria (Australia). Outputs of the applications of spatial data analysis discussed in this paper have major implications for mineral resource assessments and exploration targeting in those regions.

2. Methods for spatial analysis of point patterns

2.1. Overview of methods and modelling strategies

A point pattern within a study area can be characterised by statistical measures and properties describing the pattern as a whole, as well as by indicators of more local properties of the spatial distribution of points within the pattern. The former can be described by a series of summary statistics providing information on the geographic centre, spread and directional anisotropy (centrographic and directional distribution spatial analysis) and the average spatial density of the point pattern. Estimates of average spatial mineral deposit densities have been extensively used in quantitative mineral resource assessments to estimate numbers of undiscovered deposits in a study area based on average deposit densities in geologically similar areas (Singer et al., 2001; Singer and Kouda, 2011). In contrast, methods for analysing centrographic and overall directional properties have rarely been applied to investigate mineral deposit patterns (Mamuse et al., 2009).

A wide range of other spatial statistical methods place more emphasis on describing local internal properties of patterns, mostly focusing on the distribution of points in relation to each other. A point pattern (e.g., representing a group of known mineral deposits in a study area) is typically compared to a simple theoretical point pattern to classify the analysed pattern into one of several basic types. Then, inferences can be made about the character of a point process and, possibly, an expected distribution of other points in the study area (such as undiscovered deposits).

Point patterns can be subdivided into several basic types (Getis and Boots, 1978; Diggle, 2003). Firstly, the average point density (the number of points per unit area) can be either uniform throughout a study area (a homogeneous distribution) or significantly vary in space (a non-uniform, or heterogeneous distribution). The latter could be a manifestation of the underlying spatial heterogeneity of major factors controlling point processes. This is commonly observed for mineral deposits (e.g., a major structural corridor controlling the location of a richly endowed metallogenic zone). Secondly, depending on the character of interpoint interaction, point patterns can be described as random, clustered or dispersed (regular).

The character and extent of interpoint interaction in an analysed point pattern is typically determined by comparison with a point pattern of complete spatial randomness (CSR). A pattern of CSR is generated by a uniform Poisson process, which (i) uniformly operated throughout a study area at a constant intensity and (ii) was characterised by the independence of the location of each point in relation to any other points in the area (Diggle, 2003; Isham, 2010).

A significant difference between an observed point pattern and a pattern of CSR, as indicated by statistical tests, is typically interpreted as evidence of significant interpoint interactions (clustering or dispersion), assuming a regionally homogeneous point process.

However, significant departures from CSR can also be due to regional-scale variations of intensity of the point process, with no significant local-scale interpoint interactions, or a combination of both factors. Unequivocally distinguishing the different interpretations is often impossible on the basis of any single statistic (Diggle, 2003, 2010). Regional heterogeneity of point processes is quite typical for many types of geographic environments, including mineral systems. Distinguishing between regional heterogeneity of mineral deposit density and more local-scale clustering of deposits could have major implications for regional exploration targeting, as mentioned earlier. Extensive exploratory spatial data analysis, using a sequence of various complementary methods, is thus required to make robust inferences regarding a point process.

2.2. Centrographic and directional distribution analysis

Simple overall measures of the geometric centre and directional anisotropy of a point pattern can be obtained from centrographic and directional distribution spatial analysis, which can be easily implemented using various GIS and specialised spatial statistical software. Common centrographic statistics for a point pattern are the mean centre, median centre, standard deviational circle and standard deviational ellipse (Ebdon, 1988; de Smith et al., 2007). The mean and median centres are simple summary statistics of a point pattern equivalent to the mean and median in the classical statistics. The mean centre MC is characterised by geographic coordinates $\{X, Y\}$ equal to the