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Letter

Consequences of fractal grade distribution for bulk sorting of a copper porphyry deposit

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A B S T R A C T

We show the presence of fractal ordering of copper grade in bore core data at short range in the Cadia Ridgeway porphyry deposit and measure its persistence after mining by monitoring the output of the mine every 20 s for a month using a large scale, zero field magnetic resonance sensor. A simple model is used to investigate this connection and its consequences for sorting of the ore. Fractal distributions, and their associated power laws, have two features highly favourable for segregating ore: a large proportion of low-grade pods and the large scale spatial clustering of grade.

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1. Introduction

The amounts of copper available to mine, falling head grades, and the impact of technology on supply are topics of recent discussion (Herrington, 2013; Kerr, 2014). Pod ore sorting, where batches of crushed rock are diverted based on copper grade, is one potentially high impact technology to address dropping head grades in copper deposits. To date, sorting of crushed ore has generally taken place at low rates on a rock-by-rock basis (Salter and Wyatt, 1991). For pod sorting to be effective a sensor must exist that is capable of rapidly measuring the grade of a bulk stream of copper ore, and there must be sufficient variation of grade at relevant size scales in the production stream. The presence of fractal behaviour in the distribution of copper in the deposit, as has been suggested in past studies of the mechanisms of grade concentration (Monecke et al., 2005), would have a profound effect on the scaling behaviour of variation with pod size and the relative amount of pods that have low levels of copper.

Fractal methods have been used successfully in analysing bore core data from copper porphyry deposits showing a power law or near power law distribution of copper grade (Monecke et al., 2005) and vein sizes (Monecke et al., 2001; Sylvie et al., 2007). They have been used to analyse grade tonnage curves (Wang et al., 2010; McGraw, 2013) and classify regions within a deposit (Afzal et al., 2011, 2013). The analysis for fractal behaviour involves studying the spatial distribution of grade. In a classic self-similar fractal (for instance the view of a rocky coastline from above, Turcotte, 1997) increasing the magnification results in a statistically similar image. When analysing a bore core where one dimension is the length along the core and the other is copper grade, both dimensions can no longer be scaled uniformly. The definition of self affine fractals describes how statistical behaviour changes as scale changes (Turcotte, 1997) for fractals in this circumstance. For instance, in terms of the standard deviation of the copper grade $SD(x,g)$ along a bore core, such as shown in Fig. 1.

$$SD\left(x,g\right) = SD\left(rx, r^{\mathrm{Ha}}g\right) \tag{1}$$

for a self affine fractal distribution, where x is the spatial ordinate along the core and g is the grade. When the x scale is changed by the factor r, the grade scale must be adjusted by r^{Ha} to retain the same value of standard deviation, where Ha is known as the Hausdorff measure and equals one (Afzal et al., 2011) for a self similar fractal. Furthermore, the probability of a rock or pod of a given size having grade g ($P(g)$) is described by the power law $P(g) \propto g^{-D}$, where the index D is given by 2-Ha and is commonly called the fractal dimension. Furthermore, for deterministic self affine fractals, if

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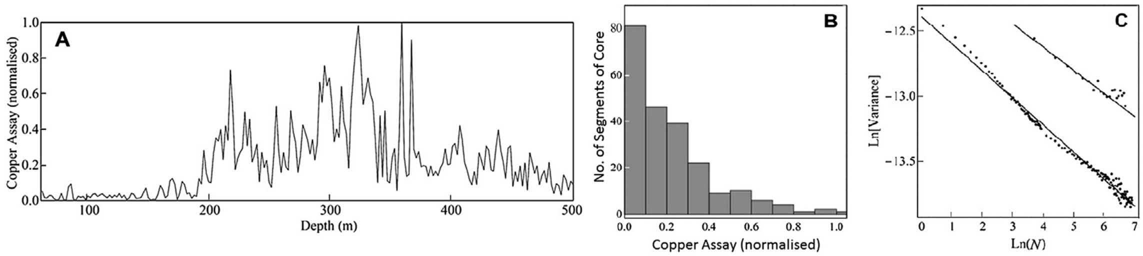

Figure 1. The 2 m average copper concentration along one bore core (A) is analysed as a histogram in (B) and by calculating the variance after averaging over *N* neighbouring points (C). This is carried out for the assay data as well as for thermal infra-red reflectance data (TIR) which is available on a 10 cm scale. The assay data is shifted to the right so that *N* for both graphs represents equivalent lengths.

present such behaviour provides a simple formula to calculate the statistical properties as scale changes.

2. Bore core study

The study presented here involves the Cadia East and Ridgeway Au–Cu porphyry deposits, which are located in the Cadia district of NSW Australia (Wilson et al., 2003; Sillitoe, 2010). Fig. 1 shows an analysis of data from one bore core from the Cadia East Au–Cu Porphyry deposit. The average copper assay for every 2 m of core is plotted in Fig. 1A. This core was also measured by thermal infrared reflection (TIR) at higher spatial resolution of 10 cm. Spectral data can be used as a proxy for alteration, or the presence of veins, in the rock and the statistical properties of the spectral data compared to that of the grade measurement (Yang et al., 2005). In this case, reflectance at 12,280 nm was used as it gave the best correlation to copper content in the core and is a proxy for quartz (Weinrich and Christensen, 1996). A first step in the fractal analysis is to calculate the variance of the grade as a function of N, the number of neighbouring points along the core accumulated and averaged into one spatial bin. Therefore, for a given N, the spatial bins span $2N$ metres for the copper assay and $0.1N$ metres for the TIR data. As N is increased the number of points used in calculating the variance decreases until, on the scale of 40 m, the calculation is terminated. If the data set is self affine, the variance will be proportional to $N^{-2\mathrm{Ha}}$ and a log-log plot of variance vs. N will result in a straight line (Ivanov, 1995). Fig. 1C shows the log-log plot of variance vs. N for the two sets of core data superimposed. The straight-line trend for each data set implies fractal behaviour. The interesting feature is the similarity of the two slopes (−0.145 for copper assay and −0.208 for the TIR data), and hence the statistical properties of the spatial distributions of copper and veins in the rock. This suggests that the veins in the rock do exert a controlling influence on the distribution of copper and that fractal behaviour continues to small size scales in this deposit.

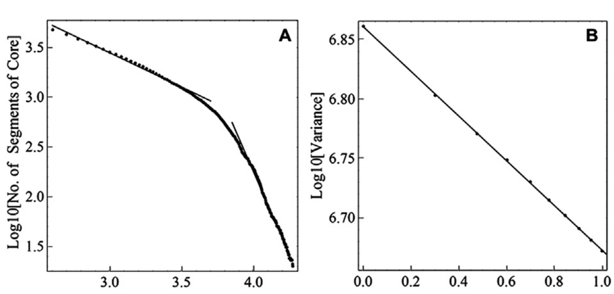

Figure 2. The grade of the combined bore cores is analysed for possible power law dependency by the examining the log-log plot of the cumulative histogram (A). Two linear regions in the plot have been fitted. After spatially averaging *N* neighbouring points the variance vs. averaging parameter *N* is displayed in (B).

Fig. 2 shows the analysis of the combined core data from eighteen cores (5890 data points each representing 2 m of core length) that intersect the current mining zone and the nearby volumes at Ridgeway. There is sufficient data to analyse the cumulative grade histogram for power law behaviour, as shown in Fig. 2A. Two linear trending regions may be fitted, with a knee at a grade of 7300 ppm copper. As was the case in the similar analysis of the Waterloo deposit by Monecke et al. (2005) this is evidence of truncation of the power law at higher grades. They ascribed this to the concentration mechanism approaching an upper limit in grade. At larger scales it may also be necessary to account for systematic variation of the mean grade, possibly by a combination of fractal techniques and more traditional geostatistical methods (Agterberg, 2012a,b). The spatial analysis however shows a good fit to a single power law with a slope of −0.193 of the log-log graph of variance vs. averaging parameter N.

2.1. Grade model formation

A simple fractal model of short-range grade variation in the rock can be constructed from the core data using the spatial analysis. As the core data is treated in one dimension an assumption is required to convert metres of core to tonnes of ore. In the first instance x metres of core will be taken as representative of a sphere with diameter x centred at the bore core. For the minimal 2 m length this represents about 13 tonnes. The toy fractal model for grade variation in the rock can then be constructed by assuming a power law distribution of grade, where $D = 1.942$ is derived from the slope of the fit to the variance observed for Ridgeway in Fig. 2B. The power law extends from a minimum to a maximum grade representing in principle the background grade of the rock and the truncation enrichment grade respectively. The choice of assumptions for converting the core data to tonnes, from linear combination to the toy model's spheres, results in a range of dimensions from 1.942 to 1.903 due to the small value of Ha.

3. Magnetic resonance measurements

This toy model can then be compared with production data from the mine to measure how well any fractal signature in the rock is preserved by the mining process. The variability in the rock will be reduced and modified by the mining process as it presents crushed ore on the main conveyor. Ridgeway is a block cave mine consisting of 15 parallel drives under the ore body, on each side of a drive there are 8 or 9 active draw points. The rock from these draw points is removed by loaders to one of two crushers at either end of the mine, this primary crushed ore is then mixed onto a portal conveyor. During the month of this evaluation 250 draw points were used to provide ore with an average of approximately 86 draw points used in a given hour. The loaders have a capacity of approximately 14 tonnes and drop the load into hoppers for the crushers with a maximum capacity of 200 tonnes.

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