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Spatial Variability Analysis of Cu Content: A Case Study in Jiurui Copper Mining Area

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ABSTRACT

Conventional variogram has been widely applied to study spatial variability of geochemical data. In case of data is not normally distributed, the conventional estimator is biased. In this study, Cressie variogram and Moran correlogram were used to identify the degree of spatial variabilty of Cu content using 1341 stream sediment samples in Jiurui copper mining area. Cressie variogram was applied to reduce the influences of high values in identifying spatial variability in different directions. Moran correlogram was employed to study spatial correlation at different distances and the influences of data distribution on the results in quantitative ways. It was found that Cressie variogram yields stable robust estimates of the variogram with the maximum spatial variability of 12km for all directions; Moran correlogram provided more information, directly viewed and stable than variogram. Moran correlogram identified a strong positive spatial correlation at distances below 6km for the raw data and a strong positive spatial correlation at distances below 11km for Box-Cox transformed data.

KEYWORDS

Copper Mining Area, Cu Content, Moran Correlogram, Spatial Variability, Variogram

INTRODUCTION

Geochemists examine the spatial patterns of geochemical elements to understand the mechanisms and that control their spatial distribution, therefore, an understanding of the spatial variability of geochemical elements has important implications. It has been argued that all spatial data fulfill the generalization that values from samples near to one another tend to be more similar than those that are further apart (Liebhold & Sharov, 1998; Epperson, 2000). This tendency is termed spatial autocorrelation or spatial association (Cliff & Ord, 1981). Consequently, there has been an increasing interest in the use of variogram, spatial correlograms and covariance functions for describing patterns of spatial variability and measuring degree of spatial autocorrelation (Frogbrook & Oliver, 2001; Zhang & McGrath, 2004; Frutos et al., 2007; Borcard & Legendre, 2012; Legendre & Legendre, 2012).

The classical regional variogram estimator proposed by Matheron (1963) was first used to spatial variability of spatial data. However, according to Cressie and Hawkins (1980), the sample variogram can give a poor estimate of the regional variogram if there are outliers in the data. The sample mean is not stable estimator of theoretical mean. Genton (1998) shows that one single outlier can destroy this estimator completely. For that reason, several types of estimators based on robust estimation of scale and quantiles have been proposed, such as typical robust variogram proposed by Dowd (1984) is the median of the magnitude of increments, variants proposed include the quantile variogram (Armstrong & Delfiner, 1980), the jack-knifing (Chung, 1984) and a variogram estimator based on a highly robust estimator of scale (Genton, 1998). Especially the variogram of order ½ proposed by

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Cressie and Hawkins (1980) has been widely used. The robust estimation of the Cressie variogram using of a fourth-root transformation was proposed when the distribution is normal-like in the central region but heavier than normal in the tails. The usual product moment covariogram estimator of a Gaussian process can have bias. In order to decrease the bias, the sample mean in the estimator is replaced with the sample median (Cressie & Hawkins, 1980). Variograms decompose the spatial variability of observed variables among distance classes (Legendre & Legendre, 2012), thus they have been widely used in modeling and interpreting ecological spatial dependence and spatial structure (Legendre & Legendre, 2012; Saraux et al., 2014; Roy et al., 2015), soil science (Iqbal et al., 2004; Tripathi et al., 2015), studies of spatial patterns of sill physico-chemical variables (Abu et al., 2011; Jiménez et al., 2011), quantifying the distribution of spatial patterns and changes in soil organic carbon in environmental science (Frogbrook & Oliver, 2001; Zhang & McGrath, 2004).

Spatial correlograms are another commonly used method for spatial variability analysis. Spatial correlograms (Cliff & Ord, 1981) can be computed for single variables using Moran's I or spatial statistics, or the spatial correlation function or even for multivariate data using multivariate variogram and Mantel correlogram. Spatial correlograms have been widely applied in soil science (Ducarme & Lebrun, 2004), land use studies (Overmars et al., 2003), environmental studies (Arbia et al., 2009; Huo et al., 2012), biology studies (Torres, 2003; Legendre & Legendre, 2012), especially in ecology studies (Frutos et al., 2007; Uuemaa et al., 2008; Borcard & Legendre, 2012). Spatial correlograms are also sensitive to extreme values (outliers) and to asymmetry in the data distributions. Extreme values and asymmetry increase the variance and the kurtosis of the data, therefore, this makes difficult to reach significance in statistical tests.

Geochemical data commonly have skewed and non-normal distributions (Reimann & Filzmoser, 2000; Nguyen et al., 2013, 2014), this has negative influences on spatial variability identification. Thus the purposes of this study were (I) to identify the degree of spatial variability and (II) to examine the influences of outliers and asymmetry in the data distributions on spatial variabilty identification in quantitative ways by using Cressie robust variogram estimator and Moran spatial correlogram. The experiment was carried out using 1341 stream sediment copper samples collected at scale of 1:200,000 in Jiurui copper mining area. The results of this study will provide geochemist more suitable methods to measure spatial variability for geochemical data.

STUDY AREA AND DATA USED

According to requirements of 1:200,000 regional stream sediment survey, a multi-element sediment geochemical survey of streams was carried out in Jiurui area (China). A total of 1341 composite samples representing about 5364 km^2 were collected. Some sampling areas at the upper part of the study area were not able to access. The sampling density was 1 composite sample per 4 km^2. There are more than 20 indexes in a composite sample, including Ag, As, Au, Be, Cd, Cu, Hg, Li, Mn, Mo, Nb, Pb, Sb, Sn, Th, V, W, Y, Zn, Al_2O_3, CaO, K_2O, Na_2O. A total of 13 ore deposits were found marked by numeric characters from 1 to 13 (Figure 1). Copper is one of three ore-forming elements caused anomalous area in the study area, Cu content was thus chosen to study it's spatial variability.

METHODOLOGY

Variogram

Let $\left\{Z\left(x_1\right),Z\left(x_2\right),\ldots,Z\left(x_n\right)\right\}$ be a sample of such a spatial stochastic process. The classical variogram estimator proposed by Matheron (1963), based on the method of moments, is:

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