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Determination of the geochemical background and anomalies in areas with variable lithologies



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ABSTRACT

Studies that delineate the geochemical background and anomalies are essential for exploration geochemistry. Lithology has a significant impact on the background values of many elements in both stream sediments and soil samples. However, uniform threshold values are not available for delineation of all anomalies in areas with complex geologic conditions. Here, the influence of lithology on background concentrations of metals is described based on the relationships between metal element concentrations and oxide concentrations (in particular SiO₂) in geochemical samples. The anomaly thresholds of metal elements, influenced by lithology, can be determined from the residual error confidence band based on a linear regression model. This method can help eliminate the influence of lithology on background concentrations of metals and allows more effective detection of anomalies than a simple constant threshold method.

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1. Introduction

The delineation of the geochemical background and anomalies with respect to that background is a key factor in geochemical exploration and research. Background concentrations of elements vary with, for example, underlying lithology and landscape parameters, even within a particular area. The application of a uniform threshold value to delineate anomalies causes elemental anomalies to be ignored in areas with low background values and magnified in areas with high background values, which often weakens the utility of geochemical exploration on search for mineral resources. A reasonable way to solve this problem is to find possible relationships between the geochemical anomalies found and the geological processes. Using rock types to represent geological processes seems to be a simple solution. The geochemical background of elements is influenced by many factors; however, assuming that landscape characteristics remain relatively constant, the underlying geology (lithology in particular) is a key factor influencing the geochemical background. The background values of different metal elements vary considerably in different areas with various rock categories (Cheng and Xie, 2006). For example the background values of Cr, Co, Ni, Zn and Cu are higher in mafic-ultramafic rocks than felsic rocks due to substitution of those elements in ferromagnesian minerals.

The use of a uniform threshold value to delineate anomalies within areas with variable lithologies has long been an issue for exploration

* Corresponding author. *E-mail addresses*: haolb@jlu.edu.cn (L. Hao), zhaoyuyan@jlu.edu.cn (Y. Zhao). geochemists and several methods have been proposed to determine an anomaly threshold. The applicability of the subarea division method is limited owing to its high computational demands and strict division of geologic unit boundaries in survey areas; therefore, it is unsuitable for areas with variable lithologies. This method is also limited by the preconceptions of study of the researchers involved, such that the delineation of different divisions can result in variability and uncertainty in the threshold (Li and Sun, 2004). The moving average and trend surface methods require a continuous range of elemental contents and consider the distribution of data to be a smooth (differentiable) and continuous curved face (at least parts of which are smooth). However, the distribution of elemental contents is extremely complicated and irregular and is not always differentiable (Li et al., 1995). For the trend face method, after acquiring the fluctuation value of the background, the residual value can be acquired by subtracting this fluctuation value from the original data. However, the residual value still masks anomalies and errors and makes calculation of the anomaly threshold remains difficult (Xie, 1979). Conversely, selection of a window in the moving average method is achieved subjectively, which would increase subjective error. For example, using a large window will ignore low anomalies, or selecting a small window can't eliminate random errors. In recent years, several researchers (Arias et al., 2012; Cheng, 2012; Cheng et al., 1999, 2000; Li et al., 2003) have attempted to apply the multifractal techniques to determine geochemical background values and related anomalies, which provided good results in complex geological areas. However, the applicability of these methods has yet to be verified in areas with variation in lithology.

In this study, the influence of lithology on background values of metals is delineated on the basis of the relationships between metal

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elements and oxide concentrations (in particular SiO_2) in geochemical samples. The anomaly thresholds of metal elements, influenced by lithology, can be determined from the residual confidence band based on a linear regression model. This method can help eliminate, to a large extent, the influence of changing lithology on the background concentrations of metals and can allow effective detection of anomalies with respect to background concentrations.

It is well known that metal element contents obviously vary with rock types (Cohen et al., 2012a, 2012b; Reimann and Garrett, 2005; Yan and Chi, 1997). Geochemical data from the magmatic rocks in East China (Fig. 1) indicate that the concentrations of some metal elements are close-ly related to SiO₂ contents, which in turn vary with lithology. Conversely, some elements exhibit no correlation with SiO₂ content; this is thought to be a result of various factors affecting the affinity of the elements. Stream sediments and soils are composite materials derived from the weathering and erosion of rocks and the chemical composition of which appear in distinct succession (Hao et al., 2004, 2005). Therefore, evaluating anomalies obtained from stream sediment samples should consider the influence of lithology on the element background concentration.

2. Data processing methods

When the concentration of a type of metal element exhibits a clear correlation with that of SiO₂, their relationship can be defined as follows:

$$C_i = \alpha + \beta \times C_{\text{SiO}_2} + \varepsilon \tag{1}$$

where C_i is the concentration of metal element *i* in the sample, C_{SiO_2} is the SiO₂ content of the sample, and α and β are the undetermined coefficients. The term $\alpha + \beta \times C_{\text{SiO}_2}$ refers to the linear change of the concentration of element *i* with change in lithology, while ε refers to the summation of the influence of all associated random factors (sometimes referred to as random errors). The random error terms are assumed to be independent, identically distributed, and follow the normal distribution with mean 0 and covariance σ^2 . The fitting of the above relationship is equivalent to forming a straight line (see Model 1, Fig. 2). The estimated

values $\hat{\alpha}$ and $\hat{\beta}$ are acquired via the least square method, incorporating the concentrations of metal elements and SiO₂ derived from analyses. The empirical regression equation acquired is as follows:

$$\hat{C}_i = \hat{\alpha} + \hat{\beta} \times C_{\text{SiO}_2}.$$
(2)

The variance of the difference between the actual value (C_i) and regression estimate value ($\hat{C}i$) can be acquired via the mathematical statistics method (Fang et al., 1988):

$$\operatorname{Var}(e) = \left[1 + \frac{1}{n} + \frac{\left(C_{\operatorname{SiO}_{2}} - \overline{C}_{\operatorname{SiO}_{2}}\right)^{2}}{\sum_{i=1}^{n} \left(C_{\operatorname{SiO}_{2}} - \overline{C}_{\operatorname{SiO}_{2}}\right)^{2}} \right] \sigma^{2}.$$
 (3)

When *n* is high and $\frac{(C_{SiO_2} - \overline{C}_{SiO_2})^2}{\sum\limits_{i=1}^n (C_{SiO_2} - \overline{C}_{SiO_2})^2}$ is low, $Var(e) \approx \sigma^2$. The value of σ is usually unknown, but σ^2 can be estimated via the

The value of σ is usually unknown, but σ^2 can be estimated via the residual standard deviation, $\hat{\sigma}^2 = \frac{1}{n-2} \sum_{i=1}^n (C_i - \hat{C}_i)^2$. The residual confidence band can be acquired by substituting $\hat{\sigma}$ for σ :

$$\begin{cases} C_i - \hat{C}_i = -2\hat{\sigma} \\ C_i - \hat{C}_i = 2\hat{\sigma} \end{cases}.$$
 (4)

The term $C_i = \hat{C}_i + 2\hat{\sigma}$ can be considered to be the threshold value. For metal elements that are not influenced considerably by lithology, i.e., those with no obvious relationship to SiO₂, Eq. (1) can be simplified as follows:

$$C_i = \alpha + \varepsilon. \tag{5}$$

In this instance, C_i relies on α but is not determined in reference to SiO₂; thus, the fitting of this model is equivalent to deriving the

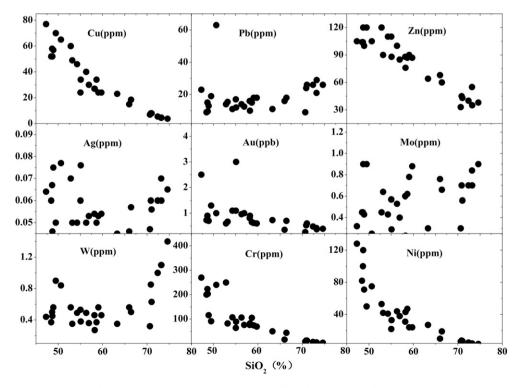


Fig. 1. Relationship between metal element and silicon dioxide contents of rock samples.

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