Application of a multi-fractal model for identification of Cu, Au and Zn anomalies in Western Yunnan, Southwestern China

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Abstract: Western Yunnan Province covers an area of about 220 000 km² in Southwestern China, and is located at the boundary between the Indian Plate and the Yangtze Plate. It is an important part of the Eastern Tethyan ore-forming belt. The region contains numerous base and precious metal deposits, including a few super-large ore deposits, such as the Pulang porphyry Cu deposit, the Beiya and the Laowangzhai hydrothermal Au deposits, and the Jinding MVT Pb-Zn deposit. It is difficult to decompose anomalies related to mineralization from the geochemical data with multi-patterns using conventional statistical methods, such as multi-variate statistical analysis. In this study, the spectrum-area (S-A) fractal method based on a multi-fractal model is adopted to separate anomalies from Cu, Zn and Au stream sediment data. The model results are as follows. Using the S-A method, both Cu and Au local anomalies can be effectively decomposed from the high geochemical backgrounds that arise from the Permian basalt, while the local geochemical anomalies of Zn are identified along a North-South trending fault. The local Cu, Au and Zn geochemical anomalies are useful for indicating areas where new deposits may exist. Regional and local anomaly maps of Cu were depicted based on different thresholds obtained from the log–log plot. We showed that multi-fractal methods effectively and efficiently decompose geochemical data with complicated patterns into different, meaningful indicator components compared to conventional statistical methods.

Keywords: multi-fractal, geochemical anomaly, spectrum-area method, Cu-Au-Zn, Western Yunnan

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Geochemical concentrations generally comprise two parts: background and anomaly. Assume the observed field T(x, y) represents the bulk value of a geochemical element concentration in surface media. The field T was created by various large-scale geological and small-scale ore-forming processes. The former usually produces the ore-forming background, and the latter the ore-forming anomaly. The background and anomaly produced by these two different processes may cause distinct distributions of the same element concentration in the same area denoted as B(x, y) and A(x, y), respectively. T can be considered as a combination of B and A, and can be expressed as

\[ T(x, y) = B(x, y) + A(x, y) \]  

where T(x, y) represents the bulk value measured at location (x, y), B(x, y) is a background value reflecting regional large-scale geological processes, and A(x, y) is the anomaly value reflecting local small-scale ore-forming events. There are a number of techniques available for decomposing T into B and A, for example histograms (Sinclair 1976), probability graphs (Sinclair 1974), trend surface interpolation (Sinclair 1967), geostatistics-based residual anomaly decomposition techniques (Matheron 1963; Houlding 2000), frequency-based filter techniques (Griffin 1949; Krige 1966), spectral analysis (Bath 1974; Muggleston 1998), etc. Each of these techniques is based on the basic assumption that concentration values obey a normal or lognormal distribution. In reality, the values in mineralized areas do not usually satisfy statistical normality but instead obey a Pareto distribution or fractal distribution (Agterberg 2007, 2011). Thus the methods based on conventional statistics are generally not applicable to separating an anomaly from its background when using geochemical samples from mineralized areas, especially in the case of regions that represent complex mixed patterns where multi-epochs (stages) of ore-forming events have occurred (Cheng 1999; Lovejoy 2005; Zhao & Chen 2011; Chen & Zhao 2012). Fractal and multi-fractal models have been applied to geochemical data for separation of anomalies. Examples include the concentration-area model (C-A) (Cheng et al. 1994), spectrum-area model (S-A) (Cheng et al. 1999; Cheng 2000, 2006), concentration-distance model (C-D) (Li & Liu 2003), singularity index (Cheng 2004, 2007a, b, 2011), and concentration-volume model (C-V) (Afzal et al. 2010). These methods are gradually being adopted as powerful and efficient means of identifying geochemical anomalies and/or determining geochemical baselines in geochemical exploration (Huang & Zhao 2009, 2011; Zuo 2011a, b). In this paper, after a brief discussion of the S-A method, we describe the application of multi-fractal modeling in a systematic geochemical stream sediment survey for identifying areas potentially favourable for copper, gold and zinc. For demonstration purposes, the Western Yunnan will be studied as an example.

Fractal filtering technique for the power spectrum-area (S-A)

In addition to the spatial characteristics of an element concentration anomaly, the frequency characteristics of the element concentration anomaly caused by different geological processes may be useful for anomaly identification (Chork & Mazzucchelli 1989). For example, geochemical patterns in the spatial domain caused by rock-forming processes commonly represent low-frequency features in the frequency domain. The geochemical signatures related to ore-forming processes are commonly dominated by high frequencies, while those associated with
Tectono-intrusive process are commonly dominated by intermediate frequencies. Fourier transformation can convert element concentration in the spatial domain into its spectrum energy density in the frequency domain where the geochemical patterns at different frequencies can be identified. The geochemical patterns with certain ranges of frequencies in the frequency domain can be converted by inverse Fourier transformation back to corresponding patterns in the spatial domain, reflecting the regional background related to large scale geological processes, regional anomalies caused by tectonic-magmatic events, and local anomalies associated with ore-forming events (Cheng et al. 2000).

The S-A method developed by Cheng et al. (2000) constructs fractal filters on the basis of distinct power-laws determined by fitting different relations. The self-similarity of structural anisotropy field data is often reflected in the power spectrum domain. This self-similarity can be measured using the proper method based on power spectrum analysis (Cheng et al. 2000). The relationship between area \( A(>S) \) in the frequency domain where the spectrum energy density values are above a threshold \( S \), and the threshold spectrum energy density \( S \), follows a power-law relationship. This can be expressed as:

\[
A(>S) \propto S^{-\beta}
\]  

Values of \( \beta \) are estimated by plotting \( \log A(>S) \) against \( \log(S) \) and fitting a straight line by the least square (LS) method for various ranges of \( S \), and depend on which fractal filters can be constructed. Usually, several straight line segments can be fitted to the relation (2) on a log–log plot. Different straight line segments represent different fractal relationships. The intersection between two straight-line segments determines a breakpoint which can be regarded as the threshold for defining a filter. Three kinds of fractal filters may be constructed: low-pass, high-pass and band pass spectrum energy density filters. For example, if two straight line segments are fitted, the intersection \( S_0 \) can be set as a threshold, and two filters can be defined as: \( G_B(\omega) = 1 \), if \( S(\omega) > S_0 \), and otherwise \( G_B(\omega) = 0 \); the second filter is \( G_A(\omega) = 1 \), if \( S(\omega) \leq S_0 \), otherwise \( G_A(\omega) = 0 \). From the definition of \( G_A(\omega) \) and \( G_B(\omega) \), the shapes of the filters could be irregular depending on the complexity of the spectrum energy density distribution. However, in general, the
wave numbers in filter $G_A(\omega)$ are relatively larger than those in $G_B(\omega)$. In this sense, $G_A(\omega)$ corresponds to a relatively high-frequency component and $G_B(\omega)$ to a relatively low-frequency component. $G_A(\omega)$ and $G_B(\omega)$ can be defined in such a way that the spectral energy density distributions in the two filters satisfy distinct power-laws or have different anisotropic scaling properties. Generally, the spectrum energy density may be inversely proportional to the frequency (Li & Cheng 2004). That is, the spectrum energy density in $G_A(\omega)$ is relatively lower than that in $G_B(\omega)$, thus $G_A(\omega)$ corresponds to a relatively low spectrum energy density and $G_B(\omega)$ to a relatively high spectrum energy density, which means that the spectrum energy has been filtered. Therefore $G_A(\omega)$ is usually regarded as an anomaly filter and $G_B(\omega)$ as a background filter. By applying the inverse Fourier transformation with these two filters to the Fourier transformed functions of the decomposed components, the anomaly and background can be obtained in the space domain:

$$B = F^{-1}[F(T)G_A], \ A = F^{-1}[F(T)G_B]$$

where $F$ and $F^{-1}$ represent the Fourier and inverse Fourier transformations of $T$, respectively (Cheng 2008). The S-A method has been implemented in GeoDAS4.0, a GIS software system developed by the Geomatics Research Group at York University, Canada, in collaboration with the Geomatics Research Group at China University of Geosciences, China (Cheng 2009).

Application

Geological setting

The Western Yunnan area, located at the boundary between the Indian plate and the Yangtze plate, covers about 220,000 km$^2$ in Southwestern China. It is an important metalliferous regime of the Eastern Tethyan ore-forming belt (Fig. 1). The Western Yunnan area experienced intense tectonic deformation, metamorphism and tectonic-magmatic activity during its geological evolution (Chen & Zhang 2000), which make the geological particularity complicated. From the late Palaeozoic, there was active deep tectogenesis and crust-mantle interaction as well as the collision and orogenesis of the Indian and Eurasian plates. Multicycle tectonic-magmatic activity formed complicit geological particularity and
multi-geochemical patterns in this region. There are numerous base and precious metal deposits within this area, including some world class deposits, such as Pulang porphyry Cu deposit (Li et al. 2011), the Beiya hydrothermal Au deposit (Yang 2010), the Laowangzhai hydrothermal Au deposit (Bian & She 1998) and the Jinding MVT Pb-Zn deposit (Wang et al. 2009). It is difficult to decompose anomalies related to mineralization from the geochemical data with multi-patterns using conventional statistical methods, such as multi-variate statistical analysis.

**Sampling and analysis**

The Cu, Zn and Au data were collected as part of China’s National Geochemical Mapping Project at 1:200,000. The stream sediment sample was taken with a density of 1 km². The concentration value was the average of the composite sample taken with 2 km × 2 km grid cells (Fig. 2). The collection protocols are described in detail by Xie (1979). In the study area, a total number of 66,254 composite samples were analyzed by ICP-OES for Cu and Zn, and GF-AAS for Au. The detection limits were 0.80 ppm, 0.70 ppm and 0.04 ppb, respectively. Statistical results show that the Cu, Au and Zn mean values were 37.80 ppm, 2.33 ppb and 88.28 ppm, respectively, presented in Table 1. The elemental values in the data set were transformed into histograms shown in Figure 3 and are nearly normal. If mean values are assumed as threshold values, they are 37.80 ppm for Cu, 2.33 ppb for Au and 88.28 ppm for Zn. As Table 2 shows, the abundance of Cu, Au and Zn in different strata are 24.89 ppm, 0.21 ppb and 74.41 ppm, respectively. It is clear that the mean values of Cu, Au and Zn are higher than the abundances, which suggests that element enrichment may occur in the Western Yunnan area.

The data show large differences between the minimum and maximum values (Table 1). The Cu, Au and Zn concentrations were first converted into the frequency domain using the fast Fourier transformation. A pair of data components consisting of the power spectrum density and phase can be obtained. The S and the number of cells with values greater than or equal to S were plotted on a log–log graph. If elements display non-uniform behavior on the log–log coordinate, the plot will have different slopes and various straight-line segments. The components with higher

| Table 1. Statistical parameters of Cu, Au and Zn |
|---|---|---|---|---|---|---|---|---|
| element | mean | median | Std. deviation | min | max | Coefficient variation | Skewness | Kurtosis |
| Cu(ppm)  | 37.80 | 25.30 | 92.51 | 0.80 | 14440 | 245 | 73 | 9574 |
| Au(ppb)  | 2.33 | 1.50 | 29.12 | 0.10 | 5400 | 1251 | 136 | 21732 |
| Zn(ppm)  | 88.28 | 69.10 | 377.48 | 1.00 | 40700 | 428 | 76 | 6909 |

SD: standard deviation  
CV(%): coefficient of variation
**Table 2. Abundances of chemical elements in strata in the Nujiang-Lancangjiang-Jinshajiang region (West Yunnan) (Ye et al. 1992)**

<table>
<thead>
<tr>
<th>element</th>
<th>unit</th>
<th>K</th>
<th>J</th>
<th>T</th>
<th>P</th>
<th>D</th>
<th>S</th>
<th>O</th>
<th>ε</th>
<th>Z</th>
<th>Pt</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cu</td>
<td>ppm</td>
<td>11.28</td>
<td>33.76</td>
<td>24.42</td>
<td>38.38</td>
<td>3.56</td>
<td>7.77</td>
<td>21.6</td>
<td>22.06</td>
<td>9.95</td>
<td>17.1</td>
<td>24.89</td>
</tr>
<tr>
<td>Au</td>
<td>ppb</td>
<td>0.06</td>
<td>0.26</td>
<td>0.16</td>
<td>0.42</td>
<td>0.12</td>
<td>0.21</td>
<td>0.28</td>
<td>0.25</td>
<td>0.22</td>
<td>0.09</td>
<td>0.21</td>
</tr>
<tr>
<td>Zn</td>
<td>ppm</td>
<td>46.76</td>
<td>313.49</td>
<td>62.64</td>
<td>59.04</td>
<td>20.93</td>
<td>31.83</td>
<td>60.76</td>
<td>52.94</td>
<td>24.39</td>
<td>101.63</td>
<td>74.41</td>
</tr>
</tbody>
</table>

K, Cretaceous; J, Jurassic; T, Triassic; P, Permian; D, Devonian; S, Silurian; O, Ordovician; ε, Cambrian; Z, Sinian; Pt, Proterozoic; All, all strata in the Nujiang-Lancangjiang-Jinshajiang region

**Fig. 4.** Log–log plot of power energy v. area of Cu, Au and Zn (log base e).
frequencies (low values of the power spectrum) suggest that these components behave in a multi-fractal manner caused by mineralization. Three straight lines with two thresholds, obtained from the least squares method (Fig. 4), can be fitted using these pairs of data components. Two breaks were obtained at lnS_1 and lnS_0, respectively (Table 3). The first thresholds of S_0 for Cu, Au and Zn were 3178 (lnS = 8.064), 465 (ln = 6.141), and 59 (ln = 4.082), respectively. The second thresholds of S_1 for Cu, Au and Zn were 11743 (lnS = 9.371), 5399 (ln = 8.594), and 11362 (ln = 9.338), respectively. Based on these thresholds, low-, band- and high-pass filters were constructed for decomposing the anomaly at different scales. The PS (power spectrum) value ranging from 3178 to 11743 is the regional Cu anomaly. A PS value less than 3178, 465 and 59 were defined as local anomaly filters for Cu, Au and Zn, respectively. These three frequency components were converted back into the spatial domain using the inverse Fourier transformation and different spatial patterns: background, regional anomaly and local anomaly maps (Figs 5–7).

Comparison with geological patterns

Comparison of the geological characteristics with the regional anomalous area created using thresholds from the S-A method (Fig. 5a) shows that two anomalous belts are situated along the main identified faults. These deep-seated faults may control the spatial distribution of elemental copper. Clearly, the anomalous centers on the northeastern part of the map are highly coincident with the Permian basalt where the average Cu concentration is up to 196 ppm (Chen et al. 2003; 2005) (Fig. 5b).

The northeastern part of the Cu local anomaly map coincides with the Au local anomaly, which suggests that the copper and gold may have been enriched in the Permian basalt at the same time (Fig. 5a). The Cu local anomalies are positively related with the ultra crustal faults, whereas most of the Au local anomalies are located at the conjunction of the ultra crustal faults and their secondary faults (Fig. 5b). Conversely, Zn local anomalies are more closely related to the secondary faults, especially the northeastern faults (Fig. 5c).

Comparisons of the known copper, gold and zinc occurrences against the local anomaly area created using thresholds from S-A method (see Fig. 7a–c) show that these coincide with most of the occurrences, which suggests that these local Cu, Au and Zn anomalies arise from copper, gold and zinc mineralization, respectively. There are still no known deposits or occurrences for Cu and Au in several local anomaly areas, while these anomalous districts can be defined as potential areas where new mineral deposits may exist. The

<table>
<thead>
<tr>
<th>element</th>
<th>Cu</th>
<th>Au</th>
<th>Zn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log (Value)</td>
<td>10.621</td>
<td>9.371</td>
<td>8.064</td>
</tr>
<tr>
<td>Log (Area)</td>
<td>5.29</td>
<td>6.51</td>
<td>7.35</td>
</tr>
<tr>
<td>K</td>
<td>-1.56</td>
<td>-2.34</td>
<td>-8.93</td>
</tr>
</tbody>
</table>

Fig. 5. Relationships between Cu regional geochemical anomaly map based on (a) the S-A method and faults (b) Permian basalt and granitic rock (see Fig. 1 legend).
Anomalies identification using multi-fractal model

Zn local geochemical anomaly map suggests that the spatial distribution of Pb-Zn deposits in Western Yunnan has a positive relationship with the north-northeastern lines marked on the map (Fig. 7c), which should be considered for future Zn deposit prospection.

Conclusions

In this paper, the S-A fractal model is used to identify different geochemical anomalies associated with Cu, Au and Zn mineralization. The main conclusions are as follows: (a) The traditional statistical methods (i.e., mean) can only consider the element concentration and ignore the spatial relationship between samples. (b) Using the S-A method, both Cu and Au local anomalies can be effectively decomposed from high geochemical backgrounds that arise from the Permian basalt. Some of the identified local anomalies provide new target areas for prospecting new Cu and Au deposits. (c) The local geochemical Zn anomalies were identified along the NNE trend. The longest line cut across the whole study area and hit several large Pb-Zn mineral deposits, including the world class Jinding Pb-Zn deposit. The spatial distribution of local Zn anomalies have good correlation with these secondary faults, especially the northeastern faults, which should be considered for prospecting favourable Pb-Zn deposits. (d) Regional and local anomaly maps of Cu were depicted based on different thresholds obtained from the log–log plot. Multi-fractal methods decomposed geochemical data with complicated patterns effectively and efficiently into different, meaningful indicator components compared with conventional statistical methods.

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