第31回日本情報地質学会講演会 講演要旨集 11-12頁 2020年

Pluri-Gaussian simulation combined with principal component analysis for delineating mineralized zones and ore solution flows

Vitor Ribeiro de Sá* and Katsuaki Koike*

*Graduate School of Engineering, Kyoto University, Katsura C1–2, Kyoto 615–8540, Japan.
E–mail: koike.katsuaki.5x@kyoto–u.ac.jp (K. Koike)

Key words: Geostatistics, Stochastic simulation, Principal component analysis, Pluri-Gaussian simulation, Geological model

1. Introduction

Sparsity and shortage of information is inherent to most geostatistical projects. This pitfall makes modelers puzzle over approaches to mitigate the setbacks and optimize the available information. The combination of data-characterization and geostatistical methods can be a plausible way to minimize the problem.

This study aims to apply a combination of methods, such as principal component analysis (PCA), and spatial modeling techniques using conditional geostatistical simulations, turning bands (TBSIM) and pluri-Gaussian (PGSIM), to a real geochemical data set and lithologic log data. The goal is to construct plausible 3D models of geochemical compositions and lithotypes in the study area in order to identify the zones with more occurrence of mineralization and propose a geological interpretation of fluid circulation in the study area.

The next sections introduce the study area and set out the methodology and its perks to the current scenario. Besides, the results are presented and discussed. Although the methodology is applied to a specific environment of this study, such combination can be widely used for a myriad of geological contexts.

2. Model Domain and Dataset

Following our preceding study (de Sá et al., 2020), a 200m×700m×250m domain, located around 1500m below the sea level (mbsl) was selected (Fig. 1). Previous geochemical studies have indicated that this area is rich in Ba-Zn-Pb. The proposed methodology uses a multi-variate geochemical set (52 elements) and visual core description information alongside X-ray diffraction (lithotypes) as input data for TBSIM and PGSIM implementations, respectively. These data were sampled from six boreholes (black dots) spread along the E-W direction, with variable lengths from 46m (borehole I) to 180m (borehole III). The lithotypes classification is broadly based on whether polymetallic sulfide minerals and hydrothermal alteration are present.

Borehole I was drilled in a mound and is regarded as a discharge zone of the hydrothermal system. Borehole VI presented little evidence of sulfide and altered material in its sample core descriptions and geochemical analysis, being more likely a recharge zone. In addition, a seismic survey of the area identified the development of a fault between boreholes V and VI (dashed line).

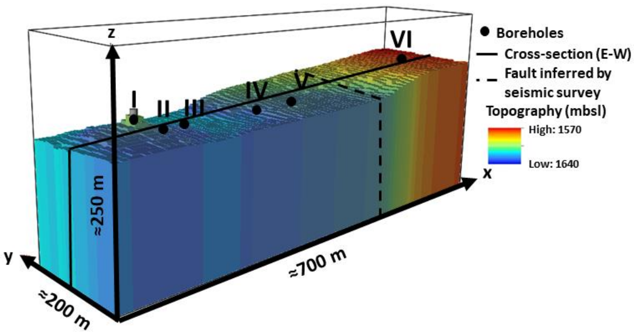

Figure 1: Dimension of study area and its spatial distribution of boreholes. The black line shows the location of cross-section for geostatistical results in Figure 2. The dashed line shows the location of fault identified by a geophysical survey.

3. Methods

The proposed methodology integrates geochemical measurements and lithotypes. Firstly, the entire multivariate geochemical data is centered log-ratio (clr) transformed and eight moderate-highly correlated elements are selected, such as Zn, Pb, Cu, Ag, Ba, Cd, Sn and Mn. These elements are not only statistically correlated but also are the most representative ones in mineralized zones in hydrothermal systems (Pirajno, 2009). Next, this subset is used as input to apply PCA, which main products are principal component values (PC values). TBSIM uses this variable to spatially locate highly mineralized zones and set iso-surfaces to separate the sulfide-rich zones from impoverished materials. Finally, PGSIM is individually run in each zone. The following subsections briefly describe the main characteristics under PCA, TBSIM and PGSIM.

3.1. Principal component analysis (PCA)

PCA is a powerful tool to examine the interactions between the various variables and find the most efficient linear combination of them. Its efficiency stems from its capability of the first two or three principal components, PCs, to gather the greatest amount of total variance. PCA method reduces the dimensionality of data with many measured variables by transforming these to a new, considerably smaller set of variables, PCs.

3.2. Turn bands simulation (TBSIM)

The principle of TBSIM is to produce a non-conditional simulation at first. That is, yielding a map that reflects the variogram, but the data is not honored. Afterwards, in order to correct it, a map is obtained by interpolating the experimental error between the measured data and non-conditional simulated value at each data point (Chilès and Delfiner, 1999).

3.3. Pluri-Gaussian simulation (PGSIM)

This methodology aims to simulate categorical variables by combining multiple multi-Gaussian variables using multiple thresholds. The gist of PGSIM is to yield two continuous Gaussian fields using standard multi-Gaussian techniques. Therefore, these fields are truncated to produce categories, which the thresholding relies on the value of both Gaussian fields (Mariethoz and Caers, 2015).

4. Results and Discussion

Three cross-sections along E-W were selected to depict a conceptual model for an expected lithotypes distribution (Fig. 2a).

By applying PCA considering the eight geochemical elements, the eigenvalues and total variance of eight PC's are computes. PC1 retains most of the information of the input data and accounts for 73% of total variance whereas PC2's variance is 12.3% and the sum of the variances from PC3 to PC8 is as small as 14.7%. Therefore, only PC1 was selected for TBSIM to locate high-metal-content zones and interpret the sulfide/sulfate mineralization process.

The TBSIM result is shown as an E-W vertical cross-section (Fig. 2b) with iso-planes of the PC1 values which reveal that PC values greater than PC1 = 4 are thickly distributed underneath the sulfide mound, suggesting stockwork formation, and a horizontal and stratiform mineralization seems to occur from the mound toward the east until the inferred fault. Considering the stratiform mineralization and effects of hydrothermal activity from the western boundary to the inferred fault, this subarea was divided into three zones following the iso-plane of PC1 = 4 for PGSIM. The top zone is mainly unrelated to hydrothermal alteration and composed of primary and reworked sediments. The middle zone is a major mineralization zone containing the massive sulfide mound, stockwork, and horizontal and stratiform subseafloor sulfide layer. The bottom zone mainly consists of pervasively altered rock.

These results resize the model domain to optimize the PGSIM application. The easternmost limit was rearranged to suit the distal edge of the polymetallic sulfide body, shortening the E-W length from 700 to 500 m, while the vertical range remained unaltered.

The results of the PGSIM in each zone defined by TBSIM are shown in the resized domain (Fig. 2c). According to this model, the distribution of sulfide rock suggests two fluid flows with high probability (red arrows). The ascent flows toward the sulfide mound and the lateral flows from the stockwork zone toward its adjacent permeable layers. The former flow may be predominant because mineralization is concentrated on the seafloor and in the shallow subseafloor. The latter flow induces large heat loss without forming a chimney or mound and causes horizontal and stratiform alteration and mineralization.

5. Conclusion

The combination of PCA and two geostatistical simulations, TBSIM and PGSIM are very efficient to clarify geologic structure and 3D distribution of metal contents in the model domain. They can contribute to (i) construction of proper geologic and mineralization models and (ii) identification of hydrothermal fluid-flow systems and the accumulation mechanism of base metals in seafloor hydrothermal fields.

Acknowledgement: We sincerely thank Dr. Tatsuo Nozaki and Dr. Yutaro Takaya for providing the chemical analysis data obtained by D/V Chikyu.

References

Chiles, J. P., Delfiner, P. (1999) Geostatistics: Modeling spatial uncertainty. Wiley.

de Sá, V. R., Koike, K., Goto, T.-N., Nozaki, T., Takaya, Y., Yamasaki, T. (2020) A combination of geostatistical methods and principal components analysis for detection of mineralized zones in seafloor hydrothermal systems. *Natural Resources Research*. https://doi.org/10.1007/s11053-020-09705-4

Deutsch, C. V. (2002) Geostatistical reservoir modeling. Oxford, Oxford University Press.

Mariethoz, G., Caers, J. (2015) Multi-point geostatistics: Stochastic modeling with training images. Wiley.

Pirajno, F. (2009) Hydrothermal processes and mineral systems. Springer.

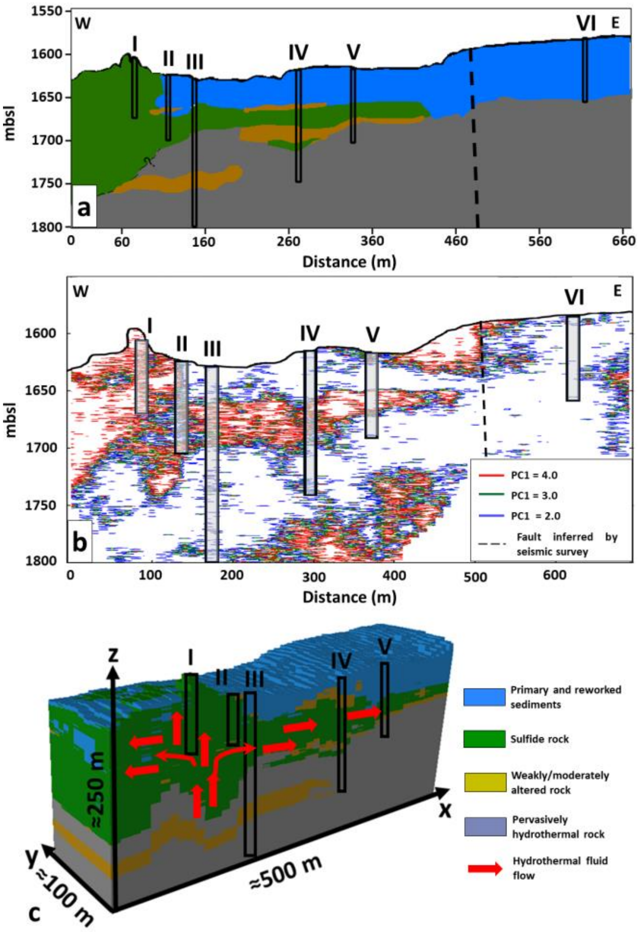

Figure 2: Cross-sections along E-W showing (a) a conceptual model of study area, (b) E-W vertical cross-section along the line in Figure 1, and (c) spatial modeling results of lithotype by PGSIM. The arrows in (c) show the interpreted hydrothermal fluid flows.