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Effectiveness of Geostatistical Simulation for Sparse Geologic Dataset

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1. Introduction

Geostatistics is founded on its pioneer methods developed by Krige and Matheron in 1950's and 1960's, whose works aimed to estimate values of random variables in unknown locations using spatial linear regression approaches, called kriging techniques (Olea, 2003). These methods provide the most likely value at every cell in the model as their outcome. Such methods are known to smooth the data because the kriged values have less variability than the original data from which they were calculated (Deutsch, 2002). Stochastic methods have been turned out to bring light to aspects which traditional geostatistical techniques do not properly cover, such as the assessment of uncertainty innate to their proposed models. Uncertainty may be understood as the error associated with the model. These methods yield numerous equiprobable realizations as their results and the data variance tend to be honored and are preferable approaches to deal with heterogeneous environments.

Based on those background, this study aims to compare the effectiveness of two different stochastic methods, Sequential Gaussian Simulation (SGS) and Turning Bands Simulation (TBSIM), for a spatial modeling of metal concentration in a hydrothermal area. Both methods are conditional simulations, i.e., the original data values can be reproduced at their location. SGS is regarded as fast and straightforward due to the modeling of a Gaussian conditional cumulative distribution function (ccdf) at each location and the need of solving only a single cokriging system there (Chilès and Delfiner, 1999), whereas TBSIM simulates the variable along 1-D lines and then combined into a 3-D model: one of its main advantages is to handle with non-stationary data which SGS does not consider (Deutsch, 2002). Since stochastic methods provide several equiprobable scenarios, the modeler must select one or few of them to present as reality's illustration. To make the best informed decision, this professional may use the assessment of uncertainty of each realization and its expected spatial distribution, once a conceptual model, also known as Empirical model, of the geologic structure of target area was previously designed. These criteria are also applied not only to decide which the best model of each conditional simulation methods fits better but also which method is more indicated for the current study area, a volcanogenic massive sulfide (VMS) deposit type in the seafloor under survey. This type of deposits account for important source of economic mineral, to wit: Zn, Cu, Pb, Ag, and Au.

Due to their capacity to quantitively characterize the spatial distribution of grades and physical parameters of lithotypes, the importance of numerical models in targeting potential areas for mineral exploration cannot be overstated.

2. Model Domain and Dataset

Fig. 1 depicts the 250mx700mx300m model's domain located around 1500m below sea level (mbsl). This area is rich in Ba-Zn-Pb according to previous geochemical studies. Logarithm values of Pb concentration are used as input data for implementing SGS and TBSIM, which were sampled from six boreholes (black dots) practically distributed along the E-W direction, with variable lengths from 46m (borehole 1) to 180m (borehole 3).

The borehole 1 was drilled in a mound and is considered as a discharge zone of the hydrothermal system, whereas borehole 6 presented few evidences of sulfide and altered material in its sample core descriptions and geochemical analysis, being more likely a recharge zone. Core descriptions were used to identify shear zones, such as presence of breccias and lack of hydrothermally altered materials.

3.Methods

The same semivariogram model was set for both conditional simulations. However, in order to reach the best cross-validation score and preserve the data variance, different search neighborhoods were adjusted. The following subsections briefly describe the main characteristics under SGS and TBSIM.

3.1. Sequential Gaussian Simulation (SIS)

As Olea (1999) succinctly describe, SIS method consists of generating a partial realization using multivariable normal random function where its kernel dwells in drawing from this multivariate distribution and drawing from a sequence of univariate distributions are conditioned to univariate realizations. That is, its principle is to sequentially draw the value at each new simulated point from the conditional distribution through the data and the values simulated previously (Chilès and Delfiner, 1999).

3.2. 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).

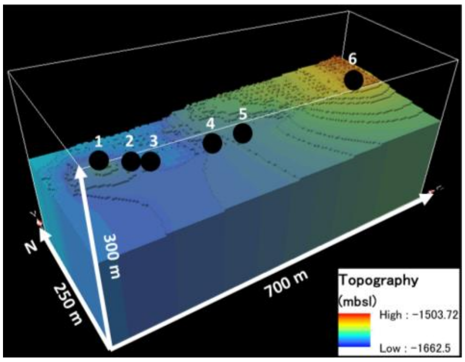

Fig. 1: Dimension of study area and its spatial distribution of boreholes (black dots).

3.3. Method Evaluations

To assess which method, SGS or TBSIM, is more suitable for the current study area, the best model must fit to empirical model and its uncertainty. The former can be based entirely on facts, such as field observations, geochemical and geophysical data, or theoretical based on conceptual ideas generally borne out of experience and knowledge, and extrapolation from known mineral districts (Pirajno, 2009). Regarding the latter, such model must reproduce the first- and second-order statistics of the conditioning data, the histogram, and variogram of the samples (Deutsch and Journel, 1998).

4. Results and Discussion

The set semivariogram is considered as omnidirectional along XY with a normal component to this reference plane. Applying the spherical model, its nugget effect is 0.3186. Considering the plane XY, its range and sill are 100 m and 0.34, respectively, while, for its normal component, its range is 112m and sill is fixed to 1.32. As Chilès and Delfiner (1999) asserts SGS tends to show much shorter range than the domain, a suggested and followed solution was to set a larger neighbourhood. In spite of the cross-validation scores for both SGS and TBSIM reached similar values, 0.80 and 0.82, respectively, increasing the neighbourhood implies a higher risk of estimating the mean values of the samples, which decreases the variability of realization outcomes. Even cautiously setting all parameters, SGS' outcome realizations presented lesser variability and are not consistent with the first- and second-order statistics of the original data contrasting with their TBSIM's counterparts.

Fig. 2 illustrate three cross-sections along E-W, where the conceptual model (Fig. 2A) shows the expected lithotypes distribution, and Figs. 2B and 2C represent the spatial distribution of log (Pb) of SGS' and TBSIM's realizations respecting the assessment of their outcomes. SGS method depicts better the concentration of higher values in the sulfide layers as well as in the mound. On the other hand, TBSIM properly reflects locations with lower values of the random variable.

5. Conclusion

Both methods have their own merits. SGS is straightforward and not a time-intensive method. Conversely, sequential simulations tend to yield smoothed outcomes. TBSIM may be considered as a powerful tool to depict the spatial distribution of metal concentrations in a deposit, once TBSIM broadly preserves the characteristics of original data.

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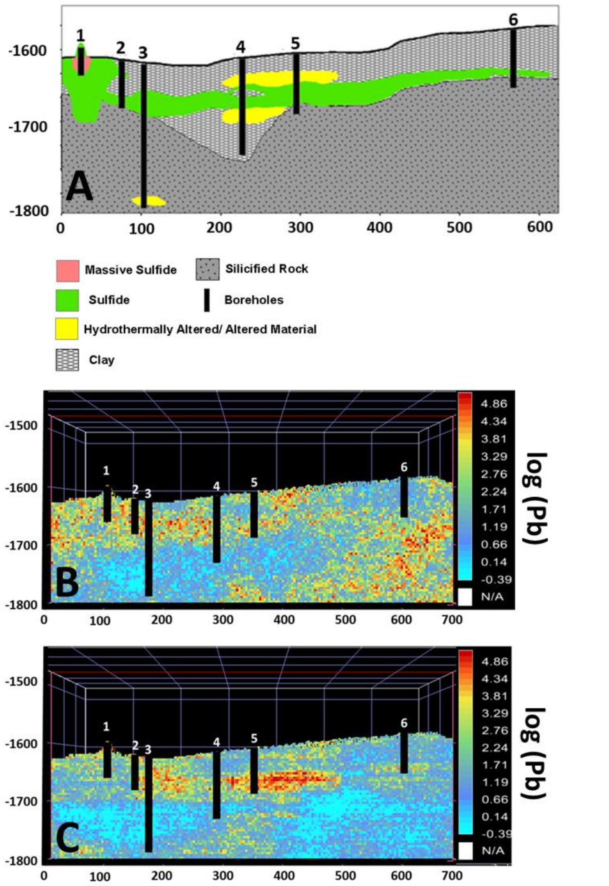

Fig. 2: Cross-sections along E-W in which (A) illustrates the conceptual model of study area, and (B) and (C) depict spatial distributions of log (Pb) using Sequential Gaussian Simulation (SGS) and Turning Bands Simulations (TBSIM), respectively.

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