Risk quantification with combined use of lithological and grade simulations: Application to a porphyry copper deposit

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A B S T R A C T

The uncertainty in the recoverable tonnages and grades in a mineral deposit is a key factor in the decision-making process of a mining project. Currently, the most prevalent approach to model the uncertainty in the spatial distribution of mineral grades is to divide the deposit into domains based on geological interpretation and to predict the grades within each domain separately. This approach defines just one interpretation of the geological domain layout and does not offer any measure of the uncertainty in the position of the domain boundaries and in the mineral grades. This uncertainty can be evaluated by use of geostatistical simulation methods. The aim of this study is to evaluate how the simulation of rock type domains and grades affects the resources model of Sungun porphyry copper deposit, northwestern Iran. Specifically, three main rock type domains (porphyry, skarn and late-injected dykes) that control the copper grade distribution are simulated over the region of interest using the plurigaussian model. The copper grades are then simulated in cascade, generating one grade realization for each rock type realization. The simulated grades are finally compared to those obtained using traditional approaches against production data.

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1. Introduction

Currently, the most common approach to model the uncertainty in the spatial distribution of mineral grades in an ore deposit is to define geological domains deterministically, then to predict or to simulate the mineral grades within each domain conditionally to the data belonging to this domain. This approach consists in interpreting the geological domains, using experimental data of lithology, mineralogy and/or alteration and geological knowledge of the deposit (Dowd, 1986; Duke and Hanna, 2001; Sinclair and Blackwell, 2002; Rossi and Deutsch, 2014). However, it suggests only one interpretation of the geological domains and fails at measuring the uncertainty in the spatial configuration of these domains. By constructing multiple numerical outcomes or realizations of the geological domains, geostatistical simulation helps to improve the geological interpretation and to measure the uncertainty in the position of the domain boundaries. This ability of geostatistical simulation allows assessing, in a realistic way, the risk of a mining project by considering the uncertainty in both the geological interpretation and the grade distribution. Several methods can be used to this end, including sequential indicator (Journel and Alabert, 1990; Journel and Gómez-Hernández, 1993; Deutsch, 2006), multiple-

point (Strebelle, 2002; Mariethoz and Caers, 2015), truncated Gaussian (Matheron et al., 1987; Galli et al., 1994) and plurigaussian (Galli et al., 1994; Le Loc'h et al., 1994; Armstrong et al., 2011) simulation. In particular, plurigaussian simulation has gained popularity and proved to be versatile to reproduce complex configurations of geological domains (Riquelme et al., 2008; Yunsel and Ersoy, 2013; Talebi et al., 2013, 2014; Rezaee et al., 2014; Madani and Emery, 2015).

The aim of this study is to investigate the impact of simulated models instead of deterministic geological models for studying the risk in the evaluation of mineral resources and ore reserves, through a case study on the Sungun copper deposit, located in northwestern Iran. This deposit has been identified both as a skarn and a porphyry-type deposit. It is characterized by the presence of late-injected dykes with variable density, size and geometry into the main intrusion mass of the deposit. These dykes often do not have any mineralization and consequently dilute the mill feed (Hezarkhani and Williams-Jones, 1998), while porphyry and skarn correspond to ore with different grade distributions and structures. In this type of deposits, the risk due to uncertainty of geological contacts is essential. First of all, the plurigaussian model is applied to the three main rock types (porphyry, skarn and late-injected dykes) in order to reproduce the spatial variability of the rock type domains and to assess the uncertainty in the position of their boundaries. One hundred realizations (outcomes) are generated and, afterwards, each of these is used to further generate a copper grade

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realization constructed with the sequential Gaussian simulation (Goovaerts, 1997). The realizations are then used to quantify uncertainty in recoverable tonnage and grade. The results are compared against traditional approaches and against production data.

2. Methodology

2.1. Principles of geostatistical simulation

An ore deposit can be characterized by one or more regionalized variables, i.e., variables that are distributed in space and exhibit some continuity, such as the grades of elements of economic interest or of contaminants, the rock type or the alteration intensity, to name a few examples. The exact values of these variables are known at a finite set of sampling locations, but unknown elsewhere. In order to quantify the uncertainty in the values at unsampled locations, one assumes that each regionalized variable is a realization of a spatial random field, characterized by its finite-dimensional distributions (Chilès and Delfiner, 2012). Once the random field model is specified, it is possible to draw different realizations or outcomes of this field and to constrain these realizations to reproduce the known values at sampling locations (conditional simulation). A variety of random field models and simulation algorithms have been developed in the past decades; the reader is referred to the textbooks by Lantuéjoul (2002) or Chilès and Delfiner (2012) for an overview.

2.2. Sequential simulation of grades

Let us denote by $z(\mathbf{x})$ the grade of an element of interest at a specific location $\mathbf{x}$ in the deposit, and by D the domain in which the grade is studied. The regionalized variable $\{z(\mathbf{x}): \mathbf{x} \in D\}$ is viewed as a realization of a parent random field $\{Z(\mathbf{x}): \mathbf{x} \in D\}$. Commonly, this random field is modeled as a monotonic transformation of a stationary standard Gaussian random field $\{Y(\mathbf{x}): \mathbf{x} \in D\}$, which implies that the grade data have to be transformed into normally-distributed data prior to simulation and that, after simulation, the realizations have to be back-transformed into grades, a procedure known as anamorphosis (Chilès and Delfiner, 2012). A stationary Gaussian random field is characterized by its mean value, constant over space, and by its auto-covariance function or its variogram.

The simulation of the Gaussian random field at a set of target locations can be performed through the following steps (Goovaerts, 1997; Deutsch and Journel, 1998; Remy et al., 2009):

1. Obtain a representative histogram for the input data.

2. Transform the data into normal scores (anamorphosis).

3. Calculate the sample variogram of the normal scores data and fit a variogram model.

4. Select a target location for which the value has not been yet simulated.

5. Perform simple kriging at the target location, using the input normal scores data and the already simulated values. Obtain a prediction and a variance of the prediction error.

6. Draw a random value from a Gaussian distribution with mean equal to the simple kriging prediction and variance equal to the simple kriging variance.

7. Incorporate the value drawn into the conditioning data set.

8. Repeat steps 4–7 until all the target locations are visited.

9. Back-transform the simulated Gaussian values into the original grade scale.

10. Repeat steps 4–9 to generate another realization.

2.3. Plurigaussian simulation of geological domains

Let now $z(\mathbf{x})$ denote the value of a geological domain (codified as, say, an integer between 1 and n) at location $\mathbf{x}$. In the plurigaussian model, this value is interpreted as a realization of an integer random field $\{I(\mathbf{x}): \mathbf{x} \in D\}$ obtained by truncating one or several underlying Gaussian random fields, according to a given truncaertn rule.

Specifically, consider a set of m stationary Gaussian random fields $\{Y_i(\mathbf{x}): \mathbf{x} \in D\}$ with $i = 1 \dots m$, which can be viewed as the components of a vector Gaussian random field $\{\mathbf{Y}(\mathbf{x}): \mathbf{x} \in D\}$. Also consider a partition of R^m into n disjoint subdomains $D_1, \dots, D_n$ and define an integer random field by.

$$\forall \mathbf{x} \in D, I(\mathbf{x}) = i \text{ if and only if } \mathbf{Y}(\mathbf{x}) \in D_i. \tag{1}$$

The geometry of the partition $(D_1, \dots, D_n)$ defines the so-called truncation rule, which controls the spatial relationships between the geological domains. Usually, the subdomains forming the partition are cuboids of R^m (Emery, 2007; Armstrong et al., 2011). The specific values that define the boundaries of such cuboids are known as the truncation thresholds and are related to the proportion of space covered by each geological domain.

As an example, consider two independent Gaussian random fields (Y_1 and Y_2) and the following truncation rule to define the domain at location $\mathbf{x}$:

$$I(\mathbf{x}) = \begin{cases} 1 & \text{if } Y_1(\mathbf{x}) < t_1 \\ 2 & \text{if } Y_1(\mathbf{x}) \geq t_1 \text{ and } Y_2(\mathbf{x}) < t_2 \\ 3 & \text{if } Y_1(\mathbf{x}) \geq t_1 \text{ and } Y_2(\mathbf{x}) \geq t_2 \end{cases} \tag{2}$$

where t_1 and t_2 are the threshold values. Geometrically, this truncation rule can be represented by a two-dimensional flag, where each axis represents a Gaussian random field and the rectangular areas correspond to the couples of Gaussian values associated with each domain (Fig. 1). The choice of the truncation rule may be based on topological or chronological relationships between geological domains. For instance, domain 1 may correspond to a younger domain that crosscuts the other two domains (Madani and Emery, 2015). The values of thresholds t_1 and t_2 determine the proportion of space covered by each domain. For example, if they are equal to zero (median of the standard Gaussian distribution), then the Gaussian random fields take values below the thresholds half of the time and values above the thresholds half of the time, which means that domain 1 will have a proportion of 0.5, while the proportions of domains 2 and 3 will be 0.25.

To complete the specification of the model, one has to infer the correlation structure of the vector Gaussian random field $\{\mathbf{Y}(\mathbf{x}): \mathbf{x} \in D\}$. This is done in order to fit the correlation structure of the integer random field $\{I(\mathbf{x}): \mathbf{x} \in D\}$, which is experimentally known from the available data on the geological domains prevailing at the sampling locations (Armstrong et al., 2011).

The steps for simulation are the following:

1. Define the truncation rule.

2. Define the truncation thresholds.

3. Define the correlation structure of the underlying Gaussian random fields, via its impact on the indicator variograms of the integer field $I(\mathbf{x})$.

4. At the sampling locations, transform the integer data into Gaussian data. This can be done with an iterative method known as Gibbs sampler (Lantuéjoul, 2002).

5. Simulate the Gaussian random fields at the target locations, conditionally to their values at the sampling locations. This can be done with the sequential algorithm described in the previous section.

6. Truncate the simulated Gaussian random fields to obtain an integer random field.

7. Repeat steps 4–6 to generate another realization.

2.4. Cascade simulation of geological domains and grades

The cascade approach consists in simulating first the layout of the geological domains, then the mineral grades within each domain