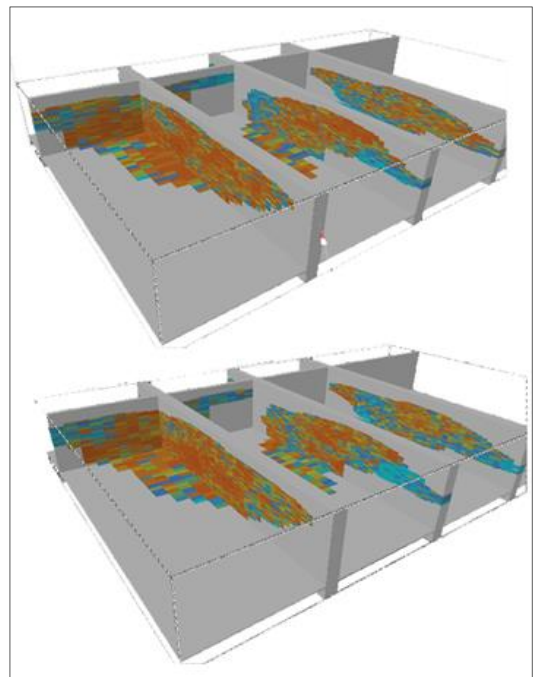




White Paper



Use of Simulations for Mining Applications

How geostatistical simulations can help in resource estimation and classification?



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How geostatistical simulations help in resource estimation and classification?

Use conditional simulations which are alone in capturing the whole grades variability for correct resource estimation.

Linear interpolation techniques like kriging are inappropriate to deal with issues that require a full characterisation of the spatial distribution. (E.g. probability of exceeding a threshold, variability of product specifications per mining period, recoverable resources at various cut-offs etc.).

Only the conditional simulations reproduce the real variability in your orebody. They provide a huge flexibility to deal with the complexity of the mining process and an access to the uncertainty assessment.

Over the last decade Geovariances has gained multiple experiences in developing successfully various simulation strategies in different environments: kimberlite pipes, turbiditic and carbonate reservoirs, porphyry copper, alteration and hydrothermal type deposits.



Does your resource classification process reflect the variability you see at your operation?

Kriged grades do not reproduce the real variability observed in the orebody. Using kriging for selective mining could lead to systematic bias.

Why simulations?

By definition **kriging aims at predicting a value from a linear combination of surrounding data** at any location: the criterion of minimizing the variance of the error between the estimated and the actual value leads to necessarily reduce the range of values compared to the actual range. The more extreme values are not represented in the kriged estimates while they exist in reality and may have a significant impact on the deposit value.

This property is known as the **kriging smoothing effect**. At the production stage, the density of the ultimate information reduces drastically that smoothing effect, but it cannot be ignored at the exploration stage. Forecasting ore and metal tonnages from a kriged block model leads to systematic bias when mining selectively.

In some particular cases, e.g. open pit mining, the actual distribution of SMU's grades (Selective Mining Unit) can be obtained globally as well as locally by using non-linear kriging techniques either based on indicator kriging or on gaussian models and Uniform Conditionning. But these techniques have important limitations, the main ones being:

- They suppose the selectivity criterion is one of the variables of the model;
- The uncertainty on tonnages and grades after cut-off is generally not accessible, except in simple cases like Confidence Intervals available in Isatis software in the univariate case.

Benefits

By construction, **geostatistical conditional simulations deliver models that accurately represent the actual distribution and spatial variability** of the studied variables. Applying cut-offs on a simulated block model is a correct approach, particularly if the criterion is a complex and non-linear transform of several grade elements. Moreover by generating many simulations, each being considered as a plausible "reality", we have access to a characterisation of uncertainty that can lead to the production of E-type estimates.

Simulations also provide a practical platform for **resource classification**. That use of simulations for resource classification is completely in line with three factors that must be taken into account for classification:

- The probabilistic framework of the geostatistical model underlying the generation of simulations naturally opens the way to risk analysis;



By using a change of support model, we can get, for each simulated block value, a point value correlated with the block.

That opens the way to practically consider Information Effect in risk and sensitivity studies.

- The concept of support being at the centre of geostatistical models, simulations refer explicitly to a given support. If chosen small, regrouping given supports into bigger units allows characterizing the influence of the size of the support on the valuation of the resource; and,
- The criterion chosen for deciding between ore and waste is not restricted to the elementary variables.

Methodology

Conditional simulations allow generating many realizations of a random function conditioned to actual data for reproducing its statistical distribution and its spatial correlation (e.g. variogram). The simulations may refer to block values by means either of a discretization of the block or a change of support model.

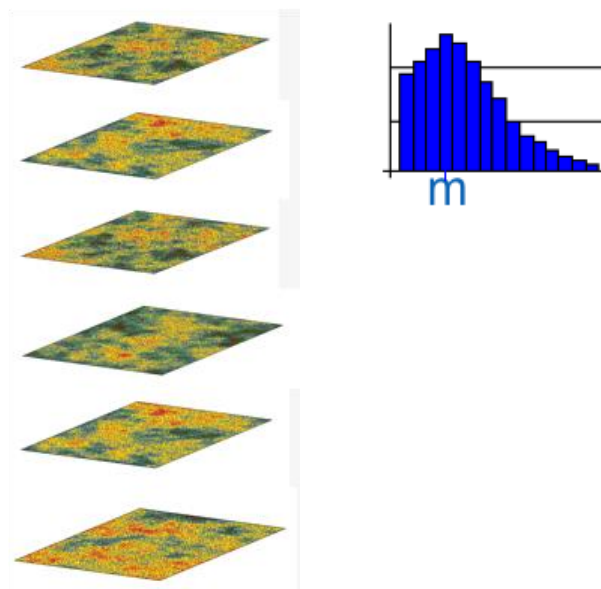


Figure 1: A few realizations of a Random Function characterized by an histogram and a variogram model.
Left: several images of XOY sections
Bottom right: experimental variograms of simulations compared to the model (in green).

Geostatistical simulations of grades may be obtained by different techniques for simulating continuous variables (Turning Bands, SGS) and according to the case categorical variables linked to geological domains (TGS, PGS, SIS, MPS).

Example 1: Estimation of recovered tonnages and grades from simulations of multiphase deposits (lateritic type nickel deposits)

In these deposits, the mineralization is concentrated in the altered part of the rock. The grade is not additive and cannot be estimated nor simulated directly but is derived from the ratio of the metal quantity to the altered ore tonnage. This issue can be overcome through the simulations of SMU's tonnage and metal quantity. Tonnage and metal quantity are then obtained after applying the cutoffs on the ratio of metal to tonnage. The process may be repeated on many simulations. Statistical post-processing



of the simulated figures will then deliver E-type estimates and confidence intervals.

Information effect can be introduced in the process to mimic the selectivity at the mining stage when ultimate pre-production information will be available to estimate the SMUs.

The workflow may be summarized as follows:

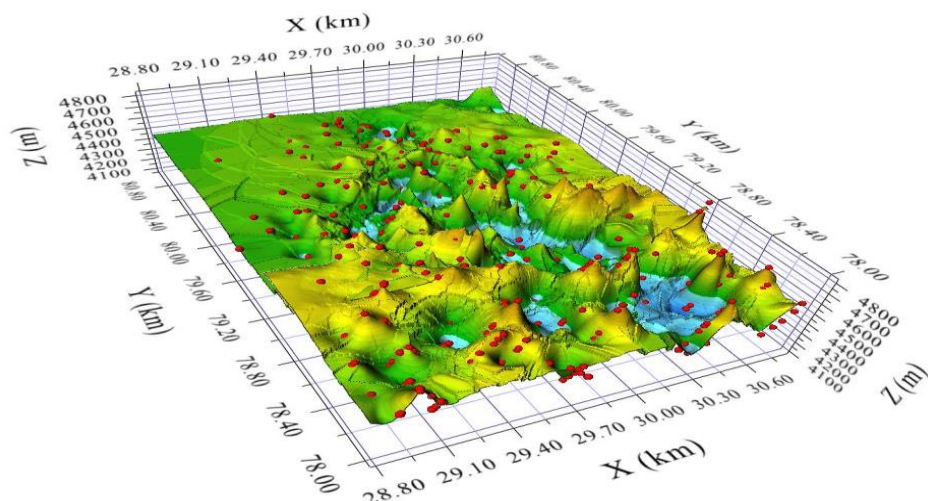
1. For each SMU, a simulated composite value is extracted at random;
2. A selection corresponding to the pre-production sampling grid is made on the simulated points;
3. SMU values are re-estimated from the sampling set;
4. Then for each cut-off grade:
 - a. For each realization of the simulation platform: select the smu's such that the estimated values kriged at step 3 are above the cut-off grade ;
 - b. For blocks regrouping n smus calculate tonnage and metal contents for all variables and all smus making it past the cut-off;
 - c. Looping on all realisations calculate the recoverable estimates as the average of the values obtained at step b for all the realisations;
5. Repeat for all cut-offs.

This example can be modified when the selection criterion is complex and based on several economic and/or pollutant elements.

Example 2: Sampling optimization, example of a Porphyry Copper deposit

Mineralization occurs in breccias below a leached zone. As in the previous example, tonnage and grades cannot be estimated directly and resorting to simulations is a possible solution. Three stages have to be carried out:

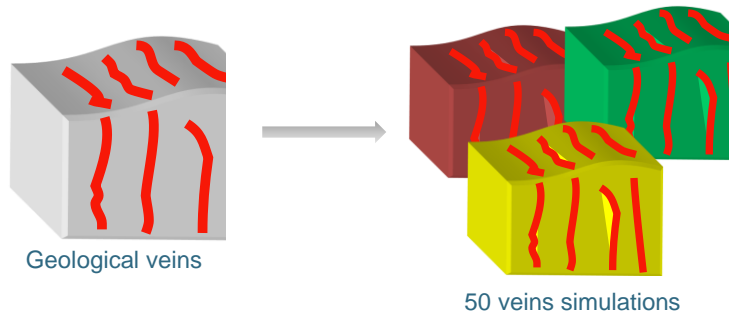
- ➔ **Stage 1** Simulation of the leaching bottom surface



Example of 1 simulated surface from a set of 50



⇒ **Stage 2** Simulation of the breccia lithologies

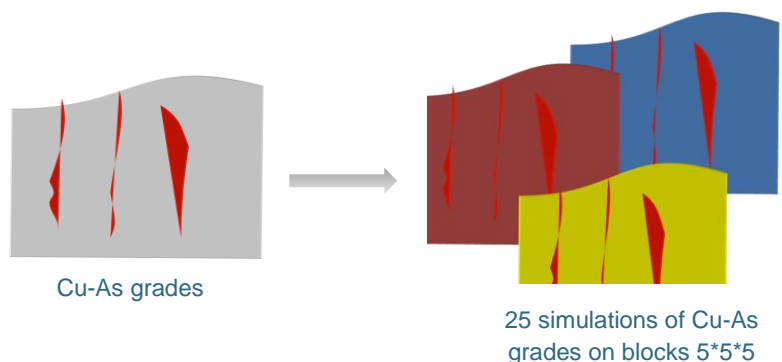


References:

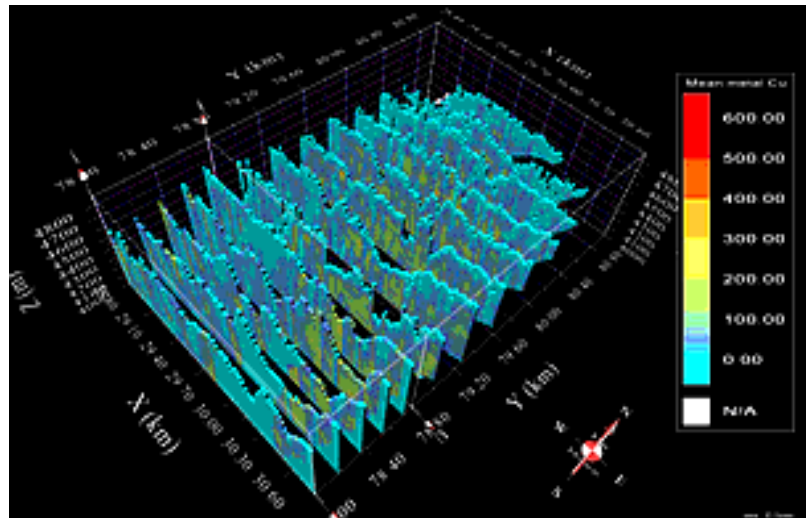
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Example of 1 simulation of veins

⇒ **Stage 3** Simulation of the Cu-As grades



At the end of the process, 25 realizations of tonnages and metal quantities are averaged to get an estimate. Then statistical analysis of the estimation errors as well as risk analysis can be achieved.



Mean metal Cu derived from simulations

In a second stage the simulated models (point values) may be sampled according to a provisional drilling pattern. The same simulation procedure based on the existing drill holes plus the simulated “fictitious” drill holes can be run. The new resulting errors are then analysed as previously to quantify the gain in the estimates confidence.

| | | Actual Drillholes | Fictitious Drillholes | Gain on Stdev |
|----------------------|-------|-------------------|-----------------------|---------------|
| | Count | Mean | Mean | |
| Stdev error Tonnage | 2192 | 95.9 | 70.93 | 26.0% |
| Stdev error Metal Cu | 2192 | 1710.4 | 1406.8 | 17.8% |
| Stdev error Metal As | 2192 | 49374.8 | 44217.7 | 10.4% |

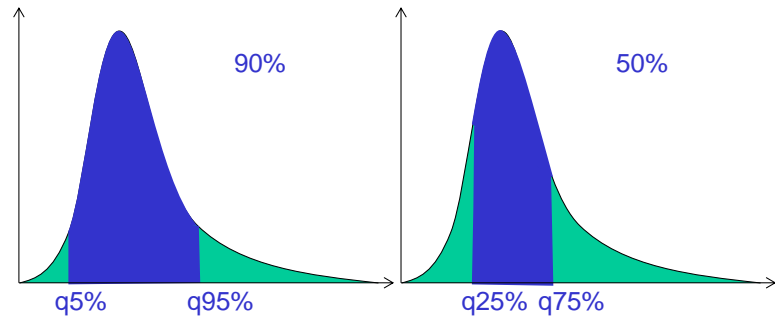
Table 1 : Example of final outputs of a sensitivity study of the error standard deviation to additional drilling.

Example 3: Resource Classification

The conditional simulation can provide an histogram for each block from which any probability can be derived.

A quality index may be calculated to classify each block into three categories. An example of confidence intervals classification could be:

$$Confidence = \begin{cases} High = 1, & \text{If } \frac{(Quantile\ 95\% - Quantile\ 5\%)}{mean} \leq 0.3 \\ Medium = 2, & \text{If } \frac{(Quantile\ 75\% - Quantile\ 25\%)}{mean} \leq 0.3 \\ Low = 3, & \text{If Block is Inside High Grade Wireframe} \end{cases}$$



For resource classification, we cannot be satisfied by counting the blocks of high quality to transform them into Measure Resource.

It makes more sense to apply the same approach to a bigger support related to the category of the classification, as originally proposed in the early 2000's by Dr Harry Parker:

Measured = $\pm 15\%$ with 90% Confidence on Quarterly Basis

Indicated = $\pm 15\%$ with 90% Confidence on Annual Basis

Perspectives

Conditional Simulations are very powerful tools, requiring care when examining the validity of their field of applications, but obviously also offering the ability to tackle the characterization of risk and uncertainty in many varied situations. Geovariances White Paper on Facies Simulation gives an opening into what is available in the field of geological simulation.

The ability to capture the uncertainty attached to the geological interpretation by means of a geostatistical model has actually been the subject of very stimulating research over the past decade and is at the core of G2DC.

[G2DC](#) is a research consortium on Geological and Geostatistical Domain Modelling carried out by Geovariances and the [Centre of Geosciences from Mines ParisTech](#) with the sponsorship of five leading mining companies.

G2DC has been a remarkable vehicle for research and innovation around two main topics:

- Automatic spatial clustering of information to rapidly create a partition of the variable space conducive to the creation of consistent geological ensembles; and;
- Implicit modeling of these partitions using the potential method to create geologically coherent 3D envelopes.

Another research consortium Geovariances is involved with is worth to be noted, as it will certainly **help overcome the main practical issue that has prevented a more widespread use of conditional simulations by the mining industry, which is**



Who is Geovariances?

Geovariances is a specialist geostatistical consulting and software company. We have over 45 staff, including specialist mining consultants and statisticians.

Our software, Isatis, is the accomplishment of 25 years of dedicated experience in geostatistics. It is the global software solution for all geostatistical questions.

Other technical specialties

Geovariances are world leaders in developing and applying new and practical geostatistical solutions to mining operations. We have strong experience in all commodities, and have gained trust from the biggest international companies.

Our expertise is in applying geostatistics to resource evaluation. Our services are through consulting, training, and software.

the difficulty of manipulating and considering multiple models simultaneously.

This consortium named [S2RM](#) (for Scenario Reduction in Mining) is a consortium carried out by Geovariances and the Cerna (Centre of industrial economics of MinesParisTech) which is developing a computationally efficient method for selecting the best subset of a predetermined size, k , from an original set of N simulations. The k simulations selected are no longer equiprobable: some simulations represent "typical" deposits that are likely to occur; other ones are less likely and some other ones are outliers. The consortium has resulted in the creation of a plug-in in Isatis that is currently being adapted to handle multivariate simulations and temporarily remains the property of the sponsors.

Our expertise

Geovariances has more than 15 years of experience in developing new simulations methods into Isatis and applying them in reservoir and orebody modelling worldwide.

Isatis is the most complete solution for simulation methods.

Geovariances can provide a unique expertise through both our French and Australian offices.

Geovariances is dedicated to applied geostatistics and has set the standards in geosciences, providing the mining industry with the Isatis software for more than 20 years.

For more information

Let us help you design your tailored simulation workflow for a better quantification of your uncertainties.

Contact our consultants: consult-mine@geovariances.com.

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