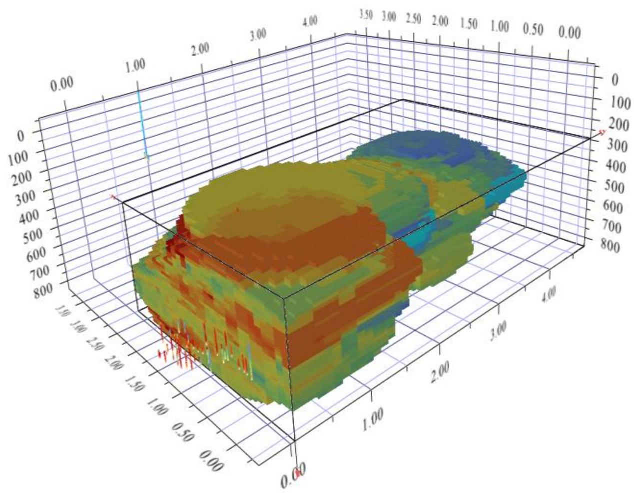
Geovariances

Where no one has gone before

White Paper



Uncertainty of Mineral Resource Estimates

From Confidence Intervals to Resource Classification

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Geostatistics and Uncertainty

Resource classification is an essential part of mineral resource management as resource estimates have to be classified and reported in a manner that is compliant with varied mining codes.

The methodologies to apply though are still under research and debate. Most of the time, ad hoc techniques, based on simple and easy to get criteria, are applied.

Classification methodologies hints and pitfalls are worth deeper thinking about. The probabilistic framework of geostatistics seems adapted to provide quantitative inputs to that process as it is particularly appropriate to assess uncertainty in resource models and thus appraise the risk.

What geostatistics method for reliable resource classification?

Are you confident with the technique used to classify your resources?

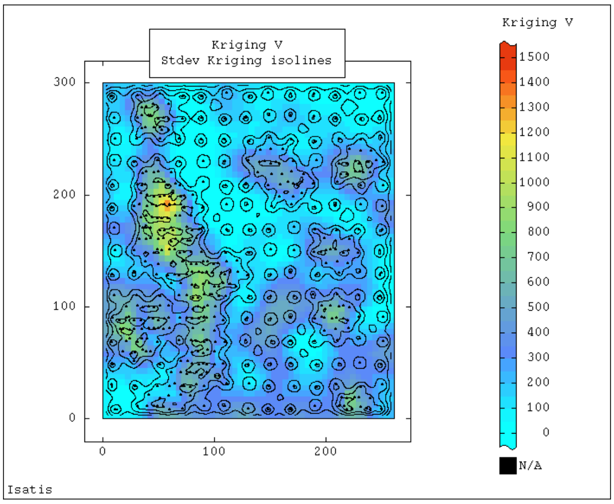
1/ Linear Kriging

Linear interpolation techniques like kriging provide kriging variances, a first measure of uncertainty.

The kriging variance σ_K^2 is the variance of the error "true value Z-estimated value Z*". It is tempting to use its square root for calculating a confidence interval, e.g [Z-2x σ_K, Z+2x σ_K] for a confidence interval at the risk level of 5%. Doing so relies on the assumption that the error is symmetrical and Gaussian, which cannot be checked and can be sometimes absurd as it may lead to an interval overlapping negative values.

Other arguments can be opposed to the use of kriging variance for calculating confidence intervals:

- The kriging variance is only depending on the variogram model and the data geometrical configuration. By looking to maps representing the kriging variance, the bull eyes effect appears immediately making the use of such parameter suspicious.



Standard deviation map:
bull eyes effect around data points

- The kriging variance is not conditioned by data values. For instance it has the same value whatever the local variability, generally higher in rich ore zones than in poor zones, which is unintuitive: the uncertainty should not be the same. Some authors propose empirical solutions like combined variance approach with the drawback to be unstable and without rigorous background.

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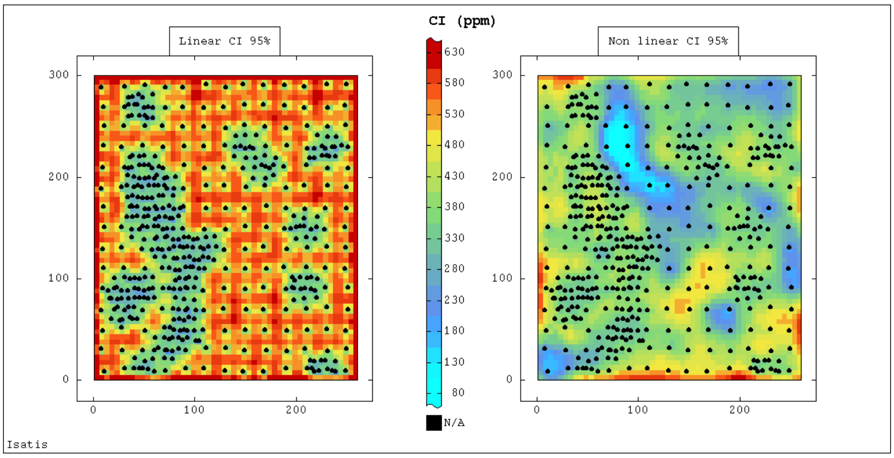
- The kriging variance only applies to the error incurred in directly estimating in situ block grades. When the grade (g) is estimated as a ratio between Accumulation (A) and Tonnage (T) a last resort solution is to use approximation formulae based on intrinsic correlation hypothesis between both quantities, i.e.: $\frac{\sigma_g^2}{g^2} = \frac{\sigma_A^2}{A^2} + \frac{\sigma_T^2}{T^2} - 2 \times \rho_{AT} \times \frac{\sigma_A}{A} \times \frac{\sigma_T}{T}$.
- It is a common situation for 2D deposits or for 3D deposits when grades depend on a variable fraction of the ore (multiphase ore, granulometric fraction). The kriging variance of estimated quantities after cutoff cannot be calculated in the general frame work of linear geostatistics.

Using non-linear interpolation techniques is better but restricted to simple cases.

2/ Non-linear Kriging

Non-linear techniques can be used to estimate the grade distribution on SMU support: method based on indicator kriging or on Gaussian models and Uniform Conditioning. But these techniques have important limitations, the main ones being:

- They suppose the selectivity criterion is one of the variables of the model (and not a ratio for instance);
- The uncertainty on tonnages and grades after cut-off is generally not accessible. In the general framework of the Discrete Gaussian Model (DGM) and in simple cases, Confidence Intervals can be obtained: in Isatis software, its use is limited to the univariate case.



Confidence intervals at the risk level of 5% calculated from kriging standard deviation (Linear CI) or from Gaussian model (Non linear CI)

References:

- Roth C. and Armstrong M., Confidence intervals for local estimation: application to the Witwatersrand basin. 26th APCOM 1996, Ramani ed.
- Stoker P., JORC and Mineral Resource Classification APCOM 2011, Woolongong.
- D.S.F. Silva, and J.B. Boisvert, Mineral resource classification: a comparison of new and existing techniques. Danie Krige Commemorative Edition – Volume I (2014), SAIMM Journal
- Jacques Deraisme, Olivier Bertoli and Pierre Epinoux, Multivariate block simulations of a lateritic type Nickel deposit and post-processing of a representative subset. Danie Krige Commemorative Edition – Volume II (2014), SAIMM Journal.

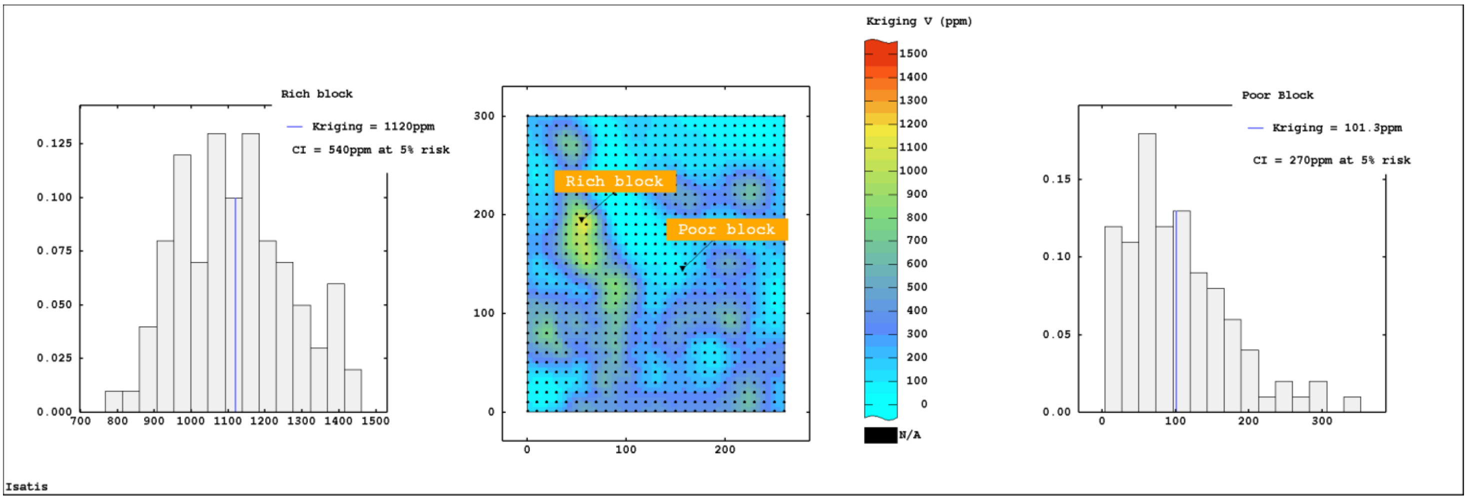
3/ Conditional simulations

The simulations provide more flexibility to assess the uncertainty in the estimates

Running conditional simulations is the option that delivers the maximum information on the error distribution even in complex situations regarding selectivity on combinations of different elements.

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.

When considering a block where many simulated values have been generated, that set of values can be used as an estimate of the distribution of actual values. Its dispersion variance is a measure of the variance of the error between the actual values and its estimate by the average value. It can be different for two blocks with the same data configuration because of a different variability of the input data.



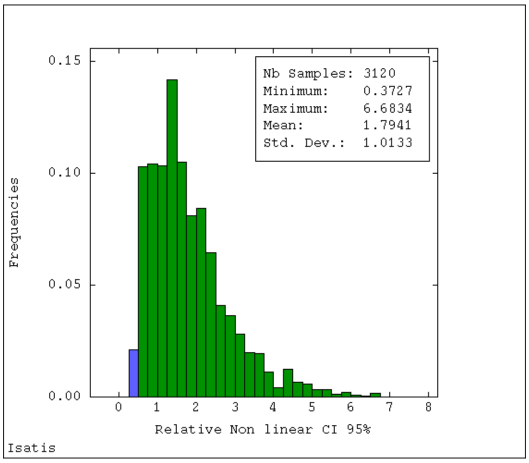
Simulations allow going further in solving resource classification issues

When dealing with resource classification, the first idea coming up to mind is:

- To calculate a Confidence Interval for each estimated block as explained above;
- To choose a criterion based on the relative Confidence Interval, i.e. divided by the kriged value, that will assign each block to one category measured-indicated-inferred according to some arbitrary thresholds; and,

- To sum up all blocks of the different categories to constitute the resource estimate categories.

Such a procedure leads to some kind of **absurd** figures. In the Walker Lake example used in the present illustrations, it would lead to nothing in the measured category and 2% of the whole domain in the indicated category. Common sense disagrees with such conclusions because the data density is high enough to know that the resource is there.



The reason is not due to the criterion used but much more to the support on which it applies. Having relatively high uncertainty for the estimate of a small block does not mean the resource is inferred. The right approach is to apply similar criteria to estimates of much larger volumes that can be reasonably estimated with a **realistic** level of confidence.

In that sense, simulations provide a practical platform for resource classification because it is always possible to simulate small units, regroup them and get the distribution of errors of bigger units from which confidence intervals may be calculated. This property is not applicable to kriged estimates as the kriging variance of a big unit cannot be simply deduced from the kriging variance of the small units inside.

That use of **simulations for resource classification is completely in line with 3 factors that must be taken into account for classification**:

Are you dealing with the right support?

- The **probabilistic framework** of the geostatistical model underlying the generation of simulations naturally opens the way to risk analysis;
- The concept of **support explicitly** used for making the simulations; and,
- The **criterion chosen for deciding between ore and waste** is not restricted to the elementary variables, but may apply on combinations of these variables and still more important on ore and metal recovered after cutoff.

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One cannot be satisfied by a method based on a counting of estimated blocks assigned to different categories.

Now the question is **how to choose the right support for making the categorization**? While being conscious that the limit between resources and reserves becomes a bit fuzzy, the proposed contribution just intends to remedy to important drawbacks of weak approaches based on block estimates confidence interval calculations. In our opinion moving a bit away from a strict acknowledgement of mineral resource definition helps to better understand the potential of a deposit and the risk in its estimation.

In the early 2000's Dr Harry Parker proposed that approach with the following rules:

Measured = ± 15% with 90% Confidence on Quarterly Basis

Indicated = ± 15% with 90% Confidence on Annual Basis

Nevertheless grouping small units into bigger units remains an issue when the quarterly/yearly lots are not already defined, which is the case at the feasibility stage.

A possibility could be to choose among two extreme situations:

- The unit (3 months or 1 year) is made of a set of contiguous simulated blocks: the volume of the unit is divided into n volumes of small blocks approximated by a parallelepiped. Averaging of simulated blocks into these parallelepipeds give the experimental distribution of tonnage/metal/grade on which confidence intervals may be calculated;
- The unit is made of a blending of blocks coming from different areas. By considering the case where these areas are far one from the others, the quantities of the blocks are independent. The distribution of the unit may then be considered as Gaussian, with a variance over the period that is the variance of one block divided by the number of blocks making the unit. Aiming at getting the relative standard deviation of the lot less than a given threshold determines the threshold of the standard deviation of the small blocks, contributing to the measured or indicated resources.

A meaningful method of resource categorization has to clearly account for the support, the applicable criterion and the level of risk.

Example: t represents the time period; the relative standard deviation of the distribution of possible values over that period can be calculated as follows:

$$CI_{90\%} = (q_{95\%} - q_{5\%}) = (2 * 1.64) * \sigma_t = 3.28 * \sigma_t$$

$$3.28 * \sigma_t < 2 * (0.15 * T_t^*) \quad i.e. \quad \frac{\sigma_t}{T_t^*} < 0.092$$

Consequently the relative standard deviation of a single block should be $\frac{\sigma_e}{T_e^*} < 0.092 * \sqrt{\mathrm{n}}$.

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.

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 better resource quantification.

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

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