Estimation of iron ore resources integrating diamond and percussion drillholes.

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Abstract

The technology of percussion drilling is well mastered. The lower cost of percussion drilling allows more holes to be drilled for the same budget. However significant differences are often observed between percussion and diamond drill assay data. This is due to the increased level of contamination associated with the percussion drilling process. Statistical studies on twinned drillholes show that diamond and percussion assays cannot simply be merged in a traditional kriging approach. The question then arises on how to use both types of data to produce reliable resource estimates.

To take into account the lower reliability of the percussion assays, a noise characterized by a variance is added to these data. The methodology consists of two steps:

1. Cokriging of the equivalent diamond value at the percussion assay locations.

2. Block kriging using diamond assays and equivalent diamond values, calculated previously, adding to these data a noise, whose variance is the cokriging variance of step 1. This particular way of achieving kriging is called kriging with variance of measurement error.

The paper illustrates this innovative methodology with an application on an iron deposit. The results of this method is compared to block kriging using only diamond assays and the gain in precision is quantified. An extension of that approach to multi-element cokriging is also presented.

Introduction

The area being investigated includes samples from both percussion and diamond (core) drilling phases. As the drilling was not always done on a regular grid per se, it is difficult to predict grades with the same confidence throughout the deposit if using only diamond or percussion boreholes. The existence of significant statistical differences and bias between diamond and percussion assays forbids mixing together both types of data without care.

An acceptable way of combining these two types of data for estimation purposes is to assign to each weights that take into account their respective degrees of confidence. Generally the diamond assays are considered to be more reliable than percussion assays. The uncertainty associated with percussion data may be characterized by a variance of measurement error. Iin short it means that the percussion assays are considered to be equivalent to diamond assays polluted by a random error with a variance.

The technique for integrating values with different level of confidence is known as kriging with a variance of measurement error (Chilès and Delfiner, 1999). In order to calculate that variance of error, the equivalent diamond value is interpolated at percussion drill-hole locations by a cokriging from the existing diamond and percussion assays. The cokriging variance of the estimated value is then used as the variance of measurement error required by the block kriging with variance of measurement error technique.

The quality of the estimates obtained using this method may be compared to estimates obtained from diamond assays only and to estimates mixing all diamond and percussion drillholes together (hence ignoring the heterogeneity between these data). Three criteria have been used to compare the different estimates: the kriging standard deviation (square root of the kriging variance), the slope of the linear regression between the actual grade value Z knowing the estimates value Z* (which measures the conditional bias), and the weight assigned to the mean in simple kriging, which is related to the capability of the estimate to predict the local block value.

Methodology

Let's recall the general definition of co-kriging (Wackernagel 1998) in the case of two variables Z_1 and Z_2 (in our case Z_1 is the grade from diamond assays and Z_2 the grade from percussion assays):

$$Z_{1CK}^{*} = \sum_{i=1}^{n_1} \lambda_i^1 \times Z_{1,i} + \sum_{j=1}^{n_2} \lambda_j^2 \times Z_{2,j} \qquad (1)$$

The weights λ^1 and λ^2 assigned to the variables Z_1 and Z_2 at the data locations, are calculated by solving the cokriging system, which minimizes the estimation variance knowing the spatial correlation between the data (variogram).

If the second variable is a measure of the same element but of lesser quality of the same element than the first variable, the variables can be considered as only one with different level of uncertainty. It means that the variable is the sum of the actual value plus a random noise $Z_{1,i} + \varepsilon_i$.

When the data i is a measure considered as certain (in our case a diamond assay) the noise ε is nil. When it corresponds to a measure with some uncertainty, the noise is characterized by its variance: the higher the uncertainty the higher the variance. Generally we consider that the noise is not correlated to the actual value and is purely random (nugget effect). This leads to a simple solution to the kriging solution because only the diagonal part of the kriging system is changed as the specific nugget effect of each data is added. The consequence is that the weights assigned to data (in comparable dat a configuration) with increasing uncertainty are getting closer to the weights of the arithmetic average. This method of kriging with variance of measurement error requires as an input the numeric value of the noise variance. In many mining situations the measurement error comprises laboratory analytical error plus the sum of all other sampling errors. Sampling QA/QC data may quantify at least part of the total measurement error. Analytical error may be known from the laboratory (hence the name given to the method), but otherwise the question of determining that variance is an issue. We propose here to get an estimate of that variance by the cokriging variance at data locations, where the second variable (here percussion assay) is available, of the variable Z_1 by the other data (variables Z_1 and Z_2).

The procedure is then rather straightforward:

1. Perform the cokriging of the variable Z_1 using variables Z_1 and Z_2 at the data locations. If the data is known, the cokriging, that is an exact interpolator, keeps it. If not the actual value of variable Z_1 at that location x_j is: $Z_{1,CK}^{*}(x_j) + \varepsilon(x_j)$.

$\varepsilon(x_j)$ is a random variable of zero-mean and variance equal to the cokriging variance.

2. Perform kriging with variance of measurement error using all data but adding to the uncertain data (i.e. percussion data) the random error $\varepsilon(x_j)$.

This methodology allocates more weights to "good quality" samples compared to a classical kriging that mixes all data. Moreover the method accommodates different statistical populations for both sets of data. This is achieved in the first step of the procedure by using ordinary cokriging that guarantees that the estimates of the variable Z_1 are unbiased, i.e. the estimates have the mean of Z_i whatever the mean of the other variables.

Case study

The raw data consist of 257 vertical drillholes. Each sample interval includes a specific gravity measurement, assay data for 6 elements and a drilling type code. In total 1614 Diamond assays and 3090 Percussion assays are available (see Figure 1).

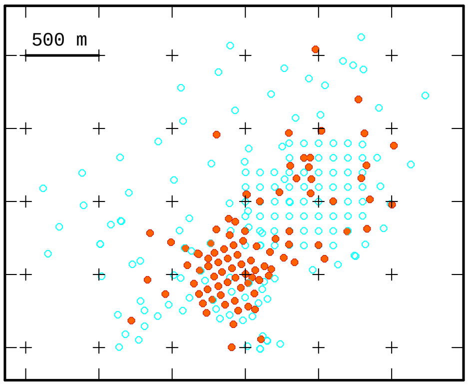

Figure 1: Base Map of the drillholes with Diamond in red (full circle) and Percussion in blue (empty circle).

The statistics have been calculated on 1m composites of the main mineralized geological codes, covering the central part of the drilled area represented on Figure 1. The statistics of both sets of drillholes indicate two different populations (see Figure 2 and 3). In particular the mean Fe grade is under-evaluated by percussion drillholes (by 6% in relative percentage).
Investigation on the other deleterious elements in Iron Ore, %SiO2, Al2O3, and K2O, all show significant statistical difference (in all these cases showing general over-estimation by percussion holes).

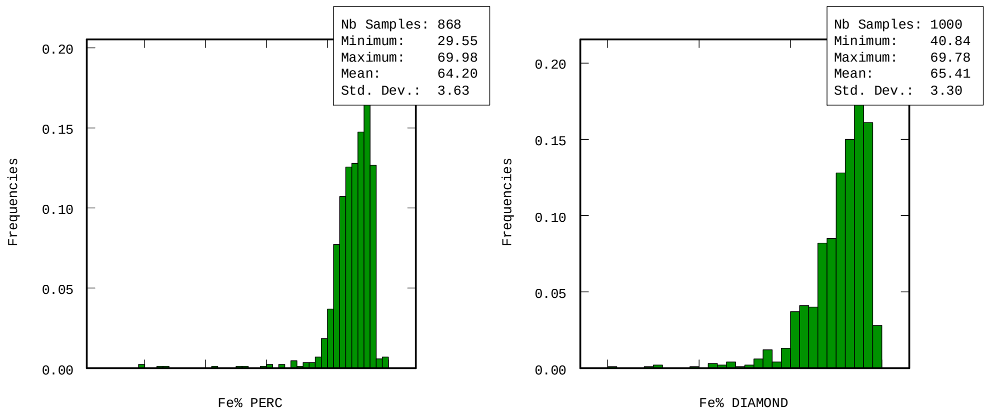

Figure 2: Histograms of %Fe from percussion and diamond assays.

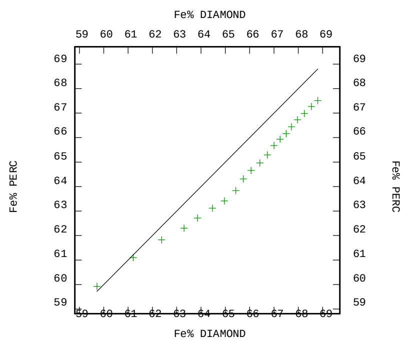

Figure 3: Q-Q plot of %Fe from diamond and percussion drillholes.

Geostatistical Analysis

The variograms (see Figure 4) calculated on diamond composites show a vertical trend noticeable after a distance of 13m. The vertical extension of the kriging neighborhood was limited by this drift. A nugget effect representing about 30% of the variability is present.

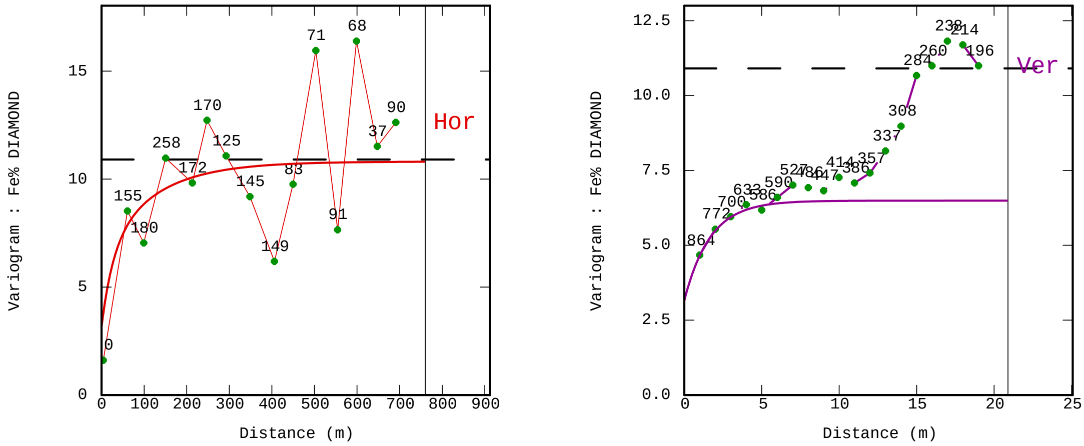

Figure 4: Experimental and modeled variogram of %Fe on diamond composites (horizontal on the left and vertical on the right).

The variograms of percussion drillholes show similar behavior, with less marked vertical trend and weaker horizontal correlation.

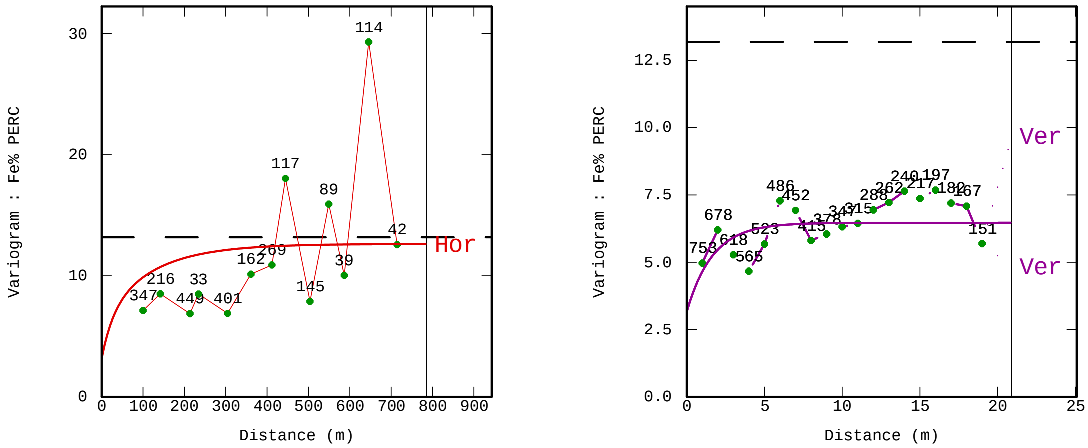

Figure 5: Experimental and modeled variogram of %Fe on percussion composites (the model is the same as on the figure 4).

To achieve the cokriging of the diamond value by diamond and percussion assays a bivariate model is required. The bivariate model characterizes the spatial correlation of diamond and percussion assays. It also requires the spatial correlation between a diamond assay and a percussion assay at any distance. That bivariate model can be characterized by a variogram model containing two simple variograms (one for each diamond and percussion assays) and a cross-variogram, whose definition is:

$$\gamma_{Z_1 Z_2}(h)=1/2\ E\{[Z_1(x+h)-Z_1(x)]x[Z_2(x+h)-Z_2(x)]\} \qquad (2)$$

In this case the cross-variogram between diamond and percussion drill data cannot be fitted because we cannot calculate any experimental cross-variogram. This is a consequence of the heterotopy of the

data: at a given drill hole location we have either the diamond assay or the percussion assay, but not both values.
A first idea would be to assume a so-called intrinsic correlation of both variables, which means that the spatial correlation is the same whatever the distance. The consequence is that the two simple variograms and the cross-variogram are proportional. In practice making that model only requires to choose the scaling factors, that is in the case of the cross-variogram derive from the coefficient of correlation between both variables.

A more general solution consists of calculating the centered cross-covariance, which will consider at a given distance the paired of diamond and percussion assay:

$$\mathrm{Cov}\ Z_1\ Z_2\ (h) = E\{[Z_1(x) - mZ_1] \times [Z_2(x+h) - mZ_2]\} \qquad (3)$$

Modelling covariances instead of variograms has two drawbacks:
- it is necessary to enter the value of the mean for both types of data, which is not an easy task,
- the first point of the cross-covariance is generally at a distance already large compared to the range of the variogram.

Concerning the second point we used the information on the correlation at small distance provided by assays of 6 twin drill holes to fix the cross-covariance at the origin. The experimental and modelled cross-covariance (see Figure 6) is not symmetrical as the cross-variogram is. However this feature will not be kept in the cokriging as only the even part of the covariance will be used. We can also observe that these covariances show important statistical fluctuations making the fitting difficult. We have nevertheless kept that model that is clearly different from a model with intrinsic correlation: this is visible on the cross-covariance that shows a positive correlation for the short range component and a negative correlation for the long range component (the cross covariance decreases then increases again with distance).

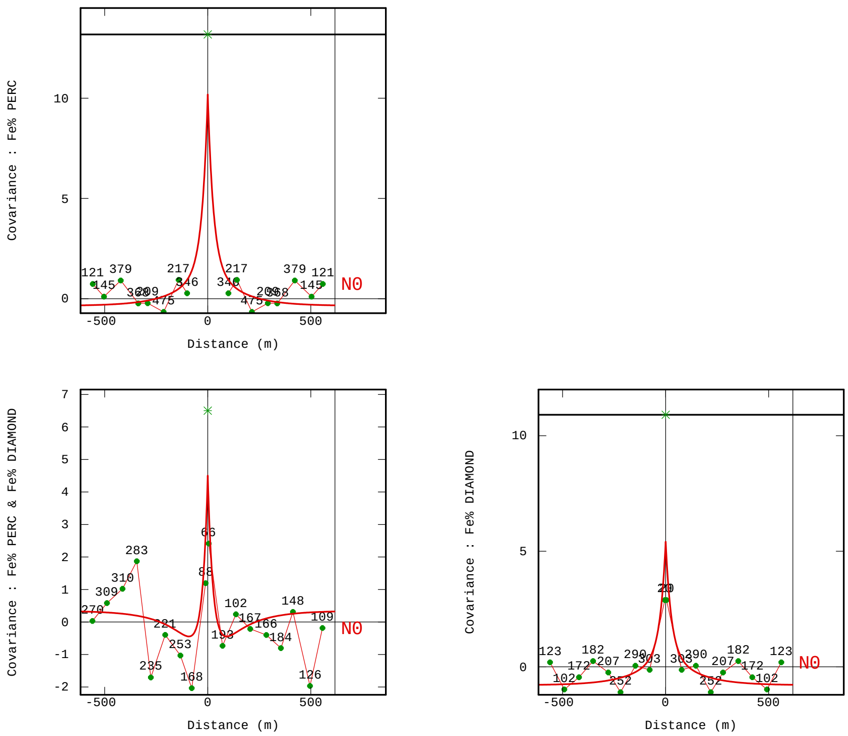

Figure 6: Horizontal covariances and cross-covariance of %Fe from Diamond and Percussion assays (the numbers are the number of pairs).

Cokriging of the diamond values at percussion assays locations.

This model has been used for interpolating the diamond grade (Z_D) at all locations of the percussion assays (Z_P):

$$Z_D^*(x_P) = \sum_\alpha \lambda_D^\alpha Z_D^\alpha + \sum_\beta \lambda_P^\beta Z_P^\beta \qquad (4)$$

The scatter diagram of the original percussion assays values and the interpolated diamond values shows that the shift that is applied to the percussion assays decreases as grade increases (Figure 7).

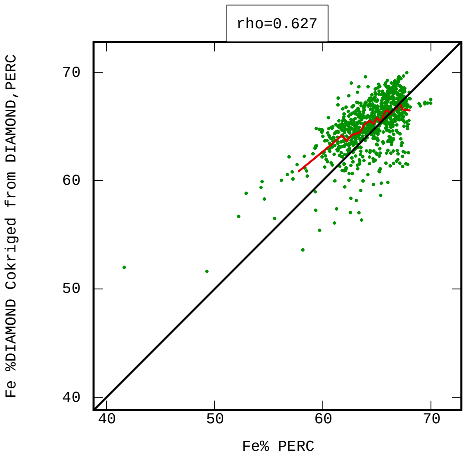

Figure 7: Scatter Diagram of the Cokriging of %Fe with diamond and percussion assay value (the red double line is the conditional expectation curve).

Block Estimation

About 3500 blocks of size 20m x20m x10m have been estimated by three different methods:

- Method 1: Kriging from the diamond assays only (ignoring the percussion drillholes completely).
- Method 2: Kriging from the diamond assays and the percussion assays together (ignoring completely the statistical differences).
- Method 3: Kriging from the diamond assays and the percussion assays with a variance of measurement error for the latter data. That variance is nothing but the cokriging variance calculated when cokriging the diamond values at the percussion assays locations.

To highlight the impact of the data used and the estimation algorithm and methodology, each of the 3 methods is tested using the same variogram model, fitted on the diamond assays (see Figure 4). The same neighborhood search (with octants) has also been used for the three estimates.

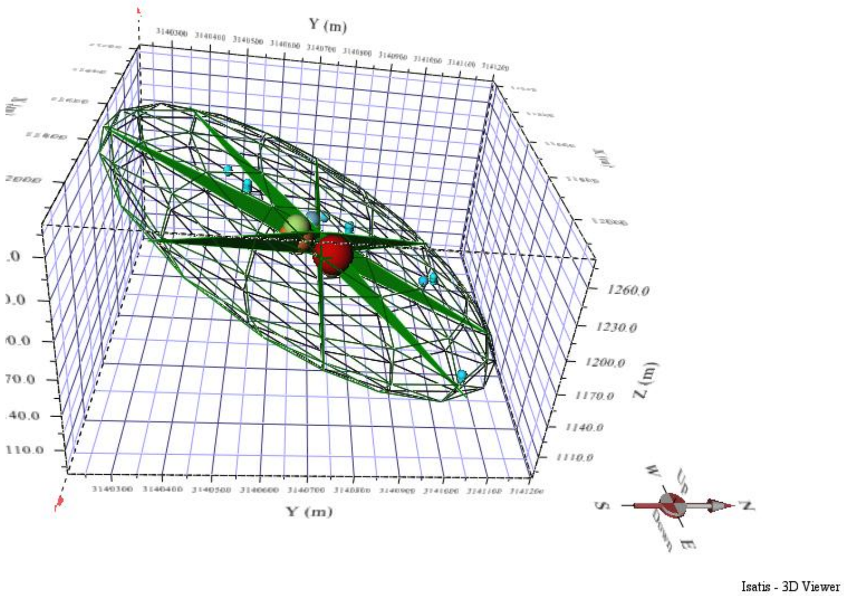

Figure 8: Example of neighborhood search for kriging: the selected data are represented by spheres with colors from blue to red according to the kriging weights (the Z axis is magnified by a factor of 3).

Table 1 shows the statistics on all blocks for the average estimated grade, the kriging standard deviation, the slope of the regression of Z|Z* and the weight assigned to the mean.

Table 1: Global statistics of the Fe kriged grades by the 3 methods.

Method	Mean %Fe	Kriging Standard deviation	Slope of Z|Z*	Weight assigned to the mean
Method 1	64.95	1.95	0.65	0.42
Method 2	64.18	1.61	0.87	0.20
Method 3	64.83	1.68	0.84	0.24

It appears that the percussion drill holes are adding significant information which improves the kriging based only on the diamond assays by a lot. It is particularly impressive when considering the slope of Z|Z*. There are mant more blocks with low conditional bias (i.e. slope Z|Z* close to 1) with method 3 than method 1 (Figure 9).

Method 2 appears to give the best results but this is illusory because it ignores the fact that the percussion drill holes belong to a different population than the diamond drill holes. Mixing the two data types leads to a systematic underestimation of the grade as shown in Table 1.

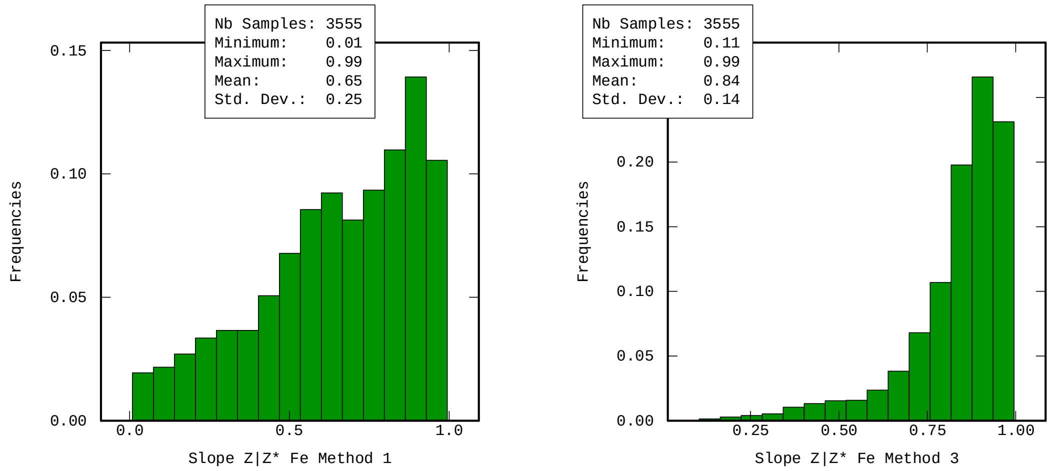

Figure 9: Histograms of the slope of Z|Z* for %Fe estimates for the method 1 (kriging from diamond drillholes alone) and method 3 (kriging from diamond and percussion drillholes with variance of measurement error).

The same approach can be carried out in a multi-element cokriging based on a linear model of co-regionalization with the variance of measurement error applied on the main variable. The cokriging is run as many times as elements by changing in turn the main variable. The results are difficult to compare with the element-by-element approach, because the multivariate model is a compromise for fitting all variograms and cross-variograms (the multivariate model may differ significantly from the models fitted specifically on a single element). It should nevertheless be noted that in the case of systematic analysis of all elements, said isotopic case, the advantage of co-kriging is reduced anyway.

CONCLUSIONS

The question of the best way to integrate different types of data in order to optimize the use of the information during estimation is rather common. Resource databases commonly include drill hole and channel sample data, data from two or more drilling methods, data from drill holes of different diameter, data from primary samples of different mass, assay data determined by different analytical techniques, or different core recoveries.

From a statistical point of view, simply ignoring data heterogeneity by merging all data together may lead to significant estimation errors and bias . Re-drilling holes to reduce data heterogeneity is usually economically prohibitive.

A satisfactory solution to this common problem is provided by the method of kriging with variance of measurement error. This nmethod guarantees unbiasedness in the estimates and improves the quality of the estimation.

The only difficulty is to model the spatial cross-correlation between the two types of data, which requires to have both data sets mixed together and to have available a certain number of twinned holes.

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