GEOSTATISTICS APPLIED TO GEOMETALLURGICAL MODELING

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ABSTRACT

Many factors influence on ore processing efficiency and a better understanding of these aspects and their impact on the processing plant can help to improve the ore recovery. The construction of a geometallurgical model is fundamental for achieving this objective, since the knowledge of ore properties allows a more accurate forecast of mass recovery by the process, improving mine planning. Most geometallurgical variables are non-additive, i.e., the output value from a combination of samples does not depend only of the values and masses of the initial samples, but also from a complex relationship with other variables. Due to these complex relationships, it is not recommended the use of conventional estimation methods like Inverse Distance to a Power or Ordinary Kriging (OK), once this estimates use a linear weighted average. Non-linear geostatistical methods were developed to estimate a local probability distribution of possible values for a variable. Among these methods, Indicator Kriging (IK) can be used to estimate the probability of a block to be above (or below) a determined cut-off or the likelihood to belong to a certain class or category. This study uses IK combined with the information from the geometallurgical tests to build a short term block model of a phosphate mine at Vale Fertilizantes S/A. It is expected the use of a geometallurgical model for the mine planning will improve the recovery prognostic of each selective mining unit and may be used as a tool to help in the decision making process beyond the simple cut-off grade on the P_2O_5 grade. At the end, the model generated by the linear methods (OK) is compared against the model proposed using IK. The prevision by the IK geometallurgical proved to be accurate and the results were compared against production figures.

KEYWORDS

GEOMETALLURGY, GEOSTATISTICS, INDICATOR KRIGING, NON-ADDITIVE VARIABLES

INTRODUCTION

Ore characterization is mandatory in all mining projects. The results normally obtained from the pilot plant can integrate the models used for predicting the processing plant recovery. This process is referred as geometallurgy (Braga, 2015).

In this scenario, geometallurgy provides the interaction among physical/chemical rock properties such as mineral assemblage, hardness and chemical composition, with process variables including mass recovery and energy consumption. Therefore, it is possible to estimate with accuracy and reasonable precision the process performance, helping to improve mine planning and project risk evaluation (Mendonça, 2015).

The incorporation of geometallurgical variables in short term block model helps in predicting processing plant efficiency. However, it is necessary to be cautious when estimating geometallurgical models. Mass recovery and concentrate grades are non-additive variables, i.e., their values do not average linearly.

Inverse Square Distance and Ordinary Kriging (Matheron, 1963) are estimation techniques that use a weighting average to combine sample values to estimate a block depending on its distance and covariance, respectively. Since results are based on the weighted average of the data without considering their relationship with other variables or their non-additivity, the use of such estimation technique is not recommended for building a geometallurgical model. Conversely, indicator kriging (Journel, 1982) estimates probabilities by a categorical transformation of a dataset based on cutoff grades or thresholds. As a result, it is possible to derive at each block the probability to be above or below a determined cut-off. This paper evaluates the applicability of indicator kriging as estimation method for building a geometallurgical model of a phosphate mine located at a carbonatite complex in central Brazil.

METHODOLOGY

The processing plant efficiency is probably one of the most influential aspects to improve profitability in a mining project. Due to this fact, it is vital to have a deep understanding of the geometallurgical aspects of the ore, as they directly affect recovery. Through the application of a methodology to estimate the geometallurgical model, it is expected to be possible to predict the processing plant performance and introduce data to assist mine planning.

The carbonatite complex used in this case study belongs to an ultramafic-carbonatitic alkaline intrusion related to ultrapotassic intense magmatism of the Upper Cretaceous (Gibson et al., 1995). The complex is composed by silicate (predominantly ultramafic), carbonatite and foscoritic rocks containing significant phosphate and titanium deposits, which are currently being mined for apatite (Brod et al. 2000). The apatite (P_2O_5) and anatase (TiO_2) deposits are located at the weathering mantle on these alkaline rocks. The supergene concentration of these minerals is given by solubilization and leaching of the most mobile components contained in the original rocks. Moreover, in shallower horizons, apatite was partially transformed into secondary phosphate. However, in deeper portions, it remained in the weathering mantle as resistive mineral. The anatase is a product of weathering originated from the decalcification of perovskite ($CaTiO_3$) in the original rock.

In this case study, the prior data separation into domains precedes the estimation. The classes were separated according to the weathering zones, since for this kind of deposit geometallurgical behavior is directly related to the weathering intensity, the domains description is shown in Figure 1, presented in a typical cross section.

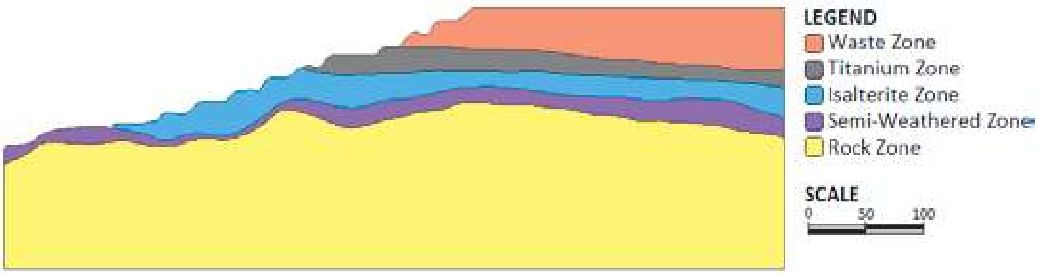

Figure 1 – Weathering Zones Separation.

This study starts by geometallurgical tests to obtain data. A pilot plant mimics the processing plant on a smaller scale, in order to provide indicators of process recovery and concentrate grades. The variables considered for this case study was the concentrate grade, also the metallurgical and mass recovery, as shown in Table 1. The dataset is heterotopic comprising 5369 samples. Univariate statistics for each variable is depicted in Table 2.

Table 1 – Variables and their description.

Variable Name	Description
P_2O_5CON	Apatite Concentrate
RECTOT	Metallurgical Recovery
RMTOT	Mass Recovery

Table 2 – Samples basic statistics.

Variable Name	Number of Data	Minimum	Maximum	Mean	Standard Deviation
P_2O_5CON (%)	2434	11.50	38.00	34.59	2.70
RECTOT (%)	5369	1.77	99.32	56.49	14.10
RMTOT (%)	5369	0.78	55.10	14.98	6.32

Since the samples of the concentrate grade have different mass recoveries, it was necessary to transform it into accumulated variables, by weighting each grade sample in function of its mass.

Knowing that these geometallurgical are non-additive was proceeded the estimative by indicator kriging, which transforms the original dataset (u_a) into categories based on threshold limits (Z_k) according to, as shown in Equation (2). In this case, the cut-off grades were chosen considering the deciles of the distribution.

$$i(u_a, Z_k) = \begin{cases} 1, & Z(u_a) \leq Z_k \\ 0, & Z(u_a) > Z_k \end{cases} \tag{1}$$

The spatial continuity analysis started with the indicators defined for the median (Q50). As all the variograms have the same form and spatial continuity major axes, with large continuity for low grades and short for the high grades, the median model was applied with a range reduction factor for the higher quantiles, and an increase factor for the lower quantiles. It was not possible to use domains separation for the spatial continuity analysis due to the small number of samples within some domains in the dataset. The multiple indicator probabilities were kriged and the E-type model derived from each estimated block conditional probability distribution function.

The E-type mass recovery estimates were validated using swath plots, comparing sample averages against block averages within regions and histograms reproduction. These validations proved to be ok and the models were accepted. The next stage was to compare the block models derived from IK and OK and evaluate the geometallurgical model constructed against production results.

RESULTS AND DISCUSSION

Average Difference Analysis

The average difference measures the discrepancy of two values. In this case study, the difference was calculated for each block value (n blocks in the model) from the IK and OK estimates, with the objective to identify if there is a significant divergence between the methods. An average difference near to zero indicates the methods lead to similar results on average, while very negative or positive results shows substantial discrepancy between the methods. The average difference was calculated using Equation (4):

$$Average\ Difference = \frac{1}{n}\sum IK_{estimate} - OK_{estimate} \tag{2}$$

The differences should have average error close to zero and minimum spread, i.e. the average close to zero (unbiasedness) is not sufficient, since high and low magnitude errors can compensate each other (need also to be precise). The average difference histograms for the three variables considered in this study are displayed in Figure 2.

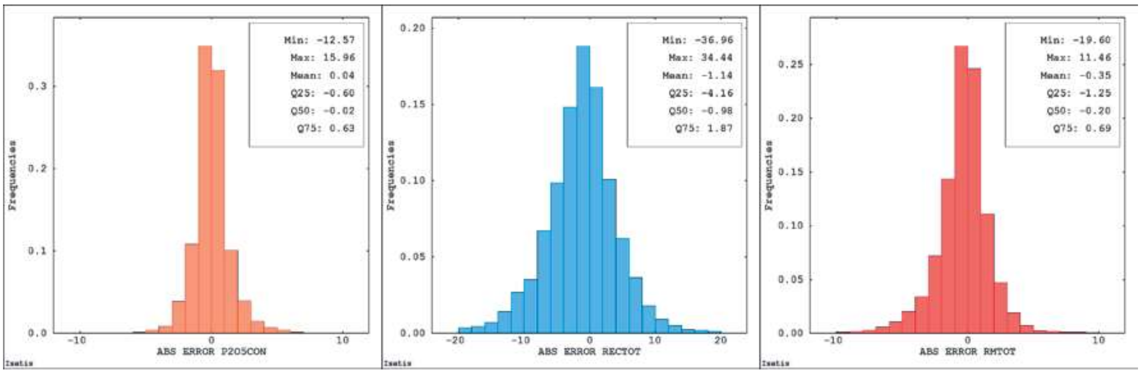

Figure 2 - Absolute differences for the variables P_2O_5CON, RECTOT and RMTOT, respectively.

Significant differences in the two estimation methods were detected. Mass recovery (RECTOT) presented an average difference of -1.14%, indicating that the blocks were overestimated by OK, when compared to the IK estimates. From the histogram of differences, it is noticed that 50% of the blocks presented difference exceeding 1.87%. Considering the importance of mass recovery at the processing plant, these errors were considered significant.

The metallurgical recovery (RMTOT) presented an average difference near zero, not showing global difference between the two models. Even tough global differences were not noticed, 25% of the blocks error exceeded 1.25%. The apatite concentrate (P_2O_5CON) also showed differences, but less significant. Although this comparison is not capable to identify which estimation method is more accurate, it shows that ignoring non linearity and non-additivity can significantly affect geometallurgical variable estimates.

Estimated Grades vs. Real Grades

This analysis is introduced as a reconciliation scheme between the grades obtained from the processing plant (herein referred as real grades) and the grades estimated by the kriged models. It is expected that the IK and OK estimated block models approximate on average the real grades.

Ten planned blending piles were selected along 2015 production, and it was compared the average grade of all blocks forming each pile against the real grade. The closer to zero the difference is, the more similar the real and estimated grades are.

It is important to observe that in this study case there is no sampling at the blending piles. Therefore, it became impossible to detect if the differences founded between the estimated and real grades are due to mine planning deviations, processing plant inefficiency or the estimated method itself. This fact limits some of the analysis but do not invalidates the comparison made.

IK models approximates better the metallurgical recovery (RMTOT) for 70% of the analyzed piles and was more accurate than OK. The average relative error reaches -10% for IK prediction, while OK to -20%. The reconciliation results for each planned pile tested can be seen in Figure 3.

For mass recovery (RECTOT) both kriged models led to similar results. Their reconciliation results are depicted in Figure 4. For the apatite concentrate (P_2O_5CON), 60% of pile grades were better approximated by IK derived block grade estimations (Figure 5). The average relative error was -1% with IK, while the OK presented a relative error of -2%.

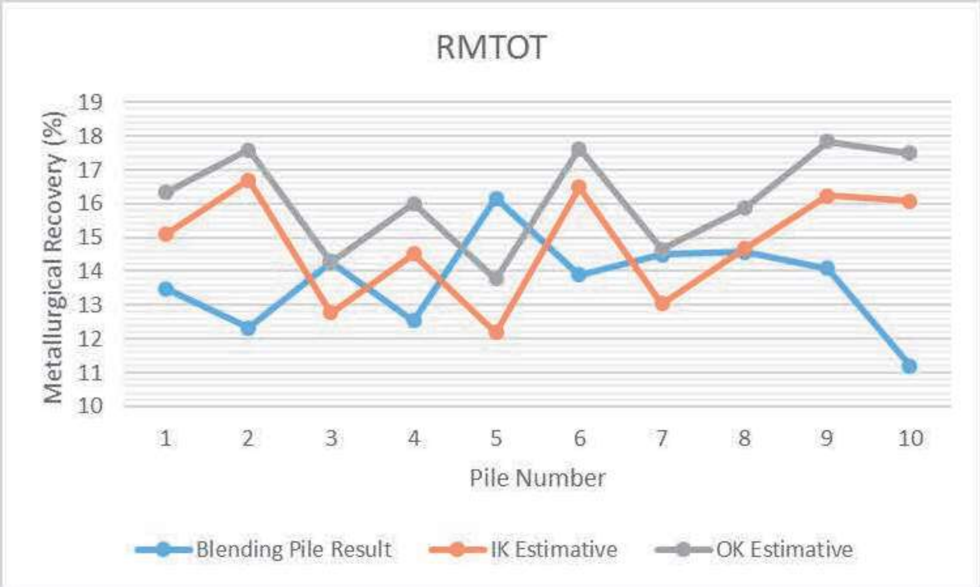

Figure 3 - Metallurgical recovery reconciliation results.

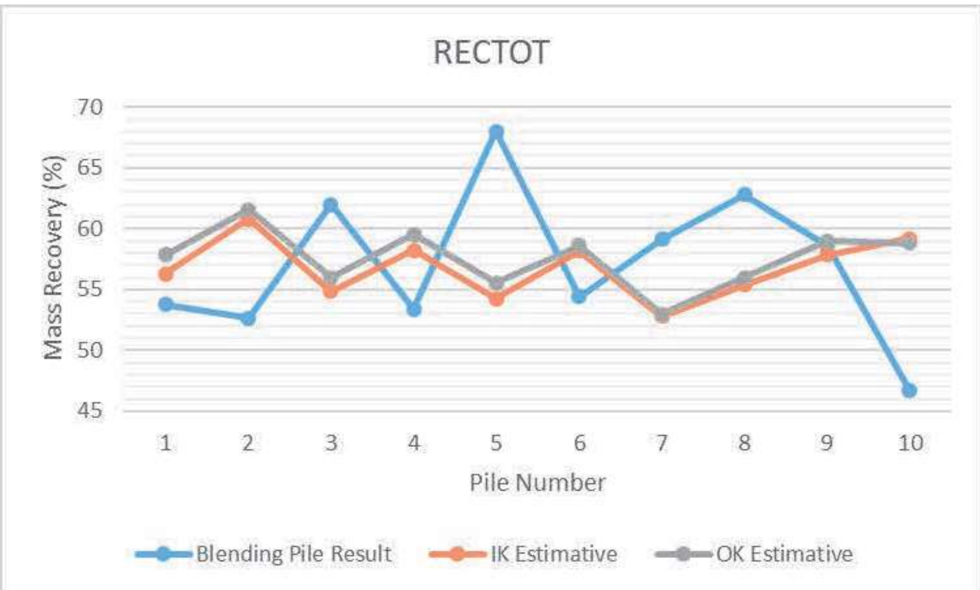

Figure 4 - Mass recovery reconciliation results.

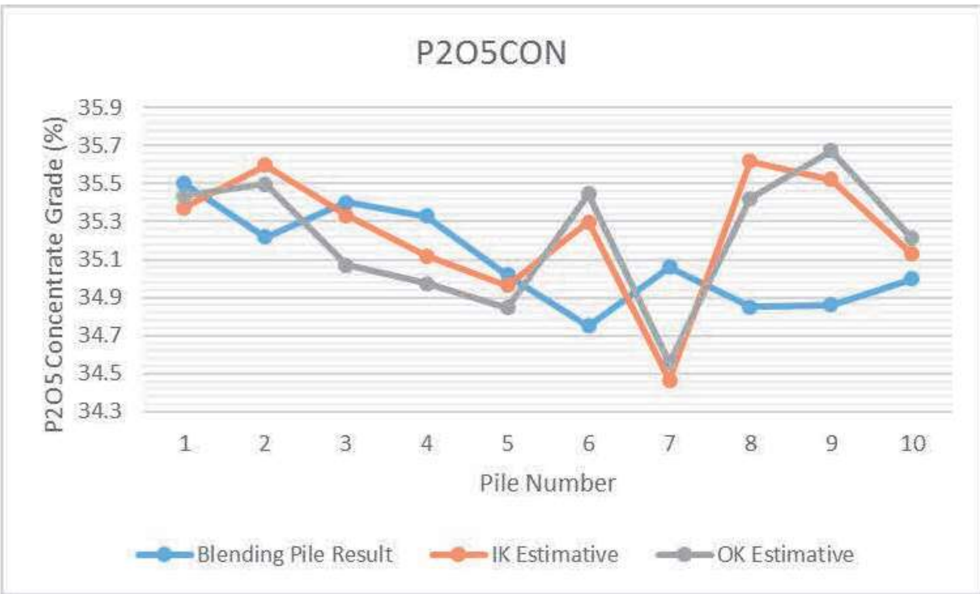

Figure 5 - Apatite concentrate grades reconciliation results.

It is possible to observe a considerable difference between the measured at the plant results and the estimated ones. The probable causes for this discrepancy are: the upscaling effect (error) from the pilot plant tested to the processing plant, estimation error at each block value associated with the interpolation process (kriging minimizes the error but do not eliminate it), discrepancies caused by operation lack of geometric adherence between the planned blocks to be mined and the ones really extracted, and last but not least important the sampling error at the processing and pilot plants. Even though these probable causes are known, it is not possible to accurately nominate which one is more or less responsible for this discrepancy.

CONCLUSION

Combining mineralogical characterization into mineral processing studies is of paramount importance for defining ore types and to understand their behavior at the processing plant. Incorporating geometallurgical response into mine planning can lead to a more effective and profitable operation.

The use of non-linear methods to deal with non-additive geometallurgical variables provide more precise and accurate models. In this case study, results from reconciled models against production data showed IK is more accurate than OK for the purpose of estimate geometallurgical variables.

The error analysis showed a significant difference between the estimation methods. This is important to show the impact on the chosen method to estimate a block model. The reconciliation analysis presented a slight improvement in estimating using IK, even considering the discrepancies between the real and estimated grades. These discrepancies are not only caused by the estimation method, but for a combination of factors.

In future studies, other alternatives will be investigated to build models with geometallurgical variables modelling including stochastic simulations.

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