Forecast the mineral processing destinations based on spatial interpolation of geometallurgical variables

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EXTENDED ABSTRACT

Mine planning is a crucial part of all mining industry projects, and nowadays, geometallurgical mapping through advanced computer technologies provides an opportunity to involve metallurgical responses of a deposit into 3D block model in order to optimise mine planning activities, especially for production forecasting. Including these metallurgical parameters apart from traditional geology and grade-based attributes into resource modelling leads to an extensive approximation for the economic maximisation of mine production due to better forecasting, planning and increasing certainty and the reliability of the resource model (Macfarlane and Williams, 2014). Commonly, geostatistical techniques and algorithms are used to produce models with the high resolution (Brissette et al. 2014; Deutsch et al. 2014; Tolosana-Delgado et al.
2015). The accuracy of the modelling procedure deeply depends on a reliable block model, produced by spatial analysis of corresponding variables that define the geological, metallurgical, mineralogical and chemical behaviour of the deposit. However, there are special cases, where the application of enhanced geostatistical methods is required, to solve the occurred difficulties between variables with multivariate complexities. For example, in oxide copper deposits, the soluble copper grade is a percentage of total copper grade and recoverable by heap leaching processes (Emery, 2012; Hosseini and Asghari, 2015). Hence, the joint spatial modelling of these variables has two difficulties.

The first problem of geostatistical estimation of total and soluble copper is geological inequality constraint, in which the value of soluble copper grade cannot exceed the total copper grade. Conventional estimation methods such as co-kriging fail to reproduce that critical condition. According to Dubrule and Kostov (1986), Leuangthong and Deutsch (2003) and Emery (2012), several solutions for inequality constraint are available, and the change of variables can be implemented to eliminate constraint for further modelling steps. The idea of changing variables is to convert one variable with dependency on another variable that will be free of inequality constraint. In the case of the oxide copper deposit, the soluble copper grade is changed into solubility ratio, which is the ratio of soluble copper grade to total copper grade. Thus, the co-kriging can be applied unquestionably to the data after removal of the multivariate constraint. Nevertheless, the second problem that frequently happens in practice of joint modelling, is about utilization of theoretical cross-variogram structure for co-kriging estimation, because the fitting of the experimental direct and cross-variogram to the theoretical structure is time-consuming in case of large grid size or involving more than two variables into the estimation process (Goovaerts 1993; Leuangthong and Deutsch, 2003).

The possible solution is to transform cross-correlated variables into the factors that will be decorrelated in a new space without any spatial interrelationship. There exist required transformation methods such as Principal Component Analysis (PCA) and Minimum/Maximum Autocorrelation Factors (MAF) that exclude the usage of cross-variogram by decorrelation variables (Bandarian et al., 2008; Switzer, 1985; Desbarats and Dimitrakopoulos, 2000;). MAF theory is based on PAC that is needed for two successive spectral decompositions. As a result, the spatially cross-correlated variables are converted into uncorrelated orthogonal factors through the linear transformation. Once the factors are prepared, ordinary kriging for estimation purposes can be conducted (Bandarian et al. 2008; Swither and Green, 1984). This method is a commonly used interpolation method that estimates value at the particular point/block in the certain area considering the near neighbourhood data with known variogram model, whereas co-kriging investigates cross-variogram of several variables for the estimation.

Four major aims of this study are established as follows: 1) change of variables to the new variables free of inequality constraint has been applied for a dataset composed of total and soluble copper grades in a porphyry copper deposit (converting the total and soluble copper grades to total copper grade and solubility ratio, respectively); 2) apply MAF factorization methodology for joint estimation of the underlying converted

variables; 3) comparing the proposed methodology (via MAF) with conventional co-kriging; 4) provide geometallurgical map with four classifications: leaching plant, floatation plant, low-grade stockpile and waste dump.

The results of the proposed methodology coincide with expectations. Figure 1 demonstrates the base maps of estimated total (tCu) copper grade and soluble (sCu) copper grade for both co-kriging and MAF-kriging. The corresponding values of blocks in the models are similar to each other: therefore, a suggested modelling algorithm works extremely well, and multivariate complex interrelation of variables is regenerated without any deviation from the primary inequality constraint.

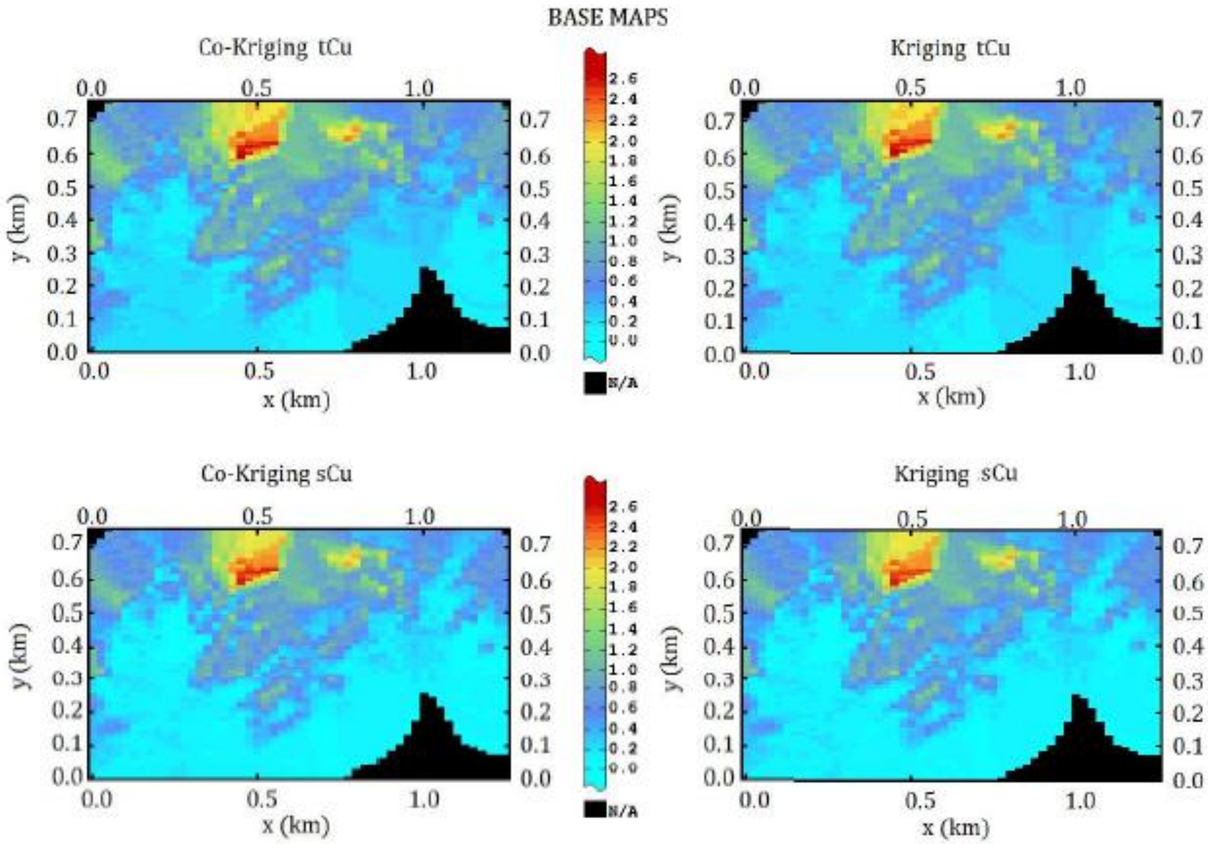

Figure 1 – Base maps of co-kriging and MAF-kriging for total and soluble copper grades.

The classification map for forecasting is produced based on two methods of geostatistical estimation, and the results can be seen in Figure 2. Hence, forecasting of special cases similar to this oxide copper deposit can be done based on geometallurgical maps that reproduced by the proposed optimised methodology. Moreover, those maps help to develop possible advanced forecasting activities that not only optimise the mineral production and processing but also increase the certainty in future mine sustainability.

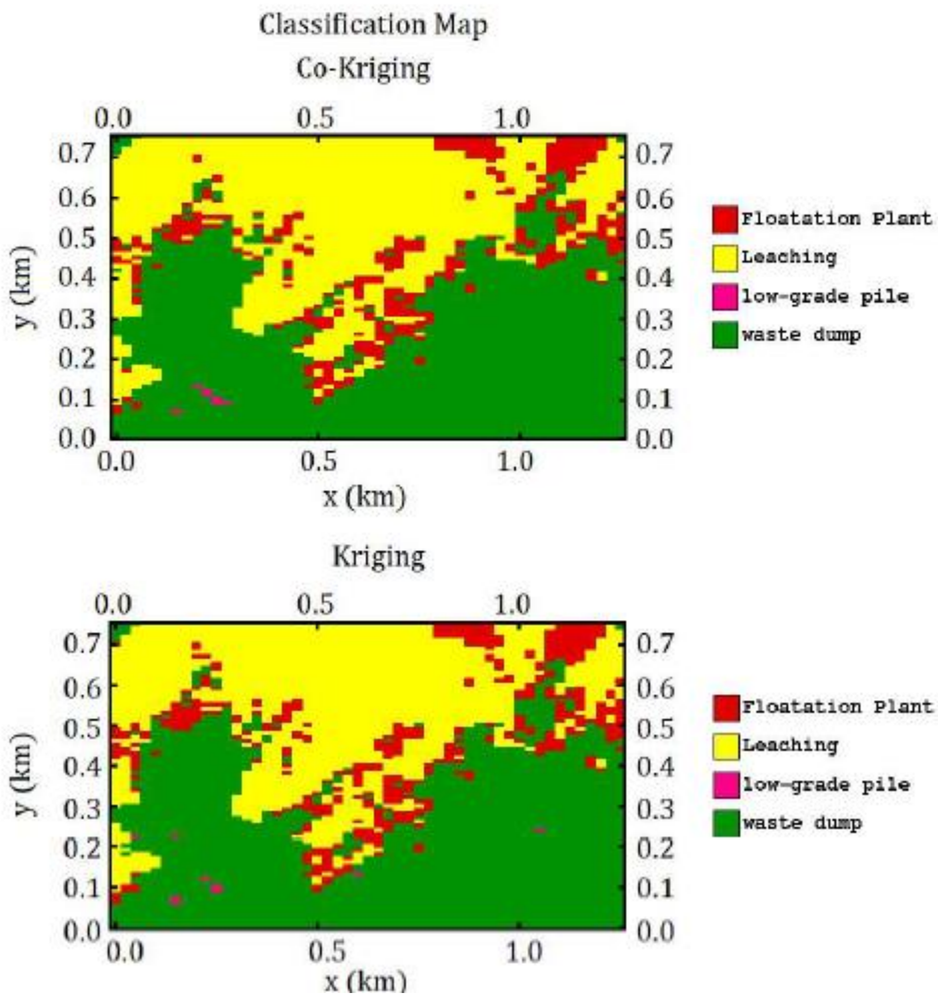

Figure 2 — Geometalurgical classification map based on four processing destinations.

ACKNOWLEDGEMENTS

The first and second authors are grateful to Nazarbayev University for funding this work via "Faculty Development Competitive Research Grants for 2018-2020 under contract no. 090118FD5336".

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