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GENERACIÓN E IMPLEMENTACIÓN DE MODELOS GEOMETALÚRGICOS: GUÍA MULTIDISCIPLINARIA PARA LA DEFINICIÓN DE RESERVAS MINERAS

TESIS PARA OPTAR AL GRADO DE DOCTOR EN CIENCIAS, MENCIÓN GEOLOGÍA

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GENERACIÓN E IMPLEMENTACIÓN DE MODELOS GEOMETALÚRGICOS: GUÍA MULTIDISCIPLINARIA PARA LA DEFINICIÓN DE RESERVAS MINERAS

La tesis de doctorado Generación e implementación de modelos geometalúrgicos: Guía multidisciplinaria para la definición de reservas mineras se enmarca en el contexto geo-minero-metalúrgico de depósitos de pórfido cupríferos, donde se muestra la importancia para los proyectos mineros la generación de modelos geometalúrgicos y su implementación práctica en planificación de corto y largo plazo para definir reservas mineras dentro de los estándares internacionales de reporte de reservas NI 43-101, impactando en la disminución de los costos operacionales de tratamiento, además de la disminución del riesgo de un proyecto. El objetivo general de la tesis es establecer un método de estándar internacional para cuantificar reservas mineras considerando modelos geometalúrgicos en la planificación minera. Para esto, (1) se generaron modelos geometalúrgicos integrados considerando incertidumbre geológica y metalúrgica; (2) se realizó una descripción de método genérico para incluir modelos geometalúrgicos en planificación minera de corto y largo plazo; (3) se generó un manuscrito guía de buenas prácticas para la declaración de reservas considerando la geometalurgia como un factor modificante clave.

El artículo 1 titulado 'Cambio de soporte usando variables no aditivas con Gibbs Sampler: Aplicación a recuperación metalúrgica de minerales sulfurados' (Computer and Geoscience 2019) describe una metodología para la integración de la base de datos de diferentes fuentes y soportes, donde se discuten las ventajas y desventajas de esta nueva metodología desde un punto de vista geoestadístico. El artículo 2 titulado 'Simulación de bases de datos de exploración y geometalúrgica de depositos porfidos cupriferos con fines educacionales' (Natural Resources Research 2020) describe una metología de simulación de atributos geometalúrgicos, el cual permite la generación de base de datos sintéticas para múltiples propósitos.

Se adjunta documento publicado en Predictive Geometallurgy and Geostatistics Lab, Queen's University el cual presenta una guía de buenas prácticas para la declaración de reservas considerando la geometalurgia como un factor modificante, basado en las definiciones de reservas minerales del código NI 43-101.

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TABLA DE CONTENIDO

INTRODUCCIÓN

En esta tesis se resumen 2 artículos de publicación científica orientadas a la generación e implementación de modelos geometalúrgicos de sulfuros de cobre.

CONTEXTO

La geometalurgia busca la integración de diferentes áreas de conocimiento a través de modelos predictivos que puedan ser utilizados en la disminución de costos operacionales ante procesamiento mineral. El estudio geológico del mineral extraído, tanto de mena como de ganga, es una ciencia ampliamente desarrollada por la geología a través de diferentes mediciones que permiten generar una completa caracterización del mineral. Así mismo, ensayos metalúrgicos permiten caracterizar el comportamiento operacional que se esperará en la planta de procesamiento mineral (desde conminución, hasta la separación de la mena y ganga o refinamiento). Los comportamientos geometalúrgicos de las rocas, unidades geológicas de un yacimiento, se determinan comúnmente mediante la realización de ensayos mineros. Propiedades como dureza, moliendabilidad, recuperación de cobre, consumos de insumos en procesamiento, entre muchos otros aspectos, se determinan en forma empírica, normalmente sobre un número limitado de muestras, esto debido a los altos costos que implican. El comportamiento del material procesado dependerá tanto de factores operacionales como geológicos. Los procesos metalúrgicos requieren procesar el 100% de la roca, los costos de producción y la eficiencia de recuperación no solamente dependen de las características de los minerales de mena, más bien mayoritariamente de los de ganga. El enfoque clásico en explotación y procesamiento mineral de yacimientos se centra principalmente en la mena, las características de ganga normalmente quedan relegadas a las características geológicas de un yacimiento.

La generación de modelos geometalurgicos es una herramienta necesaria en cualquier proyecto minero, por lo tanto su incorporación dentro de la planificación minera es un objeto de estudio inminente y de innovación para entidades especializadas en el área de investigación y desarrollo. La innovación en esta área generará nuevos estándares en el reporte de reservas mineras para la industria a nivel mundial de yacimientos polimetálicos a través de la generación de guías de buenas prácticas para definir formalmente metodologías para incluir modelos geometalúrgicos durante el proceso de evaluación de yacimientos.

En esta tesis se trabajó una guía metodológica que permite incluir los modelos geometalúrgicos dentro de la definición de reservas mineras de una compañía. El concepto de reserva se basa en aquellos recursos mineros estimados con buena confiabilidad que tienen posibilidades de ser explotados, por lo tanto son considerados parte de los activos económicos de una empresa minera. Para que recursos minerales sean valorizados como reservas mineras, deben ser evaluados por una serie de factores modificantes, por ejemplo, proceso minero/metalúrgico, geotecnia, hidrología, medio ambiente, factores de mercado, etc. Y la geometalurgia es un factor modificante dentro del proceso minero/metalúrgico que debe ser considerado para la definición de reservas mineras. No considerarlo implica en aumento de costos operacionales y aumento del riesgo del proyecto. El concepto Reserva Minera está relacionado con la industria que genera estudios bancables, puesto que es esencial comunicar los riesgos asociados de manera efectiva y transparente a fin de obtener el nivel de confianza necesario para respaldar actividades mineras. CRIRSCO es el Committee for Mineral Reserves International Reporting Standards, del cual miembros de todo el mundo, por ejemplo la Comisión Calificadora de Competencias en Recursos y Reservas Mineras de Chile, CIM de Canadá, SAMREC de África del Sur y JORC de Australia siguen guías de buenas prácticas para definir las reservas mineras.

MOTIVACIÓN

Al integrar el área de geometalurgia en la evaluación de recursos y planificación minera se logra una disminución de costos de procesamiento, y disminución de la incertidumbre del mineral a procesar. El principal desafío que limitan las actividades en el área de la geometalurgia es la integración de conocimiento especializado, de esta forma el geometalurgista debe tener un conocimiento transversal sobre geología, producción minera, procesamiento mineral, medio ambiente y sostenibilidad minera. En enfoque actual del geometalurgista se basa en el conocimiento geológico, cuya tarea de incluir estos factores geometalurgicos normalmente es delegado al minero, generando interferencias en el entendimiento geometalúrgico y perdiendo el enfoque principal, cuyo objetivo es disminuir costos e incertidumbre del procesamiento mineral.

Actualmente en la geometalurgia no se modelan procesos de interacción agua/roca desde molienda en adelante, donde las condiciones de composición mineral y de agua son las que regulan reacciones de equilibrio químico, reacciones que controlan las condiciones fisicoquímicas (pH, Eh, EC entre otros) e hidroquímicas del agua de proceso. Estas condiciones a su vez afectan los parámetros de operación, costos de insumos y eficiencia de recuperación, como también la calidad y condiciones del agua y material de descarte a relaves. La geología/ mineralogía de alimentación a planta incide sobre la operación, costos y eficiencia, por lo que modelar atributos geometalúrgicos en forma predictiva es fundamental para disminuir los riesgos de un proyecto minero.

A pesar de los estudios para generación de modelos geometalúrgicos, la metodología y su implementación en la cadena productiva minera aún presenta dudas, se desconocen sus potenciales usos y no se cuenta con una guía clara para su manejo. La planificación (de mina como de planta) permite generar planes de respuesta en el corto, mediano y largo plazo a fin de aumentar la vida del proyecto minero, disminuir costos operacionales y maximizar el beneficio económico de retorno. El proyecto minero se basa en una buena planificación para minimizar los riesgos asociados a la extracción, procesamiento y venta del mineral. Los modelos geometalúrgicos no son considerados explícitamente dentro de la planificación minera, ya que no existe una guía clara y concisa de cómo unificar estas áreas multidisciplinarias y las herramientas comerciales adecuadas para su ejecución.

HIPÓTESIS DE LA INVESTIGACIÓN

La hipótesis de esta investigación es que la integración de modelos en geometalurgia permite mejorar resultados en procesamiento de minerales, disminuyendo la incertidumbre y costos de proceso.

OBJETIVOS

El objetivo principal de la investigación es establecer un método de estándar internacional para cuantificar reservas mineras considerando modelos geometalúrgicos en la planificación minera. Para esto, se ha separado en 3 etapas, con diferentes objetivos específicos:

1. Metodología para generación de modelos geometalúrgicos integrados considerando incertidumbre geológica y metalúrgica.
2. Desarrollo e implementación de método genérico para incluir modelos geometalúrgicos en planificación minera de corto y largo plazo para operaciones de rajo abierto.
3. Generar un manuscrito guía de buenas prácticas para la declaración de reservas considerando la geometalurgia como un factor modificante, basado en las definiciones de reservas minerales de códigos internacionales.

ESTADO DEL ARTE

Los modelos geometalúrgicos predictivos permiten estimar, con diferentes niveles de confianza y riesgo, el comportamiento insitu de un material en base a su caracterización mineral. Este resultado es escalado a nivel industrial en la planificación de corto plazo para poder optimizar los parámetros operacionales y disminuir los costos asociados al tratamiento del mineral. En un yacimiento mineral del tipo pórfido cuprífero es posible tener una diversidad de unidades litológicas, de alteración, de mineralización y estructuras, cuya combinatoria implica una alta variabilidad en los materiales de alimentación a planta de procesamiento. Comportamientos diferenciales según alimentación, ya sea de frentes de extracción singulares o bien mediante programas de mezcla controladas, son lo esperable en producción. Estudios que aborden los impactos geológicos / minerales, composición de aguas de proceso, reacciones de equilibrio agua / roca en procesamiento y los impactos de estos en flotación y recuperación, o en lixiviación en el caso de procesamiento mediante lixiviación en pilas, son escasos.

En la conferencia Procemin-GEOMET del año 2019 realizada en Chile se han discutido varios temas relacionados con esta investigación, destacando los siguientes problemas relacionados con la generación de modelos geometalúrgicos y su implementación en la planificación minera:

1. Integración de datos con diferentes fuentes de muestreo, diferentes incertidumbres asociadas y representatividad de muestras.
2. Variables claves que permitan generar modelos predictivos con una confiabilidad aceptable dependiendo de la etapa del proyecto minero (estudio de perfil, estudio preliminar, pre-factibilidad, factibilidad y operación mina).
3. Predicción de variables de naturaleza no aditivas, y su cuantificación del riesgo en la estimación.
4. Optimización del valor del proyecto que considere costos asociados a la roca, por ejemplo, minerales con alta presencia de arcilla presentan problemas operacionales en la planta de flotación, disminuyendo la recuperación metalúrgica y aumentando los costos de procesamiento.

A continuación, se describe los 3 objetivos principales de esta tesis:

1. En la generación de modelos geometalúrgicos integrados, considerando incertidumbre geológica y metalúrgica, el objetivo específico es generar modelos geometalúrgicos integrados considerando incertidumbre geológica y metalúrgica combinada, que sirvan como input en la segunda etapa de planificación minera. Además, los modelos geometalúrgicos pueden ser utilizados en planificación de corto plazo para definir parámetros operacionales en el procesamiento de diferentes minerales de alimentación. Herramientas de medición en linea permiten proveer estimaciones de minerales en corto plazo.
2. En el desarrollo e implementación de metodología para integrar modelos geometalúrgicos en planificación minera de corto y largo plazo para operaciones, el objetivo específico es establecer un método genérico para incluir modelos geometalúrgicos en planificación minera de corto y largo plazo. Dentro de los resultados académicos, se incluye una

publicación científica-tecnológica relacionada con el área de planificación minera y utilización de modelos geometalúrgicos para disminuir los riesgos del proyecto minero.

3. En la generación de un manuscrito guía de buenas prácticas para la declaración de reservas considerando la geometalurgia como un factor modificante, el objetivo específico es generar un manuscrito guía de buenas prácticas basado en las definiciones de reservas minerales de códigos internacionales. El resultado tiene un impacto directo en el sector productivo de empresas mineras y consultoras privadas que prestan servicios de apoyo.

ARTÍCULOS PUBLICADOS

ARTICLE 1: CHANGE OF SUPPORT USING NON-ADDITIVE VARIABLES WITH GIBBS SAMPLER: APPLICATION TO METALLURGICAL RECOVERY OF SULPHIDES ORES.

El artículo 1 adjunto a continuación permite cambiar de soporte para variables no aditivas (en este caso, aplicado al ensayo geometalurgico de recuperación rougher) conservando características geoestadísticas de la base de datos para evitar artefactos matemáticos en la consolidación de base de datos de diferentes fuentes de información (logeo geológico, geoquímico, mineralógico, geofísico, geomecánico y geometalúrgico). La consolidación correcta de la base de datos permite generar modelos georeferenciados en el espacio de atributos geometalúrgicos.

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Change of support using non-additive variables with Gibbs Sampler: Application to metallurgical recovery of sulphide ores

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ABSTRACT

Flotation tests at laboratory scale describe the metallurgical behavior of the minerals that will be processed in the operational plant. This material is generally composed of ore and gangue minerals. These tests are usually scarce, expensive and sampled in large supports. This research proposes a methodology for the geostatistical modelling of metallurgical recovery, covering the change of support problems through additive auxiliary variables. The methodology consists of simulating these auxiliary variables using a Gibbs Sampler in order to infer the behavior of samples with smaller supports. This allows downscaling a large sample measurement into smaller ones, reproducing the variability at different scales considering the physical restrictions of additivity balance of the metallurgical recovery process. As a consequence, it is possible to apply conventional multivariate geostatistical tools to data at different supports, such as multivariable exploratory analysis, calculation of cross-variograms, multivariate estimations, among others. The methodology was tested using a drillhole database from an ore deposit, modelling recovery at a smaller support than that of the metallurgical tests. The support allowed for the use of the geochemical database, to consistently model the metal content in the feed and in the concentrate, in order to obtain a valid recovery model. Results show that downscaling the composite size reduces smoothing in the final model.

1. Introduction

The sample support of drillholes (whether geochemical grades, geological logging, metallurgical testing, etc.) is often different. In the case of geochemical grades, the drillholes are composited to a constant length to perform conventional statistical and geostatistical analyses, for example exploratory data analysis, variogram analysis, estimation or simulation (eg. (Chiles and Delfiner, 2012), (Deutsch and Journel, 1998), (Goovaerts, 1997), (Isaaks and Srivastava, 1989)). In the case of metallurgical variables, compositing methods can cause problems of statistical bias given the non-additive nature of these variables (Carrasco et al., 2008). In the particular case of the metallurgical recovery in the flotation process, it is calculated as the ratio between the mass of metal in the concentrate and the mass of metal in the feed (Mular and Barratt, 2002). The metal of the concentrate and feed are additive variables from a statistical point of view (mass properties), but the recovery is not (Carrasco et al., 2008).

Flotation tests are usually performed to describe the behavior of a mineral in the metallurgical process plant. The metallurgical response will depend mainly on two factors: the geological properties of the

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[1] Contribution: Conceived the methodology, worked in the implementation and contributed to the writing of the article.
[2] Contribution: Reviewed and improved the methodology, extensively reviewed the paper and contributed to the writing of the article.
[3] Contribution: Worked on implementation of the methodology.
[4] Contribution: Provided insight about mineral processing and reviewed the paper.
[5] Contribution: Provided insight about the geological aspects and reviewed the paper.
[6] Contribution: Contributed with the implementation and reviewed the paper.

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material and the operational parameters. There are different studies where the relations between geology and the metallurgical response are observed (Garrido et al., 2016), (Hu et al., 2009), (Hunt et al., 2011), (Lund and Lamberg, 2014), (Solozhenkin et al., 2016), (Haga et al., 2012). Clay minerals associated with alteration negatively affect the process to recover copper (Bulatovic et al., 1999). Faced with these materials, different operational responses can increase recovery by improving the effectiveness of the process. Other sulphide minerals such as pyrite also negatively affect the copper recovery (Mular and Barratt, 2002). Usual recovery values range from 90% to 95%, but in the face of these geological variations the recovery may decrease to 80% or less (Metso, 2006).

Linear regression models are used to estimate the recovery of an ore body (Weisberg, 2005). This methodology requires to find statistical correlations between recovery and other variables such as total copper, solubility ratio, analytical acid consumption, etc. Gaussian simulations have been used to model metallurgical parameters since they do not assume additivity of the study variable (Deutsch et al., 2015). The methodology proposed in this research allows estimating/simulating the recovery using samples of variable length/support, maintaining basic statistics, the spatial variability and the physical conditions or restrictions associated to the problem of additivity. The methodology can be easily applied or adapted to other cases related to geometallurgical performance.

Geostatistical modelling needs defining the estimation units (domains) on which the study is being performed (Hunt et al., 2014). These domains assume a constant statistical behavior of the variable within the entire volume (second order stationarity) (Matheron, 1973).

In the case of recovery, domains are established on geological and metallurgical information. Within these domains, variables are estimated or simulated using classical statistical and geostatistical algorithms such as multivariate regression and Gaussian simulation (Deutsch, 2016). If the geological characteristics are constant in two flotation tests, then the metallurgical response must have the same behavior in both tests without making operational changes. This hypothesis is debatable given the high variability of geological conditions in the ore body, and many of these geometallurgical relationships have not been exhaustively described yet.

Another complication associated with modelling the recovery is the scaling problem going from laboratory small scale test to production volumes (Truter, 2010). Many models have been created based on these tests (Boisvert et al., 2013), (Coward and Dowd, 2015). The models generated based on laboratory tests are used to determine the expected behavior in the processing plant, and must be over-dimensioned on an industrial scale (Suazo et al., 2009). Laboratory tests are performed as a batch process. On the other hand, in industrial applications flotation is performed through a continuous flow (serial and parallel Rougher, Scavenger and Cleaner cells) (Mular and Barratt, 2002). These and other problems complicate the correct modelling for the prediction of the geometallurgical variables.

This research deals with the issue of downscaling the support of geometallurgy tests done at the laboratory to match the support of geochemical and mineralogical composites. Downscaling methodologies have been developed by different authors, where change of support accounts for the statistical consequences (Pardo-Iguzguiza et al., 2006) (Tran et al., 1999) (Deutsch, 2016). This article covers the problem of downscaling integrating different sources of information through auxiliary variables (in the case of the flotation of sulphur minerals, the metal in feed W_f and metal in concentrate W_c explained in section 2 Methodology. It is based on the Gibbs Sampler (Geman and Geman, 1984) and allows to estimate/simulate samples on a smaller support consistent with the original data reproducing their basic statistics, spatial variability and constraints associated to the nature of the variable. The article is explained through a simulated synthetic case and applied to a case study (exploratory drillholes).

The objective of applying this methodology is to reduce the support of the metallurgical recovery variable in order to facilitate the application of conventional geostatistics tools. The upscaling procedure is not considered in this article because it generates a decrease in the variance of data and, consequently, predictive models with low resolution. The objective of this research is the assimilation of small support samples (eg, geochemical variables) with large support samples (eg, geometallurgical variables) to generate high resolution models. To find multivariate correlations usual statistical tools are correlation coefficients, principal component analysis, cross variograms, scatter plots, etc. (Wackernagel, 2003). These tools require that the data be collocated (all variables measured in the same sample (Chiles and Delfiner, 2012),) and at the same support, a condition that can be achieved through this methodology without losing resolution of the local variability. The proposed methodology is built on the hypothesis that specific geometallurgical parameters and hence mineral behavior in processing are a function of geological/mineralogical properties. These properties may be identified on a much smaller scale, hence improving resolution of geometallurgical properties and models.

2. Methodology

Samples with geological information are usually measured on supports different from the metallurgical tests. Metallurgical tests require much larger sample volumes, in order to analyze the different attributes and their operational characteristic ranges. To integrate geological and metallurgical information, it is convenient to change the variable different supports to a standardized support for all measurements. For non-additive categorical variables (e.g. lithology or mineralogy code), the majority code can be assigned to the composite or the sample code located in its center. In the case of continuous variables, there are different tools to increase or decrease the sampling support:

– Composite: method of up-scaling, is based on averaging an attribute based on the sampling lengths. This is not recommended for non-additive variables because it biases the result by using a linear average.
– Gibbs sampling: down-scaling method, allows to simulate samples with higher sampling density by scaling basic statistics and spatial continuity. It also allows to consider mathematical restrictions in the simulation.

A schematic example of down-scaling with 3 samples (Z_1, Z_2 and Z_3) is shown in Fig. 1.

The value of Z_1 with support of 3 m is downscaled to the values of z_{11}, z_{12} and z_{13} with supports of 1 m respectively. These values are related through $f(\cdot)$ which represents the physical constraints associated with metallurgical processes, for example mass balance. The change of support implementation considers the following aspects:

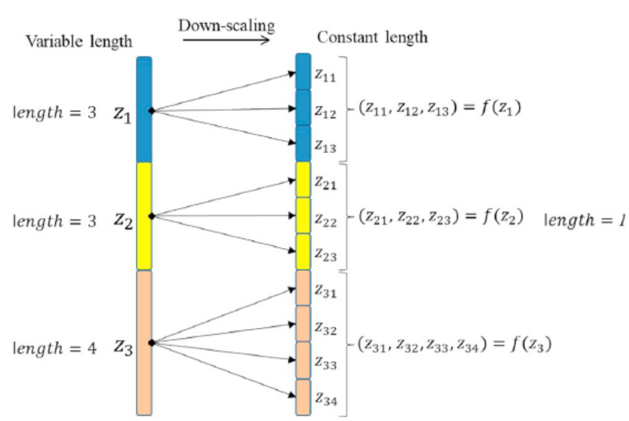

Fig. 1. Diagram of down-scaling for 3 samples Z_1, Z_2 and Z_3.

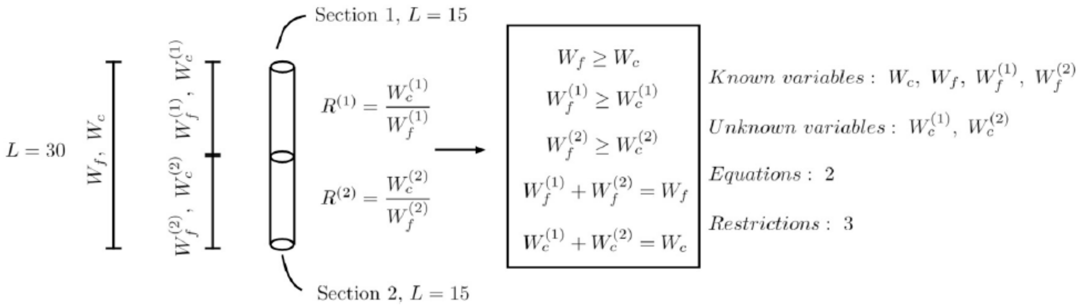

Fig. 2. Diagram of variables, equations and physical restrictions of the change of support problem for recovery.

1. Scaling of basic statistics.
2. Scaling of spatial variability (smaller support implies increased variability).
3. Integration of measured geochemical variables to small support.
4. Physical constraints of the problem (inequalities and relationships).

The methodology is now presented for the particular case of separating a composite of length L into 2 composites of length $L/2$ subject to the conditions described above. For the composite of length L, let W_f be the mass of metal in the feed and W_c the mass of metal in the concentrate. Fig. 2 shows a diagram depicting the known variables, equations and constraints of the problem.

$W_f^{(1)}$ and $W_f^{(2)}$ are the mass of metal in the feed from the top and bottom halves of the original composite. Similarly, $W_c^{(1)}$ and $W_c^{(2)}$ are the mass of metal in the concentrate. $R^{(1)}$ and $R^{(2)}$ are the corresponding recoveries, which are not additive variables:

$$R \neq \frac{R^{(1)} + R^{(2)}}{2} \tag{1}$$

$$\frac{W_c}{W_f} \neq \frac{\left(\frac{W_c}{W_f}\right)^{(1)} + \left(\frac{W_c}{W_f}\right)^{(2)}}{2} \tag{2}$$

Equation (2) is the expanded form of equation (1). Under unusual conditions, the equality of equation (1) can be met, for example when the sample has homogeneous behavior, i.e., $R^{(1)} = R^{(2)} = R$. The variables W_f and W_c are additive variables (mass). The methodology uses these variables to calculate R in each sub-composite. The methodology consists of the following steps:

1. **Transformation.** Given a set of data at support L, transform W_f and W_c independently to standard Gaussian distributions y_f and y_c, respectively. The anamorphosis functions are given by the equations:

$$y_f(x) = \phi_f(W_f(x)) \tag{3}$$

$$y_c(x) = \phi_c(W_c(x)) \tag{4}$$

where $W_f(x)$ and $W_c(x)$ are the mass of the metal in the feed and in the concentrate, respectively, from composites at support L. ϕ_f and ϕ_c are the transformation functions (anamorphosis) and $y_f(x)$ and $y_c(x)$ are the transformed variables (also at support L). These variables are distributed as Gaussian distributions with mean of 0.0 and variance of 1.0.

2. **Variogram analysis.** The variograms of the transformed variables $y_f(x)$ and $y_c(x)$ are calculated and modelled to capture their spatial continuity and anisotropy. The variogram models obtained for the transformed variables at support L are used to simulate the same variables at support $L/2$. This is a reasonable assumption when the nugget effect is small, considering that the variance is normalized to 1.0, since we are considering the normal scores and we can assume the shape of the variogram does not change significantly. The variance reduction is corrected after back transformation, as explained later, to account for the change of support. In cases of larger nugget effect, the variable at support $L/2$ can be simulated with a variogram that includes the increase on the relative nugget effect, as computed using the variogram scaling approach (see, for example (Chiles and Delfiner, 2012)).

3. **Simulation at support $L/2$ using a Gibbs sampler.** The Gibbs sampler to obtain the downscaled values of $W_f(x)$ and $W_c(x)$, specifically the values $W_f^{(1)}(x)$, $W_f^{(2)}(x)$, $W_c^{(1)}(x)$ and $W_c^{(2)}(x)$, which represent the mass at support $L/2$, is implemented as follows (we illustrate the process for $W_f^{(1)}$, but the four variables are simulated at every location in order to check compliance with the constraints):

(a) Every location where a sample at support L exists is divided into two simulation locations, representing the two downscaled values at support $L/2$ (Fig. 3).

4. Backtransformation to calculate $W_c^{(1)sim}$, $W_f^{(1)sim}$, $W_c^{(2)sim}$ and. $W_f^{(2)sim}$

5. Calculation of the recovery at support $L/2$ through the empirical formula of metallurgical recovery, for each sub-composite:

$$R^{(1)sim} = \frac{W_c^{(1)sim}}{W_f^{(1)sim}} \tag{9}$$

$$R^{(2)sim} = \frac{W_c^{(2)sim}}{W_f^{(2)sim}} \tag{10}$$

The condition $0 \leq R \leq 1$ is verified by the rejection conditions imposed earlier.

Notice that the back transformations $\phi_{c(sub)}^{-1}$ and $\phi_{f(sub)}^{-1}$ account for the variance increase due to the smaller support of sub-composites. An affine correction is applied over the distribution of the original composites, to account for the new support. In the case of small variance reductions, an affine correction will do well. If larger variance corrections are needed, a different model such as the Discrete Gaussian model could be used, although this does not change the suggested approach. The variance increase (used in the affine correction for the back transformation, step 4) is calculated using classic variance-support relationships (for more information see (Chiles and Delfiner, 2012)). In particular, the scaling of the variance is given by the following relation:

$$C(0) = C(V, V) + \bar{\gamma}(V, V) \tag{11}$$

Where $C(V, V) = \gamma_V(\infty)$ is the sill (or modelled variance) of the variogram at support L before transformation to Gaussian units, $C(0) = \gamma(\infty)$ is the sill of the variogram at point support and $\bar{\gamma}(V, V)$ is the average variogram value of vectors defined within the volume V. It is given by the following relation:

$$\bar{\gamma}(V, V) = \frac{1}{|V|^2} \int_V \int_V \gamma(x - x')dxdx' \tag{12}$$

In our case, it is easy to show that:

$$\sigma_L^2 = \sigma_{L/2}^2 - (\bar{\gamma}(L, L) - \bar{\gamma}(L/2, L/2)) \tag{13}$$

The relationship can be graphically observed in Fig. 4.Where σ^2 is

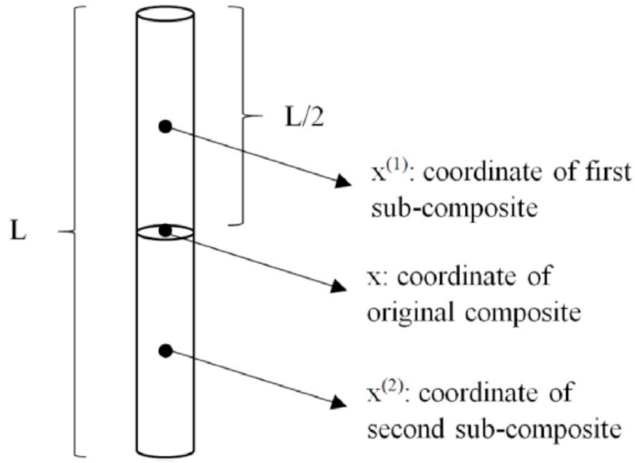

Fig. 3. Support L division to two sub-composites $L/2$.

(b) Downscaled simulation locations are visited in a random order.
(c) At every simulation location, perform simple kriging of the sub-composites previously simulated to determine the mean and variance of the conditional distribution at a new sub-composite location.

$$y_f^{(1)*}(x^{(1)}) = \sum_{i=1}^{n} \lambda_i \cdot y_f^{(1)}(x_i) \tag{5}$$

$$\sigma_{SK}^2(x^{(1)}) = 1.0 - \sum_{i=1}^{n} \lambda_i \cdot C(x_i - x^{(1)}) \tag{6}$$

$$y_c^{(1)*}(x^{(1)}) = \sum_{i=1}^{n} \lambda_i \cdot y_c^{(1)}(x_i) \tag{7}$$

$$\sigma_{SK}^2(x^{(1)}) = 1.0 - \sum_{i=1}^{n} \lambda_i \cdot C(x_i - x^{(1)}) \tag{8}$$

(d) Simulate $y_f^{(1)sim}(x^{(1)})$ and $y_c^{(1)sim}(x^{(1)})$ by Monte Carlo simulation, from the Gaussian conditional distribution with mean $y_f^{(1)*}(x^{(1)})$, and variance $\sigma_{SK}^2(x^{(1)})$ for $y_f^{(1)sim}(x^{(1)})$ and with mean $y_c^{(1)*}(x^{(1)})$, and variance $\sigma_{SK}^2(x^{(1)})$ for $y_c^{(1)sim}(x^{(1)})$.
(e) $y_f^{(1)sim}$ is back-transformed to get $W_f^{(1)sim}$ and $y_c^{(1)sim}$ is back-transformed to get $W_c^{(1)sim}$.
(f) Test 1: rejection condition $W_c^{(1)sim}(x^{(1)}) \geq W_f^{(1)sim}(x^{(1)})$, where $W_c^{(1)sim}(x^{(1)}) = \phi_{c(sub)}^{-1}(y_c(x^{(1)}))$ and $W_f^{(1)sim}(x^{(1)}) = \phi_{f(sub)}^{-1}(y_f(x^{(1)}))$. If rejected, return to (d) and resimulate $y_f^{(1)sim}(x^{(1)})$ and $y_c^{(1)sim}(x^{(1)})$.
(g) Calculate $W_f^{(2)sim}(x^{(2)}) = W_f(x) - W_f^{(1)sim}(x^{(1)})$ and $W_c^{(2)sim}(x^{(2)}) = W_c(x) - W_c^{(1)sim}(x^{(1)})$.
(h) Test 2: rejection condition $W_c^{(2)sim}(x^{(2)}) \geq W_f^{(2)sim}(x^{(2)})$, where $W_c^{(2)sim}(x^{(2)}) = \phi_{c(sub)}^{-1}(y_c(x^{(2)}))$ and $W_f^{(2)sim}(x^{(2)}) = \phi_{f(sub)}^{-1}(y_f(x^{(2)}))$. If rejected, return to (d) and resimulate $y_f^{(1)sim}(x^{(1)})$ and $y_c^{(1)sim}(x^{(1)})$.
(i) Once simulated values are accepted, add to conditioning information and go back to (c) until all nodes have been simulated.

the variance of the data W_c at point support (unknown), σ_L^2 variance at support L and $\sigma_{L/2}^2$ variance at support $L/2$. More details in (Chiles and Delfiner, 2012).

Rejection tests (conditions of inequality) are based on the physical constraints in the recovery calculation. It can be observed that with more rejection conditions, the variance of the data simulated at support $L/2$ increases. Simulation using Gibbs sampler has been used in other conditional simulation methodologies based on random fields with Gaussian distribution (Geman and Geman, 1984). The simulation is done sequentially (Gomez-Hernandez et al., 1993).

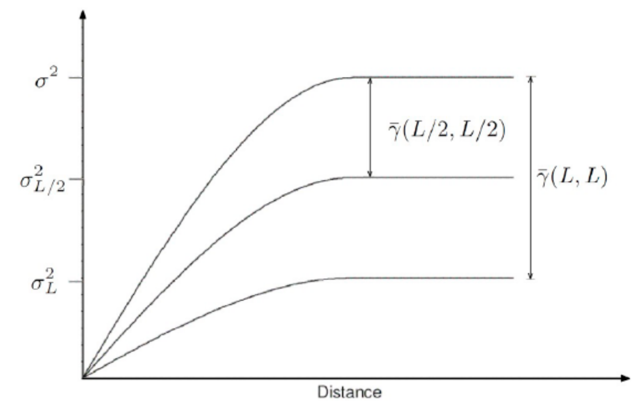

Fig. 4. Schematic relationship between variances of the same variable at different supports.

3. Synthetic case analysis

The change of support methodology was applied to a basic case study in 2D. Statistical validations are presented.

3.1. Synthetic case study

Copper grades and metallurgical recovery values were simulated in 10 drillholes. The support used is $L = 30\,m$. Fig. 5 shows the simulated values, the grade distribution of W_c and the variogram of this variable transformed to Gaussian scores.

The 30 m composites are uniformly spaced every 150 m in the horizontal and every 30 m in the vertical direction. The distribution of mass of metal concentrate is log-normal with a coefficient of variation of 50%. The experimental variogram is calculated on the Gaussian values of the variable W_c at support of 30 m. The distribution of W_f is known at support 30 m. From metallurgical tests, the recoveries R are known over 30 m samples. Thus, W_c can be inferred.

We apply the methodology previously described to obtain W_c and W_f in sub-composites (support 15 m) at composite locations (Fig. 6).

3.2. Statistical validations

Using the copper grade (W_f in mass) and metallurgical recovery, the mass of recovered ore (W_c in mass) was calculated. Fig. 7 (A) shows the statistical reproduction of W_c at a support of 15 m and (B and C) shows the multivariate reproduction of the relation $W_c \leq W_f$.

The quantile-quantile comparison of the distributions of W_c using supports of L and $L/2$ is shown in Fig. 7, (A). The number of data points was doubled, the mean of the data remained constant (W_c additive variable) and the standard deviation increased (the decrease in support implies an increase in the variance of the data). The relation $W_c \leq W_f$ with support at $L/2$ remained similar in comparison to this relation with support L. A slight decrease in the correlation coefficient is observed due to the increased variance at smaller support.

Estimated W_c was plotted at support $L = 30\,m$ and $L = 15\,m$ for two of the drillholes (Fig. 8). In Fig. 9 the increase in the variance that entails the decrease of the support can be observed. From 100 simulations the variogram reproduction at support of $L = 15$ m was checked in Fig. 9.

4. Case study: application to drillhole samples

The following case study corresponds to a campaign with 50 real drillholes where some samples have been selected for flotation analysis calculating the metallurgical recovery of copper in sulphide minerals. The samples for the flotation rougher test have different lengths with a

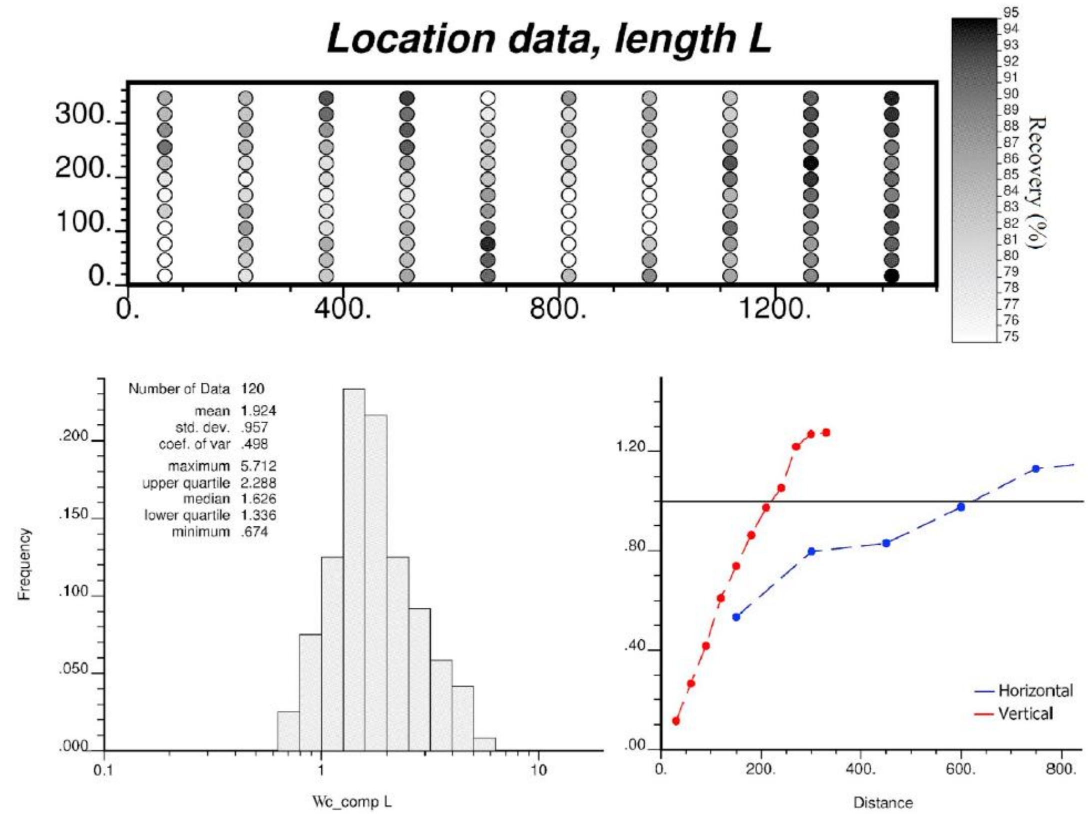

Fig. 5. Simulated case study, 10 drillholes with their statistical distribution and normal score variogram for mass of metal in concentrate.

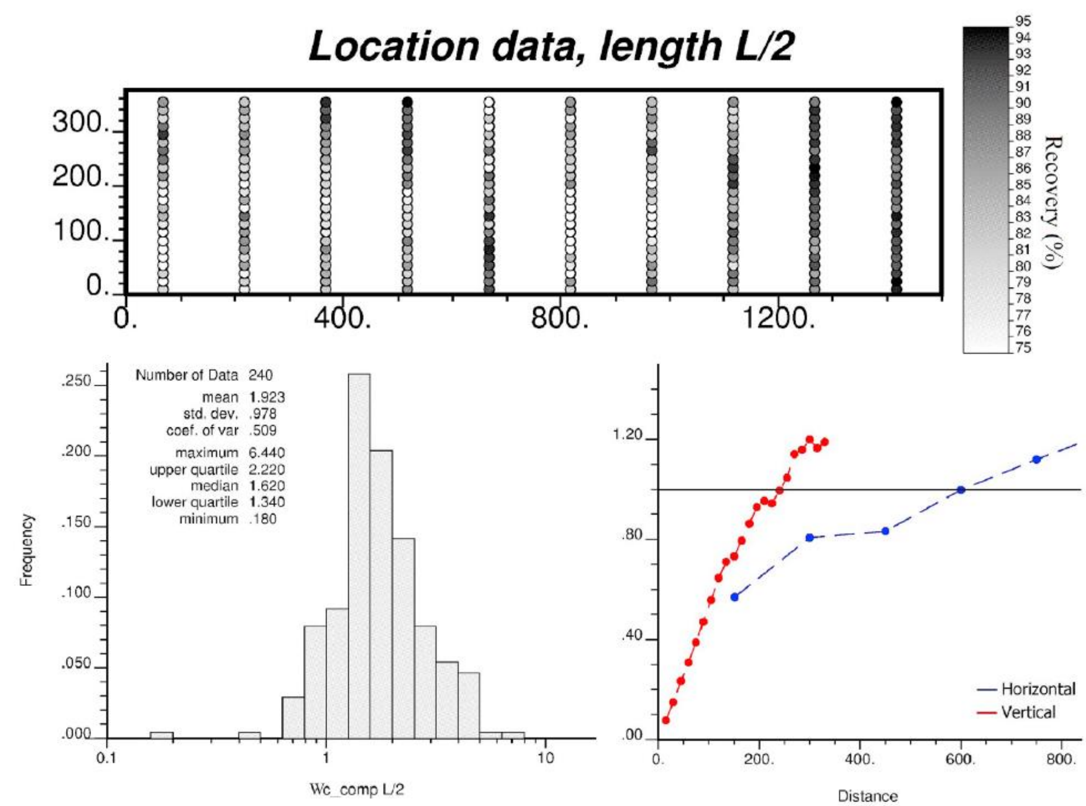

Fig. 6. Resulting simulated 15 m composites, their histogram and normal score variogram (only 1 simulation is shown).

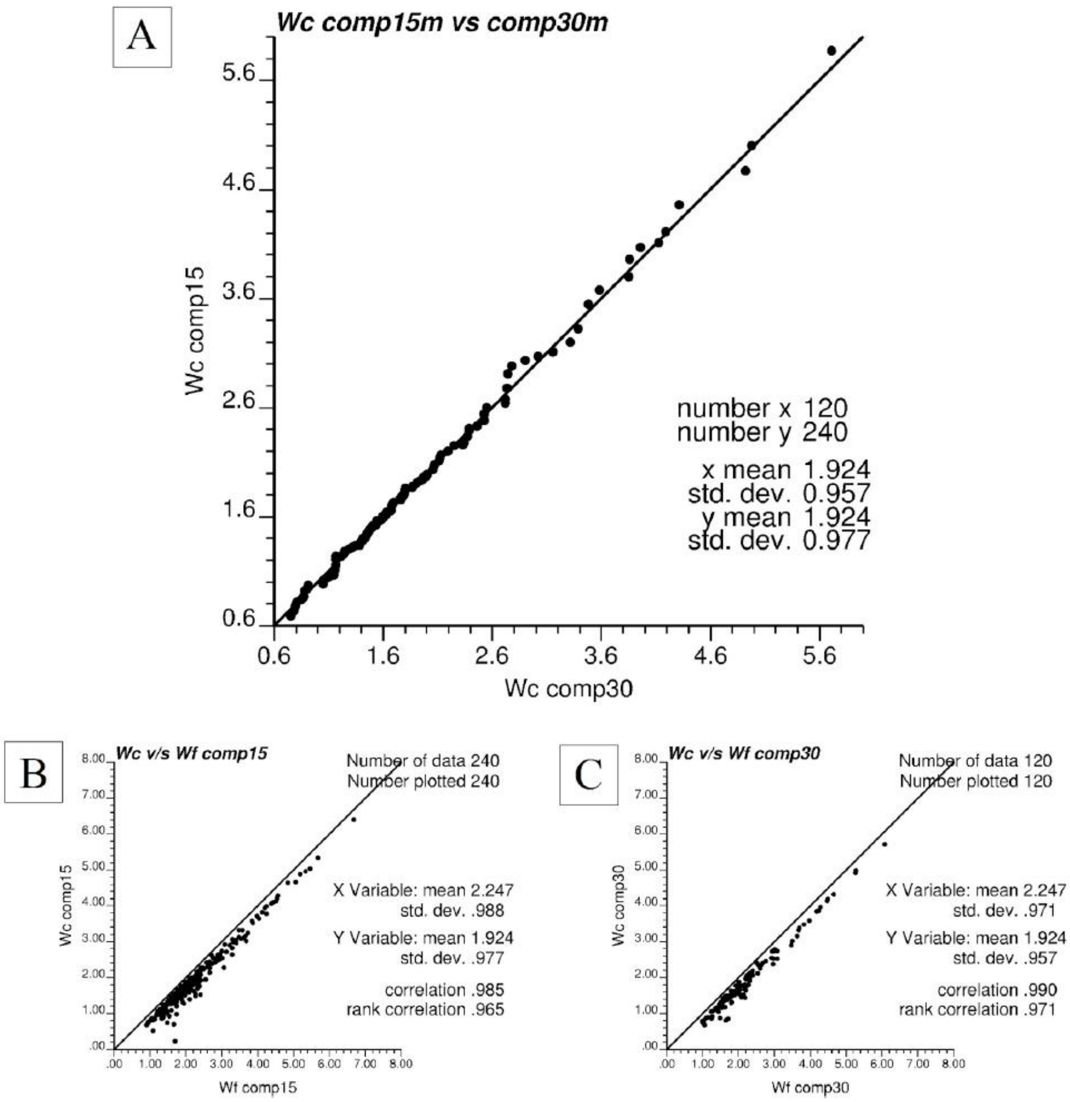

Fig. 7. Statistical comparison of W_c and bivariate relations $W_c \leq W_f$ using support of L and $L/2$.

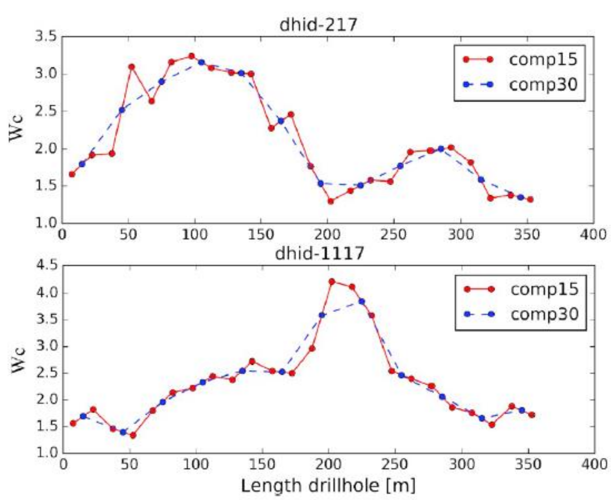

Fig. 8. Reproduction of grades from two drillholes, length $L = 15\ m$ and $L = 30\ m$.

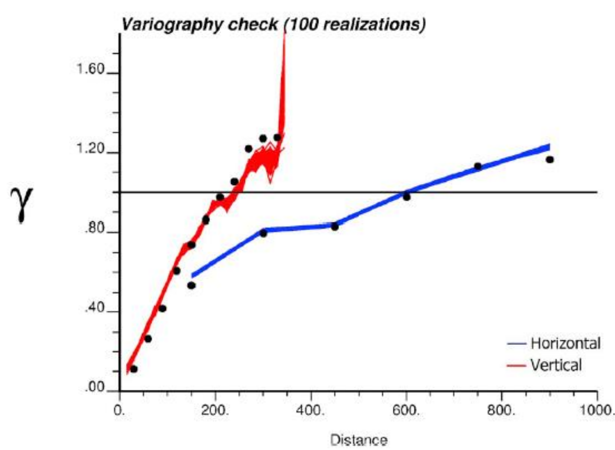

Fig. 9. Reproduction of spatial variability.

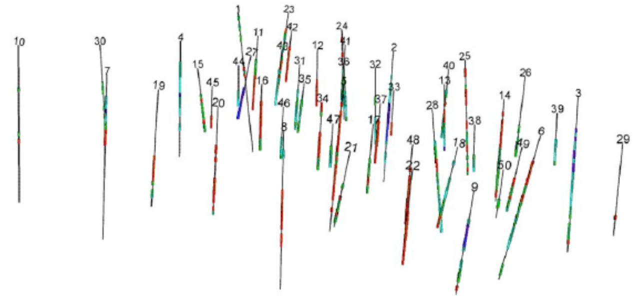

Fig. 10. Graphical display using metallurgical recovery samples.

mean of 40 m. As a simplification (given the low variability in sample length) these have been regularized to a nominal length of 40 m. The samples have similar geological conditions, and are part of the same geometallurgical domain. Fig. 10 shows a graphical display of the samples selected for the flotation analysis at laboratory scale.

The copper grades have been composited at a nominal length of 20 m (block size of the estimation model) using the proposed methodology. 99 simulations using the Gibbs sampler were performed at the 20 m support. For each realization, the cooper recovery in each block of the model was calculated as ratio between the sum of W_c divided by the sum of W_f and the average/uncertainty expected were calculated. The respective validations were done obtaining satisfactory results from a statistical point of view.

Fig. 11 shows the quantile-quantile comparison for W_c using 20 and 40 m composite length. The number of composites was doubled, the mean remained constant and the variance increased as expected. The graphs (B) and (C) show the bivariate relations between W_f and W_c to the supports of 20 and 40 m, evidencing notorious similarities and conservation of the behavior $W_c \leq W_f$.

The next step is to estimate metallurgical recovery in the block model with 40 m composites (conventional methodology) and using the 20 m composites obtained with the proposed methodology.

The estimates from 20 m composites show greater variability. Smoothing can be observed in Fig. 12. Fig. 13 shows a histogram of the block-to-block estimation difference between estimated recovery with 20 m and 40 m composites.

The mean difference is close to 0.0 (-0.073) with a standard deviation of 0.9. Approximately 1% of blocks is estimated with a bias of 3% (red box in histogram). This is explained by the difference of the change of support using a non-additive variable. This bias is not statistically significant with respect to the total of the blocks but locally it can generate important differences on the ore which is recovered in short-term planning.

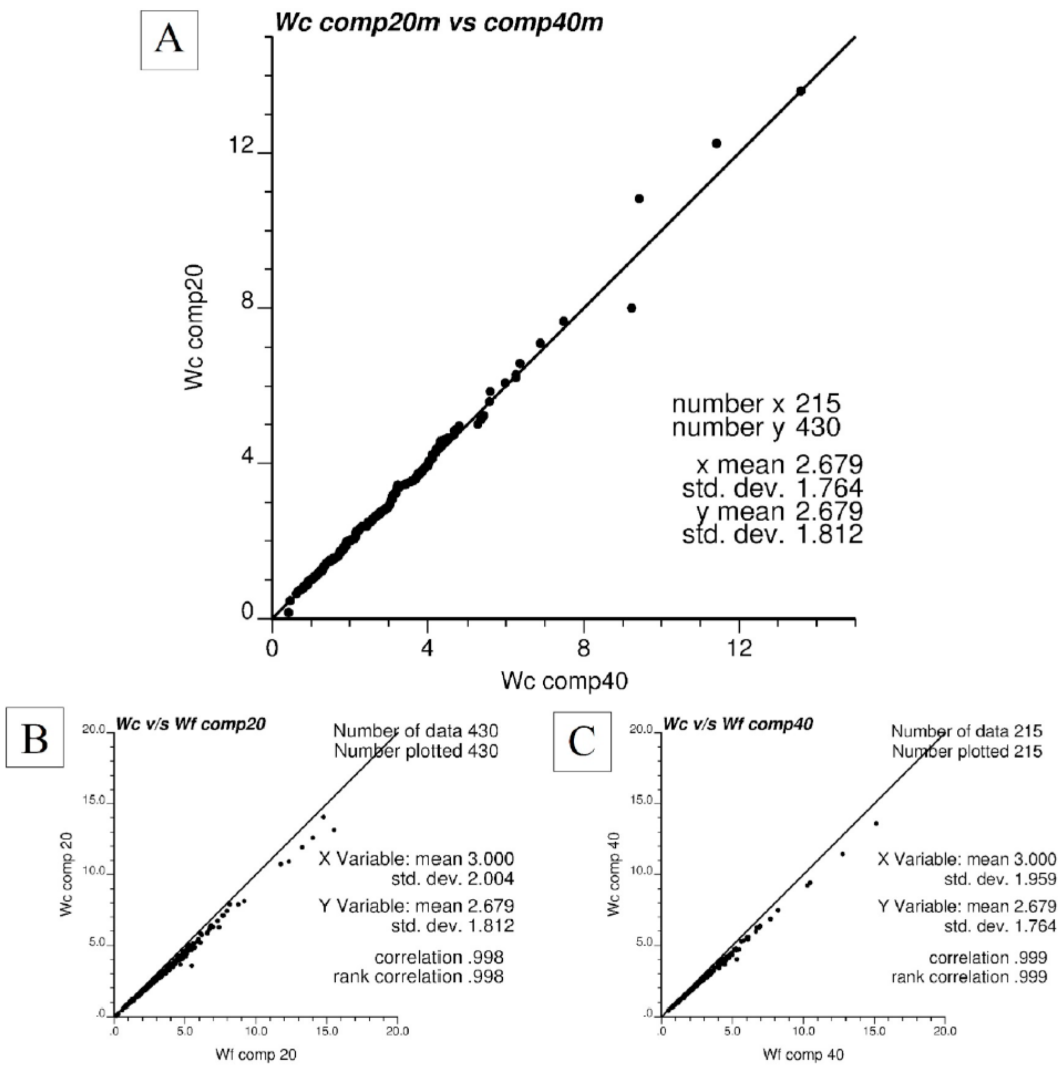

Fig. 11. Statistical validation of composites at 40 m–20 m.

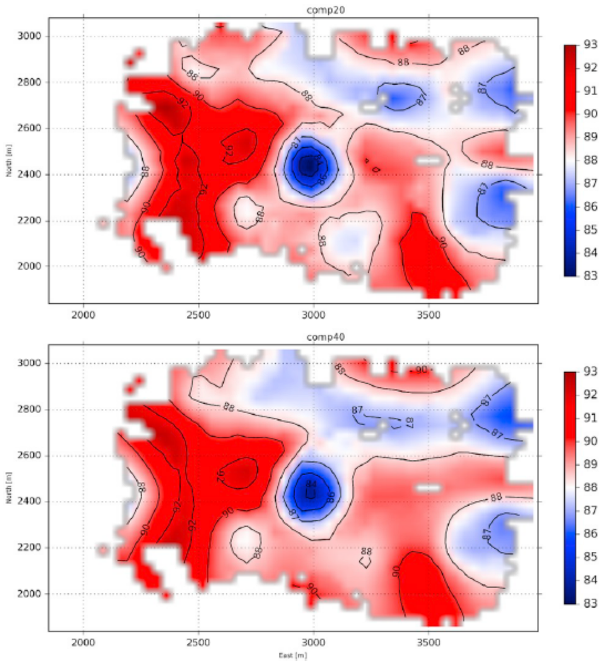

Fig. 12. (Left) Estimation of metallurgical recovery using composites of 20 m. (Right) Estimation using composites of 40 m.

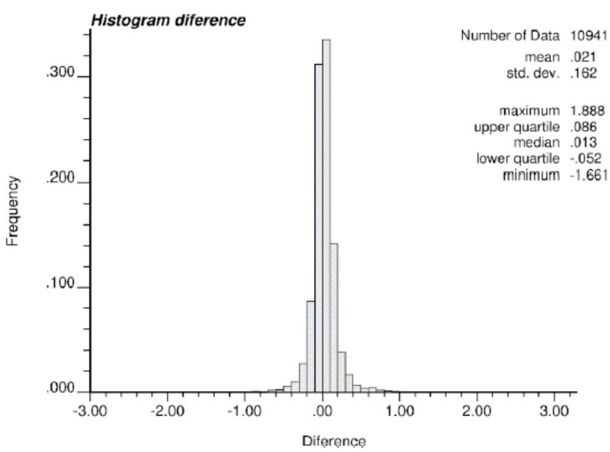

Fig. 13. Histogram of diference between estimated recovery using composites 40 m and E-Type of simulation.

Fig. 14 shows a scatter plot between estimated values with 20 m and 40 m composites. Fig. 14 highlights the area with metallurgical recovery lower than 80% These values may generate operational problems at the metallurgical process plant. The estimation using a support of 40 m does not capture their range due to smoothing. This could be used as an alarm from a predictive point of view to apply operational modifications to the treatment of this material.

This result shows the difference in the estimate considering the size of the sampling support. This affects the resolution of a predictive model. The estimate with a larger support will not capture extreme data (high or low metallurgical recovery) that are usually important results from an operational point of view. Therefore reducing the sampling support to perform an estimation or simulation allows generating models of better resolution to capture small-scale variability, which may help improving the performance of the mining project.

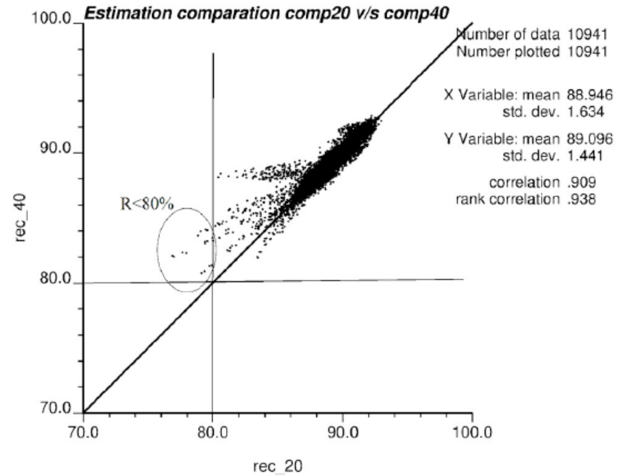

Fig. 14. Cross-validation between estimated recovery using composites of 20 and 40 m.

5. Conclusions

Modelling geometallurgical variables often causes problems when conventional geostatistics tools are applied. The main causes are the condition of heterotopic sampling and differences in the measurement supports. This article provides a new compositing approach based on simulations through a Gibbs Sampler. Statistical and geostatistical characteristics are preserved with this methodology: global mean, spatial variability and bivariate relations. The simulated values at smaller support can be used as input for simulations, in order to account for the uncertainty stemming from the variability of small support samples, or they can be averaged for estimation purposes, as shown in the case studies presented in this paper.

In this article, two advantages of the method were highlighted:

– Reduction of support allows data assimilation (geological samples and metallurgical tests) for the application of conventional geostatistics tools; for example search of multivariable correlations for generation of geometallurgical predictive models.
– Reduction of support allows generating estimation models or simulation models with higher resolution and less smoothing. These models allow the description of local variability on a smaller scale, identifying extreme value zones that are important from a metallurgical point of view.
– The expected metal of the simulation is 28,263 ± 870 tons of Cu. If the metal is calculated based on an estimate with 40 m support, the result is 28,484 tons of Cu.

The advantages of estimating metallurgical recovery using this compositing methodology was illustrated through a case study. The results were compared with the traditional methodology to estimate recovery, with important local biases that can generate operational problems in the mineral processing plant.

Reducing the size of the composite is associated with an increase in local variability that was captured in the estimation. This information is captured in the methodology through scaling the variance of the distribution. The methodology was applied to metallurgical recovery data that fulfil the physical conditions associated to the non-additivity of this variable.

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ARTÍCULOS PUBLICADOS

ARTICLE 2: SIMULATION OF SYNTHETIC EXPLORATION AND GEOMETALLURGICAL DATABASE OF PORPHYRY COPPER DEPOSITS FOR EDUCATIONAL PURPOSES.

El segundo artículo adjunto a continuación entrega una metodología para simular geoestadísticamente variables geometalúrgicas considerando gran parte de los problemas y desafíos que implica este proceso a nivel industrial, donde incluye una robusta revisión bibliográfica de las metodologías disponibles para este procedimiento. El primer artículo describe una metodología para consolidar diferentes fuentes de información, el cual puede ser usado como base de datos input en la metodología propuesta del artículo 2. Además, se ha dado un enfoque de innovación al permitir, en base a estas simulaciones y escenarios geometalúrgicos, generar base de datos sintéticas con distribución espacial y coherencia geológicas creíbles con fines de uso académico. Esto presenta una gran ventaja desde un punto de vista de investigación ya que uno de los principales problemas en el desarrollo del área geometalúrgica es la escases y dificultad para acceder a bases de datos.

Simulation of Synthetic Exploration and Geometallurgical Database of Porphyry Copper Deposits for Educational Purposes

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Original Paper

Simulation of Synthetic Exploration and Geometallurgical Database of Porphyry Copper Deposits for Educational Purposes

Mauricio Garrido,[1,5] **Exequiel Sepúlveda**,[2,3] **Julián Ortiz**,[4] **and Brian Townley**[1]

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The access to real geometallurgical data is very limited in practice, making it difficult for practitioners, researchers and students to test methods, models and reproduce results in the field of geometallurgy. The aim of this work is to propose a methodology to simulate geometallurgical data with geostatistical tools preserving the coherent relationship among primary attributes, such as grades and geological attributes, with mineralogy and some response attributes, for example, grindability, throughput, kinetic flotation performance and recovery. The methodology is based in three main components: (1) definition of spatial relationship between geometallurgical units, (2) cosimulation of regionalized variables with geometallurgical coherence and (3) simulation of georeferenced drill holes based on geometrical and operational constraints. The simulated geometallurgical drill holes generated look very realistic, and they are consistent with the input statistics, coherent in terms of geology and mineralogy and produce realistic processing metallurgical performance responses. These simulations can be used for several purposes, for example, benchmarking geometallurgical modeling methods and mine planning optimization solvers, or performing risk assessment under different blending schemes. Generated datasets are available in a public repository.

KEY WORDS: Geometallurgy, Geostatistics, Synthetic database, Uncertainty.

INTRODUCTION

At present, access to large mining exploration and/or geometallurgical databases from industry, for academic and/or educational purposes, is difficult, and this due to confidentiality restrictions and/or budget limitations. Development of realistic synthetic geometallurgical databases as proposed in this paper may allow an alternative to such problem and may also offer a robust tool for the purposes of benchmarking exploration and/or geometallurgical modeling, mine planning methods or reserves estimations (Garrido et al. 2019).

Geometallurgy has become an important field in mining engineering because of its benefits on the ore quality on mine planning, plant performance, lower costs and product quality. To incorporate these benefits into the mining value chain, key metallurgical responses and proxy variables need to be incorporated into the block model, which is the main input to solve many optimization problems in

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mine planning (Ortiz et al. 2015; Dominy et al. 2018). This enriched block model with geometallurgical variables is commonly termed a geometallurgical block model (GMBM), and the methodology of this research is based on the transfer of the simulated attributes of the GMBM to a geometallurgical database (GMDB), referred to a drill holes of a geological exploration campaign. From the point of view of practitioners, researchers, teachers and students, there is another issue with GMDB; that is, the important lack of available GMDB that can be used because the data needed are usually subject to confidentiality agreements. This fact is the motivation to offer a methodology for the simulation of GMDB, exemplified here with a porphyry copper type deposit, but it can be applied to any other type of mineral deposit.

There are several methodologies for building such GMBM (Garrido et al. 2018b). The primary-response framework for building geometallurgical models is a very solid methodology for geometallurgical modeling (Coward et al. 2009). Primary attributes, such as grades, lithology and alteration, can be proxies to response attributes such as grindability indices, recovery, metallurgical rock properties (Deutsch 2016), among others. As many of those response attributes are not additive, traditional linear estimation methods are not valid and should not be used to build the block model (Carrasco et al. 2008). Typically, there are three complementary approaches to populate the GMBM with response variables. The first approach is the use of predictive regression models, from simple linear regressions (Montoya et al. 2011; Boisvert et al. 2013), nonlinear regressions (Carmona and Ortiz 2010; Keeney and Walters 2011; Sepúlveda et al. 2017) and clustering (Hunt and Jorgensen 2011). The second approach is simulating the processing stage (Suazo et al. 2010). The third approach is the use of mineralogy as the main proxy. Mineralogy is of enormous importance for geometallurgy as it plays a fundamental role in the characterization of metallurgical responses (Lamberg 2011; Hunt et al. 2013; Yildirim et al. 2014; Lund et al. 2015). This approach, nevertheless, requires having the mineralogy characterization of the deposit, which is expensive, often resulting in limited data available.

The only related research on methodologies for the simulation of geometallurgical block models, so far according to the literature review done in this paper, is Lishchuk (2016) thesis. In this thesis, a methodology, termed geometallurgical testing framework, was proposed for building a synthetic ore deposit model with focus on geometallurgy. This framework has three main modules: (1) a geological module, (2) a mineral processing module and (3) an economic module. The first two modules are the most relevant modules for the simulation of synthetic geometallurgical ore bodies. Imposing multivariate spatial correlations, which is missing in Lishchuk's methodology, is critical to ensure that the desired spatial characteristics are reproduced with geological sense and coherence (Maksaev et al. 2007).

In the mineral processing stage, there are very limited simulation models available. A few commercial simulators exist, but these do not disclose the methods and parameters used to create the models, and in most cases, are simple nonlinear predictors that do not consider the uncertainty associated with the response variable. Commercial simulators are not designed to estimate the uncertainty associated with geological variability, since mineral characterization is a ‘‘constant'' input and does not vary over time processing.

The contribution of this paper is a robust methodology to simulate a GMDB using openly available geostatistical tools, which preserves the coherent relationship among primary attributes, mineralogy and geometallurgical response attributes.

METHODOLOGY

To simulate a GMDB, the following steps are needed:

1. Identification of variable types
2. Generation of a consolidated database
3. Simulation of geological primary variables
    a. Definition of geometallurgical domains
    b. Simulation of domains
    c. Compositional geostatistical simulation of minerals
    d. Geochemical simulation

4. Simulation of geometallurgical responses
    a. Simulation of variables for comminution process
    b. Simulation of variables for flotation process

5. Simulation of spatial drill holes
   a. Topographic simulation
   b. Simulation of density of drill holes
   c. Survey and length simulation

These steps and some tools recommended for this stage are provided in Figure 1. This methodology allows simulating a GMDB for different purposes. In this research, we show an application to geometallurgical uncertainty in mine planning (long term).

SIMULATING A GEOMETALLURGICAL DATABASE

Through a case study, we illustrate the application of the proposed methodology in a synthetic typical porphyry copper deposit. The methods presented are not new, and their details are available in the published references cited herein (Table 1); however, the proposed workflow is novel in the sense that it provides the logical steps for the construction of the exploration and geometallurgical database, including the design of a realistic drilling campaign, according to the typical exploration process.

Identification of Variable Types

Different types of variables must be treated differently. Conventionally, variables are classified as categorical or continuous; however, some considerations must be kept in mind before modeling:

Categorical variables take a unique discrete value within a pool of exhaustive and mutually exclusive outcomes, in other words, at every location one and only one of the K categories prevail. However, categorical variables may be nominal or ordinal:

- Nominal categories have no order relation between them. Typical examples are the lithological codes assigned to samples, which can also be represented with numerical codes, or the mineralization zone assigned to each sample or location. In general, estimation and simulation domains can be seen as nominal categorical variables.
- Ordinal variables are ranked categories usually with unknown distance between the categories. An example of an ordinal variable is the alteration intensity, labeled with a scale of the type absent, low, moderate, high, or the corresponding numerical values 0, 1, 2 and 3.

Continuous variables take values with an arbitrary precision, defined by the number of digits and decimal places, within a continuous range. They may be unbounded, but are most often bounded, e.g., positive. Furthermore, some continuous variables are labeled as compositional, when they are part of a multivariate observation and each represents a relative part of a whole. Typical examples of compositional variables are mineral proportions, relative weight in a particle size distribution or geochemistry. The main complication associated with compositional variables is that their pairwise correlations depend on the other variables considered in the whole.

Although not formally a variable type, it is important to distinguish between continuous variables sampled abundantly, typically grades of valuable or detrimental elements, some geotechnical parameters such as rock quality designation, fracture frequency or uniaxial compressive strength, and those sampled scarcely, typically the case for geometallurgical variables such as grindability, acid consumption, flotation kinetics, to name a few.

From a geometallurgical perspective, there are also two types of variables. Variables that are intrinsic rock properties, termed primary variables, and variables that reflect a response to a specific process, termed response variables (Coward et al. 2009). Primary variables are among others, grade, alteration, mineralization styles and density, whereas examples of response variables are grindability indices, e.g., Bond work index (BWI), semi-autogenous grinding (SAG) power index and recoveries, e.g., flotation recovery and consumption of acid in leaching. In general, response variables are not additive, which complicates the way in that these variables can be propagated in the GMBM (Carrasco et al. 2008).

We carried out a case study to show the application of the proposed methodology. The database consists of (1) geological information (logging of mineral zones and alterations, categorical variables) to define and simulate the geometallurgical units or domains (GMU), (2) geochemistry (percentage of total copper by analysis X ray fluorescence or induced plasm coupled), (3) mineral characterization (percentage of most important minerals by infrared

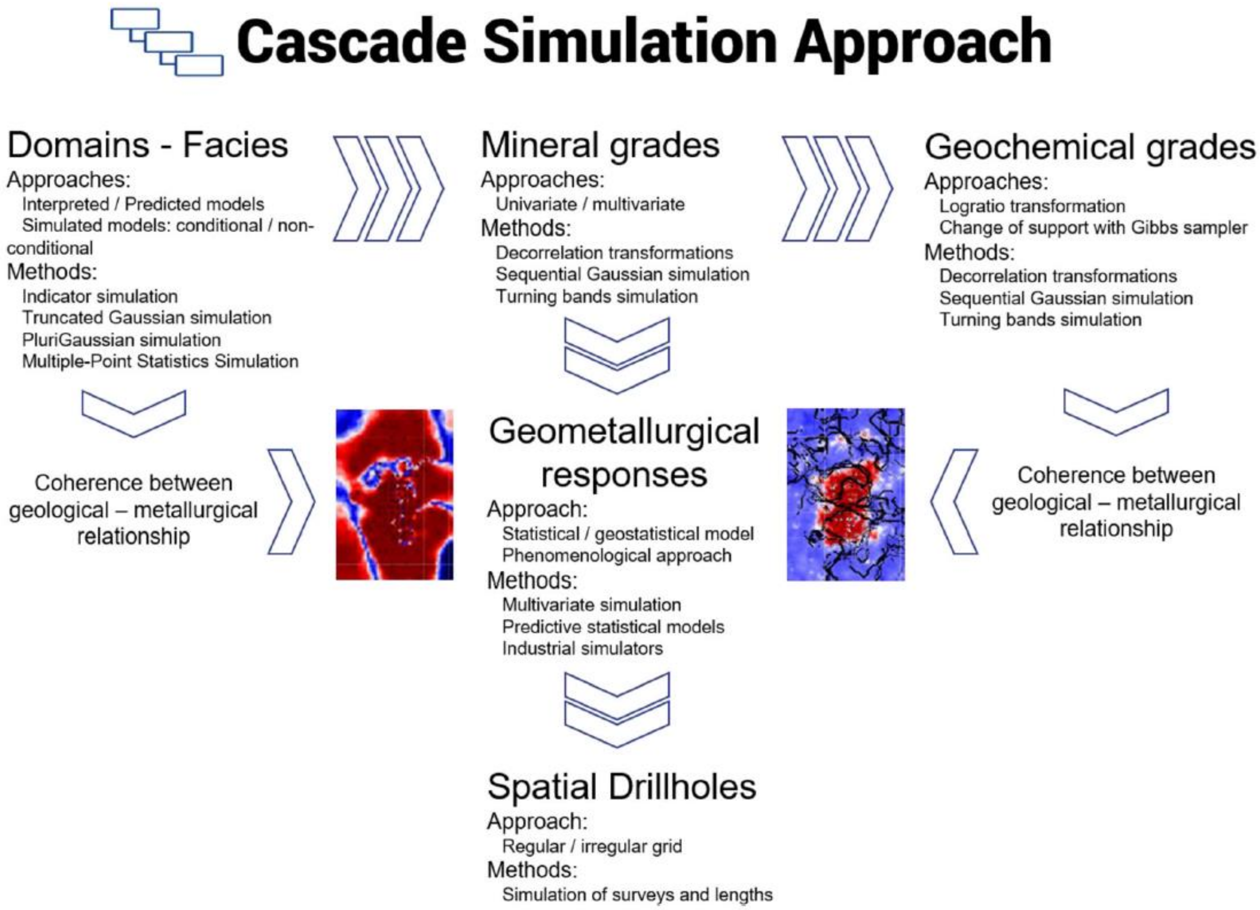

Figure 1. Global methodology and tools for each stage.

spectroscopy, continuous variables) to simulate with compositional geostatistics, and (4) geometallurgical responses (BWI test and rougher recovery test) to cosimulate with conventional geostatistics, e.g., sequential Gaussian simulation.

Generation of a Consolidated Database

The available information must be formatted for processing by the different modeling methods. This apparently trivial task may consume a significant amount of time, so it should not be minimized. The main objective is to prepare the database for the application of conventional geostatistical tools. This requires that every piece of information must be attached to spatial coordinates. This allows the calculation of spatial correlations, and also the cross correlations between variables, which are necessary for the application of estimation and simulation techniques (Isaaks and Srivastava 1989; Goovaerts 1997; Deutsch and Journel 1998);

For most multivariate statistical techniques, it is also required that the data be homotopic, that is, all variables must be available at the same location for cokriging or cosimulation, and they must be measured at a consistent volumetric support (Carrasco et al. 2008; Chiles and Delfiner 2012; Garrido et al. 2016). Imputation is necessary to replace missing data by values that are statistically consistent with the non-missing data, both in a statistical and spatial sense (Munoz et al. 2010; Barnett et al. 2013). These values should reproduce the variability expected at their location and honor the spatial relationship with neighboring samples. There are several imputation methods, among the most used are (a) impute missing values by Gibbs sampling methods, (b) multiple imputation from predictive distribution, (c) impute with regressions or (d) optimization approach.

Regarding the issue of the volumetric support, the idea is to bring all the available data to the same support. For example, geochemistry analyses, geological logging, structural information, geometallur-

Table 1. Summary of references by each stage of the methodology

Stage of the methodology	References	Comments
Consolidate database	Tran et al. (1999), Pardo-Iguzguiza et al. (2006), Carrasco et al. (2008), Munoz et al. (2010), Chiles and Delfiner (2012), Barnett et al. (2013), Garrido et al. (2016), Deutsch et al. (2016), Garrido et al. (2018a)	Discussion on the problem of multivariate simulation of heterotopic attributes, imputation of missing data, upscaling and down-scaling problems
Simulation of geological domains	Isaaks and Srivastava (1989), Goovaerts (1997), Deutsch and Journel (1998), Armstrong et al. (2003), Deutsch (2006), Maksaev et al. (2007), Carmona and Ortiz (2010), Sillitoe (2010), Mariethoz and Caers (2015), Beucher and Renard (2016), Jackson and Young (2016), Sepúlveda et al. (2017)	Discussion on ore type concept, clustering and the importance of understanding geological setting to simulate geological domains. References to conventional geostatistics methods to simulate ore body deposits, such as sequential indicator simulation, truncated Gaussian, pluri-Gaussian, multi-point simulation algorithms
Simulation of geological continuous attributes	Davis (1986), Webster and Oliver (1990), Goovaerts (1997), Desbarats and Dimitrakopoulos (2000), Pawlowsky-Glahn and Olea (2004), Babak and Deutsch (2009), Manchuk and Deutsch (2012), Mueller and Ferreira (2012), Barnett et al. (2013), Boluwade and Madramootoo (2014), Bolgkoranou and Ortiz 2019)	Tools for dimensionality reduction in the modeling process, such as principal components analysis, minimum/maximum autocorrelation factors, independent component analysis, uniformly—weighted exhaustive diagonalization with gauss iterations and projection-pursuit multivariate transform. Log ratio transformation to simulate mineralogical attributes and use of geostatistical simulation in continuous attributes
Simulation of geometallurgical industrial responses	King 2001), Suthers et al. (2004), Coleman et al. 2007), Vann et al. 2011)	To support industrial simulation of geometallurgical variables. Use of industrial processing or prediction of plant process performance, upscaling of laboratory to industrial scale, use of JKSim and mathematical models
Mine planning	Gholamnejad and Osanloo (2007), Suazo et al. (2010), Lamghari and Dimitrakopoulos (2012), Kumral (2013), Silva et al. (2015), Garrido et al. (2017)	Incorporation of geometallurgical models in mine planning and quantification of the uncertainty of the inputs to mine planning optimization problems

gical samples should be considered to enrich the model, but their volumetric supports may be different by orders of magnitude. Geochemical samples may be taken over diamond drill holes samples at 1 m support, while geometallurgical samples may be taken over bulk volumes representing 15 or 30 m of a reverse circulation hole. Upscaling by compositing is common practice (Chiles and Delfiner 2012). Down-scaling techniques are sometimes required to bring the data to the smallest support where more abundant information exists. This can be achieved by using geostatistical cosimulation and applying constraints to the simulated values to impose reproduction of the sample value at the larger support (Tran et al. 1999; Pardo-Iguzguiza et al. 2006; Deutsch et al. 2016; Garrido et al. 2018a).

Variables can be dropped if deemed irrelevant for the model, by using statistical techniques for variable selection or machine learning, and accounting for domain knowledge, that is understanding of the geological setting (Carmona and Ortiz 2010). They can also be merged, to reduce the dimensionality in the modeling process, using data integration such as cokriging (Babak and Deutsch 2009), or dimensionality reduction techniques, such as principal components analysis (Davis 1986; Webster and Oliver 1990; Goovaerts 1997). In this case study application, the consolidated database is used to learn the geometallurgical relationships required to generate realistic simulations.

Simulation of Primary Geological Variables

Definition of Geometallurgical Domains

Hydrothermal ore deposits, in general, present zoning of different mineral associations (Sillitoe 2010), which correspond to GMU and, within these domains, there is also variability in the composition of rock. The concept of ore type provides a framework to form a common perspective around the performance of material, to make decisions (Jackson and Young 2016). This implies that, depending on the perspective, the definition of GMU is given through the orebody knowledge, rock characteristics and performance engineering. For example, from a blasting perspective, the performance type is the fragmentation distribution (target to optimize process), and this depends on the geological domains (joint characteristics, rock strength, rock density and rock mass description rating) and the blast design (operational factor). However, from a mill perspective, the performance target is the throughput that depends on the fragmentation distribution, impact resistance and grinding hardness (material type and geological domains) and the milling circuit (operational factor).

To support the definitions of GMU, supervised and unsupervised algorithms can be used. For example, Sepúlveda et al. (2018a) give a methodology to clustering with spatial corrections to define GMU. It is important that the definition has geological foundation that validates the behavior of an ore type. Another common option is to combine different criteria to define the GMU through several iterations: geological knowledge, statistical analysis, multivariate iso-grades and spatial modeling. Finally, the GMU can be validated through geostatistical tools, such as spatial data analysis, cumulative probability plots and boxplot by category, among others, to discriminate the different statistical population. This is a subjective process requiring many iterations, and, in this context, there may be many valid interpretations of GMU for the same deposit.

In the case study, five GMUs have been modeled. These are associated with the copper mineral zones of the deposit:

- GMU1: Oxidized copper ores with evidence of leaching on the groundwater level of the deposit;
- GMU2: Sulfides such chalcocite and digenite (enrichment sulfides layer);
- GMU3: Primary hypogene sulfides with high chalcopyrite—pyrite ratio;
- GMU4: Primary hypogene sulfides with low chalcopyrite—pyrite ratio; and
- GMU5: Waste and gravel without economic content associated with copper.

Simulation of Domains

Simulation of categorical variables can be carried out with many different algorithms. In the geostatistical toolbox, the following methods are widely known and could be used for this stage: pluri-Gaussian simulation (Armstrong et al. 2003), sequential indicator simulation (Deutsch 2006), multiple-point simulation (Mariethoz and Caers 2015) and truncated Gaussian simulation (Beucher and Renard 2016). Most of these methods aim at reproducing the indicator variograms between the different categories. This entails reproducing the number of transitions from one category to different categories. Control over the transition's changes with different methods; therefore, some methods work well under mostly unstructured (mosaic type) categorical models (indicator simulation), while others aim at preserving specific features such as hierarchies (truncated Gaussian and pluri-Gaussian simulation) or even curvilinear features and trends (multiple-point statistical simulation).

In this research, we simulate categorical GMU and calculate the probability of occurrence. Figure 2 shows a plan view with (left) the expected GMU and the iso-curves with probability of GMU contacts, and (right) the confidence level of model (40% to 100% of confidence).

GMU are simulated in the deposit by indicator simulation. The actual implementation used here is the block sequential indicators simulations algorithm (Deutsch 2006), which implements the mapping pixel smoothing algorithm—maximum a posteriori selection (Deutsch 1998) to improve the contact among categories and preserve their imposed proportions.

Compositional Geostatistical Simulation of Minerals

Compositional variables are modeled after a so-called log ratio transformation (Pawlowsky-Glahn and Olea 2004). A full review of this approach is given by Tolosana-Delgado et al. (2019). There are several ways to approach this transformation, but the simplest is presented here. Assume $(p-1)$ variables are available and form a composition, for example, a set of mineralogical proportions. Since

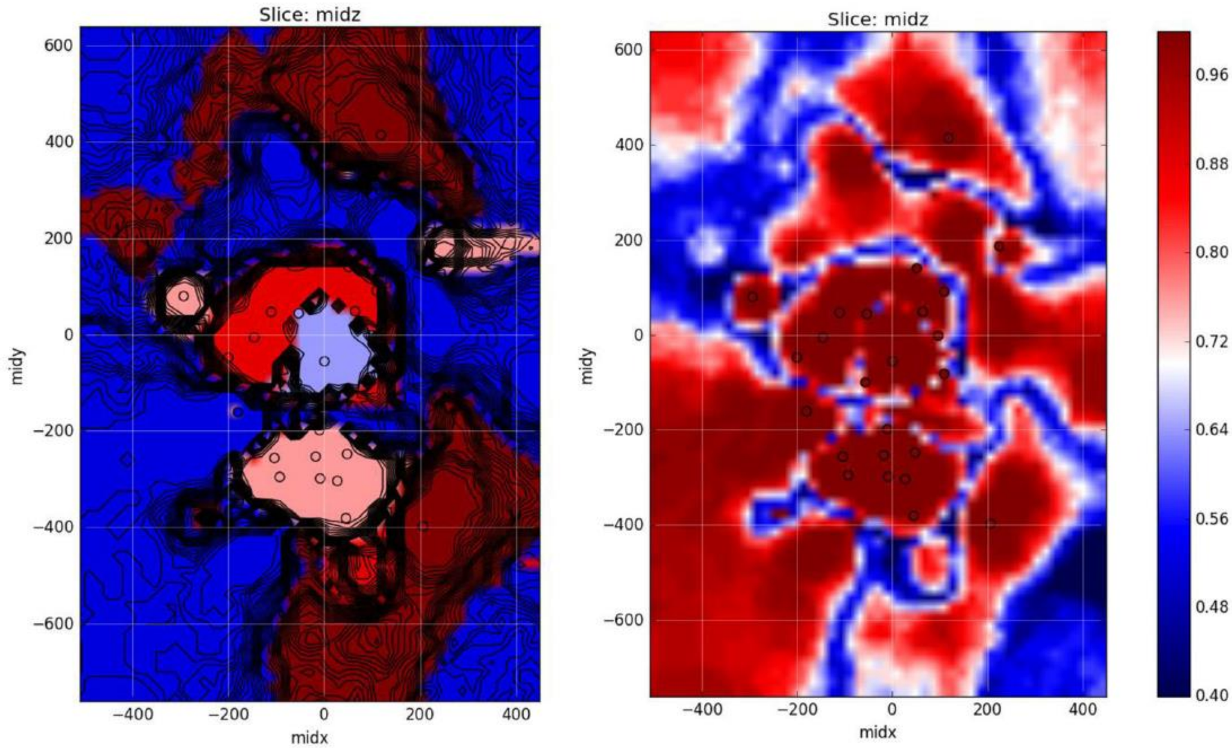

Figure 2. (Left) Plan view with the expected GMU and (right) the confidence level of model.

these variables form part of a whole, a filler variable is calculated to complete the set. For example, if proportions are reported in percent, this filler variable can be:

$$R(u_\alpha) = 100\% \ - \sum_{i=1}^{p} X_i(u_\alpha)$$

The additive log ratio transforms (Aitchison 1982) can be computed:

$$Z_i(u) = \log\left(\frac{X_i(u)}{R(u)}\right)$$

These new variables are unbounded, that is, they can take values between $-\infty$ and $+\infty$, but are also spatially correlated. Therefore, simulation can be done by applying a decorrelation transformation and simulating independently each component, or jointly simulating all the log ratio transformed variables using conventional geostatistical methods.

Decorrelation can be done by using a collocated factorization such as principal component analysis, which does not impose decorrelation of the variables in space, but most of the time significantly reduces the spatial cross-correlation of the principal components (Bolgkoranou and Ortiz 2019). Other methods for decorrelation are maximum autocorrelation factors (Desbarats and Dimitrakopoulos 2000), uniformly—weighted exhaustive diagonalization with gauss iterations (Mueller and Ferreira 2012) and independent component analysis (Boluwade and Madramootoo 2014). Projection-pursuit multivariate transform (Barnett et al. 2013) finds successively directions where the projection has the maximum univariate non-Gaussian index and performs the normal score transformation to that specific direction.

In this step, we relate mineralogy with geology. Mineralogy is often determined by mineralogical test work, such as quantitative evaluation of materials by scanning electron microscopy (Fennel et al. 2015), which provides mineralogical proportions. For each geological domain, a multivariate spatial lineal model of coregionalization (LMC) is imposed, if a correlation between variables exists. This LMC is determined according to the relationships between minerals in each geological domain, for example, cuprite and chalcocite should be found in the mixed or secondary enriched zone. The relationship can be determined by correlation matrices. The simulation

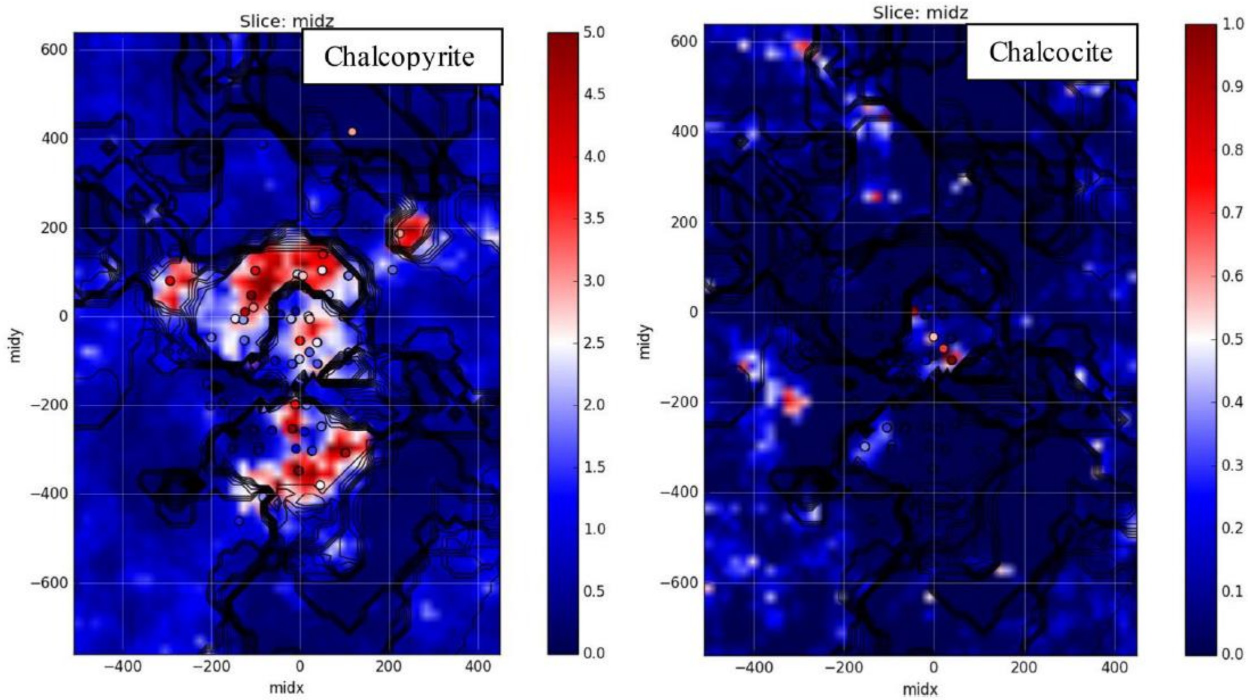

Figure 3. (Left) simulated proportions of chalcopyrite. (Right) simulated proportions of chalcocite in percent.

within each geologic domain is performed by the ultimate sequential Gaussian simulation algorithm (Manchuk and Deutsch 2012).

In this case study, compositional mineralogical simulation was performed over each realization of geological simulation (cascade approach), in order for the geological uncertainty be propagated to the simulation of mineralogical proportions. Figure 3 shows the E-Type (average of 50 realizations) of chalcopyrite and chalcocite simulated over the same plan view shown previously.

Correlations found in the exploratory data analysis were replicated in the compositional simulation. The relative proportions of minerals are preserved, which are different for each GMU. Figure 4 shows that GMU2 has a higher proportion of chalcocite's sulfides and GMU3 has a higher proportion of primary hypogene sulfides with high chalcopyrite-pyrite ratio, which is congruent with simulated GMUs.

Geochemistry

As minerals contain the chemical elements of interest, simulating the geochemistry could significantly improve the simulation of responses at the plant, which will be dependent on the mineral occurrence of these elements. In geometallurgy, the elements of interest should not only be those of economic interest, such as copper, gold, molybdenum, silver and iron, but also deleterious elements, such as sulfur, fluorine or arsenic. From the geometallurgical perspective, deleterious elements could be crucial in the beneficiation process and in minimizing contaminants that affect the quality and economic value of the final product (Lane 1988). A geometallurgical block model should include both kinds of elements.

There are two approaches to have elements and minerals in the GMBM: (1) predicting mineralogy from grades and (2) predicting grades from mineralogy. Some researchers have linked chemistry composition to mineralogy to predict the mineral proportions from element concentrations (Lamberg 2011; Townley et al. 2018; Abildin et al. 2019).

The other approach is deducing element concentrations from mineral proportions. The grade of each element is a function of the minerals present:

$$g_e = f(m_1, m_2, \ldots, m_M)$$

The g_e function is derived from the chemical composition of the M minerals. For example, if there are three minerals hosting copper: bornite, chalcopyrite and chalcocite; we have:

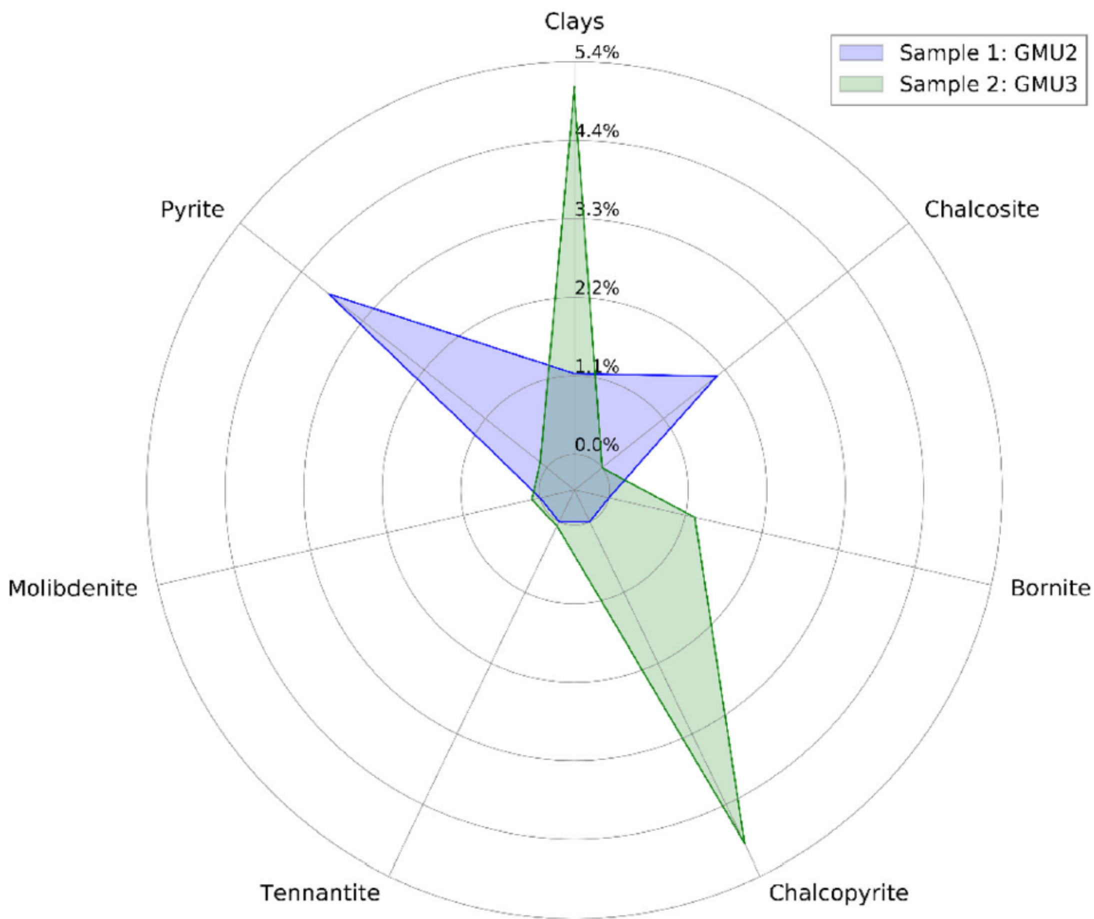

Figure 4. Radial map of mineral percentage for two samples of different GMU, validating the definition based on mineralogical approach.

$$\text{Bornite} \equiv Cu_5FeS_4 \rightarrow 63.31\%\text{Cu}$$
$$\text{Chalcopyrite} \equiv CuFeS_2 \rightarrow 34.63\%\text{Cu}$$
$$\text{Chalcocite} \equiv Cu_2S \rightarrow 79.85\%\text{Cu}$$
$$g_{\text{Cu}}(m_1, m_2, m_3) = m_1 63.31\% + m_2 34.63\% + m_3 79.85\%$$

where m_1, m_2 and m_3 are the percentage of bornite, chalcopyrite and chalcocite, respectively. The limitation of this methodology is that mineral proportions are most commonly derived from qualitative or semi-qualitative estimates, usually with high degrees of uncertainty. In addition, mineral proportions estimates would only account for the theoretical copper present but exclude trace elements such as gold or silver that may be present.

Mineralogy also helps establishing the relationship of grade and mineralization zones. For illustration, in a porphyry copper deposit, we could find the following relationships of copper grade in different mineralization zones: the total copper content in secondary enrichment, which is characterized by minerals with high copper content such as chalcocite and covellite, is in general higher than the total copper in primary rocks characterized by sulfur with high content of chalcopyrite.

In the case study, mineral proportions were used to calculate geochemical composition of total copper, molybdenum (commodities) and arsenic (pollutant). For example, the sum of copper in chalcopyrite, bornite, covellite and oxides minerals represents the total copper in minerals. The original database contains total copper (in samples), and it was compared through quantile–quantile plot with the Total copper in minerals (Fig. 5). In addition, spatial continuity was validated for total copper in minerals, at a range of 70 m approx.

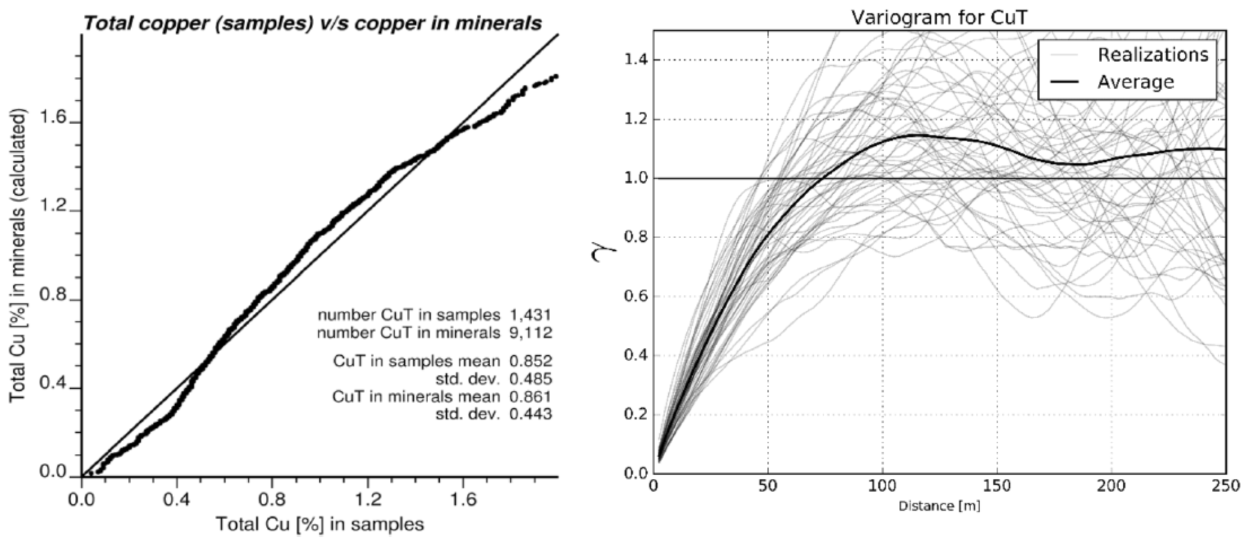

Figure 5. Validation of statistical distribution and spatial variability for total copper grade in minerals.

Simulation of Geometallurgical Response from Drill Core Samples

Metallurgical batch tests are performed on drill core samples to generate mineral processing predictive models. However, such tests are not enough to predict industrial performance as these do not necessarily account for ore rock blending of feed through the process and scale-up factors from batch to industrial scale are not always known, especially in exploration projects. Batch laboratory tests are a useful tool to identify, through geometallurgical modeling, trends and optimal conditions that are proposed to be implemented later in the plant. In this work, two instances of geometallurgical modeling are presented: comminution and flotation processes.

Simulation of Comminution Process

There are roughly two kinds of models: power-based models, which are based on grinding parameters that allow estimating the energy consumption associated with a given size reduction, and population mass balance models that can also be used to predict the behavior of the rocks, from a particulate system perspective, and how the particle size distribution evolves during grinding. In each case, the product particle size, characterized by P80, e.g., the 80% passing size is an important variable since it is directly related to the liberation degree.

The following is a list of common comminution tests: Bond work index for ball mill: the grindability test determines the hardness of the ore rock. The work index is used when determining the size of the mill and grinding power required in producing the required ore throughput in a ball mill. SAG power index or Starkey test for SAG mill: provides the time (minutes) required to perform a specific milling work, from a feed size to an output size. SAG mill comminution (Morrell 2006): it is a function between the specific energy applied and the percentage of product generated in the impact fracture of a specific particle size.

From these comminution tests, the specific energy consumption can be calculated, and later used to optimize the process at industrial scale. When simulating these variables, the use of multivariate tools is recommended as it allows improving the models' robustness.

Simulation of Flotation Process Performance

Flotation is a selective separation process that is based on the difference in hydrophobicity of minerals at given physical–chemical conditions. In this case, unlike comminution tests, the flotation tests are not standardized, and, in general, the flotation results correspond to a combination of ore characteristics and the way the flotation tests were performed, expressed in operational variables such as pH, P80, solid weight and aeration conditions. In the case of

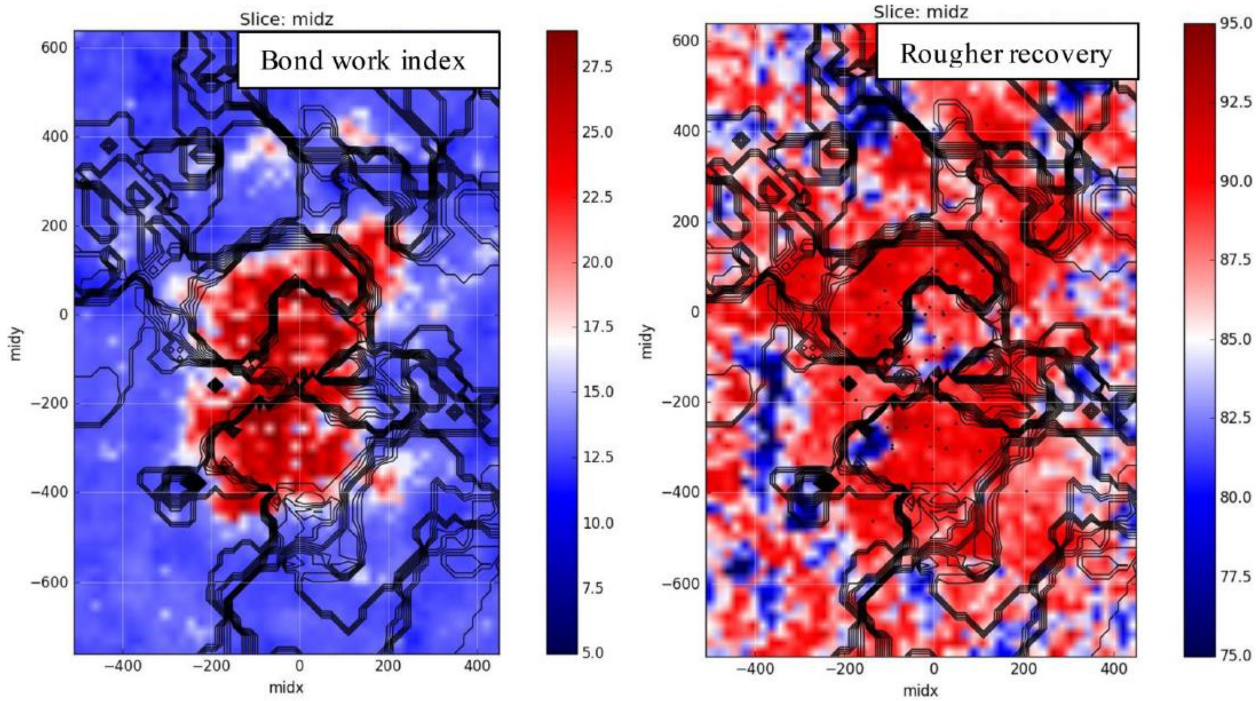

Figure 6. (Left) Bond Work Index BWI simulated (kwh/tc). (Right) Rougher recovery simulated (%).

flotation modeling, the performance depends on the head grade, rate constant, mineralogy and liberation degree, which determines the maximum recovery. All these variables can be simulated using multivariate tools to improve models' robustness without increasing unnecessarily the number of tests.

The flotation test can have many variants, for example, the most common is the open cycle test: (1) rougher primary flotation, (2) secondary flotation optional cleaner, (3) optional scavenger tertiary flotation, (4) optional re-grinding before the flotation cleaner. Combinations of these tests can be performed to replicate the industrial flotation cell to maximize the recovered ore and its concentration. The following information is usually obtained from these tests: kinetics of flotation k Klimpel, maximum recovery with prolonged flotation time or "infinity", mineral characterization and head geochemistry (feed), mineral and geochemical characterization of concentrate, at 1.5 min, 3 min, 6 min, 12 min and 15 min of flotation, mineral and geochemical characterization of tailings, at 1.5 min, 3 min, 6 min, 12 min and 15 min of flotation, among others.

The mineral characterization consists of briquette preparation, quantitative mineralogy, mineral association identifications, granulometric distribution, among others. From these tests, a database is obtained with many variables that are used to optimize the flotation process performance at an industrial scale (Jackson et al. 2011).

The metallurgical process is related with the industrial processing or prediction of plant process performance (Suthers et al. 2004) of the ore that has been removed from the in situ ore deposit. The ore is processed continuously at industrial scale, through a process of crushing, conveyor belt, grinding, flotation, thickening and filtration, among others, and this can be modeled and simulated (King 2001). Many industrial simulators are used for this purpose, for example the JKTech simulators: JKSimMet for comminution and classification circuits, or JKSimFloat (Vann et al. 2011) for simulation for steady state performance in flotation plants. The software can simulate operational parameters (e.g., flowsheet of the processing plant) and tests its performance (metal recovery and concentrate grade, water recovery, residence time, gas holdup, froth recovery, mass balance on a size by assay basis) to achieve the best consistent data set and simulate the effect of changes in the flowsheet to predict flows, size distributions and element distribution, among others.

Predictive models can be implemented by different mathematical adjustment models, such as Australian minerals industry research association to

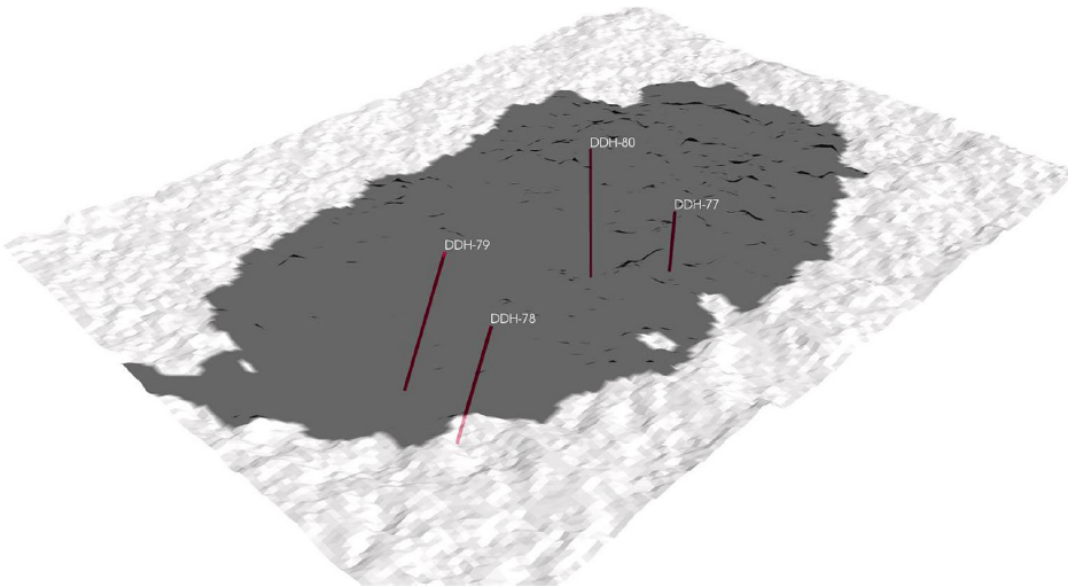

Figure 7. Topography area that is an exploration target with four drill holes.

floatability component (Coleman et al. 2007). The most important limitation of these simulators is that they allow varying the configuration of industrial machines (and other operational factors) considering a constant mineral feed, neglecting the geological variability associated with the deposit and blending factors. Another limitation of these simulators is that the simulation of geometallurgical attributes generates many possible processing scenarios, which are not directly used in these simulators (industrial simulators receive a deterministic input, not a stochastic geological input). Metallurgical response can be estimated by regression models calibrated from test work or reconciliation data, which is the approach used in this paper.

In this case study, cosimulation for BWI and rougher recovery was performed for each GMU (Fig. 6). Rougher recovery was calculated as a sum of individual mineral recoveries, assuming there is no cross-interference that affects the flotation process. Rougher recovery has a negative correlation with chalcocite, consistent with laboratory performance of assays to flotation.

Finally, the block model has been simulated with geological variables, mineralogical variables, geochemical variables and geometallurgical response. Each simulation was simplified for research purposes, but the methodology is flexible and can be implemented to other more sophistically types of simulations (see ''Simulation of Spatial Drill Holes'' section).

Simulation of Spatial Drill Holes

To generate a database that looks realistic, different conditions must be simulated for exploration campaigns. In this context, simulations of topographical area, density of information and survey of drill holes are simulated.

Topographic Simulation

To simulate elevation, non-conditional simulation was performed. Smooth simulations are appropriate for realistic surface modeling. Z-elevation collar position of drill holes is a known function of x-east and y-north coordinates. Figure 7 shows an exploration target area (estimated with geochemistry, petrological, geophysics and geochronology knowledge). This area can be simulated with categorical simulation of boundary and synthetic pseudo-drill holes. This is the first campaign whose objective is to find deep mineralized bodies.

Simulation of Density of Drill Holes

If the ore body is found in the first campaign, a second campaign is performed with different objectives: define the prospect dimensions, develop the first estimation of ore grades and improve the geological knowledge for interpretation.

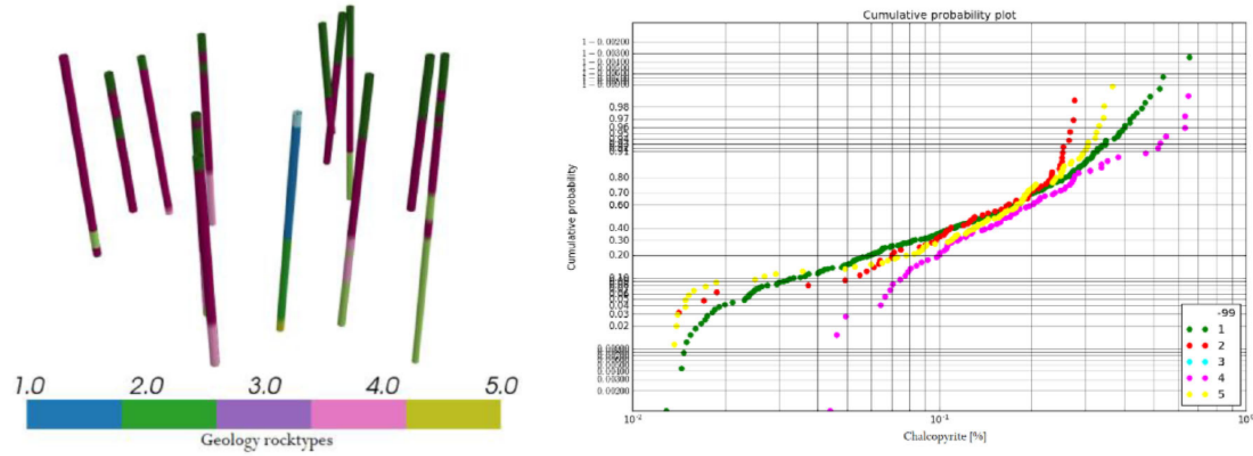

Figure 8. (Left) Plot of five geological codes in drill holes logging and (right) categorical cumulative probability plot of chalcopyrite percent.

The geological interpretation of metallogenic controls of mineralization is important at this stage to design the next exploration plan. Geostatistical tools can improve the geological knowledge to define domains, for example exploratory data analysis may help showing distributions of different geological properties (Figure 8 shows of the logging of drill holes with 5 geological codes and the cumulative probability plot of chalcopyrite in each unit), for the purpose of identifying relevant economic domains and quantifying the possible mining resources.

Depending on the exploration stage, a given drilling spacing is targeted, in consideration of the associated risks of finding the resources and budgetary constraints. The expected orebody geometry determines the orientation and depth of the drill holes. Figure 9 shows a regular mesh (collars of drill holes, in surface) that depends of the geological continuity of ore body.

Survey and Length Simulation

In depth, drill holes may be oriented in particular directions with the objective of intersecting perpendicularly a tabular body, structural vein, etc. At this stage, structural information is important to define the orientation of the drill holes (azimuth and dip). Structural zones must be identified through the oriented drill holes. Figure 10 shows oriented drill holes with an azimuth and dip calculated based on structural information.

The lengths of the drill holes depend on the depth of ore body and long-term scheduling (based on feasibility studies). In regular deposits near to surface, the length drill holes can range from 50 m to 500 m in depth. We use a normal distribution to simulate the length of the drill holes, for example a normal distribution with mean of 300 m and standard deviation of 100 m. Finally, a random subset of the available drill holes samples is informed with geometallurgical attributes, to represent the typical scarcity of geometallurgical information. In our example, 10% of all simulated samples contains geometallurgical test values.

Application to Uncertainty in Mine Planning

Uncertainty in mine planning optimization plays a critical role not only in finding the optimal economic valuation through the maximization of net present value, but also in risk assessment. Most of the research focuses on incorporating grade uncertainty in strategic mine planning, and medium- and short-term scheduling optimization problems. Because scheduling transforms a three-dimensional resource model into a temporal model, one cannot assign a profit value at block scale (or selective mining unit scale) before the decision on where, when and what to mine is made by the optimizer. Traditionally, this simplification is often done, but a realistic schedule of the profit of a set of blocks in a temporal interval should depend on geological

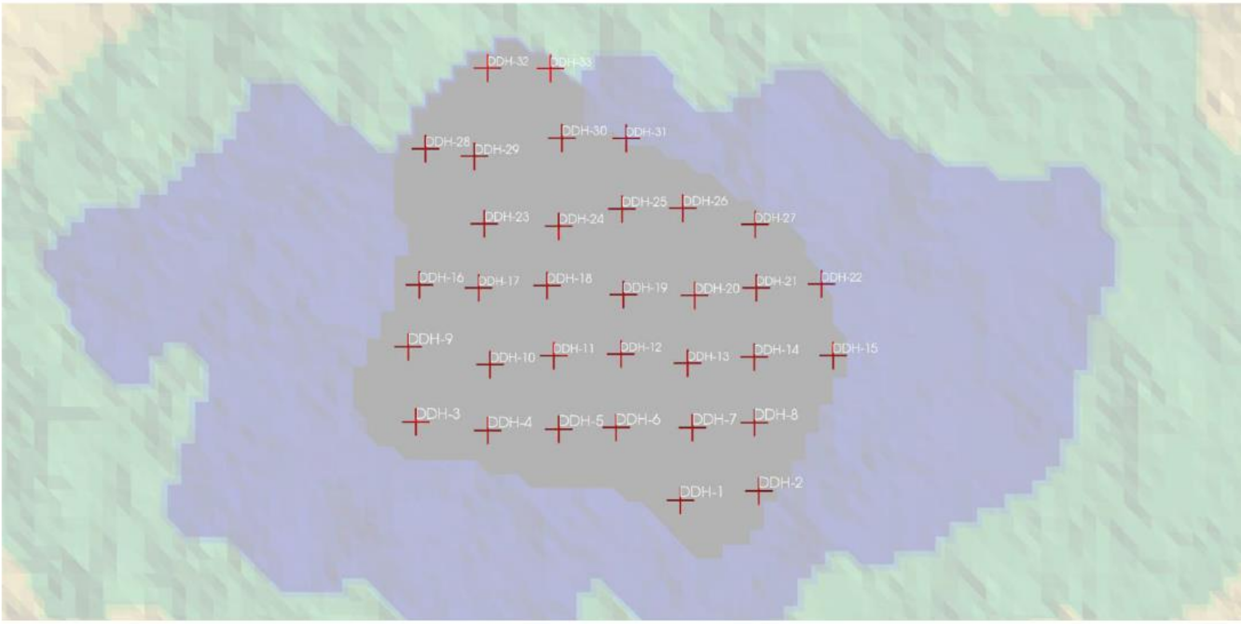

Figure 9. Collars of drill holes in regular mesh in surface.

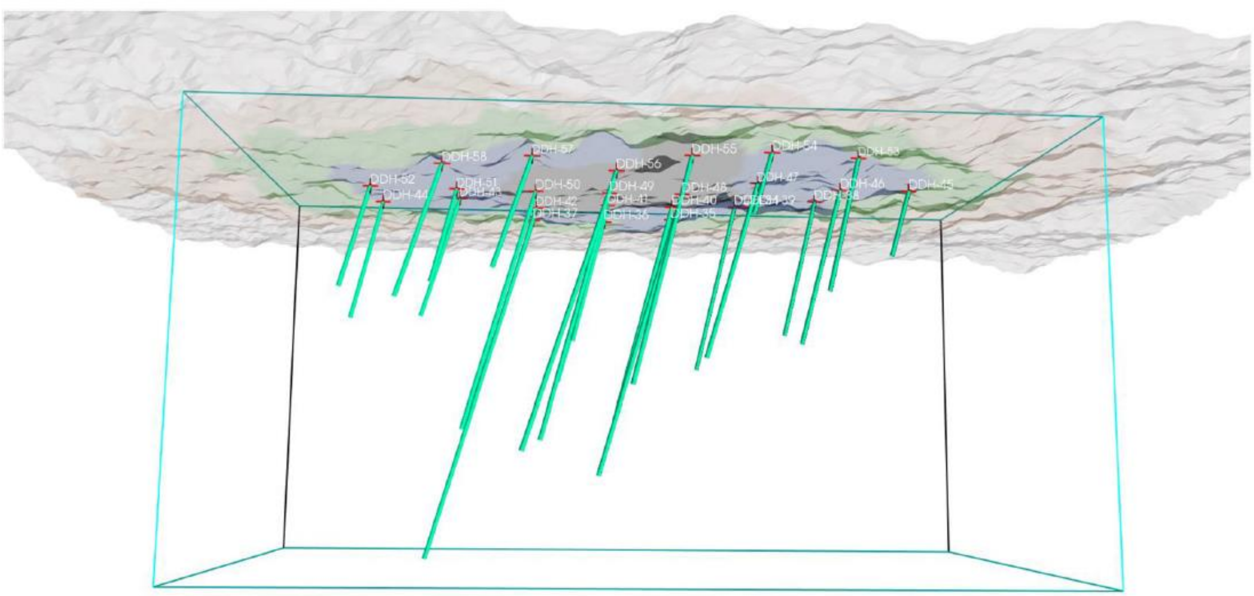

Figure 10. Oriented drill holes campaign with an azimuth and dip calculated based on structural information.

properties and response properties of the complete set of blocks, and to the specific plant conditions. In case of early stages, design plant condition needs to be used, whereas in productive stages, real plant conditions need to be considered.

Any response attribute can be modeled as a transfer function f with inputs: set of blocks B and their attributes, a set of plant parameters P, and a timeframe Δt.

$$\rho = f(B, P, \Delta t)$$

Therefore, accounting for the uncertainty of processes requires not only carrying the uncertainty of inputs to the model, but also, the uncertainty of the processes themselves. Incorporating the uncertainty of the inputs to mine planning optimization problems is a very active research topic. Grade is the main geological attribute that was incorporated to

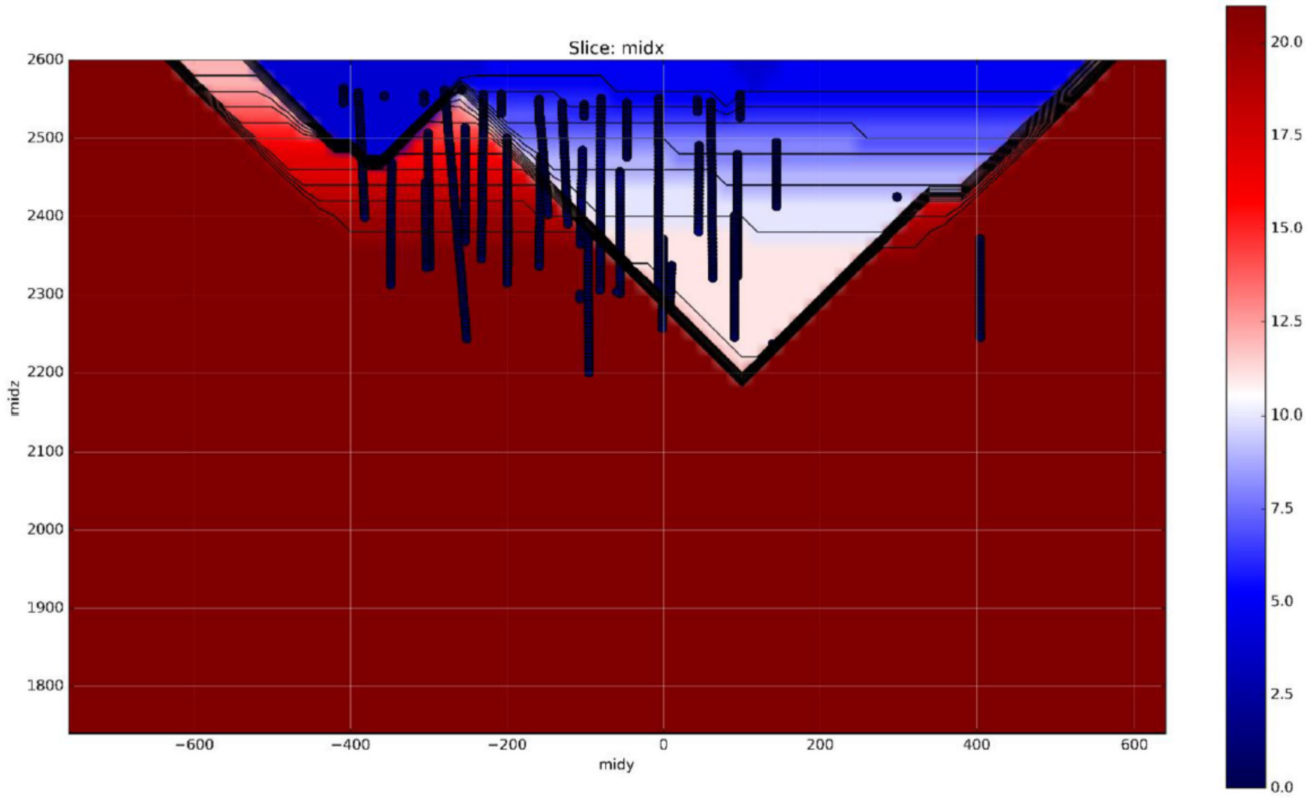

Figure 11. Graphical scheduling of 20 phases of project, LOM.

many production planning optimization problems (Gholamnejad and Osanloo 2007; Lamghari and Dimitrakopoulos 2012; Kumral 2013; Silva et al. 2015; Goodfellow and Dimitrakopoulos 2016). Nevertheless, accounting for geometallurgical uncertainty is very limited. Kumral (2011) incorporated uncertainty of revenue and cost by many scenarios based on simulations. Sepúlveda et al. (2018b) used several geometallurgical variables under uncertainty to optimize production scheduling in a block caving operation by a multi-objective approach. The uncertainty of geometallurgical attributes was quantified by geostatistical simulations of primary variables and nonlinear regression models for response variables.

One approach, which is the most used and the simplest, is defining transfer functions from standardized response variables to specific plant conditions. The approach that reflects the responses to processes of a set of blocks in a timeframe is by simulating the processes, while the optimization is being performed. Obviously, this approach is very challenging because simulating the processes requires large computing power. Populating any geometallurgical resource model with response attributes should be avoided because it implicitly assumes (1) a block responds independently to the other extracted blocks, which is not the case, and (2) the throughput is constant. However, there is limited research in this direction. Garrido et al. (2017) defined the concept of geometallurgical dilution to account for the impact of feeding blocks of different geometallurgical domains to the plant, if different geometallurgical domains have different responses. They showed that geometallurgical attributes can be effectively included as part of the optimization process. More research needs to be done to incorporate the response simulation as part of the optimization process.

In our case study, to transfer spatial variability of geometallurgical variables to temporal variability, a mining scheduling (life of mine) was calculated with the Lerchs and Grossman algorithm (Lerchs and Grossman 1965) for the E-Type of the generated simulations. Figure 11 shows the 20 phases of the project, calculated with real economic and design parameters of a porphyry copper ore body open pit.

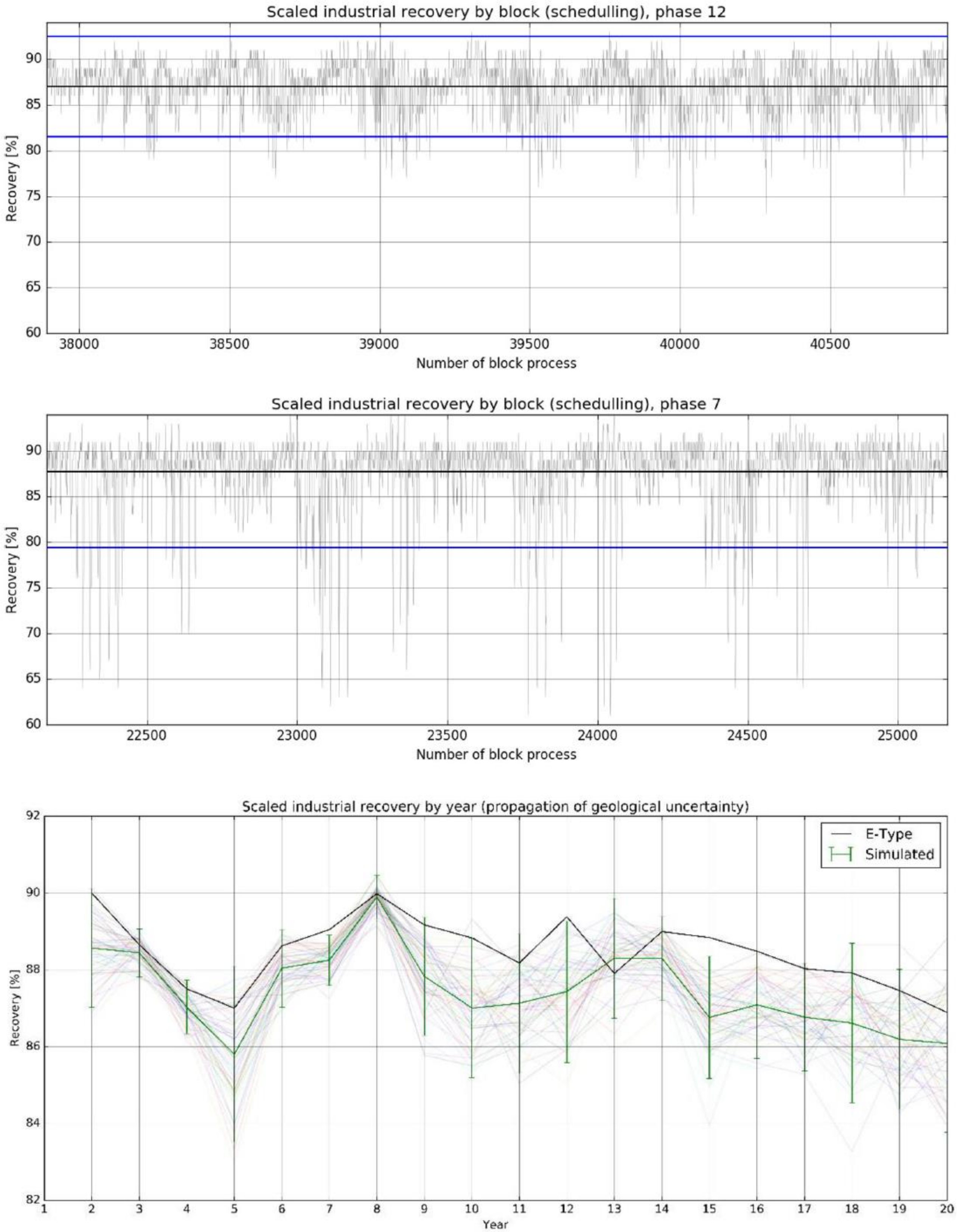

Figure 12. Re-dimensioned scaled recovery variability by blocks (for one realization) and by year (for all realizations). Mean recovery by block with 95% confidence interval is shown.

Geometallurgical variability can be measured by period (in this case, by phase or year). Known temporal behavior of mineral processing may allow industrial metallurgical simulations. In this case, to simplify the research application, a correction factor of rougher recovery was applied to calculate industrial recovery. This correction factor was calculated for each GMU, as in the Collahuasi case study (Suazo et al. 2010).

Figure 12 shows the rougher recovery variability by year (E-Type vs. uncertainty in simulations). It shows how geological variability is propagated to metallurgical variability. The results show years with low metallurgical variability (for example, phase 12) and years with high metallurgical variability (phase 7) for one realization. This variability is fully attributed to geological variability, and it does not consider the operational variability. Case phase 7 shows low recovery because sulfides mineral zones include secondary enrichment (GMU2), and chalcocite affects recovery negatively, increasing uncertainty.

This application shows how geological uncertainty is propagated to metallurgical responses. Usually, conciliations show differences that can be attributed to geological variability and operational interferences.

CONCLUSIONS

We have presented a reproducible methodology for the simulation of a synthetic geometallurgical drill holes dataset, with special interest in preserving the coherence between geology, mineralogy and grades. Response attributes were included in the drill hole database, comminution process and flotation performance. Simulations can be self-explained, any algorithm aligned with the generating method will appear to work well—other algorithms will appear to have poor performance, and this condition is a limitation to any method. One of the main contributions of this article is the summary of geostatistics tools that can be used.

Starting with real or synthetic drill holes and following the six steps in the proposed methodology, a GMDB can be successfully simulated. All programs used in the methodology can be found in open source software, free software or commercial software.

The article discusses how we understand a geometallurgical unit, which may depend on the geological setting, the metallurgical process and the implementation in the operation, unlike the conventional geological domains that only depend on geological characteristics associated with the rock.

The geometallurgical variable (associated with a rock process in situ) is differentiated from the metallurgical variable (associated with a continuous process in time). The geometallurgical variables (such as BWI, rougher recovery, specific acid consumption and soluble copper) can be simulated by geostatistical tools in spatial block model, subject to the correct definition of the GMU. The loss of predictive processing capacity generates problems in mining reconciliation, increased uncertainty and increased costs. With a correct and careful application of this methodology, the geometallurgical uncertainty can be evaluated by implementing preventive protocols to reduce processing costs.

We have also included in the complementary material the simulated inputs and GMDB of the case study for academic and teaching purposes which are also available for downloading in the public repository https://github.com/exepulveda/geomet_datasets.

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CONCLUSIONES

En la investigación se han desarrollado herramientas de tipo multidisciplinarias en el área de la geo minero metalurgia extractiva. Los principales resultados científicos se resumen en los dos artículos. El manuscrito 1,'Change of support using non-additive variables with Gibbs Sampler: Application to metallurgical recovery of sulphide ores', presenta una metodología para cambiar de soporte de variables no aditivas (en este caso, aplicado al ensayo geometalurgico de recuperación rougher) la cual conserva características geoestadística de la base de datos que evita artefactos matemáticos en la consolidación de base de datos de diferentes fuentes de información (logeo geológico, geoquímico, mineralógico, geofísico, geomecánico y geometalúrgico). La consolidación correcta de la base de datos permite generar modelos georeferenciados en el espacio de atributos geometalúrgicos.

El segundo artículo 'Simulation of Synthetic Exploration and Geometallurgical Database of Porphyry Copper Deposits for Educational Purposes' entrega una metodología para simular geoestadísticamente variables geometalúrgicas considerando gran parte de los problemas y desafíos que implica este proceso a nivel industrial, donde incluye una robusta revisión bibliográfica de las metodologías disponibles para este procedimiento. Además, se ha dado un enfoque de innovación al permitir, en base a estas simulaciones y escenarios geometalúrgicos, generar base de datos sintéticas con distribución espacial y coherencia geológicas con fines de uso académico. Esto presenta una ventaja desde un punto de vista de investigación, ya que las bases de datos geometalurgicas son de restringido acceso. Adicional a esto, se incluye en el anexo el manuscrito publicado en Predictive Geometallurgy and Geostatistics Lab, Queen's University, Canada, el cual describe una forma para validar las simulaciones generadas desde un enfoque geológico.

En adición al trabajo presentado en los artículos, se ha desarrollado un documento extendido el cual describe el uso de buenas prácticas en el área de geometalurgia para la definición de recursos y reservas mineras basadas según el código canadiense CIM Estimation of Minerals Resources and Mineral Reserves Best Practice Guidelines (documento canadiense público en mrmr.cim.org v2019). Además, se ha generado una versión resumida de este documento el cual fue publicado en Predictive Geometallurgy and Geostatistics Lab, Queen's University. Estos documentos fueron escritos en base a la revisión bibliográfica hasta el 2020 en el área de la geometalurgia, y se han basado en experiencias profesionales documentadas en conferencias internacionales, trabajos de consultoría realizados en geometalurgia y visitas industriales técnicas.

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ANEXOS

ANEXO GARRIDO ET AL. 2020A

Geostatistical simulations of ore body deposits are useful to quantify risk and uncertainty, testing mine planing algorithms, generating drill holes databases, among others. Geostatistical simulations are a common tool to generate different scenarios, but these are mathematical algorithms that need to be validated with geological approach. Tools such as histograms, correlations and variograms can validate distributions, numerical associations and spatial variability in a simulation, but many other tools can be used to validate geological coherence (e.g. lithological facies, correlations in minerals of hydrothermal alterations, mineral zones, etc). This article summarizes some of these tolos that can be used to interpret data with a geological approach, with the aim of avoiding geological inconsistencies. Validations are show in a case study, a porphyry copper deposit locate in north Peru, Cajamarca region in Andean mountain.

Validation of Geostatistical Simulations of Porphyry Deposit through Geological Approach using ioGAS[1]

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Abstract

Geostatistical simulations of ore body deposits are useful to quantify risk and uncertainty, testing mine planing algorithms, generating drill holes databases, among others. Geostatistical simulations are a common tool to generate different scenarios, but these are mathematical algorithms that need to be validated with a geological approach. Tools such as histograms, correlations and variograms can validate distributions, numerical associations and spatial variability in a simulation, but many other tools can be used to validate geological coherence (e.g. lithological facies, correlations in minerals of hydrothermal alterations, mineral zones, etc). This article summarizes some of these tools that can be used to interpret data with a geological approach, with the aim of avoiding geological inconsistencies. Validations are shown in a case study, a porphyry copper deposit located in northern Peru, Cajamarca region in Andean mountains.

1. Introduction

The access to real exploration databases is very limited in practice, making it difficult for practitioners, researchers and students to test methods, models and reproduce results in the field of geological modelling. From the point of view of practitioners, researchers, teachers and students, there is an important lack of available databases that can be used, because the data of those are usually subject to confidentiality agreements. Non conditional simulations can be used to generate different scenarios without the use of specific local data, which may be an advantage when real databases are not available. These type of simulations of ore body deposits can be useful to generate exploration drill holes campaigns (Garrido et al., 2018). For this research, geostatistics is used to generate different scenarios, because it allows to manage the distributions of the simulated attributes and their spatial covariance / correlations.

Non conditional simulation can be separated in (1) geological domains and (2) geological continuous attributes (Jackson and Young, 2016). For the first purpose, many tools are available, such as sequential indicator simulation (Deutsch, 2006) (Deutsch, 1998), truncated gaussian simulation (Beucher and Renard, 2016), plurigaussian simulations (Armstrong et al., 2011) or multiple-point simulation (Mariethoz and Caers, 2014), among others. For the second type of simulations, classic tools of geostatistics are well established (Goovaerts et al., 1997) (Chilés and Delfiner, 2012) (Isaaks and Srivastava, 1989), and for multivariate simulations, a flexible sequential Gaussian simulation program USGSIM is recommended (Manchuk and Deutsch, 2012).

Validations of these models must consider the consistency with geological knowledge. In a non conditional simulation, the spatial distribution of minerals and their relationships must be validated to make sense with different geological criteria. In the case of a porphyry copper deposit, many tools can be used to validate with a geological approach. In this research, some criteria to validate are explained.

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2. Methodology

Three different validations are considered, with different approaches based on geological knowledge:

1. *Regional metallogeny framework:* This consists on interpretative regional location of the porphyry ore body, for example basins (e.g. for Principal Andean Cordillera are Farellones, Abanico, Azapa, Loa, etc), Tectonic orogeny (e.g. Pehuenche, Incaica, K-T, etc) and use of isochronous to date the rock type. This interpretation can be use to validate the simulated facies of matrix rock or the ore body.
2. *Hypogene metasomatism water-rock contact:* This consists on interpretative hydrothermal alterations of the porphyry ore body. Minerals in alterations zones may be validated through associations (e.g. potassic alteration with principal minerals such as feldK - Biotite and secoundary minerals as qtz - mag - ser - chl). It depends on physicochemical factors such as Eh-pH, temperature, rate sulfur:oxigen, among others.
3. *Supergene metasomatism water-rock contact:* This consists on interpretative mineral zones related with mineral processing relationships. Supergene enrichment are characterized by meteoric water in oxide conditions, that generate different mineral zones (e.g. leached low copper grade; oxides minerals; secondary sulphur from enrichment process).

The methodology is summarized in Figure 1, that shows the final geological model in each step, with geological and geostatistical approach.

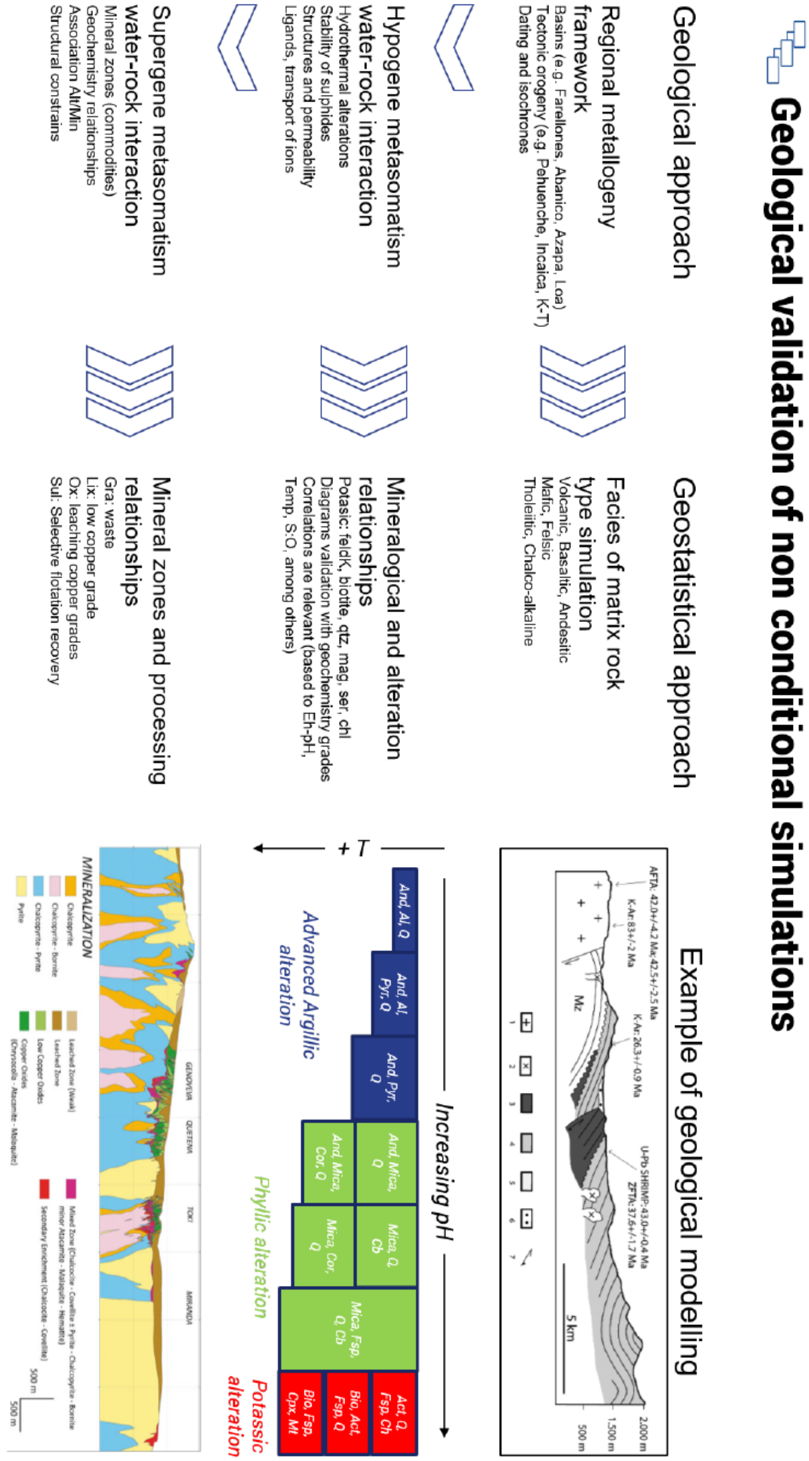


Figure 1: Summary of methodology to validate databases from geological approach, geostatistical approach to geological modelling.

3. Geological attributes in porphyry copper deposit

Usually the porphyry ore body simulation consists in a categorical simulation (geological facies) and continuous simulation (mineralization grades). The categorical simulation considers (in cascade or joint simulation approach): (1) lithology unit, (2) hydrothermal alteration unit and (3) mineral zone unit.

3.1. Lithology unit

Some lithologies are advantageous to generate economical porphyry copper deposits, in particular when related with batholith magmatic events at a regional scale. The lithology unit are interpreted with a regional metallogeny framework. The main unit is the host rock, where intrusive units modify the mineralogy and geochemistry. The regional group to classify lithology are the basins, for example, a description of Abanico Extensional Basin along the Principal Andean Cordillera is given (Charrier et al., 2009):

> "Abanico Formation is in the Principal Cordillera, between 29^{o}S and 39^{o}S, dated from middle-late Eocene to early Miocene. Cinsists of a locally strongly folded, 2000 m thick sucession of volcanic, pyroclastic volcaniclastic and sedimentary deposits including abundant subvolcanic intrusions of the same age, with a well developed paragenesis of low grade metamorphic minerals" (Aguirre et al., 2000) (Bevis et al., 2003) (Fuentes, 2004)

The regional metallogeny framework provides a geological map of surface at scale 1:1,000,000 (more details are provided at scales 1:100,000 or 1:25,000). This indicates the relationship of genetic processes in tecto-magmatic evolution of the ore body. In this context, rock types can be volcanic, basaltic, andesitic, mafic, felsic, tholeitic, chalco-alkaline, etc. Chronological dating must be consistent with rock types formation. In porphyry deposits, intrusive bodies are also important to define the origin of hydrothermal hyper-saline fluids, metallogenic deposit precursors. Other geophysics tools can be used to validate the definition of rock types, such as magnetic or gravimetric tools that show possible lithological units contacts. All of these contacts are abrupt, not transitional.

From a geostatistical approach, some tools are provided to validate some criteria:

1. **Spatial context:** Origin basin rock types was deposited horizontally (by sedimentation) but folding by compressive stress can change the shape or anisotropy. The geostatistical anisotropy is linked to the rock mass tensor stress. Figure 2 shows three diferent anisotropies; (a) logging of Andean Cordillera by different orogenic process and lithological composition (Pinto et al., 2017), NS anisotropy; (b) an horizontal anisotropy correlated with structural orientation faults of different formations (geological map of Northern Hokkaido (Niizato et al., 2010) (Takahasi et al., 1984), anisotropy controlled by structural faults); and (c) a vertical anisotropy of different lithology groups modelled in Chuquicamata district, northern Chile (Barra et al., 2013).

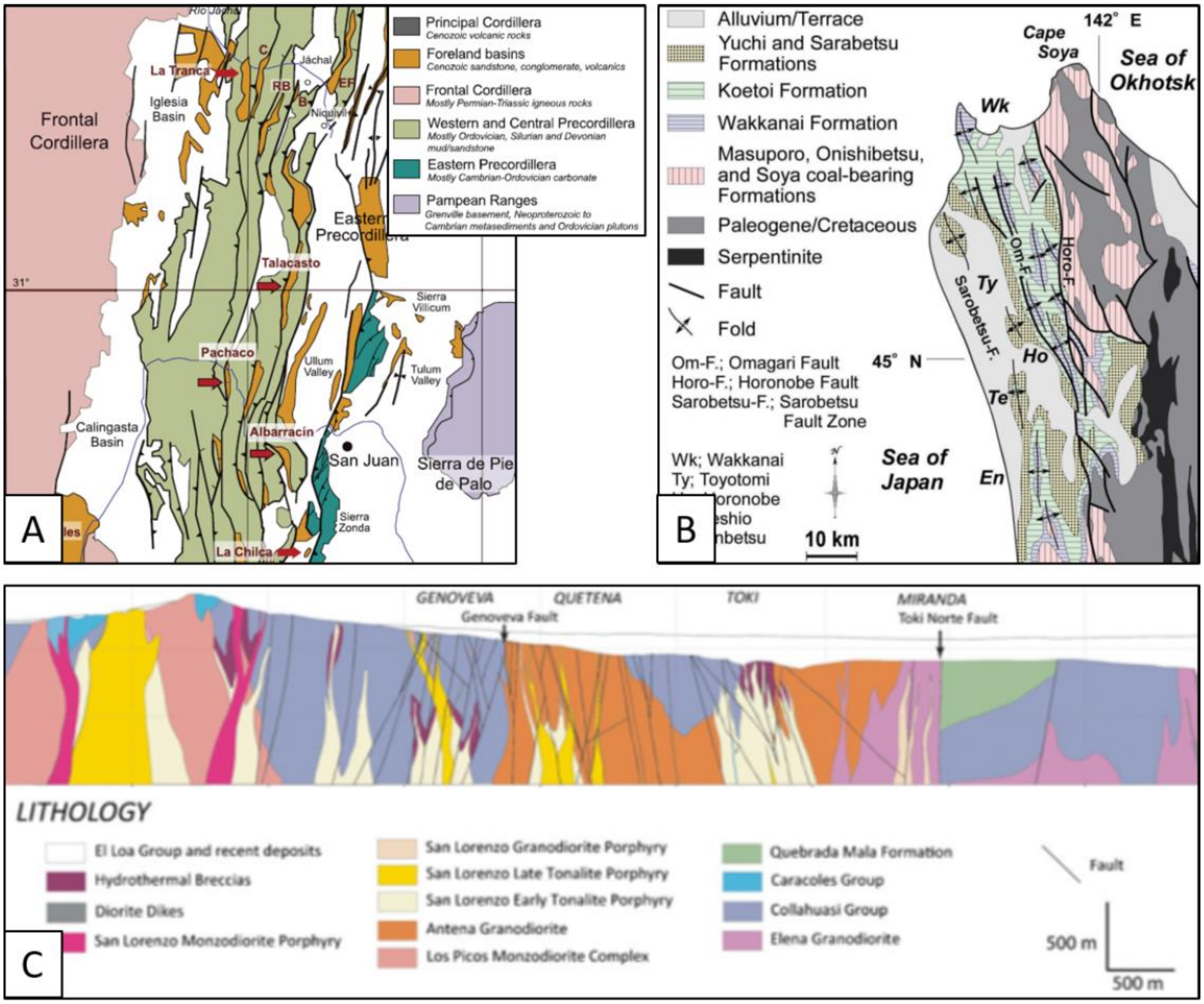


Figure 2: Schematic example of lithological modelling of rock types of different grouping criteria. (a) Andean Cordillera from (Pinto et al., 2017); (b) geological map of Northern Hokkaido, from (Niizato et al., 2010) (Takahasi et al., 1984); (c) Chuquicamata district, northern Chile (Barra et al., 2013).

2. **Statistical correlations:** Some elements trends and concentrations correspond to known formation areas. For example, Figure 3 shows two plots with different areas highlighted, based on geochemical relationships. For example, if the ratio Sr/Y is low and SiO2 is in the range 45-75, then the geochemical relationship is similar to that of barren intrusions rock type footprints, or if the rates V/Sc and Nb/Ti are high, geochemical samples are probably associated to prospective areas for porphyry copper deposits that correspond to strongly oxidized magma (Halley et al., 2015).
3. **Rock type associated to intrusive event:** Porphyry copper deposits need compatible lithologies to originate high grade mineralization, such as intrusive porphyry or dickes, for example. These bodies usually have high continuity in depth, that exploration drillholes are not able to capture. Usually, all lithological contacts are hard, no transitional facies are detected.

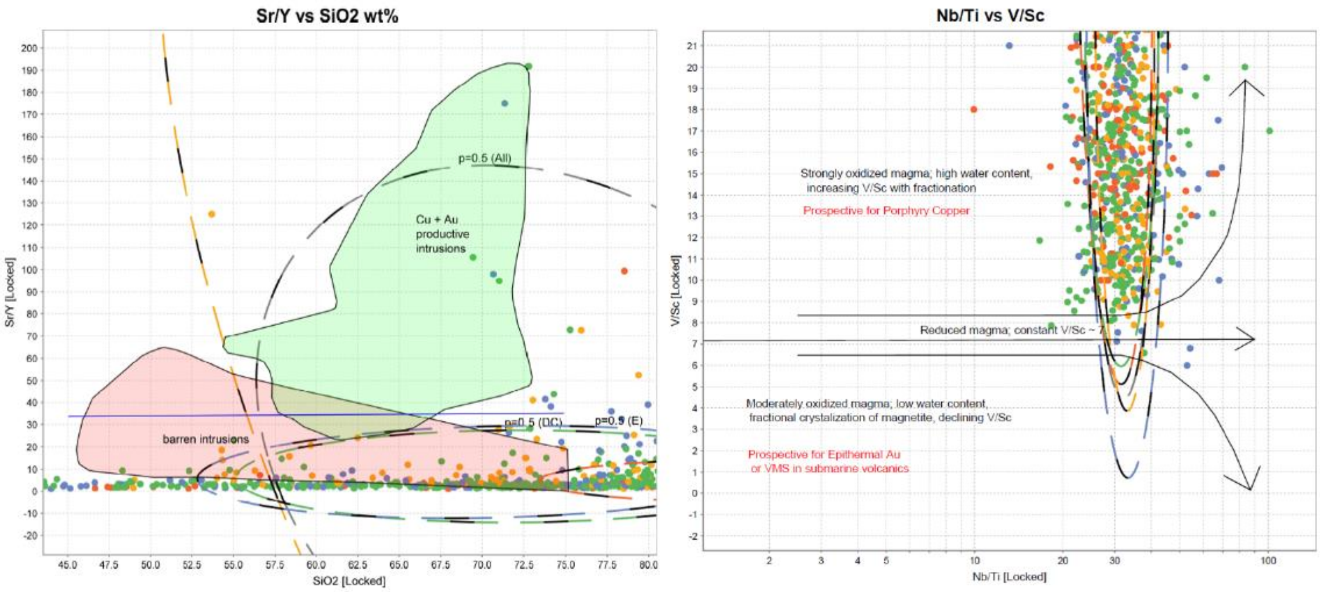


Figure 3: Examples of geological interpretation of rock types based on geochemical relationships. Geochemical ratio of Sr:Y vs SiO2 and Nb:Ti vs V:Sc are consistent with prospective areas for porphyry copper (Halley et al., 2015)

ioGAS software has implemented many tools to verify if the geochemistry is consistent with porphyry Cu exploration. For example (Richards et al., 2012) shows that adakites sub-group that contains high Sr/Y magmas reflect arc maturity, high magmatic water content, and porphyry Cu +/- Mo +/- Au potential; (Cohen et al., 2010) shows diagram related with advances in exploration geochemistry between 1998 - 2007 and (Rohrlach and Loucks, 2005) related the geochemistry of volatiles in a lower crustal magma reservoir. Many such diagrams can be provided for validation of geostatistical simulations through geochemical approach (Loucks, 2014) (Halley et al., 2015) (Maitre, 1989) (Bas et al., 1986) (Rollinson, 2013).

In this case study, Figure 4 shows the location of porphyry copper deposits. An first lithological validation is consistent with the regional extension area. The case study is located on the Cu-Au and Cu-Mo porphyry Miocene belt. Logging shows different intrusive events and dioritic phases of fine to medium textures, in addition to layer dacitic composition phases with abundant quartz and biotite crystals. Pulses of intrusive mineralization were identified, these events cross carbonate sequences from the Pariatambo and Yumagual basins.

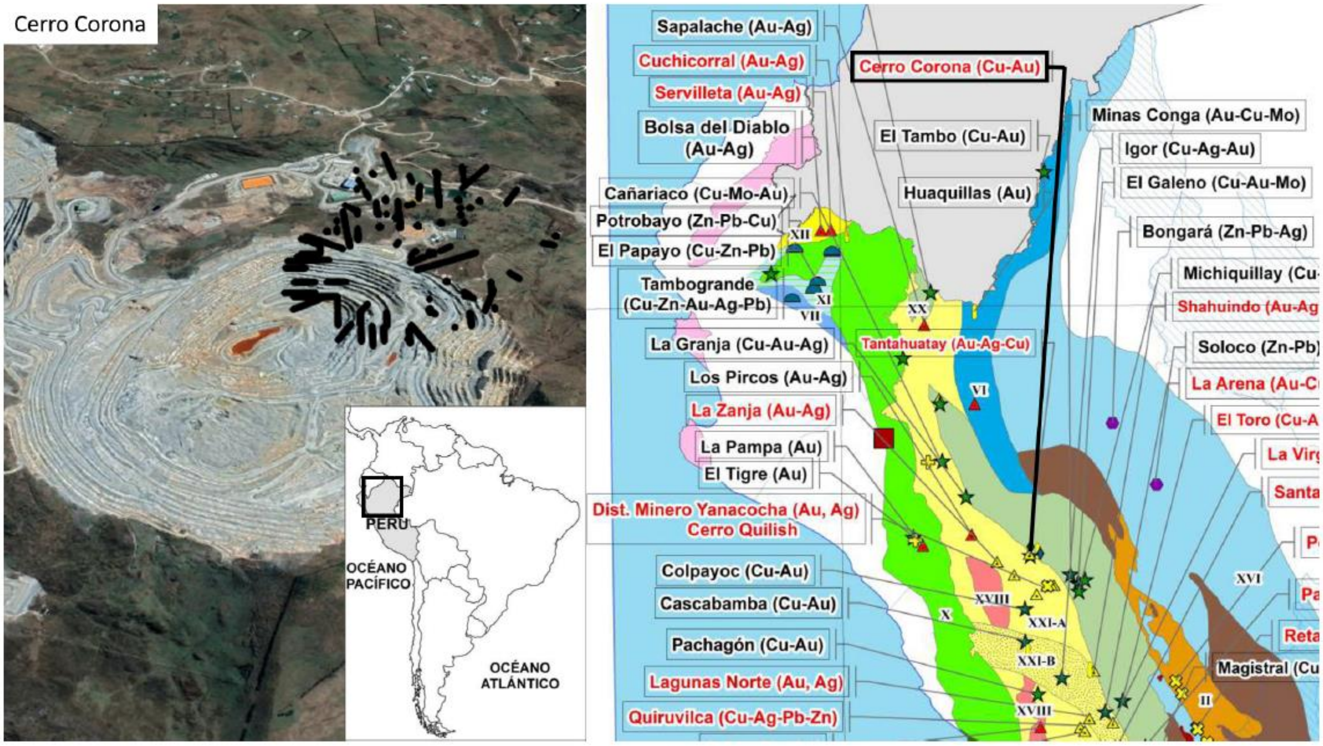


Figure 4: Location of case study in miocene belt, Cajamarca region, Peru, South America (Ramirez, 2012).

3.2. Hydrothermal alteration rock type

Hydrothermal alterations are interpreted as hypogene metasomatism in the water-rock interaction. This generates chemical instability in some minerals, and depends on the stability of sulphides, permeability of structures and transport of ions through molecular ligands. The hydrothermal alterations affect both mineral and waste rock, and it is very important to relate the set of minerals to describe any alteration.

This set of minerals can be classified through temperature and Eh-pH association. (Corbett and T, 1998) present a very complete study of mineral associations based on temperature and pH. Figure 5 shows the common alteration mineralogy relationships in hydrothermal systems.

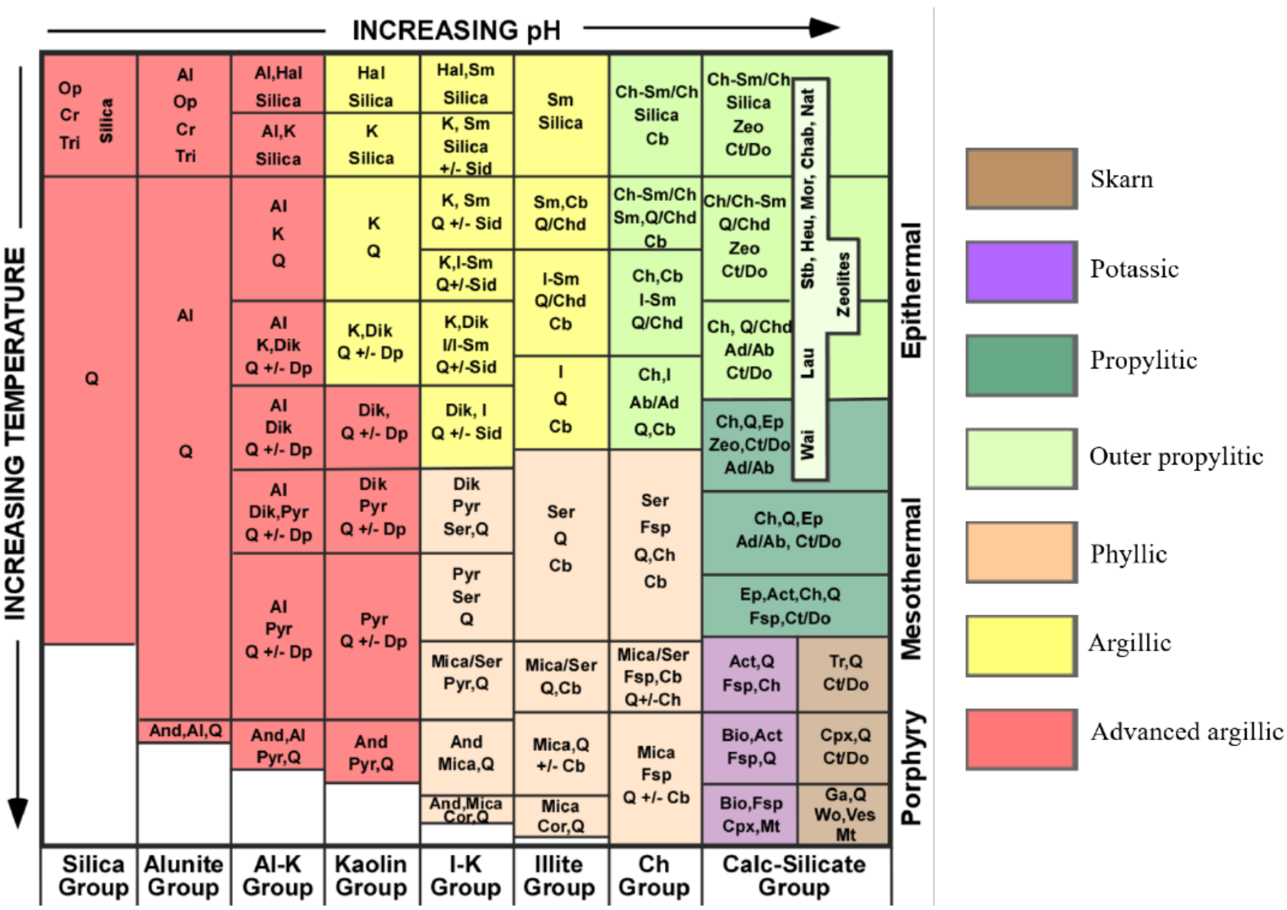


Figure 5: Common Alteration Mineralogy in Hydrothermal Systems, from (Corbett and T, 1998)

Mineral Abbreviations: Ab - albite; Act - actinolite; Ad - adularia; Al - alunite; And - andalusite; Cb - carbonate (Ca, Mg, Mn, Fe); Ch - chlorite; Chab - chabazite; Chd - chalcedony; Ch-Sm - chlorite-smectite; Cor - corundum; Cpx - clinopyroxene; Cr - cristobalite; Ct - calcite; Do - dolomite; Dik - dickite; Dp - diaspore; Ep - epidote; Fsp - feldspar; Ga - garnet; Hal - halloysite; Heu - heulandite; I - illite; I-Sm - illite-smectite; K - kaolin-ite; Lau - laumonite; Mt - magnetite; Mor - mordenite; Nat - natrolite; Op - opaline silica; Pyr - pyrophyllite; Q - quartz; Ser - sericite; Sid - siderite; Sm - smectite; Stb - stilbite; Tr - tremolite; Tri - tridymite; Ves - vesuvianite; Wai - wairakite; Wo - wollastonite; Zeo - zeolite

It is important to validate which minerals are compatible and which are not. Many hydrothermal alterations have transitional contacts, unlike lithology characterization. An important reference of hydrothermal alterations in porphyry ore body is (Sillitoe, 2010), that describes different hydrothermal alterations based on proportions of some minerals. In addition, alterations are zoned in the porphyry copper system, as show in Figure 6: sericitic alteration may project vertically downward as an annulus separating the potassic and propylitic zones as well as cutting the potassic zone centrally as shown. Sericitic alteration tends to be more abundant in porphyry Cu-Mo deposits, whereas chlorite-sericite alteration develops preferentially in porphyry Cu-Au deposits.

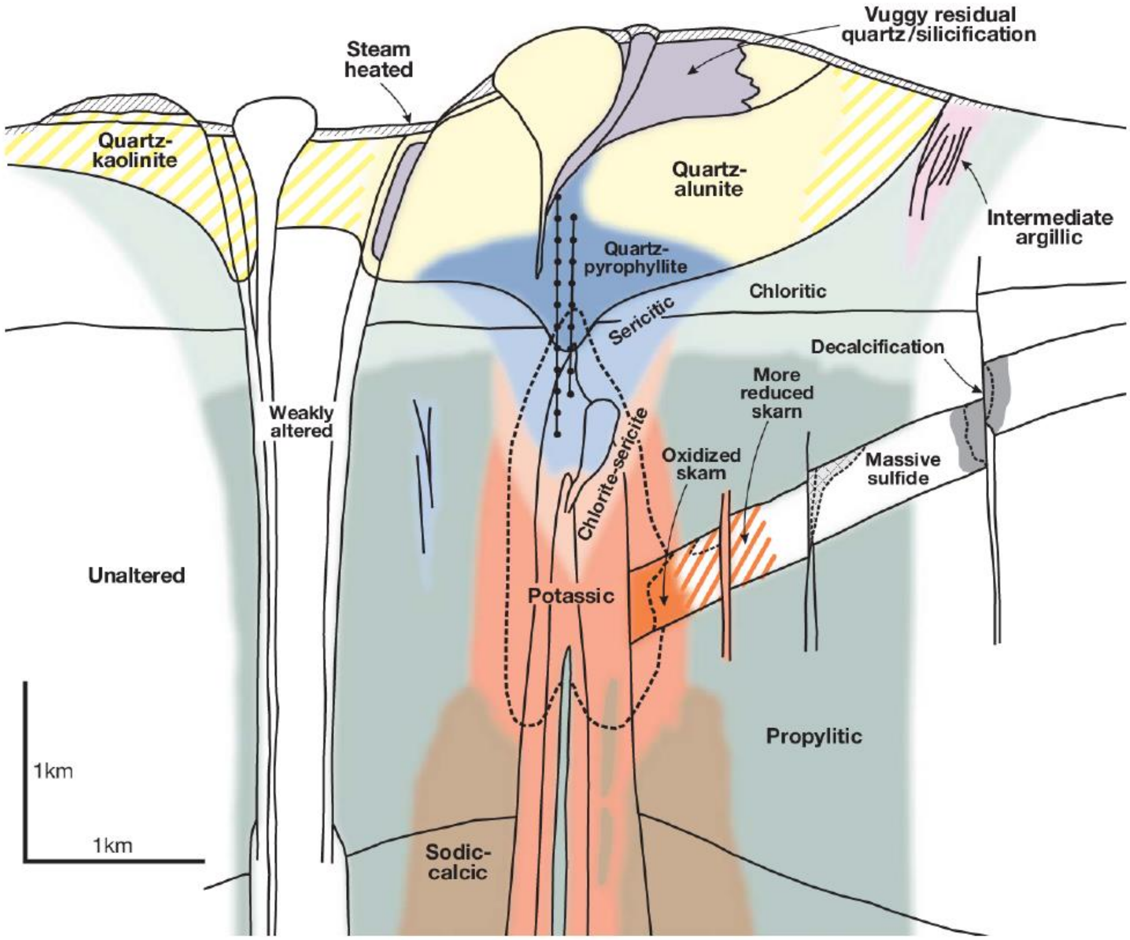


Figure 6: Generalized alteration-mineralization zoning pattern for telescoped porphyry copper deposits, from (Sillitoe, 2010)

From a geostatistical approach, validation of hydrothermal criteria are very important because much of the economical mineralization is concentrated in this stage. Some tools are provided to validate this criteria:

1. **Spatial context:** Usually alterations such as potassic, propylitic, chlorite, Sericite and Argillic are common in an hydrothermal alteration process, among others. Locations and contacts have radial anisotropy with respect to intrusive event (defined in lithological simulation). Figure 6 shows an example of the spatial distribution of some alterations.
2. **Statistical correlations:** Simulated minerals (that have coherence shown in Figure 5) are used to calculate the geochemical element proportions. For example, the molecular formula of mineral sericite is $KAl_2(AlSi_3O_{10})(OH)_2$ (Table 1). Geochemical grades are very important to validate if the elemental relationships are consistent with the hydrothermal alteration footprint. Figure 7 shows binary and ternary diagrams with relationships of elements for each hydrothermal alteration. In this case study, elements Al, Ca, Na, K and Mg are important to discriminate types of alteration: FRE (fresh rock) has high grade of Ca; ARG (argilic) has low grade of Ca and high Mg; K (potassic) has high grade of K and medium grade of Ca; SIL (sillica) has low concentration of Al and Ca; SIL ALT (sillica high degree alteration) has low grade of Ca and high of Al. These trends are transitional and it is difficult to define a hard boundary between the transitions zones.

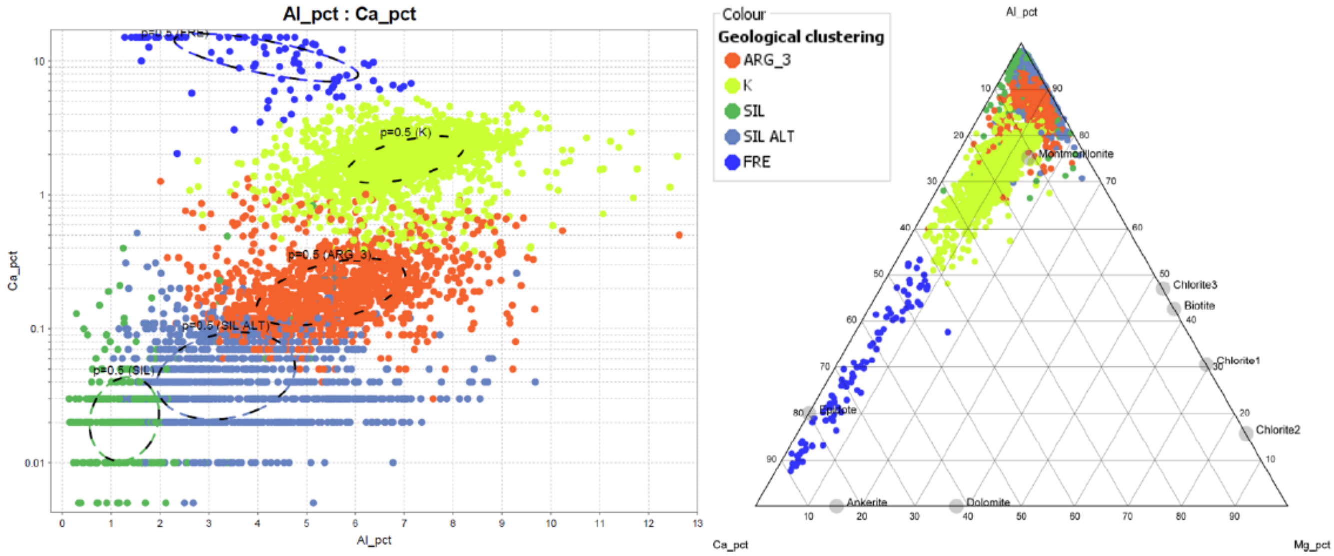


Figure 7: Geochemical grades relationship for each hydrothermal alteration and minerals.

The codes of alterations are FRE (fresh alteration), K (potassic), ARG (advanced argillic), SIL ALT (mainly silicification with argillic olverlap alteration) and SIL (fresh silicification alteration). In this context, diagrams show trends and clustering of alteration as a function of the relationship between Al - Ca - Mg ratios. In addition, FRE is characterized by epidote mineral and K for montmorillonite mineral. Chrolite, biotite, ankerite and dolomite are not present because of the lower magnesium concentration (see Table 1 for molecular formulas).

Table 1: Molecular formula

Name of mineral	Molecular formula
Sericite	$KAl_2(AlSi_3O_{10})(OH)_2$
Epidote	$Ca2FeAl_2Si_3O_{12}(OH)$
Montmorillonite	$0.66(0.5Ca, Na)Al_{3.34}Mg0.66Si_8O_{20}(OH)_4, nH_2O$
Chrolite	$Mg_5Al_2Si_3O_{10}(OH)_8$
Biotite	$KMg_{1.5}Fe_{1.5}AlSi_3O_{10}(OH)_2$
Ankerite	$Ca(Fe^{2+}, Mg, Mn)(CO_3)_2$
Dolomite	$CaMg(CO_3)_2$

In general, characteristic elements related to hydrothermal alteration are Al, Ca, Na, K, Mg, among others. A multivariate study is recommended to select the pathfinders that support the hydrothermal study (Davis and Sampson, 1986), (Webster et al., 1990) or generation of synthetics variables (Townley et al., 2018) (Yildirim et al., 2014). ioGAS software has implemented many diagrams to support the hydrothermal alteration classification based in geochemistry: (Large, 2001) (Williams and Davidson, 2004) (Warren et al., 2007) (Grunsky, 2013) (Whitbread and Moore, 2004) (Kishida and Kerrich, 1987) (Bruce, 2007) (Ishikawa et al., 1976) (Saeki and Date, 1980)

3.3. Mineral zone units

Mineral zones are interpreted as supergene metasomatism in the water-rock interaction. The meteoric water tickle through faults of geomechanical structures in an oxidizing environment, change the mineralogical compositions generating different mineral zones. These mineral zones affect directly the commodity minerals, and define the mineral processing (leaching, bio-leaching, selective flotation recovery or waste). These geological processes are known as supergene sulfide enrichment or secondary enrichment, and may take place by a simple mechanical process, by chemical means, or by a combination of these. First, the enrichment may be primarily the result of the chemical removal of a large part of the gangue minerals, in which case the copper migrates slowly downwards by gravity or is left behind as a residual component (Boyle, 1987).

Figure 8 shows a schematic view of a sulphide vein. It shows the oxidation zone, consisting of the gossan, the leached zone and the oxidised zone. The reducing zone consists of the enrichment zone and the area of primary mineralization (Asmus, 2013) (Paras et al., 2017) (Sillitoe and Mckee, 1996)

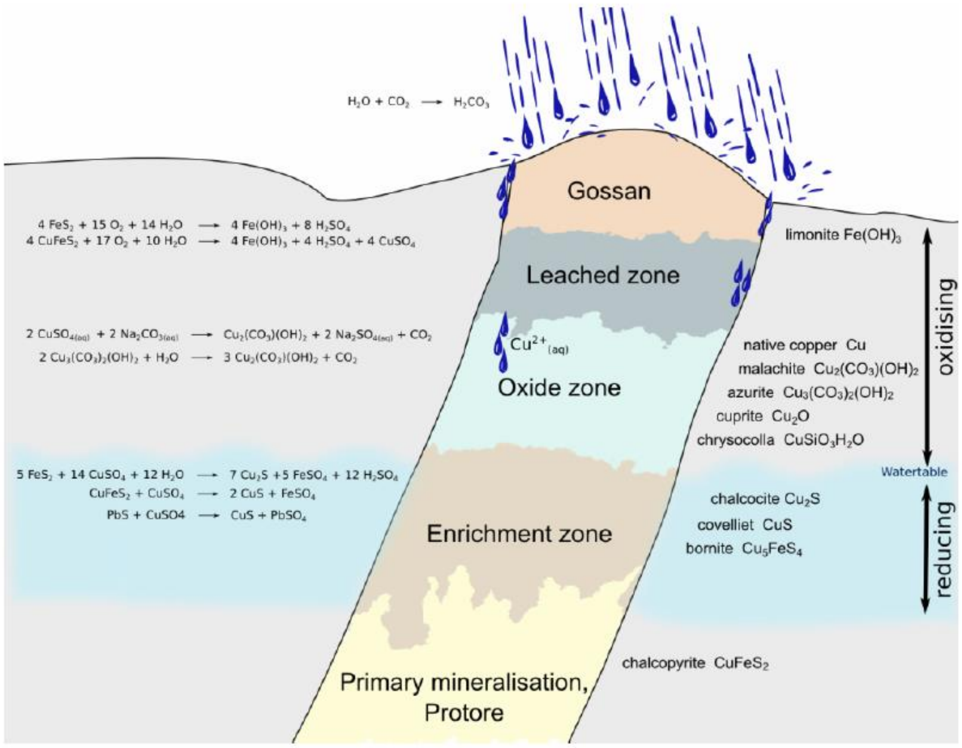
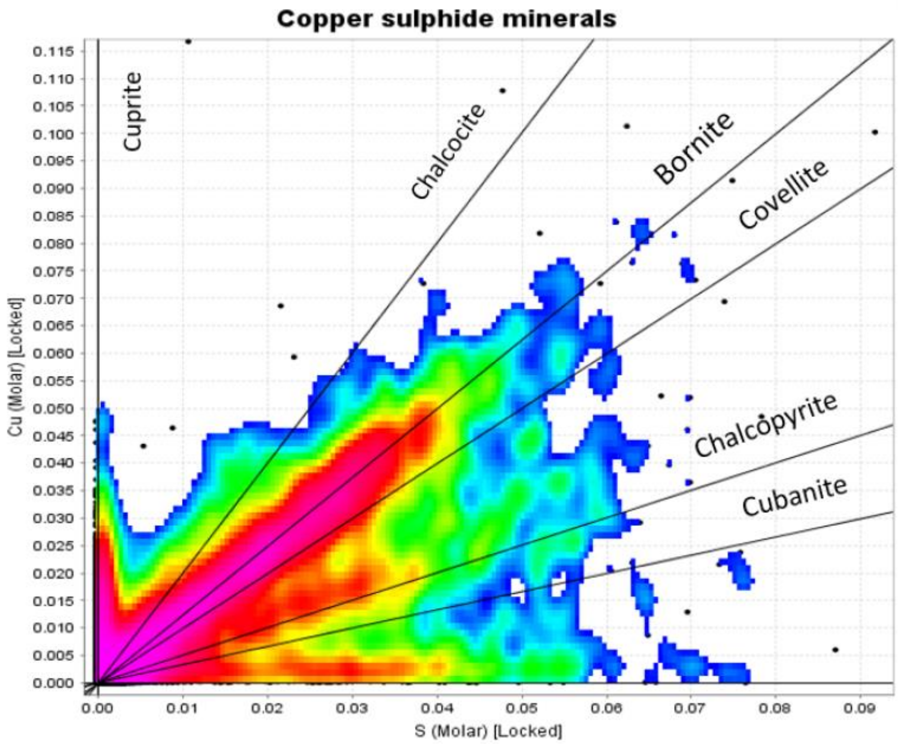


Figure 8: Schematic view of a sulphide vein. The oxidation zone can be seen, consisting of the gossan, the leached zone and the oxidised zone, modified from (Evans, 1992) and (Ottaway, 1994)

The mineral zone is related with the geometallurgical process. The main commodities must be consistent with the simulated region [for example Chilean Andes metallogenic belts are defined based in regional aspects (Sillitoe, 1981)]. From a geostatistical approach, tools are provided to validate some of these criteria:

1. **Spatial context:** Classical mineral zones are: gravel, leached, oxides, primary sulphur, secondary sulphur and host rock. In many cases, gravel, leached, oxides and secondary sulphur are presented as horizontal layers (tabular bodies, horizontal anisotropy with width of each body between $\approx$10 - 100 m) with irregular degree. Usually this order is preserved (Figure 8), but in few cases the secondary enrichment may be present in structural veins and faults (sub-vertical anisotropy).
2. **Mineral proportions:** The gravel lithofacies is usually not mineralized and is characterized by unconsolidated rock deposits. Leached lithofacies or gossan is characterized by low economic mineralization and a lot of iron minerals (goetite, jarosite, hematite, limonite, among others) (Bateman, 1950). The oxides lithofacies contains economical minerals (as cuprite, malachite, azurite, among others) that require leaching as process and is delimited from above by gossan lithofacies and from below by watertable. Secondary sulphur is the enrichment zone that may contain different proportions of minerals (chalcocite, covelliet, digenite, among others). This zone is the 'transition' to primary mineralization, then oxide minerals and sulphur minerals can both be found. Finally primary sulphur is characterized by mainly chalcopyrite and bornite. Others minerals as Tennantite are economic minerals too but with pollutants. All sulphur minerals are processed with selective flotation. Figure 9 shows the Cu:S geochemical rate and how it is correlated with mineral.



Copper minerals			
Mineral	Formula	molar Cu:S	Slope
Cuprite	CuO	1:0	inf
Chalcocite	Cu2S	2:1	2
Bornite	Cu5FeS4	5:4	1.25
Covellite	CuS	1:1	1
Chalcopyrite	CuFeS2	1:2	0.5
Cubanite	CuFe2S3	1:3	0.33

Figure 9: Copper minerals Cu:S rate and molar formula of each mineral.

To validate mineral proportion in each mineral zone the rate between economical metal and sulphur or oxide proportion are important (i.e CuT:CuS rate, total copper : soluble copper). A molar diagram for copper sulphide minerals shows different slope values that describes different copper sulphide minerals. These diagrams can be projected or corrected for the presence of barite, pyrite, galena, sphalerite, and arsenopyrite. In case of Iron ore, it uses SiO_2 and Fe data to assess mineralogical controls on iron ore grade. It is used to classify the various types of Fe ore based on Fe and clay content (Goethite, hematite, magnetite, etc) (Jeffcoate et al., 2013).

In the case study, three minerals zones are define based on CuT:CuS rate. Figure10 shows the difference between oxide zone, enrichment zone and primary mineralization.

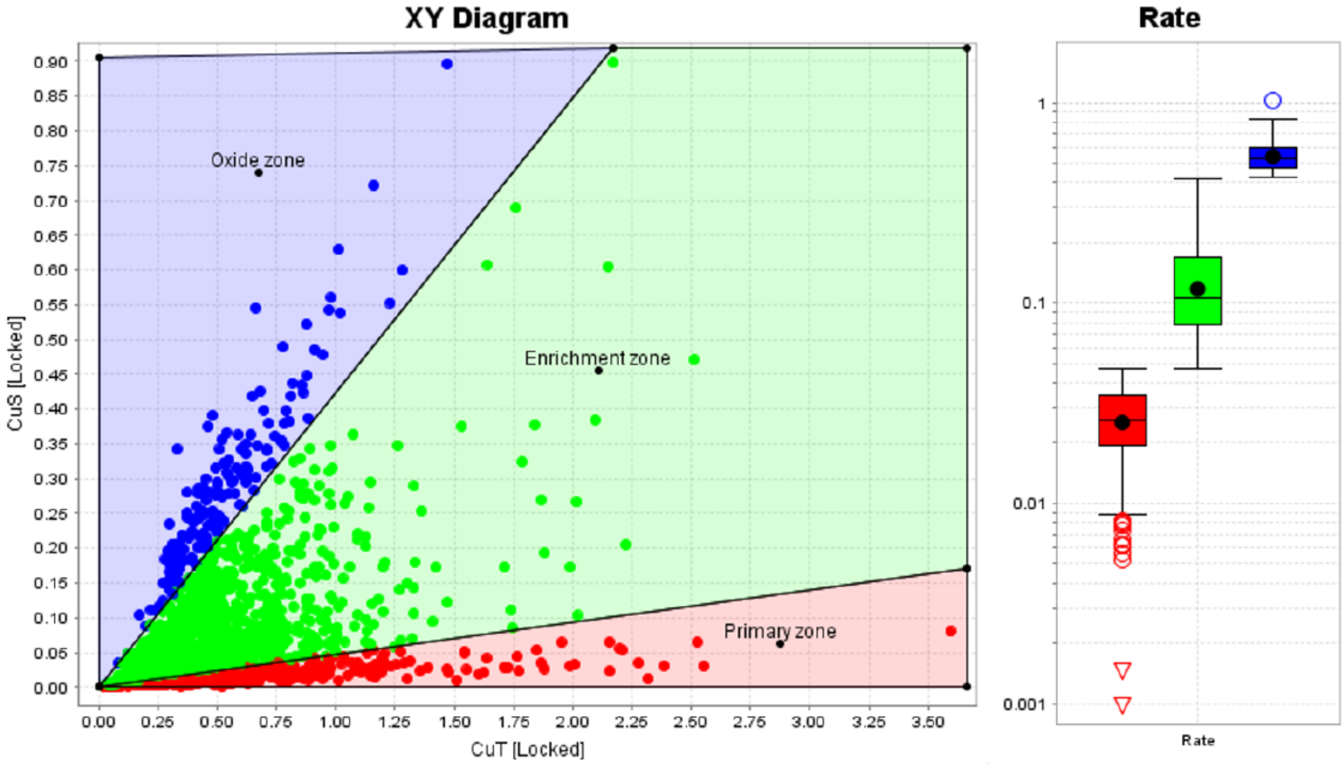


Figure 10: Mineral zone definition of oxide, enrichment and primary based on CuT:CuS rate.

This definition is important from a geometallurgical processing point of view: the oxide zone has minerals such as malachite, azurite, cuprite, chrysocolla, among others, than can be recovered by acid leaching; the enrichment zone has chalcocite, covelite, digenite, amongh others, than can be recovered by acid bio-leaching or generate blending / mixing programs to optimize the mineral processing; and primary zone has chalcopyrite mainly can be recovered by selective flotation of sulphur.

4. Conclusions

Many tools for geostatistical simulations are used to generate different geological scenarios. The aim of this article is to give some tools to validate these geostatistical scenarios from a geological approach. In conditional simulation, distributions and spatial variance can be validated, but these validations are not sufficient. To generate geological consistent simulations, we have recommended tools that can support the geological framework.

Correlations and spatial distribution are important for geologists. Mineralogical simulation in each geological unit can be performed, and geochemical grades can be calculated from molar formula. Many tools to validate the consistency of data using a geochemistry approach are provided, and ioGAS software have implemented these tools.

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ANEXOS

ANEXO GARRIDO ET AL. 2020B

To incorporate benefits into the mining value chain, for example the ore quality on mine planning, plant performance, lower costs, and product quality, key geometallurgical responses and proxy variables need to be incorporated into the mineral resources and miningreserve s estimation. The Canadian Institute of Mining, Metallurgy and Petroleum (CIM) Definition Standards on mineral resources and reserves establish definitions and guidance on the definitions for mineral resources, mineral reserves, and mining Project studies. In this research we show a case study that incorporate geometallurgical study in the mining project, and suggest of the good practices in the CIM Estimation of Mineral Resources and Mineral Reserves document about geometallurgy area. Key studies such as integrating the geometallurgical attributes to sampling and modelling, importance of mineralogical data interpretation, definition of geometallurgical units and importance of geochemical proxies in the geometallurgical modelling are highlight. Based in results, we suggest critical elements to estimate (based in geology characterization), use of nonlinear or multivariate estimation methods and the importance of relationship between geometallurgy and short-long term mine planning must be incorporated in the mineral resources and mineral reserves assessment.

Integrating geometallurgical best practices in CIM definition standards guidelines [1]

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Abstract

Key geometallurgical responses and proxy variables need to be incorporated into the mineral resources and mining reserves estimation, to improve the performance of mining projects. The Canadian Institute of Mining, Metallurgy and Petroleum (CIM) Definition Standards on mineral resources and reserves establishes guidance on the definitions of mineral resources, mineral reserves, and mining project studies. In this research we show a case study that incorporates a geometallurgical study in the mining project to demonstrate the impact of accounting for these variables, and we suggest good practices that could be added to the CIM Estimation of Mineral Resources and Mineral Reserves document about geometallurgy. Key studies such as integrating the geometallurgical attributes to sampling and modelling, the importance of mineralogical data interpretation, definition of geometallurgical units and the identification of geochemical proxies in the geometallurgical modelling are highlighted. Based on these results, we suggest critical elements to estimate (based in geology characterization), use of non-linear or multivariate estimation methods and the importance of relationship between geometallurgy and mine planning must be incorporated in the mineral resources and mineral reserves assessment.

1. Introduction

Geometallurgy has become an important field in mining engineering because of its benefits on the ore quality on mine planning, plant performance, lower costs, and product quality. To incorporate these benefits into the mining value chain, key metallurgical responses and proxy variables need to be accounted for in the block model, which is the main input to solve many optimization problems in mine planning (Ortiz et al., 2015) (Dominy et al., 2018). Many mining companies have a superintendence of geometallurgy, aimed at generating geometallurgical models to improve the mineral processing (guided with a sampling protocol, validation of dataset, data management, geological interpretations, geostatistics modelling and mine planning implementation). In this context, geometallurgy is considered an important task in the workflow of mineral resources and mineral reserve assessment. An important example is Antucoya Copper Oxide Mine, Region de Antofagasta, Chile (Avila et al., 2019) where geometallurgical studies showed that sulfate minerals with a high content of szomolnokite (hydrated iron sulfate) formed a gel that cements during the humidification, preventing irrigation and leaching of the heap. In this context, a blending program is implemented for the grade of szomolnokite to be diluted, to avoid compacting the heap, improving the performance in the leaching process. Geometallurgical practice improve the mineral processing performance, that can affect the costs and increase the heterogeneity of the product. An example is Mina Salobo in Maraba, Brazil (Sousa et al., 2019) that shows a high variability in metallurgical recovery of copper (average 82.47% +/- 14%). The application of a geometallurgy program, showed early results where the trend of metallurgical

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recovery of copper changes significantly (average 86.76% +/- 4%). Geometallurgical studies integrating data that is already available (e.g. textures, mineralogy, hardness, geophysics, geochemistry, among others) can significantly improve the planning and reduce the variability in performance during operations. It is therefore cheap (no additional cost) to account for information already available.

The Canadian Institute of Mining, Metallurgy and Petroleum (CIM) Definition Standards on mineral resources and reserves establishes guidance on the definitions of mineral resources, mineral reserves, and mining studies. The Mineral Resources, Mineral Reserve, and Mining study definitions are incorporated, by reference, into National Instrument 43-101 – Standards of Disclosure for Mineral Projects (NI 43-101). This document is intended as general guidance to assist professional geoscientists (or equivalent) and engineers (or equivalent) in preparing high quality estimates of mineral resources and mining reserves that incorporate sound geoscientific, engineering, evaluation, and design practices. They are based on well-established estimation and mine planning principles and are designed to provide general guidelines of best professional practices employed in the preparation of mineral resources and mining reserves estimates. (CIM MRMR BP 2019) The goal of this research is to improve best practices by identifying paragraphs in the "CIM Estimation of Minerals Resources and Mineral Reserves Best Practice Guidelines" document (published in mrmr.cim.org v2019) where geometallurgical best practices can complement the conventional definition of mineral resources and mining reserves. The aim is to demonstrate the importance of geometallurgical information and models in the development of mining project, particularly for metals. This will be supported through industry case studies already published in the literature.

2. Geometallurgical variables and modelling

2.1. Attributes for sampling and modelling

In general, some common geometallurgical variables that require different definitions are:

- **High Definition Mineralogy:** in this approach, grade of minerals (ore and gangue) are more important than geological code (for example lithology, alteration, mineral zone, structural zone). Understanding key minerals and distributions can support the geometallurgical models. Assays such as XRD or QEMScan are common in the mining industry, and combination of different techniques, e.g. modal mineralogy using geochemistry samples (analytic methods ICP, XRF, ASS, among others) and model calibrations using XRD or QEMScan data. In this context, grain size, degree of liberation and associations of minerals may be included.

- **Grindability:** Bond Work Index for ball mill (BWi) test determines the hardness of the rock (it is a proxy to estimate the throughput in mineral processing). The Work Index is used when determining the size of the mill and grinding power required to produce the required ore throughput in a ball mill (Bond, 1961). Simulations and modeling of this test show that factors as Particle Size, feed, % passing, makeup water, etc. are operational factors difficult to standardized (Tavares and Kallemback, 2013), and changes in these factors are critical in results. SAG Power Index (SPI) or Starkey Test for SAG mill: provides the time (minutes) required to perform a specific milling work, from a feed size to an output size. SAG Mill Comminution (SMC) is another test, grindability is a function of the specific energy applied and the percentage of product generated in the impact fracture of a specific particle size.

- **Leaching test:** aqua regia digestion or multi-acid (4-acid) digestions, are very effective dissolution procedures for multi-element analysis at trace levels of detection. However, there can be a loss of volatile elements (e.g. B, As, Pb, Ge, Sb) during these types of digestion and some refractory minerals (especially oxide minerals) are only partially digested. Other attributes are important in this test, for example soluble grade key elements, net acid consumption by tonnage processing and permeability.

- **Kinetics of Rougher Flotation:** maximum recovery with prolonged flotation time or "infinity", mineral characterization, and geochemistry (feed or concentrate) in a flotation process, etc. (SGS, 2007)

- Others: for example pollutant grades, rheological behavior, sedimentation, specific gravity, density, etc.

In case of high definition mineralogy grade, this is the most important to understand the geometallurgical behavior in mineral processing. Many case studies are known and published related with the mineral characterization in the geometallurgical studies. A case study of a porphyry copper deposits in Peru, Cerro Corona, in Cajamarca region is presented as an example a fully geometallurgical study.

2.2. Case study: mineralogical predictions

In the case study, we show an application of mineralogical information to define GMUs (Geo Metallurgical Units). Cerro Corona is a mining operation that is located in Cajamarca, Peru (1), it is a Cu / Au porphyry deposit hosted in diorite (14.4 to 13.35 million years) that intrudes the calcareous phase (yumahual-cretaceous). It has been operated by Gold Fields Limited since 2004, it has mineral reserves of 767 Mlb copper and 1.9 Moz gold.

Figure 1: Cerro Corona mine location.

A dataset of XRD (quantitative X ray diffraction ray X) and QEMScan (semi-quantitative evaluation of materials by scanning electron microscopy) are available. Characteristics of these tests are expensive and take time to obtain results. To implement geometallurgical models in short term mine planning, we use the IR (infra-red wavelet measurement) to predict mineralogical grades, calibrating the model with XRD and QEMScan values. Using Machine Learning algorithms (Random Forest regression) we identify the range of the IR curve that may predict the grade of different minerals. Figure 2 shows the spectrum of one sample (blue curve) and range of importance that is correlated with the KFeld grade estimation (gray curve).

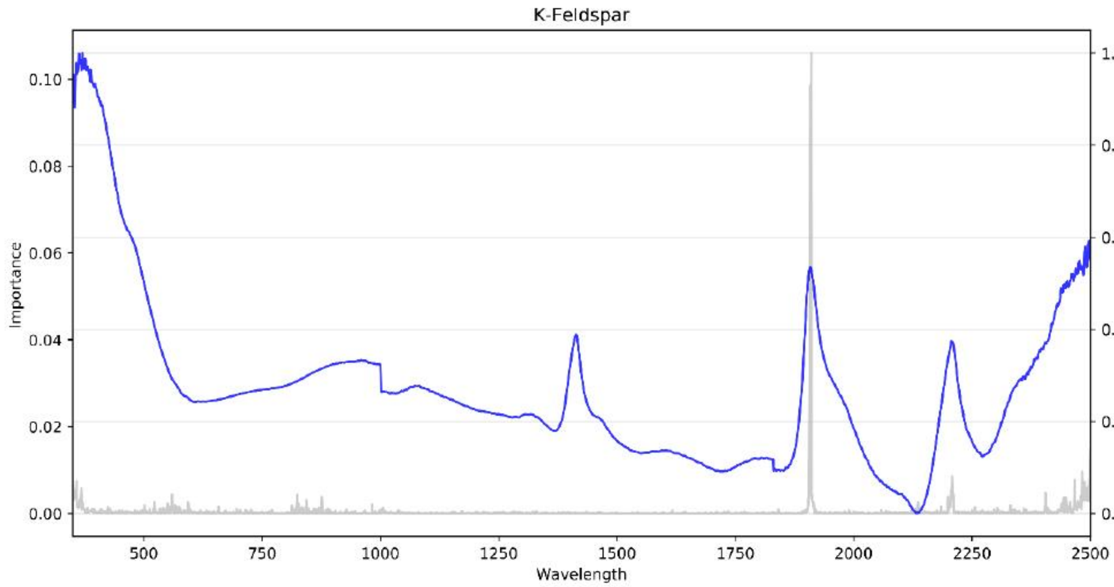


Figure 2: Standardized spectrum of one sample (blue curve) and range of importance that is correlated with the KFeld grade estimation (lead curve), algorithm Random Forest Regression.

That model to predict KFeld was calibrated with QEMScan dataset, and used to predict the KFeld in XRD dataset. Figure 3 shows the cross validation between KFeld predicted and KFeld measurement with XRD.

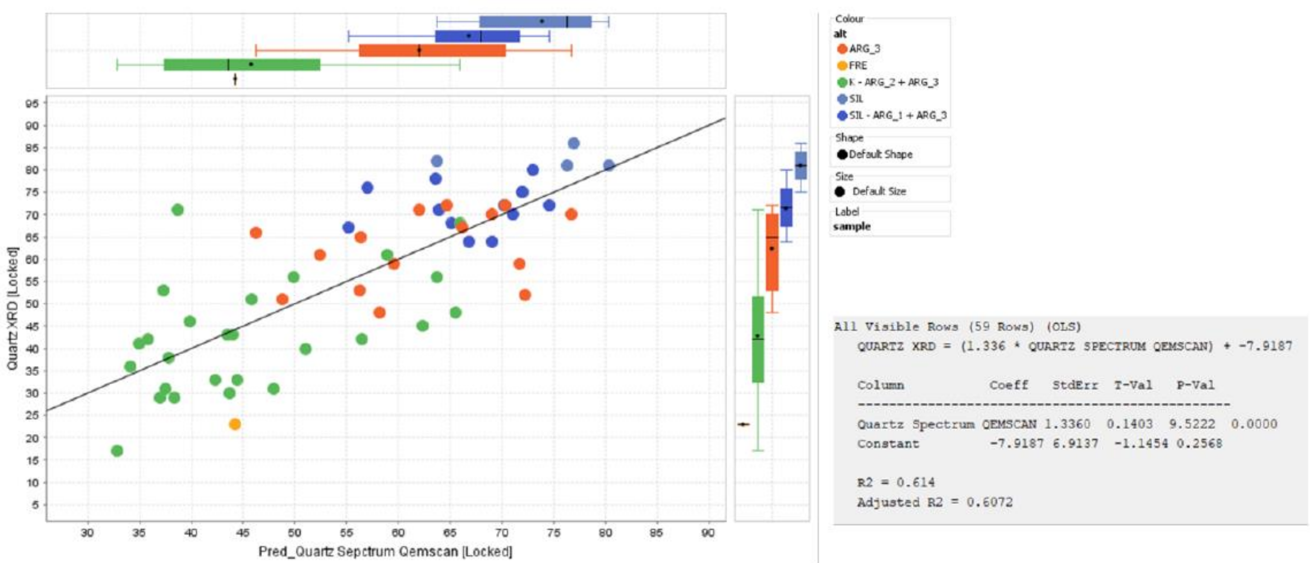


Figure 3: Cross validation between KFeld predicted with IR curve and KFeld measurement with XRD.

This calibration is performed for all minerals that are identify as key variables to predict geometallurgical attributes. The advantage of this methodology is the speed of measurement of KFeld grade, as it may take only few minutes and portable IR measurement are available in the commercial market.

2.3. Case study: definition GMUs

In this application, work index was modeled based on mineralogy to define GMUs and geochemistry as a secondary variable for multivariate estimation. A study based on geological logging and behavior of mineral processing, show that hydrothermal alteration is a good preliminary proxy to define GMUs. It is proposed to define the hydrothermal alterations based on a corresponding nomenclature with the mineral associations composition of major minerals for each type of alteration, common in porphyry copper deposits, from the mineral characterization by predominant QEMScan mineralogy of each one. These are presented in their probable paragenetic order, from earliest to latest.

- Potassium alteration – K: This corresponds to the earliest and highest temperature alteration, characterized by the association feldspar-K, albite, biotite / muscovite (sericite / illite), quartz, with accessory minerals pyrite, calcite, montmorillonite, magnetite, chlorite and chalcopyrite (Figure 4).
- Quartz-Sericite / Sericite-Chlorite alteration – QS: The quartz-sericite and / or sericite-chlorite alteration corresponds to a hydrolytic alteration superimposed with medium intensity on the earliest potassium alteration. The mineral association is composed mainly of quartz, micas (sericite) and feldspar-K, and accessories goethite-limonite, pyrite, albite, and montmorillonite.
- Quartz-sericite-clay alteration - QSCC: Alteration majority association of quartz, micas (sericite-illite), microcrystalline pyrite, reflects a process of hydrolytic alteration of increasing intensity compared to the QS alteration, alteration that overlaps and destroys previous K and QS alterations, as evidenced by the occurrence of remaining K-feldspar.
- Advanced argillic alteration – AA: The advanced argillic alteration, characterized mainly by quartz, reflects the state of greatest intensity of hydrolytic alterations, with pyrite mineralization, and mineral residuals from pre-existing alterations, such as feldspar-K and micas, and a diversity of accessory minerals.

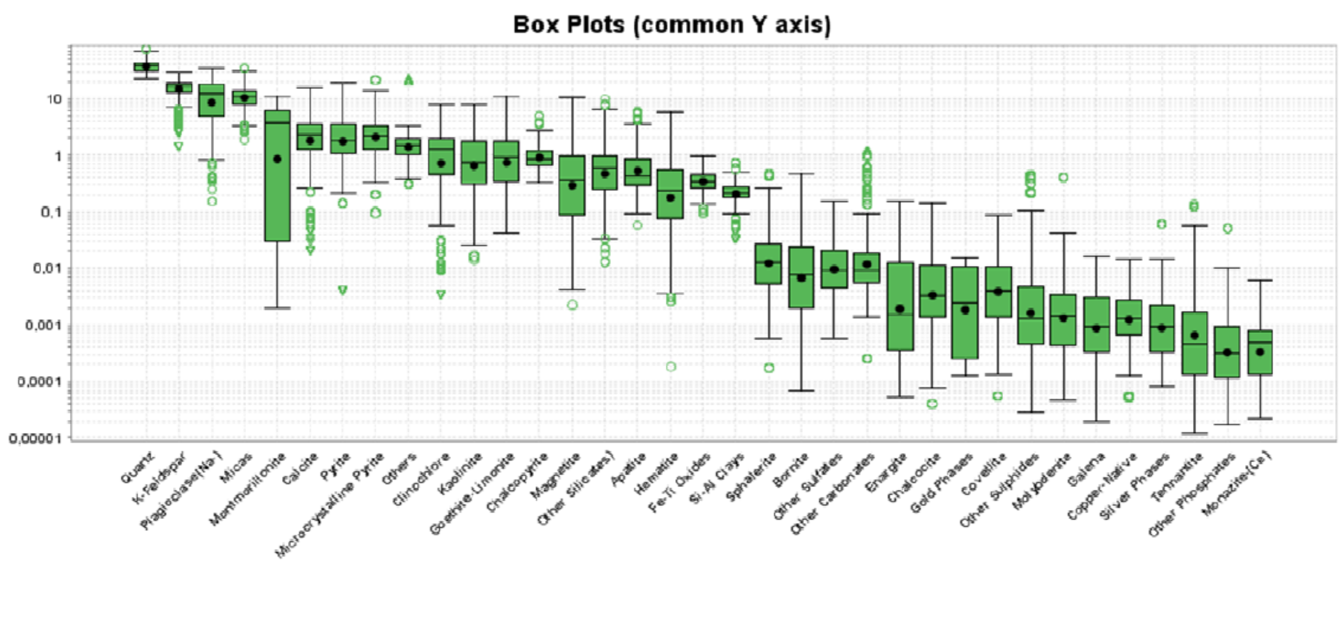


Figure 4: Modal proportion of mineral associations for potassium alteration K.

The mineralogical information is important to define the GMUs based on geological variability and trends. These GMUs can be modeled in space, generating solids with volume / tonnage that characterize the geometallurgical attribute (Figure 5). This model was validated from a statistical, geological and spatial standpoints.

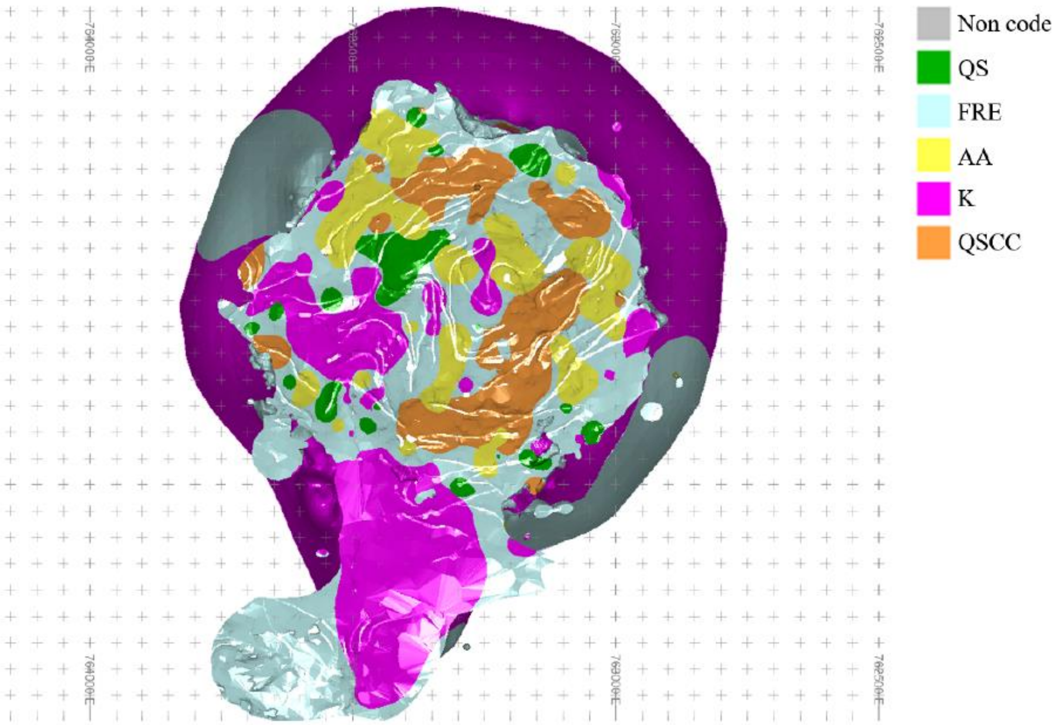


Figure 5: Modelling of geometallurgical units, plant view.

2.4. Case study: geochemical proxies

The available information must be formatted for processing by the different modeling methods. This apparently trivial task may consume a significant amount of time, so it should not be minimized. The main objective is to prepare the database for the application of conventional statistics / geostatistical tools. This requires that every piece of information must be attached to spatial coordinates. This allows the calculation of spatial correlations, and also the cross correlations between variables, which are necessary for the application of estimation and simulation techniques (Isaaks and Srivastava, 1989) (Goovaerts, 1997) (Deutsch and Journel, 1998). Figure 6 shows plots of variation of the concentrations of the elements Al, Ca, K, Mg and Na as a function of Work Index, and discriminated according to the type of hydrothermal alteration, based on their geochemical classification. Although there are overlaps between the variations of Work Indexand concentrations of these major elements according to the lithofacies of hydrothermal alteration, the trend of higher values of this parameter in potassium alteration, to lower values in advanced argillic alteration is clear.

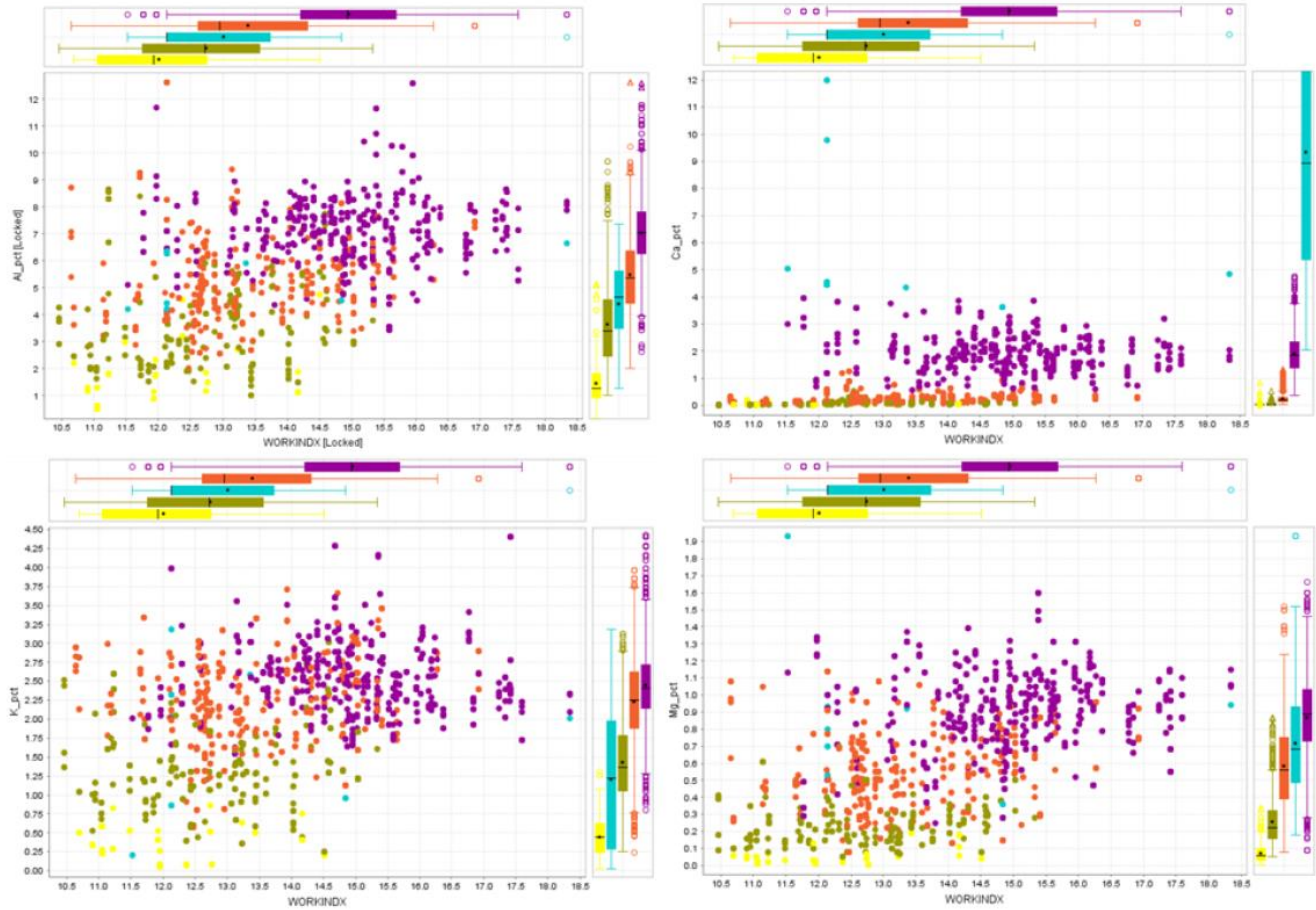


Figure 6: Plots of variation of the concentrations of the elements Al, Ca, K, Mg and Na according to WORKINDEX, determined according to the type of alteration based on geochemical classification. Legend: FRE = fresh rock; Alterations: K = potassium; QS = quartz-sericite / sericite-chlorite; QSCC = quartz-sericite-clays; AA = advanced argillic.

2.5. Case study: geometallurgical modelling

In the case study, the traditional kriging approach does not have goods performance, because the density of information for Work Index was not enough to create a robust block model prediction. Figure 7 summarizes the methodology of cross validation to select the best estimation tool to populate the block model.

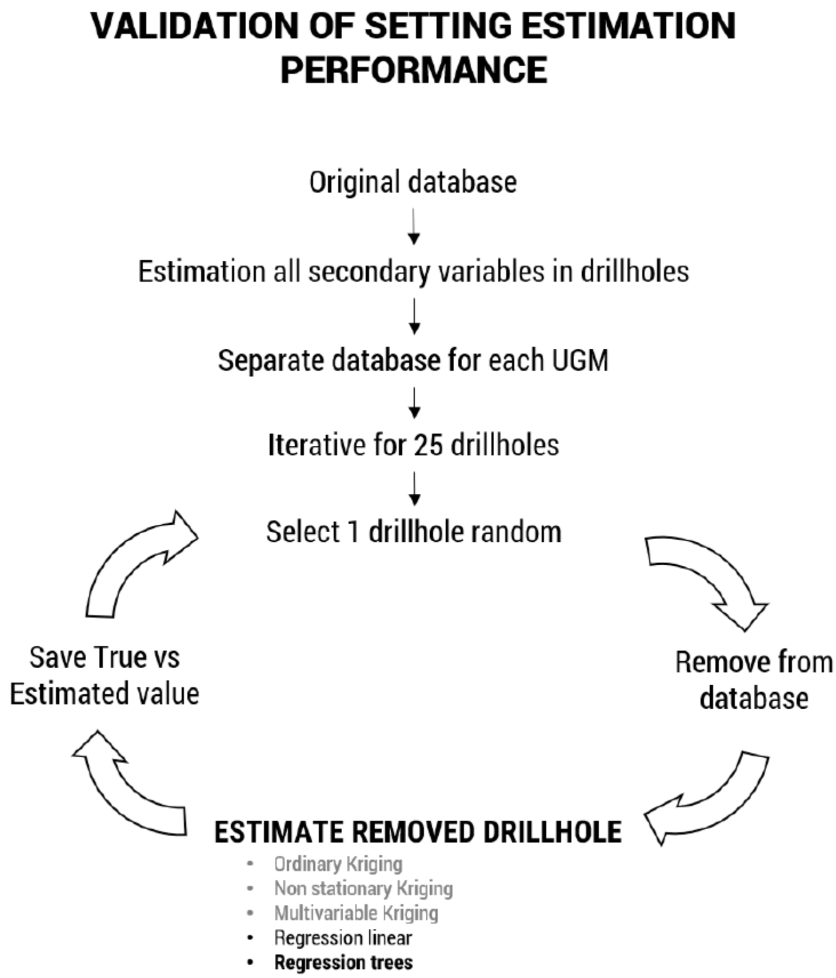


Figure 7: Cross validation methodology must be clear and reproducible to choose best estimator.

The cross validation was performed to select the best estimator in the case study based on linear correlation between true / estimated value, using Ordinary Kriging (ρ=0.36), Cokriging (ρ=0.41), Multivariate linear regression (ρ=0.79) and regression Random Forest (ρ=0.81). Figure 8 presents a workflow diagram showing the recommended methodology for estimating the geometallurgical block model. To estimate the comminution geometallurgical parameter, it is necessary to first estimate the total rock geochemistry in space. This estimation can be made; (1) considering a single domain (without separating estimation units, not recommended) thus generating soft limits, (2) considering different domains (GMUs) generating hard limits or, (3) by means of indicator kriging by domains to generate probabilistic limits. In this case, the geostatistical estimation of geochemistry was performed by domains using ordinary kriging. Once the geochemistry has been estimated, the geometallurgical variable Work Index is calculated using linear multivariate regression based only on geochemistry data.

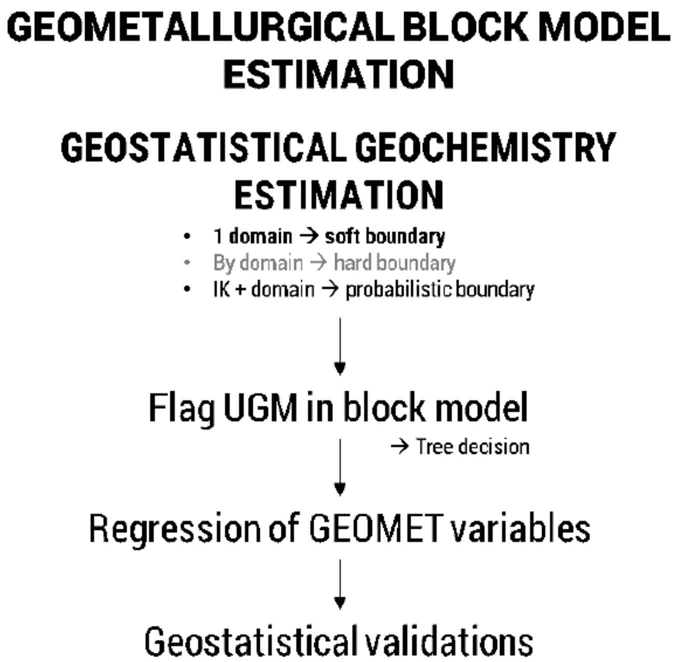


Figure 8: Recommended methodology for estimating the geometallurgical block model.

Ordinary kriging estimation was used to populate the geochemical attributes for all blocks. For each block, the linear equations were applied to calculate Work Index. Figure 9 shows a cross-sectional view (left) and a plan view (right) at elevation 3805 m.

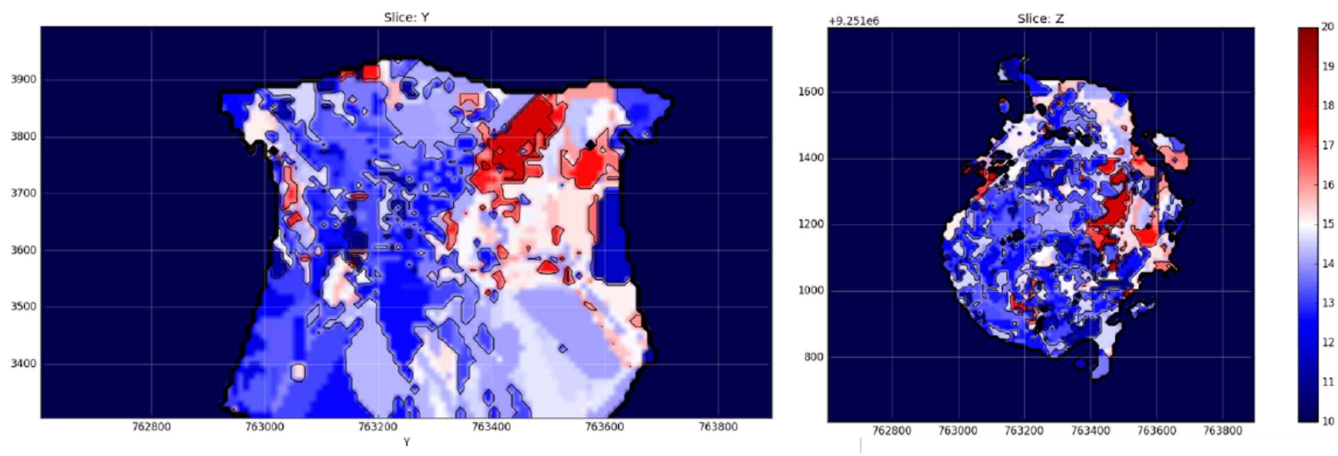


Figure 9: Estimated block model for the Work Index variable. View in cross section (left) and in plan (right). The highest values are in red and the lowest in blue.

3. Geometallurgy on CIM Estimation of Mineral Resources and Mineral Reserves

This section enumerates some paragraphs to propose good practices in the CIM Estimation of Mineral Resources and Mineral Reserves document about geometallurgy.

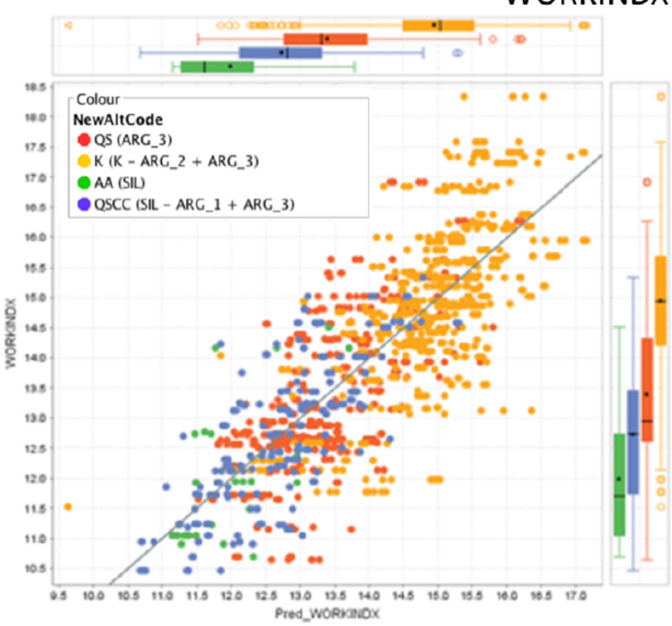
3.1. Suggestion 1: Critical elements to estimate (based in geological characterization)

Page 16 (line 17), section Mineral Resource Estimation, Introduction:

Critical elements to a Mineral Resource estimate are:

- consideration of the appropriate geological interpretation,
- assumed mining method and mining rate,
- assumed mineral processing method and recoveries, and
- the application of reasonably developed economic parameters based on generally accepted industry practice, experience, and understanding based on deposit location, shape, and available testwork of rock characteristics, product recoverability and value.

In this section, the document specifies 'critical elements to a Mineral Resource estimate are assumed mineral processing method and recoveries' but it is not clear which geometallurgical attributes, methodologies and the sources of information. We recommend using multivariate geostatistics, using geological information as input to model (e.g. logging, mineralogical, geochemical, geophysics, among others). For example in the case study shown in the previous section, the use of geochemical variables supports the estimation of Work Index. The mineralogical data was used to validate the definition of GMUs based on geological logging and geochemical grades, and the block model estimation was performed with multivariate linear regression. Figure 10 shows the cross validation and equation to calculate Work Index.



WORKINDX = (0.3786 * AG_PPM) + (-0.1553 * AL_PCT) + (-0.001801 * AS_PPM) + (-7.4813E-4 * BA_PPM) + (0.7821 * BE_PPM) + (-0.01732 * BI_PPM) + (0.3986 * CA_PCT) + (-0.05719 * CD_PPM) + (0.02691 * CO_PPM) + (9.155E-4 * CR_PPM) + (-0.3603 * CU_PCT) + (-0.1206 * FE_PCT) + (-0.003554 * GA_PPM) + (0.1338 * K_PCT) + (-0.03566 * LA_PPM) + (0.02738 * LI_PPM) + (1.2491 * MG_PCT) + (5.1287E-4 * MN_PPM) + (-9.1102E-4 * MO_PPM) + (2.604 * NA_PCT) + (-0.06083 * NB_PPM) + (0.02288 * NI_PPM) + (5.4861E-4 * P_PPM) + (0.002567 * PB_PPM) + (0.01073 * S_PCT) + (0.006196 * SB_PPM) + (0.1692 * SC_PPM) + (0.004008 * SR_PPM) + (-7.9119 * TI_PCT) + (0.01703 * V_PPM) + (-0.07155 * W_PPM) + (-0.251 * Y_PPM) + (-5.6452E-4 * ZN_PPM) + (-0.008661 * ZR_PPM) + (-0.2809 * AU_PPM) + 13.0801

Figure 10: Cross validation in estimation of WORKINDX using geochemistry variables.

3.2. Suggestion 2: Use of non-linear estimation methods or multivariate

Page 21 (line 22) section Mineral Resource Estimation, Mineral Resource Block model:

appropriate estimation method(s) or techniques for the resource model. Estimation methods include polygonal, nearest neighbour, inverse distance to a power, various kriging approaches (e.g. ordinary kriging, simple kriging, and multiple indicator kriging), conditional simulation, and other non- linear estimation methods. The choice of method(s) should be based on the geology, the attribute/variable being modelled, quantity and spatial distribution of data, complexity of grade distribution within the deposit, presence of high-grade outliers, results of reconciliation studies for projects with production histories, and the anticipated end use of the Mineral Resource block model.

In this section, the document specifies 'The Practitioners must select appropriate estimation method(s) or techniques for the resource model'. In the geometallurgical block model estimation, it is important to highlight the multivariate tools, for example the multiple linear regression. To support geometallurgical modelling, multivariate geostatistical techniques are recommended (Wackernagel, 2003). Geometallurgical samples are usually scarce and expensive, then the support of secondary variables or proxies (geochemistry as ICP, geophysical as Natural Gamma, structural information as UCS, etc.) are recommended to obtain more robust models (Garrido et al., 2020). Multi-element geochemistry can provide bulk mineral characterization of hydrothermal alteration associations to support predictive geometallurgical modeling in Porphyry copper deposits (Townley et al., 2018). The use of synthetic variables (mathematical combination of secondary variables that have good correlation with primary variable) are highly recommended to obtain robust models with acceptable time and effort of users (Baeza et al., 2018). One critical aspect of predicting response geometallurgical variables is that they are usually nonadditive (the response of block is not necessarily the average of the response of the discretization of the block), and traditional linear methods, such as Kriging, will not work well on such non-linearities. The use of non-linear regression models may alleviate this where additive proxies are used to predict non-additive responses (Sepulveda et al., 2017). Using geostatistical simulations, if they exhibit spatial correlation, is also a valid approach. In this stage, geometallurgical variables are estimated in space (Bilal, 2017), (Deutsch et al., 2015) (Deutsch, 2016) (Boisvert et al., 2013) (Coward and Dowd, 2015) but the mining scheduling and mineral processing values depend on the time (costs by tonnage processed, efficiency, recovery, tonnage per day, etc.) For example, to estimate geometallurgical variables in a block model (Deutsch et al., 2015) usually the geostatistician or orebody modeler estimates the georeferenced variables in space (corregionalized variable).

3.3. Suggestion 3: Relationship of geometallurgy and mine planning

Page 45 (line 46) section Mineral Processing, Development Stage Properties:

Mineral processing recovery, design and cost requirements in support of the preparation of Mineral Reserve statements for development-stage projects should include test work on samples of mineralized material and waste material that might be incorporated in the feed to the process plant. Test work can be performed on one or more master composites selected and prepared so as to represent the material that is expected to be delivered to the process plant. The testing objectives are to determine the optimal processing selection, the nature of the variability within the deposit, metal or mineral recovery level to a saleable product(s), mineral hardness and abrasion values, and required consumables such as reagents to achieve the predicted recovery. In the course of such testing, the handling or treatment for deleterious elements should be determined and samples for tailings disposal design will be generated.

In this context, the nature of the variability within the deposit conditions the geometallurgical factors to determine the optimal processing selection. The metallurgical performance may change with the mixing of material, then mine planning should be considered in this paragraph. In short term mine planning, the correct incorporation of geometallurgical factors can decrease operational cost (real time capacity response, mineral characterization, correlations, mixing blending, among others), in long term mine planning accounting for geometallurgical constraints can improve the NPV avoiding bias and decreasing uncertainty. In this context, the Table below shows many consequences of considering geometallurgical models in mining planning.

Table: comparison between plan with/out consider GMM model

Source	Plan with GMM	Plan without GMM
Uncertainty	High quality model	Bias VPN
SAG Mill	Cost of blending	Bottleneck problem: non-compliance
SAG Mill	Cost of blending	Increase size mill output
Recovery	Optimal recovery and grade concentrate	Low recovery and grade concentrate
Recovery	Cost of blending: Homogeneity	Lost value conditioning time

The Table shows how geometallurgical models may affect the NPVand mineral resources assessment. In this context, geological knowledge can be included in the estimation of metallurgical attributes. If estimation of geometallurgical attributes is not of good quality, mine plans will have high uncertainty (maybe bias) and the scheduling in long term will define the NPV, affect the value of the project.

In Cerro Corona case study, the long-term geometallurgical model is based on modified equations and has been used for long-term planning. High quality proxy variables were used to estimate geometallurgical attributes in long term. For example, semi-quantitative analysis may have less precision than quantitative analysis (perhaps suitable for short-term planning models). In the long-term case, geological proxies were geochemical attributes, because these samples are validated through a good sampling protocol and have reasonable quality accuracy and quality control. The models were reconciled between short / long term with good results. The conciliation is similar to mineral resources, measurements of long / short term are compared in a reasonable time frame.

4. Conclusions

The aim of the paper is to show good practices in the estimation of geometallurgical attributes considering CIM standards, for which the key points were highlighted. The importance of including geology in estimating geometallurgical attributes was discussed: estimation of these attributes requires secondary information due to the small dataset size for of information for these tests, which requires the use of secondary information with high sampling density (logging, geochemistry, model mineralogy, geophysics, etc.) The use of geological data can help from an interpretative point of view (to generate GMUs for example) or quantitatively (support of secondary variables for the co-estimation of geometallurgical attributes). In the eventual case of use as a secondary variable, the accuracy of the geological data and its representativeness in terms of QAQC sampling protocols must ensure an estimation error that is within the temporal scope of mine planning.

Mine planning is known to define NPV and long-term scheduling. Geometallurgical models affect the NPV and the evaluation of mineral resources and mining reserves: if the geometallurgical models are not considered in the planning of the mine, the real economic benefit decreases, which can generate a bias in the estimation of the value of the project (plus additional uncertainty). The best practice according to CIM must consider geometallurgical variables in the estimation of mineral resources and mining reserves, which have been described in this article.

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ANEXOS

ANEXO GARRIDO ET AL. 2017A

Modeling of geological attributes is a fundamental step in the mining process where quality resources are defined for mining and metallurgical processing. The metallurgical recovery of sulphide minerals in the flotation stage is a variable that depends not only on geological attributes such as ore type, alteration, etc., it also depends on operational parameters such as pH, quantity and quality of chemicals such as thickeners and collectors, residence time, granulometry, etc. These factors make modeling difficult, since the recovery might depend on factors external to geology. In this research we studied multivariable correlations that allow prediction of metallurgical recovery (Rec30 - percentage recovery of the ore after 30 minutes of flotation) through multivariate geostatistics: for this purpose an estimation of the recovery using co-kriging was performed taking into account variables that have high correlations.

In this case study a high correlation between iron grades and recovery in potassium-rich alterations was found, which is attributed mainly to the amount of pyrite that makes the process difficult. Additionally, the incorporation of co-kriging allows increasing the estimated tonnage, when there is little information about the primary variable (but not the secondary variable). The advantage of using classical geostatistics is that recovery models can be obtained with good results in terms of cross-validation (good prediction), which overcomes the problem of non-additivity in the case of the generation of a block model for geometallurgical variables. In addition, the advantage of using co-kriging is that the information of this secondary variable is much denser, hence provides improved model resolution. The metallurgical recovery samples are usually expensive and few, the incorporation of secondary well correlated variable then generate a more robust and reliable recovery model.

Multivariate Geometallurgical Modeling in Potassium Alterations for Sulphide minerals

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ABSTRACT

Modeling of geological attributes is a fundamental step in the mining process where quality resources are defined for mining and metallurgical processing. The metallurgical recovery of sulphide minerals in the flotation stage is a variable that depends not only on geological attributes such as ore type, alteration, etc., it also depends on operational parameters such as pH, quantity, and quality of chemicals such as thickeners and collectors, residence time, granulometry, etc. These factors make modeling difficult since the recovery might depend on factors external to geology.

In this research we studied multivariable correlations that allow prediction of metallurgical recovery (Rec30 - percentage recovery of the ore after 30 minutes of flotation) through multivariate geostatistics: for this purpose, an estimation of the recovery using co-kriging was performed considering variables that have high correlations. In this case study a high correlation between iron grades and recovery in potassium-rich alterations was found, which is attributed mainly to the amount of pyrite that makes the process difficult. Additionally, the incorporation of co-kriging allows increasing the estimated tonnage when there is little information about the primary variable (but not the secondary variable).

The advantage of using classical geostatistics is that recovery models can be obtained with good results in terms of cross-validation (good prediction), which overcomes the problem of non-additivity in the case of the generation of a block model for geometallurgical variables. In addition, the advantage of using co-kriging is that the information of this secondary variable is much denser, hence provides improved model resolution. The metallurgical recovery samples are usually expensive and few, the incorporation of secondary well correlated variable then generate a more robust and reliable recovery model.

INTRODUCTION

Modeling of geometallurgical variables has become a fundamental step in the evaluation of mining project [Brissete, 2014], [Lund, 2015]. In this context 2 different modeling approaches are considered: The former consists of adding geometallurgical parameters without scaling to the block model (SPI, BWi, Recovery, kinetic process factors, acid consumption, sedimentation rate, etc.). The latter consists of generating process models for industry scaling, in which laboratory and pilot plant tests are considered using statistical data from operation. Sampling data from plant is also used [Lamberg, 2011].

Metallurgical recovery is a non-additive variable and depends on in situ geological attributes such as: mineralization, lithology, alteration, mineral associations, among others. On the other hand, recovery also is affected by metallurgical attributes such as: flotation time, amount, and quality of collectors, frother, surfactant, pH, etc. Classical geostatistical methods cannot be applied to geometallurgical recovery due to the following factors [Deutsch, 2015]:

- Nonlinearity: Estimates at different support from measurement can lead to bias. This drawback is also present in reblocking.
- Unequal Sampling: Recovery test are expensive, hence are usually applied in few drillholes, those with economic profit.
- Multiscale Sampling: Recovery is usually measured over a support of 30 meters, much longer than other variables which are typically measured every 1 or 2 meters.

Usually, the recovery is estimated with different regression models that depend on other variables such as the amount of total copper, the solubility rate, amount of analytical acid, etc. To be able to apply these models, different geometallurgical estimation units must be modeled for the variable recovery. The definition of these units assumes a metallurgical behavior comparable between samples within each unit. In other words, 2 geometallurgical units are considered different if they show significant differences in the outcome of metallurgical processes, given a particular circuit.

This research defines potassic-rich altered rocks as a geometallurgical unit, this according to a geostatistical study [Garrido, 2016]. In addition to this, the type of potassic alteration is commonly associated with magnetite or hematite, anhydrite, and carbonates with iron while the clay minerals are absent. In some types of deposits, the feldspar is associated with biotite and anhydrite through a replacement by diffusion.

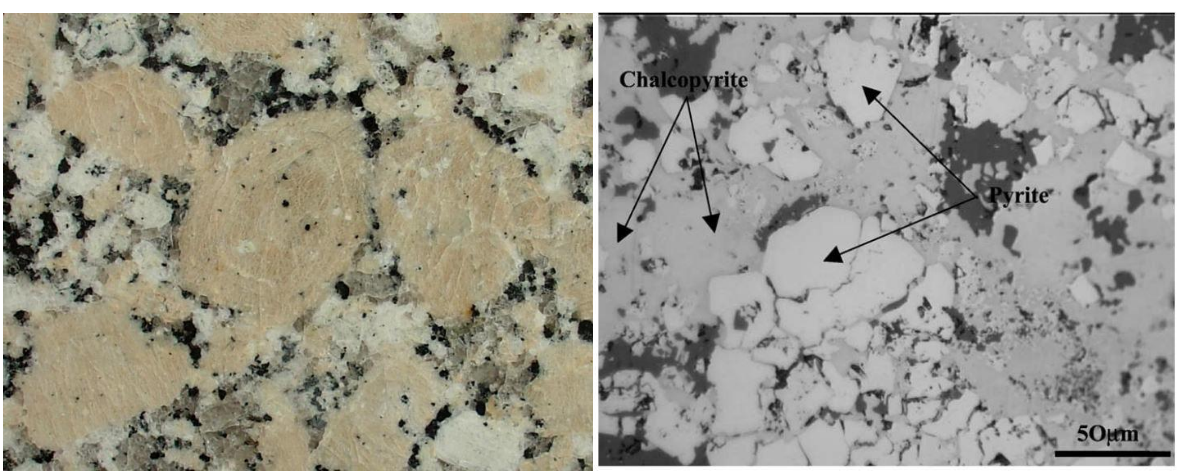


Figure 1 Optical micrographs illustrating the copper ore mineralogy and textures. Source: Benzaazoua (2002).

The sulfur/metal ratio is moderate, the proportion in pyrite being 3:1 (Figure 1, right). The pyrite (Fe_2S) is a sulfide with high content of iron present in minerals of hypogene origin, has a disseminated distribution and is strongly associated with the chalcopyrite ($CuFeS_2$), the main mineral recovered in copper flotation. Pyrite usually brings complications from an operation point of view because [Majima, 1969]:

- It generates electrochemical problems in milling, including galvanizing and corrosive effects to machinery.
- If pyrite and chalcopyrite are intergrown and liberation of chalcopyrite is low, recovery will decrease. This occurs because chalcopyrite requires at least 70% free surface for proper flotation.
- If the proportion of pyrite is very high it requires further alkalization of the flotation cell to achieve adequate depression of pyrite, problem which also increases reagents consumption.

Due to the negative impacts of pyrite on the recovery, a multivariable study was conducted [Wackernagel, 2003] between the potassic alteration units and recovery, looking for statistical correlations and space.

METODOLOGY

Geometallurgical unit and multivariate correlations

The potassic alteration associated with biotite was defined as geometallurgical unit (there are no significant presence of clays, mineralogy is relatively constant and given the lithology there should be no granulometric differences or hardness that may affect the grinding process).

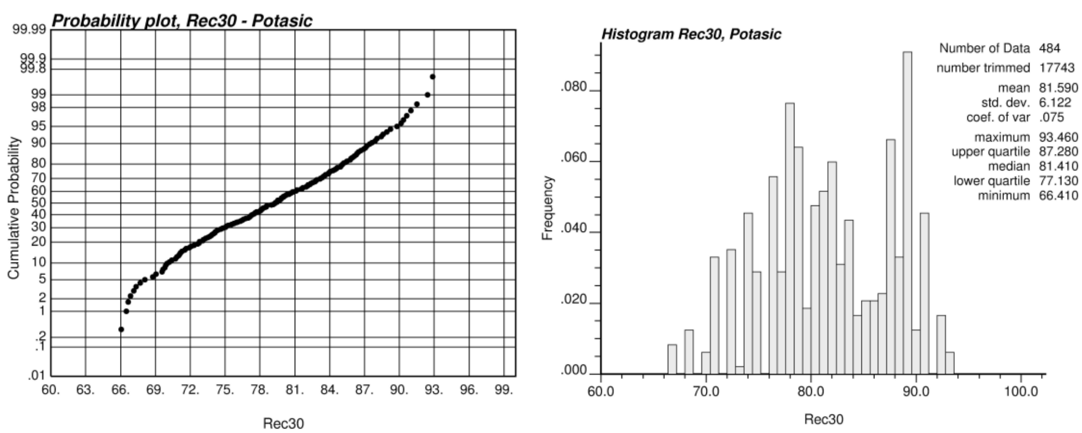


Figure 2 Statistical distribution (normal) for recuperation (geometallurgical variable)

The probability graph shows a unimodal distribution, without important breaks on the trend line. The histogram in Figure 2 shows a normal distribution for the recovery, with an average of approximately 81% considering 484 composite data over 30 m approximately. In the case where the proportion of feldspar potassium (according to login) is greater than the biotite, for sulfide minerals (mainly chalcopyrite), we found a significant statistical correlation (-0.8) between the amount of iron and the value of the recovery (Figure 3).

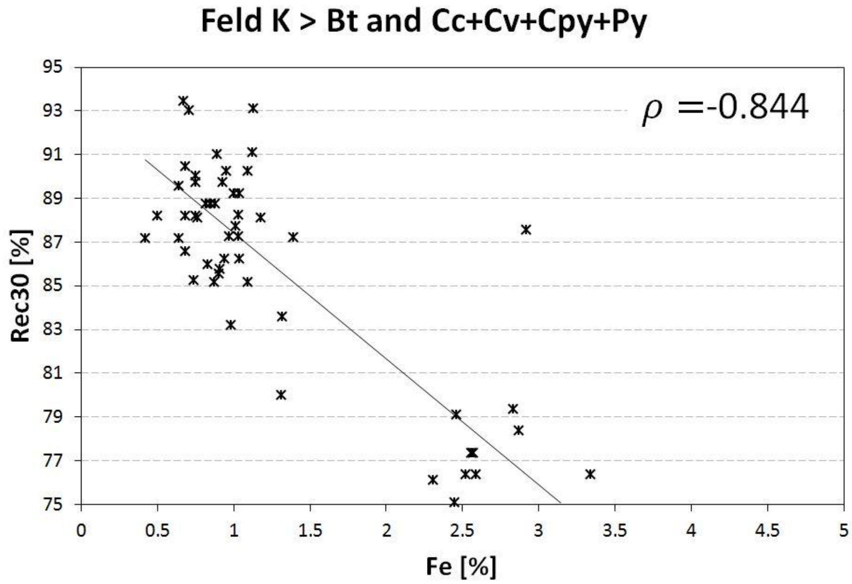


Figure 3 Scatterplot and correlation between Fe and Rec30.

This high negative correlation can be explained by the amount of pyrite present in the chalcopyrite ore rock. The pyrite has high iron content and reduces the recovery of copper due to low liberation of the chalcopyrite, when intergrown. Low iron contents (<1.5%) indicate that pyrite is not found massively to substantially decrease the free surface of chalcopyrite and affect recovery.

Estimation and study cases

Due to heterotopic condition, which is usually present in geometallurgical variables, traditional co-kriging was performed as an estimation method for the recovery, with iron as secondary variable. To estimate non-additive variables, the support of the estimation (usually block model) is the same or like the support of measurement of samples (composites). In this case, if block dimensions are like the drilling diameter and the length of the block is the length of the composite measurement, then recovery on the composite can be considerate like the recovery of the block support. This hypothesis enables discrete estimation reducing the bias that would be generated by a non-additive variable estimation.

Dense simulation of the metallurgical recovery and the iron measured in tests was performed. A total of 13 test cases were selected with different sampling density of the primary variable (recovery) and full sampling of the secondary variable total iron Fe. In this case a total of 5,000 samples are considered. The test cases are summarized in the following table (Table 1):

Table 1 study cases for testing co-kriging estimation.

Case Number	Number of samples (all)	# Fe assay samples	# Rec assay samples	Percentage
1	5,000	5,000	25	0.5%
2	5,000	5,000	31	0.6%
3	5,000	5,000	50	1%
4	5,000	5,000	100	2%
5	5,000	5,000	152	3%
6	5,000	5,000	200	4%
7	5,000	5,000	250	5%
8	5,000	5,000	500	10%
9	5,000	5,000	1,000	20%
10	5,000	5,000	1,500	30%
11	5,000	5,000	2,000	40%
12	5,000	5,000	2,500	50%
13	5,000	5,000	5,000*	100%

Percentage: Rec assay samples / Fe assay samples

*Equal sampling or Homotopic sampling

RESULTS AND DISCUSSION

In case study 1 only 0.5% of the samples contain hard data on recovery, equivalent to 25 samples compared to 5,000 Fe assays. In contrast, in case study 12, 2,500 recovery data points contrast respect to 5,000 Fe assay samples, this last case providing robust statistics:

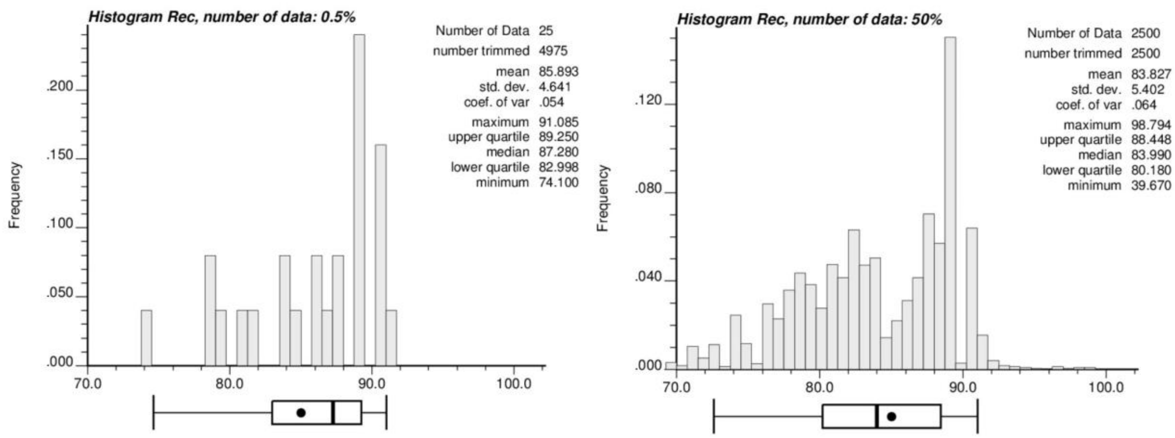


Figure 4 Histogram of rec30 for study case study 1 and 12.

For each case study, we proceeded to estimate using ordinary kriging and ordinary co-kriging to observe the changes in the predictive models in terms of robustness, precision, and accuracy.

The Figure 5 shows a comparison between the estimates of ordinary kriging and co-kriging for the 13th case (homotopic sampling), where we can visually observe that in both cases, they achieve reproduction of local means without major differences.

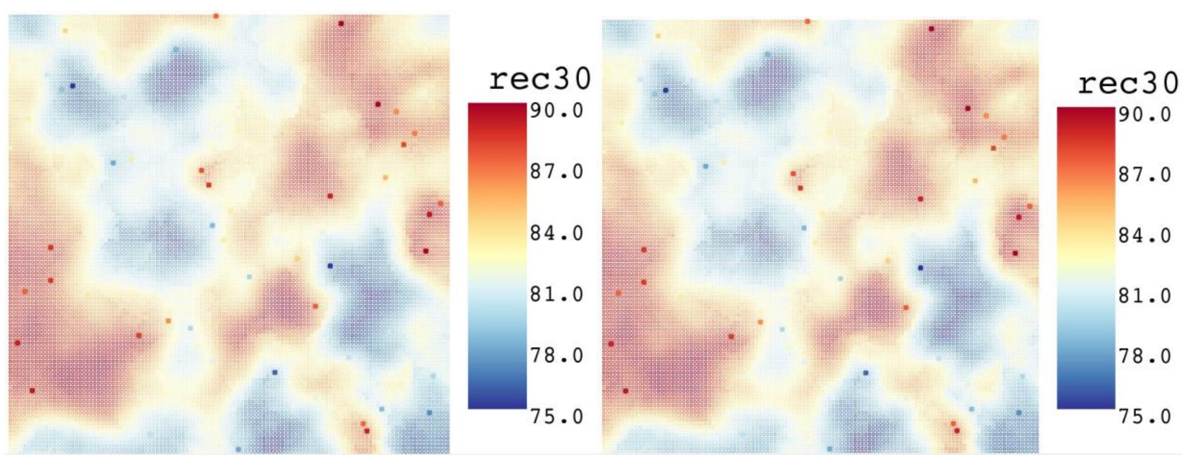


Figure 5 (Left) Estimation KO in case 13. (Right) Estimation Co-KO using Fe as second variable.

Figure 6 shows the comparison for case study 7, where 250 samples of recovery contrast respect to 5,000 Fe assay samples. In this case smoothing differences can be seen in the estimated models.

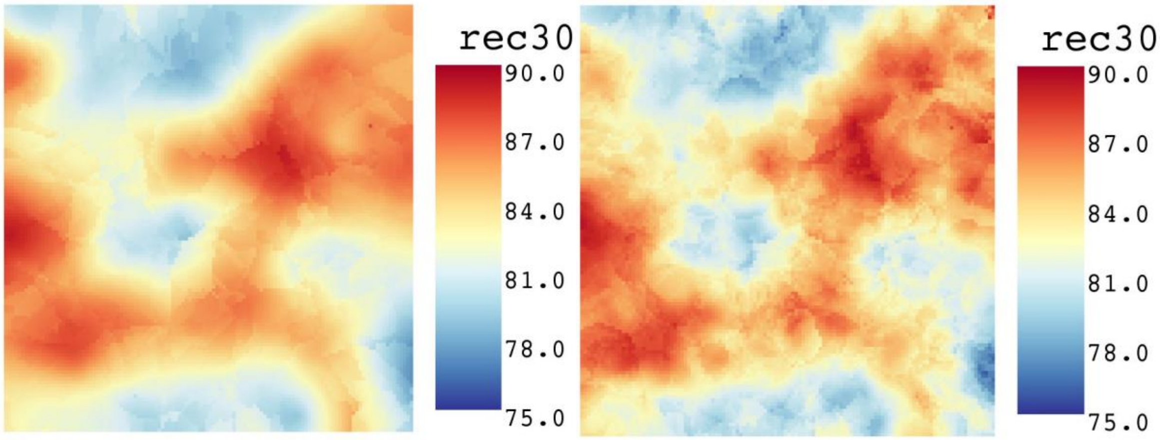
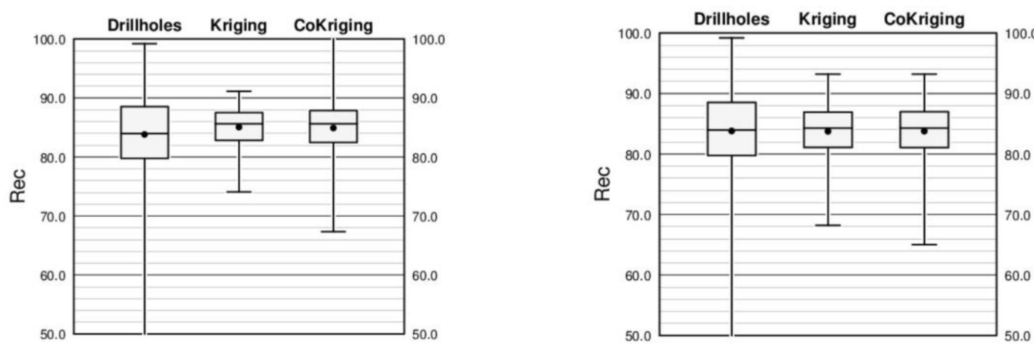


Figure 6 (Left) Estimation KO in case 1. (Right) Estimation coKO using Fe as second variable.

The results (Figure 7) indicate that co-kriging reproduces the average better than the kriging. In addition, variance is higher, thus estimating results with greater dispersion. On the other hand, the co-kriging in the first case estimated recoveries over 100% leading to incongruence.



	Drillholes	Kriging	CoKriging	
Number of data	5000	1002650	1174613	Number of data
Mean	83.8238	85.0714	84.9163	Mean
Maximum	99.2214	91.154	101.86	Maximum
Upper quartile	88.5402	87.509	87.87	Upper quartile
Median	83.9917	85.638	85.6133	Median
Lower quartile	79.7724	82.828	82.4573	Lower quartile
Minimum	39.6703	74.1	67.3619	Minimum
Variance	29.1002	11.1559	17.9392	Variance
CV	0.0644	0.0393	0.0499	CV
Skewness	-0.694	-0.5856	-0.6836	Skewness

	Drillholes	Kriging	CoKriging	
Number of data	5000	1200000	1200000	Number of data
Mean	83.8238	83.7701	83.7898	Mean
Maximum	99.2214	93.223	93.2231	Maximum
Upper quartile	88.5402	86.943	86.9876	Upper quartile
Median	83.9917	84.306	84.2998	Median
Lower quartile	79.7724	81.086	81.0632	Lower quartile
Minimum	39.6703	68.218	65.0211	Minimum
Variance	29.1002	16.1005	16.3796	Variance
CV	0.0644	0.0479	0.0483	CV
Skewness	-0.694	-0.5835	-0.5701	Skewness

Figure 7 (Left) Boxplot rec30 estimated (KO and co-KO) and composites in case 1 (Left) and case 8 (Right)

To reproduce the global means in the block model on every estimation unit, 3% of sampling is required. This can be observed in Figure 8 (left) where the global averages are summarized for different percentages of sampling, for the kriging and the co-kriging.

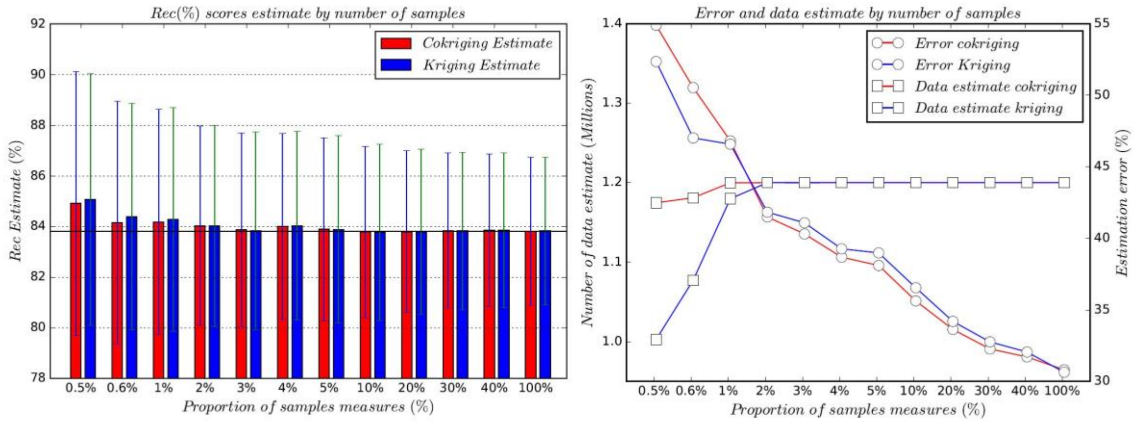


Figure 8 (Left) Average recovery estimated in diferent cases. (Right) Kriging variance (error of estimation) and data estimate with co-kriging (Red) and Ordinary Kriging (blue).

The vertical lines in Figure 8 (left) show the standard deviation of the estimate (associated with the error variance). For greater sampling densities, the estimation error decreases (precision) and the average rate is close to the real (accuracy).

CONCLUSION

According to Figure 8, it is not recommended to do estimates with sampling representing less than 3 per cent of the data as it can lead to significant bias. Figure 8 (right) shows the number of estimated data and the error estimation for different sampling densities. In this case, the technique of co-kriging presents an important improvement in low sampling densities, since (using secondary information) allows estimating more data. Despite this, the error is greater in these cases than kriging.

For a higher sampling density (> 2%), co-kriging is presented as a better estimation technique than kriging, reducing the estimation error and generating more robust models with greater variability than kriging. When sampling is homotopic (sampling density of 100%) kriging and co-kriging provide comparable results, where it is recommended to use kriging in terms of computational time and additional work modeling the LMC.

Finally, co-kriging presents advantages when correlations are detected on a geometallurgical unit of estimation if secondary variables with high information density are available. The use of this secondary information can improve the quantity and quality of results.

ACKNOWLEDGEMENTS

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ANEXOS

ANEXO GARRIDO ET AL. 2017B

Mine planning in open pit defines the material to be extracted when it will be extracted and its destination. Conventional scheduling usually considers block values based on geological parameters such as grade of the metal of interest, its mineralogy, and parameters external to geology. The latter parameters correspond, for example, to economic parameters, opportunity costs, types of plant and plant processes. The scope of this research is to consider geometallurgical constraints into the optimization problem known in mine planning as constrained pit limit problem (CPIT).

In the last years, numerous works have proven that there is a strong effect of clays on the flotation recovery process (chalcopyrite or bornite minerals). This impact generates operational problems that, if not controlled, can decrease metallurgical recovery. For example, due to clays are usually soft rocks, the grinding time is modified, thus, the recovery which is related to the granulometry. In addition, clays increase the costs associated on water input, since they require additional consumption to obtain the expected recovery. All these factors can be handled over long periods of time, but in short times operation the response is not as immediate and effective as required to be economical.

In this work, we propose a methodology which add a homogeneity condition to the optimization problem. It consists in the extraction of minerals with similar geometallurgical properties (in this case, the modeled amount of clay) on each period, and therefore the operational parameters in the plant would remain relatively the same. The algorithm was applied to a case study where zones with different levels of alteration and clay content were modeled. The valuation considered standard economic parameters of the mining industry.

Optimization of planning and scheduling of ore body with open pit extraction considering homogeneity in clays as geometallurgical variables.

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ABSTRACT

Mine planning in open pit defines the material to be extracted when it will be extracted and its destination. Conventional scheduling usually considers block values based on geological parameters such as grade of the metal of interest, its mineralogy, and parameters external to geology. The latter parameters correspond, for example, to economic parameters, opportunity costs, types of plant and plant processes. The scope of this research is to consider geometallurgical constraints into the optimization problem known in mine planning as constrained pit limit problem (CPIT).

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INTRODUCTION

An approach often used in mine planning is to maximize the net present value (NPV) subject to different operational conditions, creating a optimization problem that can consider many restrictions (Lane, 1988). In the case of an open pit, they tend to define precedence constraints, which represent a geometric constraint associated with rock slope stability (Whittle, 2009). In mining industry, algorithms which deliver satisfactory solutions by defining different pushback and final pit are widely used, in which way maximize the NPV along a mining project (Fytas et al., 1993; Ohnson, 1969). Normally, these numerically correct solutions are not operationally feasible; therefore, design modifications are applied to finally define the reserves to exploit.

Different restrictions can be added to the optimization problem, for example: mine production, plant capacity, multiple destinations (stockpile), schedule or sequences (Kim & Zhao, 1994), secondary variables of interest, among others. However, by adding additional constraints, the optimization problem becomes very complex, requiring large calculation time and sometimes surpasses the available memory. This scenario, motivate us to search alternatives methodologies that could handle such complexity from a computational point of view.

In this research, we consider geometallurgical variables for the optimization problem. Different types of clays generate operational metallurgical problems in flotation processes. Some minerals, include kaolinite (stratified silicate), illite (phyllosilicate) and others are grouped by quantity in four categories: large (> 30%), moderate (10% -30%), small (2% -10%) and minimum (<2%) (Chipera & Bish, 2001). Models of clay grades are usually built using categorical variables based on geological mapping and/or X-ray diffraction (analysis of clay speciation XRD). Clay variability in the metallurgical plant, generates many operations problems which negatively influence the recovery of the metal of interest, generating mineral and economic losses. Bulatovic quotes: *"Clays are the main reason for low recoveries of copper and gold by flotation"* (Bulatovic, 1997).

The focus of this research is to generate a multi-objective optimization algorithm, which can minimize the variation of clay to be processed in the short term. This optimization problem was modeled considering the Constrained Pit Limit Problem (CPIT) as base, which consists of the maximization of the NPV over a time horizon, subject to block precedence and operational constraints; and, additionally, the minimization of the variation of clay by period. To solve this optimization multi-objective problem, we considered the metaheuristic called Tabu Search (Glover & Laguna, 1997), which can find solutions with a high level of accuracy in reasonable computational time.

The next section will describe the methodology used to create a simulated deposit, which reproduce the problem of mixing different clays on flotation process. Finally, a case study will present the application of Tabu Search over the synthetic deposit, to maximize NPV and minimize the variation of clays. Results and conclusions are shown.

METHODOLOGY

The simulated study case corresponds to the surface area of a copper porphyry deposit. The hydrothermal system is larger than the ore body, strongly affecting the foreign rock. The rock mass is composed primarily of andesite. The deposit is dated from the late-eocene and the intrusive complex is of the diorite-type. Kaolinite clays are strongly associated to sericitic alteration, which is presented superficially and covers the largest area of the study. The mineralization is mainly composed of disseminate chalcopyrite (ore of economic value) with poor indicators of secondary supergene processes. Dimensions of the body are not known in depth, but to this research have been delimited to work with resources with low uncertainty (Measured-Indicated Resources). Figure 1 shows a cross section with the orebody shape of interest.

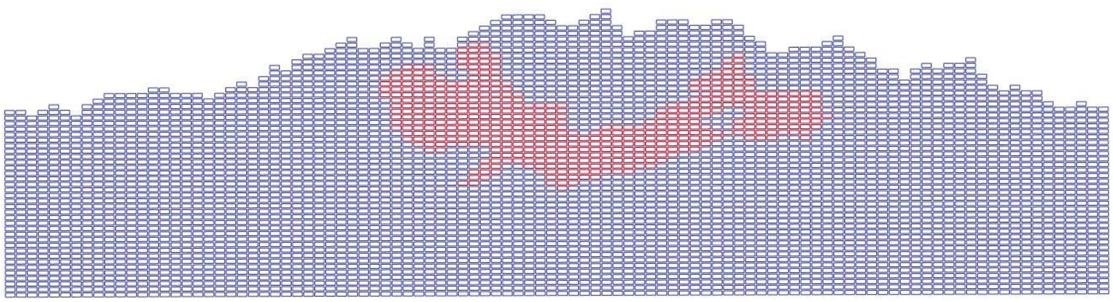

Figure 1 Ore body delimitation model section

Clays were modeled based on the model of sericitic alteration, in which four categories were proposed as areas of large, moderate, small, and minimum presence of clay (increasing towards the edges and surface of the area). The models were made based on geological mapping.

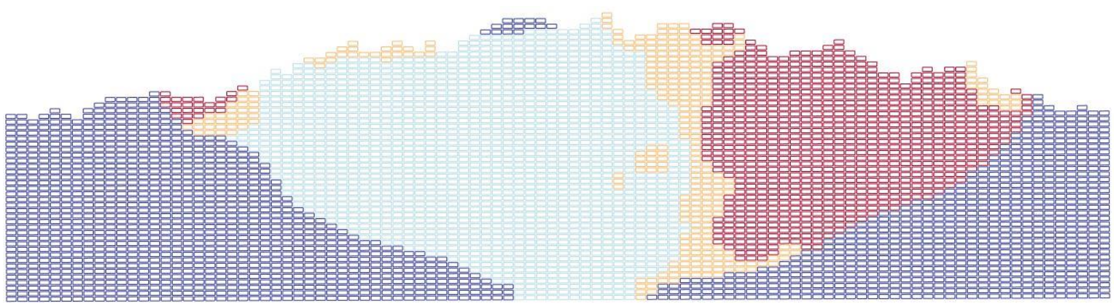

Figure 2 Clays model section: Blue is minimum clay and red is large clay.

The approach of the multi-objective optimization problem is defined as follows: The main objective is formulated according to CPIT (Espinoza et al., 2013) in which maximize NPV subject to precedence constrains (pit form) and temporality (schedule). The second objective will be addressed as **minimize dilution** of the exploitation over the time horizon T (Equation 1). Dilution (in mining) is the relationship between waste and mineral in the extraction process. In this case, mineral will be considered as the most frequent alteration in a time window, and waste represent the rest of the alterations (or grade clays). Using this definition, dilution can be described as the amount of majority material in a period (Equation 2). Clays attribute will be represented as $a_i = \{0, 1, 2, 3\}$ where 0 is minimum clays, and 3 correspond to large clays.

Then, the minimization dilution problem is described as:

$$\min \left\{ \sum_{t=1}^{T} D_t \right\} \tag{1}$$

Where D_t is dilution in the period t:

$$D_t = \frac{E_t}{E_t + M_t} \tag{2}$$

Mineral (M_t) and Waste (E_t) represented as the main alteration in the period t:

$$M_t = \sum_{i=1}^{N(t)} I_i \tag{3}$$

$$E_t = \sum_{i=1}^{N(t)} J_i \tag{4}$$

It can be calculated:

$$I_i = \begin{cases} 0, \text{ if } \ \mathrm{a}_i \neq m_t \\ 1, \text{ if } \ \mathrm{a}_i = m_t \end{cases} \qquad J_i = \begin{cases} 0, \text{ if } \ \mathrm{a}_i \neq e_t \\ 1, \text{ if } \ \mathrm{a}_i = e_t \end{cases} \tag{5}$$

And the parameters to consider if is waste or mineral are defined as:

$$m_t = mode\{a_i\} \qquad e_t = \{a_i \mid a_i \neq m_t\} \tag{6}$$

Tabu Search (TS) were created by Glover at the end of the 1980s (Glover & Laguna, 1997), which is a metaheuristic search method that take advantage of local search. Giving the combinatorial aspect of the formulation, we considered appropriate the use of these algorithms that sacrifice accuracy in the solution to significantly reduce the processing times, allowing us to have good solutions in a reasonable execution time.

RESULTS AND DISCUSION

Figure 3 shows the resources to be extracted in the different periods of time. It should be noted that the solution seeks to maximize the NPV and decrease the "geometallurgical dilution" per period. In addition, Figure 4, shows variability of dilution by periods, specifying the times where to expect higher dilution. The information generated by this process can be considered, from a predictive point of view, to manage operational parameters at the processing plant by considering the variability of clays which were modeled as dilution.

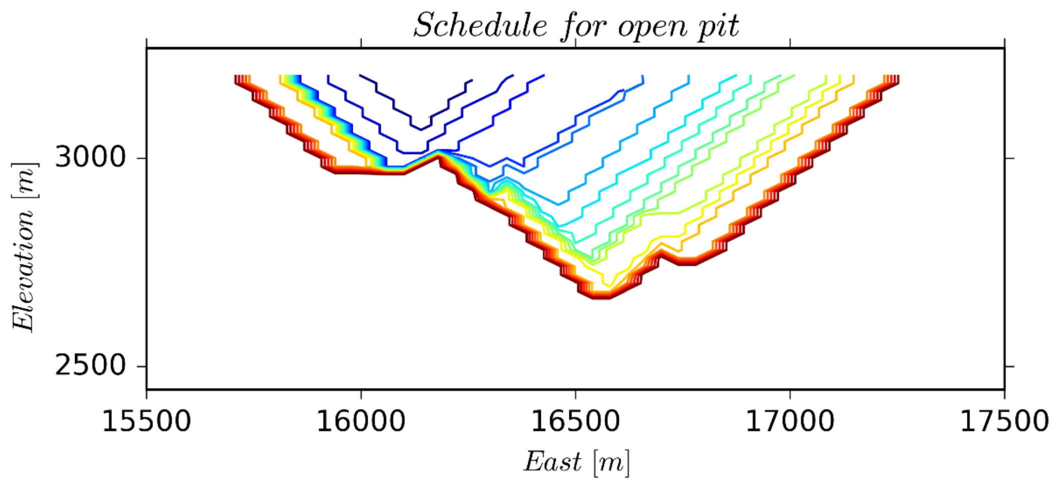

Figure 3: Schedule for different periods each color (contour plot)

In Figure 4, the chart summarizes the general planning for the different periods of time from a point of view tonnage / grade. The optimization did not consider keeping mine or plant tonnages constant over time (this condition could be added in future work).

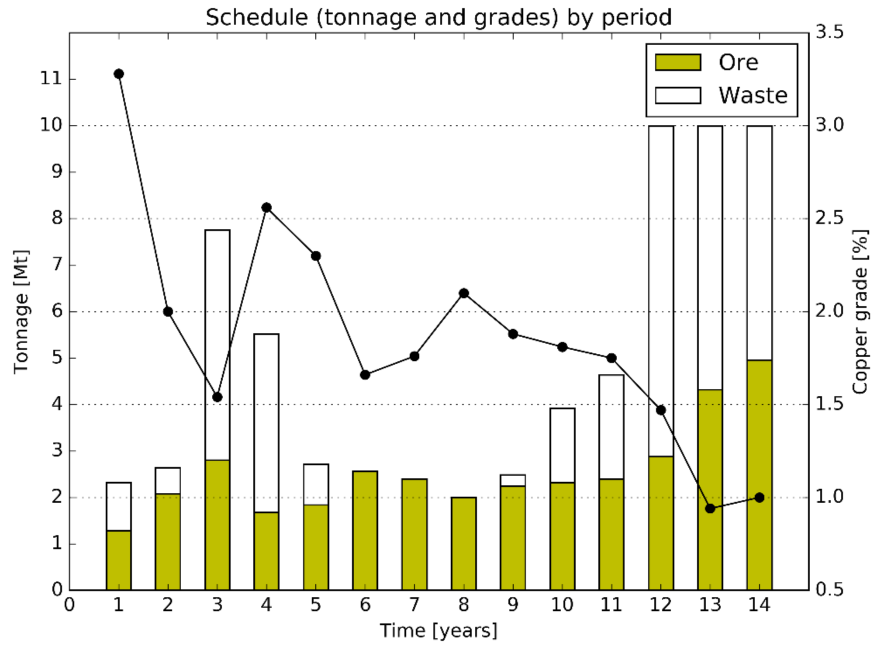

Figure 4: Tonnage and grades average by period

The results obtained with the TS algorithm, were compared with the optimization problem solved without dilution restriction (CPIT). Table 1 shows the values of NPV for Dilution case and Base case. Dilution case gives results very like to Base case in terms of grades and extracted tonnages. Both cases present low differences in tonnage for period, which causes a decrease of the NPV in Dilution case (6% of difference in average). The dilution decreases notably in most of the periods, generating a feed in the metallurgical process with greater homogeneity. The reduction of dilution avoids economic losses that are not considered in the evaluation since they are difficult to quantify.

Table 1 Comparison between base case and dilution case

	Base case**		Dilution case		Percentage difference*	
Period	Dilution	NPV [MUS$]	Dilution	NPV [MUS$]	Dilution	NPV [MUS$]
1	10%	135	2.5%	95	-76.0%	-30%
2	0.0%	249	0.0%	201	-	-19%
3	0.0%	327	0.0%	294	-	-10%
4	0.0%	413	0.0%	396	-	-4%
5	0.0%	500	0.0%	486	-	-3%
6	0.0%	577	0.0%	562	-	-3%
7	0.0%	649	0.0%	631	-	-3%

8	0.0%	716	0.0%	698	-	-2%
9	0.0%	775	0.0%	756	-	-2%
10	4.1%	825	2.4%	808	-42%	-2%
11	14%	868	15%	851	7.0%	-2%
12	32%	896	24%	879	-26%	-2%
13	28%	910	16%	883	-43%	-3%
14	9.6%	928	8.8%	901	-8.3%	-3%

* Difference: dilution case - base case

** Base case does not consider plant processing costs

CONCLUSIONS

Scheduling in mine planning is widely used in the mining industry. We propose an addition to traditional optimization of the NPV, by considering other variables. Considering additional variables can improve the operation of the short and medium term, but the complexity of the optimization problem is increased. We considered the dilution generated by the management and metallurgical process of clays, which is inherent characteristic of sericitic alterations. The problem was solved using the Tabu Search metaheuristic, which results were compared to the CPIT formulation, used as Base case. In terms of tonnage and grade of metal, the application of this methodology shown promising results. In addition to this, the methodology delivers sequences with lower temporal dilution (higher homogeneity), which improves the predictive capacity of the metallurgist.

The metaheuristic approach used in this work, helped to add new constraints that cannot be considered on traditional formulation; and, due to the complexity of the numerical model, makes impossible to find an optimal solution. We strongly recommend the use of this metaheuristic (or any other) to tackle additional constraints that in mining project are not usually considered.

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ANEXOS

ANEXO GARRIDO ET AL. 2018

The access to real geometallurgical block models is very limited in practice, making difficult for practitioners, researchers, and students to test methods, models and reproduce results in the field of geometallurgy. The aim of this work is to propose a methodology to simulate synthetic geometallurgical block models with geostatistical tools preserving the coherent relationship among primary attributes, such as grades and geology, with mineralogy and some response attributes, for example, grindability, throughput, kinetic flotation performance and recovery. The methodology is based in three main components: (i) multivariate geostatistics, (ii) froth flotation simulation models, and (iii) well known performance plant parameters. The simulated geometallurgical block models look very realistic, and they are coherent in terms of geology and mineralogy, and processing metallurgical performance responses are consistent with what is seen in practice. These simulations can be used for several proposes, for example, benchmarking geometallurgical modelling methods and mine planning optimization solvers. Simulations at small scales also serve to represent drill holes campaigns and generate sample dataset incorporating geometallurgical attributes and real spatial variability. The methodology is completely reproducible with no use of proprietary models or methods. Implementations of all methods can be found in public domain software, and different ore body types may be incorporated with little effort.

A Methodology for the Simulation of Synthetic Geometallurgical Block Models of Porphyry Ore Bodies

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ABSTRACT

The access to real geometallurgical block models is very limited in practice, making difficult for practitioners, researchers, and students to test methods, models and reproduce results in the field of geometallurgy. The aim of this work is to propose a methodology to simulate synthetic geometallurgical block models with geostatistical tools preserving the coherent relationship among primary attributes, such as grades and geology, with mineralogy and some response attributes, for example, grindability, throughput, kinetic flotation performance and recovery. The methodology is based in three main components: (i) multivariate geostatistics, (ii) froth flotation simulation models, and (iii) well known performance plant parameters. The simulated geometallurgical block models look very realistic, and they are coherent in terms of geology and mineralogy, and processing metallurgical performance responses are consistent with what is seen in practice. These simulations can be used for several proposes, for example, benchmarking geometallurgical modelling methods and mine planning optimization solvers. Simulations at small scales also serve to represent drill holes campaigns and generate sample dataset incorporating geometallurgical attributes and real spatial variability. The methodology is completely reproducible with no use of proprietary models or methods. Implementations of all methods can be found in public domain software, and different ore body types may be incorporated with little effort.

INTRODUCTION

Geometallurgy has become an important sub-field in mining engineering because of its benefits on the ore quality on mine planning, plant performance and product quality. To incorporate these benefits into the mining value chain, key metallurgical responses and proxy variables need to be captured into the block model, which is the main input to solve many optimization problems in mine planning (Ortiz et al. 2015). This enriched block model with geometallurgical variables is commonly termed a geometallurgical block model (GMBM).

There are several methodologies for building such GMBM. The primary-response framework for building geometallurgical models is a very solid methodology for geometallurgical modeling (Coward et al. 2009). Primary attributes, such as grades, lithology and alteration can be proxies to response attributes such as grindability indices, recovery, among others. As many of those response attributes are not additive, traditional linear estimation methods are not valid to be used in the block model (Carrasco et al. 2008). Typically, there are three complementary approaches to populate the GMBM with response variables. The first approach is the use of predictive regression models, from simple linear regressions (Montoya et al. 2011; Boisvert et al. 2013), non-linear regressions (Carmona and Ortiz 2010; Keeney and Walters 2011; Sepulveda et al. 2017), and clustering (Hunt and Jorgensen 2011). The second approach is simulating the processing processes (Suazo et al. 2010). The third approach is the use of mineralogy as the main proxy. Mineralogy is of enormous importance for geometallurgy as it plays a fundamental role in the characterization of metallurgical responses (Lamberg 2011; Hunt et al. 2013; Yildirim et al. 2014; Lund et al. 2015). This approach, nevertheless, requires having the mineralogy characterization of the deposit, which is expensive, often resulting in limited data available.

From the point of view of practitioners, researchers, teachers and students, there is another issue with GMBM: an important lack of available GMBM for them to use, because the data of those are usually subject to confidentiality agreements. This fact is the motivation to offer a methodology for the simulation of GMBM, exemplified here with a porphyry ore body type, but it can be applied for any other type of mineral deposit.

The only related research on methodologies for the simulation of geometallurgical block models, so far according to the literature review done in this paper, is Lishchuk's thesis (Lishchuk 2016). In this thesis, a methodology, termed geometallurgical testing framework, was proposed for building a synthetic ore deposit model with focus on geometallurgy. This framework has three main modules: (i) a geological module, (ii) a mineral processing module, and (iii) an economic module. The first two modules are the most relevant modules for the simulation of synthetic geometallurgical ore bodies.

The main weakness of Lishchuk's methodology is the naïve approach to simulate the spatial characteristic of geology and grades using just simple ellipsoids enveloping the zone of influence of a particular lithology. Imposing multivariate spatial correlations is critical to ensure the desired spatial characteristics are reproduced with geological sense and coherence.

The contribution of this paper is a robust methodology to simulate a GMBM with openly available geostatistical tools preserving the coherent relationship among primary attributes, mineralogy, and response attributes.

METHODOLOGY

To simulate the GMBM, four steps are performed: (i) **Geological simulation,** (ii) **Mineralogy simulation,** (iii) **Geochemical simulation**, and (iv) **Metallurgical simulation**.

Geological Simulation

In this step the desired geology is imposed by real or synthetic drill holes. These synthetic drill holes are built based on the geological knowledge and metallogenic characteristic of the targeted deposit type (Maksaev 1990; Sillitoe 2010).

Usually codes for lithology, alteration type and mineralization zone are assigned to samples in drill holes. These geological properties are simulated in the deposit by indicator simulation (Deutsch 1998; Chilés and Delfiner 2012; Pyrcz and Deutsch 2014). The actual implementation used here is the algorithm BlockSIS (Deutsch 2006), which implements the smoothing algorithm MAPS (Deutsch 1998) to improve the contact among categories and preserves their imposed proportions.

Mineralogy Simulation

In this step we relate mineralogy with geology. Mineralogy is often determined by mineralogical testwork, such as QEMSCAN (Fennel et al. 2015), which provides mineralogical proportions. For each geological domain, a multivariate spatial lineal model of coregionalization (LMC) is imposed. This LMC is determined according to the relationships between minerals in each geological domain, for example, cuprite and chalcocite should be found in the mixed or secondary enriched zone. The relationship can be determined by correlation matrices or by (Baeza et al. 2016). The simulation within each geologic domain is performed by the USGSIM algorithm (Manchuk and Deutsch 2012).

Geochemical Simulation

The elements of interest, such as copper, gold, molybdenum, silver and iron, and also deleterious elements, such as sulphur, arsenic and fluorine, are often simulated directly with conventional geostatistics (co)simulations methods (Chilés and Delfiner 2012). From the geometallurgical perspective, deleterious elements could be crucial in beneficiation process and also in minimizing contaminants that affect the economic value of the final product (Lane 1988).

Some researchers have linked chemistry composition to mineralogy in order to predict from elements the minerals proportions (Lamberg 2011). Our approach goes in the other direction. From the simulations of mineral proportions, we deduce element content. For illustration, in a porphyry copper deposit, we could find the following relationships of copper grade in different mineralization zones:

$$\text{CuT (\%) in EnrSec} > \text{CuT(\%) in Oxides} > \text{CuT(\%) in PrimCpy} > \text{CuT(\%) in PrimPy}$$

where CuT(%) is the total copper grade. EnrSec (rock with secondary enrichment) is characterized by minerals with high copper content such as chalcocite and covellite. Oxides are minerals affected by oxidation/reduction reactions such as cuprite and chrysocolla. PrimCpy are primary rocks characterized by sulphurs with high content of chalcopyrite. PrimPY are primary rocks characterized by low content of chalcopyrite and high pyrite. Therefore, the mineral composition in each mineralization zone can be used to derive the elements grades.

Metallurgical Simulation

Metallurgical response can be estimated by regression models calibrated from testwork or reconciliation data, which is the approach used in this paper, or by process simulation. Metallurgical simulators are based on geological and operational parameters (Lishchuk 2016). The geological parameters are mainly controlled by the mineralogical composition of the feed, whereas the operational parameters are controlled by the attributes specific to the processes, for example in flotation, reagents have a high impact on recovery. Most of the operational parameters are well-known for each mineralogy composition of the feed. Therefore, the simulated mineralogy is used as input to metallurgical simulators (we focus on flotation process) and the results are propagated into the GMBM.

CASE STUDY

This case study illustrates the application of the proposed methodology. A typical porphyry copper deposit is simulated with four mineralized zones: oxides, primary enrichments (with chalcopyrite and pyrite as main minerals), and secondary enrichment. For confidentiality, the database has been altered and transformed to Gaussian distribution.

Geological Modeling

The main mineralized zones are: **Oxides**, containing oxides minerals; **EnrSec**, secondary enrichment; **PrimCpy**, with high content of chalcopyrite; and **PrimPy,** with high content of pyrite. Figure 1 shows one realization of the mineralized zones, obtained by indicator simulation.

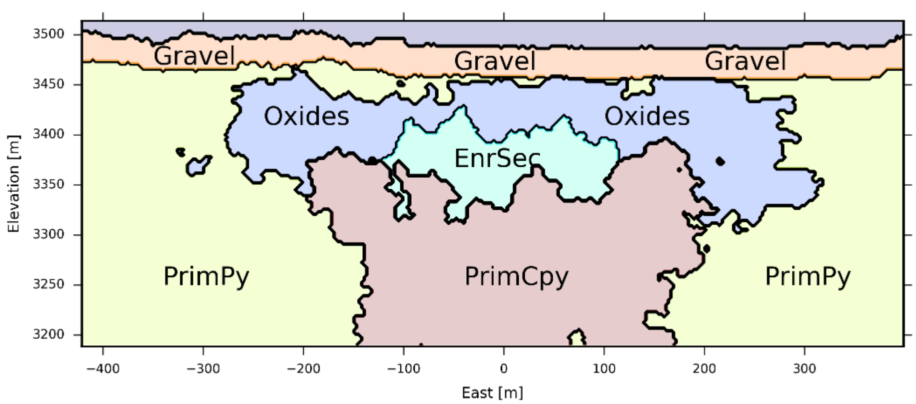

Figure 1 Distribution of mineralized zones, realization 1.

Geostatistical simulation allows to generate different equally probable scenarios conditioned to the geological profile of a porphyry copper deposit.

Multivariate mineral characterization

The bivariate correlations were calculated for all mineralization zones. This correlation matrix was used for co-simulating the proportions of minerals by multi-Gaussian methods.

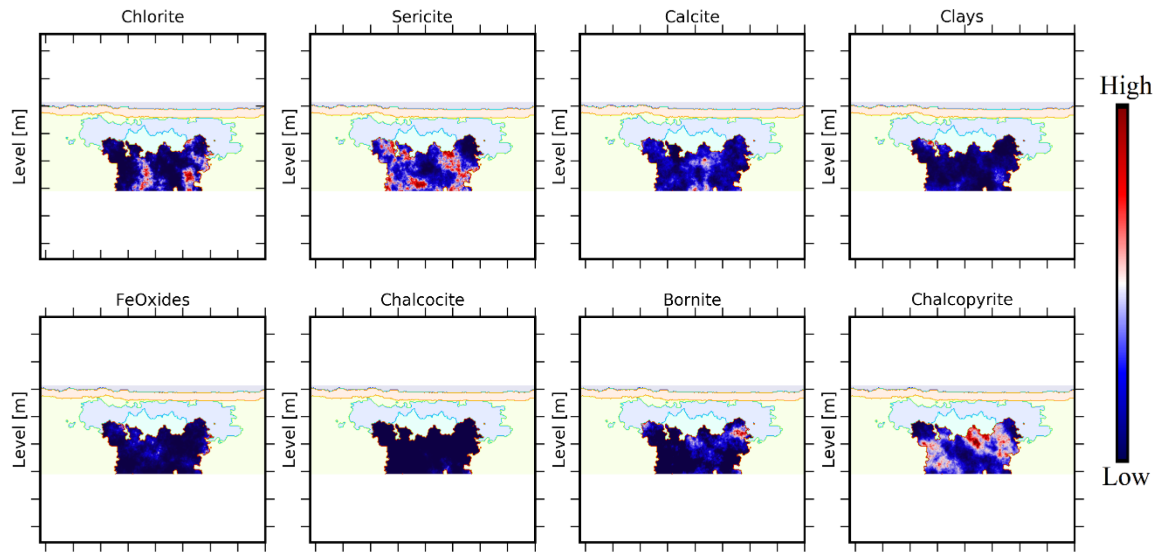

Figure 2 Plot of simulated mineral proportions in primary zone with high chalcopyrite content (PrimCpy).

Geometallurgical simulation of the head copper grade

The values of geochemical variables are simulated based on the mineral characterization in order to generate coherent element grades. For example, copper grade would be in a zone with chalcopyrite, bornite or chalcocite, which are sulphured minerals hosting copper mineralization. The total grade of copper contained in the simulated minerals can be calculated directly from bornite, chalcopyrite and chalcocite, using the proportion of copper according to their chemical formulas. For example, Bornite (Cu_5FeS_2), Chalcopyrite ($CuFeS_2$) and Chalcocite (Cu_2S) have a 63.30%, 34.61% and 78.85% of copper, respectively. The resulting copper grades calculated from minerals in PrimCpy zone are shown in Figure 3.

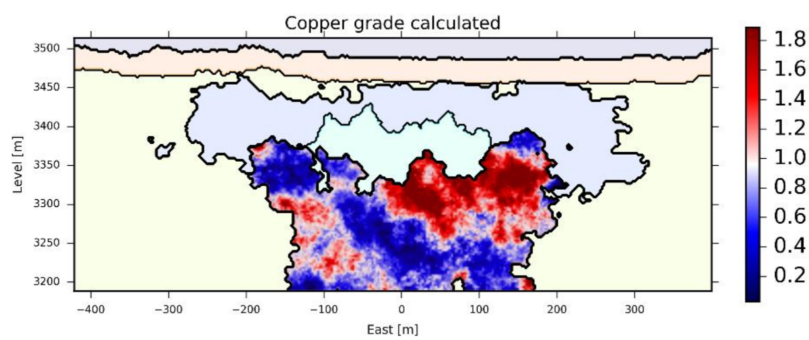

Figure 3 Derivation of copper grade from minerals containing copper in PrimCpy zone.

Geometallurgical Simulation of Grindability and Specific Energy Consumption

One index for characterizing the grindability response is the Bond ball work index (BWi). Good correlations exist with some geochemical attributes (Fe_3O_4, soluble Fe, total Fe, Ni y Ni_2O). However, a synthetic variable defined as:

$$BWi = f(Fe_3O_4, FeS, FeT, Ni, Na_2O) = Fe_3O_4 * FeS * FeT * Ni/Na_2O$$

It shows higher correlation of 0.7 approximately. This new synthetic variable, which is now a proxy for BWi, was co-simulated in order to spatially correlate BWi with mineralogy. This is used to calculate the specific energy consumption by:

$$W = \frac{P}{G_s} = 10 * E * BWi * \left(\frac{1}{\sqrt{P_{80}}} - \frac{1}{\sqrt{F_{80}}}\right)$$

where W is the specific energy consumption of work required to grind a head ore of F80 to P80 [kWh/short t], P is the consumed power [kW], Gs is the mass flow of ore [short t /h], BWi is the Bond work index [kWh/short t], F80 is the passing size below 80% of the feed [um], and P80 is the passing size below 80% of the product [um].

Doing so, the specific energy consumption can be calculated in all zones in the deposit preserving the spatial variability related to BWi.

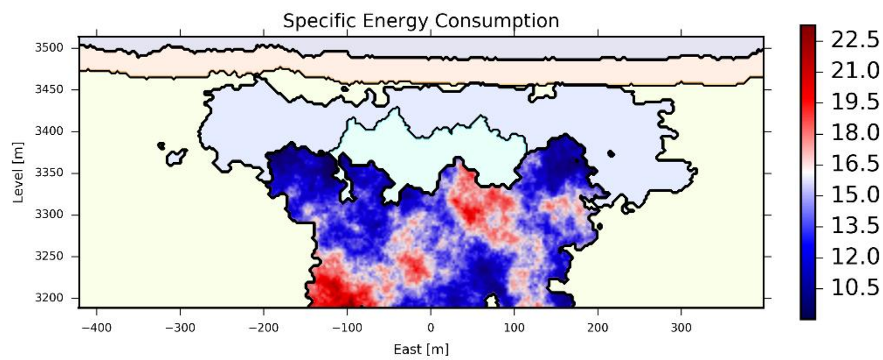

Figure 4 Spatial simulation of specific energy consumption.

Geometallurgical simulation of flotation

In order to simulate the concentrate copper grade in froth flotation, the recovery of each mineral containing copper (bornite, chalcopyrite y chalcocite) was characterized as a random variable following a normal distribution, $\mathcal{N}(\mu_m, \sigma_m)$, where m represents each mineral. The simulation is performed by Monte Carlo method using those distributions.

The copper grade in concentrate is similarly calculated to the head copper grade, i.e., each mineral will contribute with some recovered copper in concentrate. The percentage of recovered copper is calculated as the ratio between the copper grade in concentrate and the copper grade in the block. This calculation does not require additivity and is consequent from the geometallurgical perspective under the constraint:

$$R_{sim}(Bornite) > R_{sim}(Chalcopyrite) > R_{sim}(Chalcocite)$$

The parameters of the normal distribution for recovery will depend on operational factors of the flotation process and the gangue material associated to the feed. These parameters are mine dependent and can be determined by standardized rougher flotation testwork for sulphured copper minerals.
In order to scale-up recovery, the flotation kinetic K of Klimpel can be determined according to the following equation (Amelunxen et al. 2014):

$$R = R_{\infty}(1 - e^{-Kt})$$

where R is the recovery, which has been simulated, R_{∞} is the infinity time recovery, which is assumed to be 1.0, and t is the flotation time, which was set to 15 minutes.
Calculating the Klimpel's K constant allows scaling-up the recovery for any design of a flotation plant. For example, using data from the plant, Suazo et al. (2010) were able to calculate an inherent floatability parameter at laboratory scale, which is linked to Klimpel's K constant, and then use it for scaling-up at plant conditions.

CONCLUSION

We have presented a reproducible methodology for the simulation of a geometallurgical block model, with special interest in preserving the coherence between geology, mineralogy, and grades. Four response attributes were included in the GMBM, BWi, specify energy consumption, copper recovery, and Klimpel's K constant.

Starting with real or synthetic drill holes and following the four steps in the proposed methodology, a GMBM can be successfully simulated. All methods and programs used in the methodology are public and free to use.

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ANEXOS

ANEXO GARRIDO ET AL. 2019

Public reports are prepared to inform investors or potential investors and their advisers on exploration results, mineral resources, or mineral reserves. To convert mineral resources to mineral reserves, mineral processing and geometallurgical factors are used. The International Reporting Template (IRT) is a document that represents the best of the CRIRSCO-style codes: reporting standards that are recognized and adopted world-wide for market-related reporting and financial investment. In this reporting, geometallurgy represents a key component in the checklist for reserve assessments and reporting criteria: (1) mining factors or assumptions: in order to demonstrate realistic potential for eventual economic extraction, (2) metallurgical factors or assumptions: to demonstrate realistic potential for eventual economic and optimal extraction, (3) study status of mineral reserves for all modifying factors that have been considered and (4) cut-off parameters: the cut-off parameters may be economic value per-block rather than grade, and the costs of processing a block depends on geometallurgical parameters.

An overview of good practice to estimation and modelling techniques of geometallurgical data is given. A discussion is provided that of ore-type definition, types of test samples are critical, density of sampling per geometallurgical domain, relationship between mineral characterization and behavior of mineral processing to support geometallurgical modelling (some multivariable tools are proposed), how geometallurgical modelling supports the long term scheduling (costs, efficiency, recovery and mineral mixing among others); and simulations of geometallurgical scenarios to quantify uncertainty and risk of mineral processing. Currently, no guide exists for the construction of geometallurgical models and their management in the quantification of reserves, therefore, this research supports companies that declare mining reserves in bankability studies and private consultants that generate this type of reports.

An overview of good practices in the use of geometallurgy to support mining reserves in copper sulfides deposits.

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ABSTRACT

Public reports are prepared to inform investors or potential investors and their advisers on exploration results, mineral resources, or mineral reserves. To convert mineral resources to mineral reserves, mineral processing and geometallurgical factors are used. The International Reporting Template (IRT) is a document that represents the best of the CRIRSCO-style codes: reporting standards that are recognized and adopted world-wide for market-related reporting and financial investment. In this reporting, geometallurgy represents a key component in the checklist for reserve assessments and reporting criteria: (1) mining factors or assumptions: in order to demonstrate realistic potential for eventual economic extraction, (2) metallurgical factors or assumptions: to demonstrate realistic potential for eventual economic and optimal extraction, (3) study status of mineral reserves for all modifying factors that have been considered and (4) cut-off parameters: the cut-off parameters may be economic value per-block rather than grade, and the costs of processing a block depends on geometallurgical parameters.

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INTRODUCTION

In Chile, the decline in grades in deposits and the increase in operational costs mainly due to the deepening of mining operations, among others, is encouraging mining companies to investigate different areas for processes optimization [Acosta 2018]. Geometallurgy is a key factor in optimizing and understanding the risk of metallurgical mining processes.

The International Reporting Template (IRT) is a document that represents the best of the CRIRSCO-style codes: reporting standards that are recognized and adopted world-wide for market-related reporting and financial investment. In Chile, The Chilean Mining Commission is the institution responsible to ensure the assessment of mining reserves in agreement to international standards. The Qualifying Commission of Mining Resources and Reserves Competencies defines the requirements for a Qualified Person (QP) to be qualified to inform and publicly certify exploration prospects and mining resources and reserves. Topics such as sampling, drilling, laboratory tests, location of the samples, density and distribution of samples, estimation and modelling techniques, mining and metallurgical factors, mining plan and scheduling, costs and revenues, marketing, etc. are considered by the QP to certify mining reserves [Code CM2012]. In this context, the geometallurgical knowledge is essential to ensure the correct estimate of a mining reserve (expected value and risk).

There are multiple definitions of geometallurgy. Geometallurgy has been defined by SGS as the integration of geological, mining, metallurgical, environmental and economic information to maximize the net present value (NPV) of a deposit while minimizing operational and technical risk. To implement the geometallurgy applied in a mining project, it is necessary to select relevant and sufficient samples that will be subjected to tests to determine the metallurgical parameters and geostatistical distribution of these parameters along a deposit using accepted techniques to support the process of geometallurgical modelling [Chiles and Delfines 2012], [Deutsch and Journel 1998], [Goovaerts 1997], [Isaaks and Srivastava 2989]. In this research, an overview of good practices in use of geometallurgy to support mining reserves in copper sulfides has been compiled *through geometallurgical papers and case studies.*

METHODOLOGY

To compile the overview for copper sulfides processing, we considered: published articles, international conferences, public reports, academic publications and experience of mining industry professionals. The overview was summarized in the topics (1) Ore type definition, (2) Geometallurgical sampling, (3) Geometallurgical modeling and (4) Geometallurgy in support of mine planning and scheduling

RESULTS AND DISCUSSION

A compilation of literature is presented. The review of the literature has resulted in the good practices relating to the geometallurgical factors in reserves estimations being categorized into four aspects:

1. **Ore type definition:** As Geological Unit (GU) to estimate some attribute (for example copper grade [%]). The ore type is called Geo Metallurgical Unit (GMU) and depends of geology factors and type of metallurgical process.
2. **Geometallurgical sampling:** Laboratory tests are usually done in standards conditions, but geometallurgical tests can be different in some deposits (for example rougher test).
3. **Geometallurgical modelling:** In mining resources, conventional techniques are used, for example univariate geostatistics tools. For geometallurgical modelling, we recommend the use of multivariate geostatistics tools, to support the robust estimation.
4. **Geometallurgy in support of mine planning and scheduling:** mining and metallurgical modelled factors must be considered in mine planning and scheduling to estimate costs and revenues. The expected value and risk are important in this stage.

Ore type Definition

Orebody knowledge from a geometallurgy perspective involves the characterization of subsurface material to enable the prediction of how the material will respond to processes within the mining value chain. These processes include blast fragmentation, loading, material handling, crushing, grinding, flotation, leaching, among others. [Jackson 2017].

The deposits have zoning where they present different mineral characterizations (also called GMU geometallurgical units) and within these domains there is also variability in the composition of the rock and process characteristics [Hunt 2014]. According to this concept: what do we mean by ore type? What is the objective of modeling different ore types? [Jackson 2016]. The ore type is a classification of ore with similar metallurgical performance also known as domain, end member, ore zone, entity to enable optimum processing methods to be selected, expected revenue and operating costs leading to the appropriate ore blending and mine planning. Thus, the concept of ore type provides a framework to form a common perspective around the performance of material, in order to make decisions. This implies that, depending on the perspective, the definition of ore type is given through *the orebody knowledge/rock characteristics and performance engineering*. For example, from a blasting perspective, the performance type is the fragmentation distribution (target to optimize process), and this depends on the Geological Domains (Joint characteristics, rock strength, rock density, RMD rating, etc.) and the blast design (operational factor). But from a Mill perspective, the performance target is the Throughput, that depends on fragmentation distribution, impact resistance and grinding hardness (material type + geological domains), and the milling circuit (operational factor).

In general, some common geometallurgical variables that require different ore type definitions are:

- **Bond Work Index** for ball mill (BWi): The grindability test determines the hardness of the ore rock. The Work Index is used when determining the size of the mill and grinding power required to produce the required ore throughput in a ball mill [Bond 1961]. Simulations and modeling of this test show that factors as Particle Size, feed, % passing, makeup water, etc. are operational factors difficult to standardized [Tavares 2012], and a change of these factors are critical in results.
- **SAG Power Index SPI or Starkey Test for SAG mill**: provides the time (minutes) required to perform a specific milling work, from a feed size to an output size [Starkey 1994].
- **SAG Mill Comminution** SMC: It is a function between the specific energy applied and the percentage of product generated in the impact fracture of a specific particle size [Morrell 2006].
- **Kinetics of Rougher Flotation**, maximum recovery with prolonged flotation time or "infinity", mineral characterization and geochemistry (feed or concentrate) in a flotation process, etc. [SGS 2007]

The mineral associations are used to optimize flotation parameters in copper sulfides, in order to increase the grade of the concentrate and the recovery of the valuable metal. For example, Figure 1 shows two minerals after the rougher flotation test laboratory: Left shows a mineral in tail and Right shows a mineral in concentrate. In this example, mineral in concentrate is recovered because the chalcopyrite is liberated and mineral of tail contains occluded chalcopyrite, therefore it is not recovered.

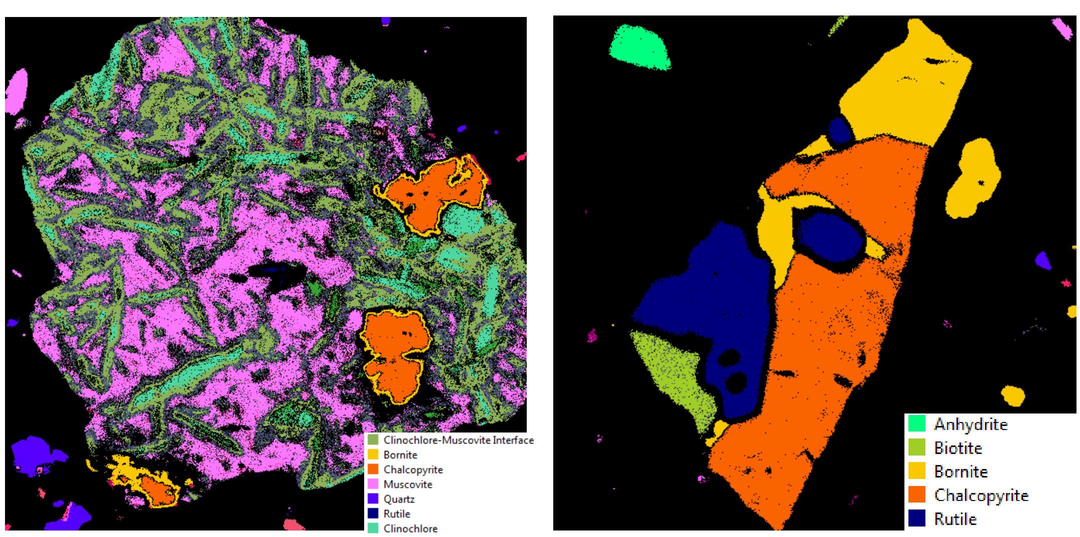

Figure 1: Mineral associations for samples in (left) tail and (right) concentrate of flotation performance

Examples of common geological factors that impact on ore type definitions for two different aspects of mineral processing in porphyry copper sulfide deposits are outlined below.

- **Grindability:** Grinding usually depends on host rock *lithology type and hydrothermal alteration* (for example in deposit Los Bronces Chile, "Sulfatos" project, phyllosilicates have high tenacity tending to behave more elastically than tectosilicates hence, more difficult to break*)*: it is related with de resistance to mill (resulting from combination of different minerals) [Gamal 2012]. Another example is *degree of alteration*: areas with greater degree of hydrothermal alteration have a lower hardness. For example, in SPENCE geometallurgical trends, high argilization zones presents destruction of feldspars replaced to clay minerals, then having a greater grinding capacity. Another example are the *structural veins (micro-structures)*: Depending of mineral present in the structure, these can increase the resistance to grinding by acting as fracture reagent in the rock (e.g. Quartz, anhydrite, calcite, among others). Another example is the *texture* [Oyarzún 2011]: In Teniente, Chile, porphyric basalt has a low grinding due to abundant microcrystals with evidence of mutual interference between adjacent crystals, unlike the gabbro lithology, which has smaller crystals that take the form of the interstices between the larger crystals, showing greater grinding. These examples demonstrate that having knowledge of the ore and gange mineralogy and texture can provide valuable information for effective design of a concentrator flowsheet [Tungpalan 2015], [Lund 2015], [Lamberg 2011]. A lot of factors can be relevant to define the GMUs, and these usually depend on geological variability. All case studies must be analyzed carefully.
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- **Flotation tests:** In this case, recovery and copper degree of concentrate is relevant. Test usually are designed for *primary sulfides minerals*, such as chalcopyrite or bornite [Hunt 2011] recovered above 80%. *Copper oxides* (chrysocolla, atacamite, etc) are not recovered in flotation test. *Secondary copper sulfides* (as covellite, chalcocite, digenite, etc) usually have low recoveries. *Clay minerals* affect negatively the test [Bulatovic 1999], increasing the makeup of water. Other factors such as *granulometry, texture, minerals associations, liberation, etc.* also are relevant, affecting the recovery and costs in production. *Pyrite* is a very common mineral in copper-porphyry deposits, but in the processing stages it usually generates many operational interferences due to its high capacity to react chemically with the medium (water-rock interaction), changes the Eh-pH during the milling and having a high reducing capacity (increases the consumption of steel in grinding) [Mular and Barratt 2002] [Hu 2009] [Garrido 2017].

The geological inputs and relationship to process parameters must be analyzed carefully. These and other factors are relevant for defining the ore type or GMU, and these geological properties can be modeled in deposits and hence GMUs can be modelled. Some techniques to define and model GMUs has been published (geological criteria, spatial and statistical criteria), for example fuzzy clustering with spatial correction has been implemented [Sepúlveda 2018].

Geometallurgical Sampling

The geometallurgical tests are different to copper grade sampling. For example, a common practice is measuring the copper grade through sampling, sample preparation and AAS measurement (Atomic Absorption Spectroscopy [Hannaford 1998]). This methodology is relatively conventional and known by the specialists, but geometallurgical test are not standard. We recommended implementing to standard methodology for geometallurgical tests, for example:

- Select samples without mixing different GMUs.
- Select several samples of each GMU.
- In case of drillholes, choose a constant length of sampling. In production, choose a constant mass.
- Use the standard conditions for testing.

The last condition is difficult to standardize, in particular for flotation tests. This test is designed for each deposit according the geological and operational constrains, also can be different for each GMU. This test should not consider mixing between different GMUs, because there are properties that depends only on the georeferenced variable (for the purpose of modelling), for the purpose of scaling up from laboratory test to industrial performance recovery, mixing should be considered according to mine planning.

A common question in geometallurgical sampling is: What density of data should be sampled to obtain efficient predictive models? It is a difficult question, it depends on the geology of the ore body, operational parameters of mining and operational parameters in mineral processing.

In general, highly variable domains (high variance) are “difficult” GMUs to model or process and require more analysis than homogeneous domains. If a database has a poor sampling density, then the short-term models will be smoothed and will not represent the real variability of the mineral feed, losing the short-term predictability [Garrido 2017] and, therefore, decreasing the metallurgist's ability to react preventively before the change of ore type occurs.

Geometallurgical Modelling

To support geometallurgical modelling, *multivariable geostatistics* techniques are recommended [Wackernagel 1995]. Geometallurgical samples are usually scarse and expensive, then the support of secondary variables or proxies (geochemistry as ICP, geophysical as Natural Gamma, structural information as UCS, etc.) are recommended to obtain more robust models [Garrido 2018]. Multielement geochemistry can provide bulk mineral characterization of hydrothermal alteration associations to support predictive geometallurgical modeling in Porphyry copper deposits [Townley 2018]. The use of synthetic variables (mathematical combination of secondary variables that have good correlation with primary variable) are highly recommended to obtain robust models in an acceptable time and effort of users [Baeza 2018].

One critical aspect of predicting response geometallurgical variables is that they are usually non-additive (the response of block is not necessarily the average of the response of the discretization of the block), and traditional linear methods, such as Kriging, will not work well on such non-linearities. The use of non-linear regression models may alleviate this where additive proxies are used to predict non-additive responses [Sepulveda 2017]. Using geostatistical simulations, if they exhibit spatial correlation, is also a valid approach.

In this stage, geometallurgical variables are estimated in space [Bilal 2017], [Deutsch 2015] [Deutsch 2016] [Boisvert 2013] [Coward 2015] but the mining scheduling and mineral processing values depends of the time (costs by tonnage processed, efficiency, recovery, tonnage per day, etc.). For example, to estimate geometallurgical variables in a block model [Deutsch 2015] usually the geostatistician or orebody modeler estimates the georeferenced variables in space (corregionalized variable). The metallurgist or material scientist estimates the variables in time when a plant is being fed (temporal variable). Mine planning generates the match between spatial variability and temporal variability, as indicated in Figure 2 (Top: short-term model with production drillholes. Bottom: Rougher recovery in process plant, block by block sequencing).

Mine planning generates mixing or blending of minerals. In geometallurgical properties, the results of blending are difficult to predict. For example, [Tavares 2013] show how the grindability of binary ore blends changes in ball mills: *The Bond work index of the mixtures is often higher than the weighed-average value of the individual components in the mixture*. This implies that predicting the behavior of blends is difficult because the additivity is questionable. The same case occurs in flotation performance, scale-up of laboratory flotation process recovery require another technique as Principle of Dimensional Similitude [Truter 2010], because interaction water-rock and physic-chemical cross effects affect the additivity properties [Carrasco 2008].

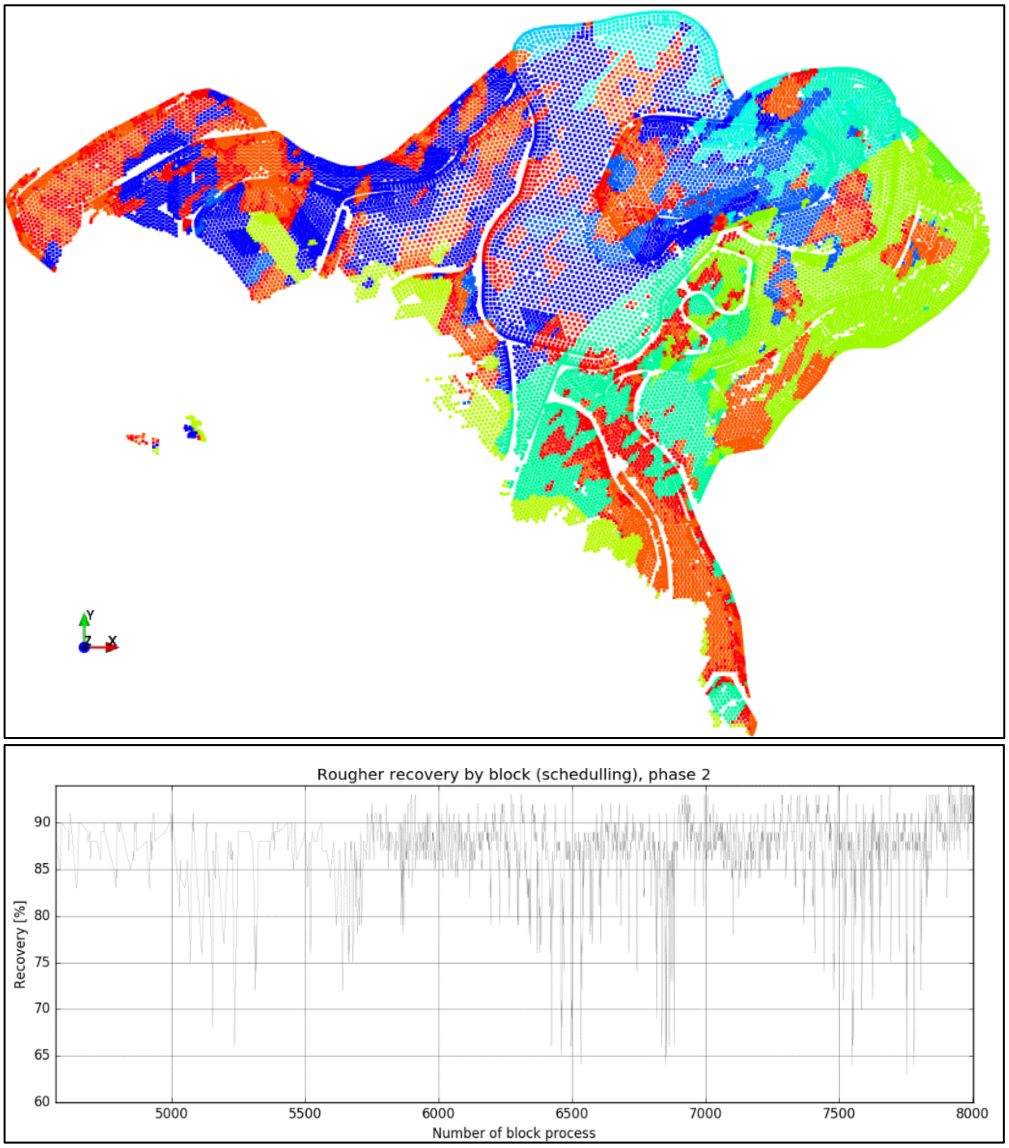

Figure 2: (Top) short-term model with production drillholes. (Bottom) Rougher recovery in process plant, block by block sequencing

Geometallurgy in support of mine planning and scheduling

The spatial variability associated with geometallurgical variables is transferred to a temporal variability when the material is extracted and processed.

It is in this transferring where geometallurgy plays the most important role. The standardized response properties must be transformed to the specific plan conditions and scale. Geometallurgical attributes with distributional scale is still challenging [van den Boogaart and R. Tolosana-Delgado, 2018]. There are several approaches to this. A scale factor for each defined GMUs was considered for scaling-up recovery from standardized flotation tests to plant in Collahuasi mine, Chile [Suazo 2010]. Other approach is using predictive models of plant performance by plant simulators or machine learning real-time predicting models. These predictive models together with the production scheduling must use geometallurgical attributes to ensure an optimal plant operation and to minimize deleterious elements in saleable products, among other factors. The next generation of plant simulators need to use geometallurgical attributes as inputs allowing the main objective of geometallurgy.

Finally, the models are validated / reconciled through short-term data to improve the predictive capacity of the geometallurgical variables that allow reducing the risk in production and improve the expected values of benefits and costs in the mining reserves assessment. The conventional use of geometallurgical variables in mine planning is the use of geometallurgical cut-off grades to define mining reserves. An example on the change of mining reserves considering geometallurgical variables has been published in [Garrido 2017] where it has been shown that the mine planning can vary considering the mining mixing of areas with clay minerals. Temporal variance of this mineral generates operational problems of makeup water, among others, increasing processing costs.

CONCLUSION

The area of geometallurgy is being very relevant to ensure the reliability of mining reserves extraction. A formal methodology of incorporation in the estimation of reserves is important. The review in this article demonstrates the complexity and non-standardization in criteria to define, model and incorporate geometallurgical parameters in the estimation of mining reserves.

Some good practices are recommended: the correct definition of UGMs based on geological-operational criteria, the use of mineral characterization variables to support the multivariable estimation of geometallurgical attributes, the operational scaling of these parameters considering mining temporal mixing, and the quantification of risk through different scenarios to quantify geological – operational uncertainty are practices that should ensure a good management of geometallurgical data and its incorporation into mining reserves.

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