

COMPARING SIMULATED AND INTERPRETED GEOLOGIC MODELS

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ABSTRACT

Geologic ore controls are usually interpreted and modeled from cross sections and plans, as they are critical to construct meaningful and accurate ore reserves models. The geologic boundaries are often modeled as two-dimensional surfaces or three-dimensional solids and used as hard boundaries to constrain the grade estimates. In many cases, the geologic model is the most important factor in estimating the mineralized tonnage predicted by the reserves model, since it is generally drawn to separate the volumes of mineralized and waste material within the deposit.

Because geologic models are interpreted from widely spaced drill hole data, the accuracy of the contacts of the different zones modeled could be poor. The lack of accuracy in the definition of geologic zones can have a significant impact on a resource model.

In this paper it is shown that the geologic interpretation can and should be checked for potential biases. In particular, an unbiased overall volume of the original drill hole information with respect to the resulting solids and codes assigned to the block model is sought. In addition, geostatistical conditional simulations can be used to simulate the geologic attributes modeled, thus providing an alternative view of the geology, and a measure of the uncertainty of the geologic boundaries. The simulated geologic model provides an assessment of the impact of alternative geologic interpretations on the overall uncertainty of the reserves model.

In the case study presented here, the uncertainty of the geologic model is quantified for a difficult-to-model, high-grade copper deposit in northern Chile.

INTRODUCTION

The importance of geologic models in resource and reserve estimation is often neglected. These models are hopefully used to define grade estimation domains and to constrain and condition the grade interpolation or simulation process.

The process of obtaining a suitable, representative geologic model is a long, involved one. It starts with the gathering of geologic data from drill hole information to describe the observed geologic features that are thought relevant. Mapping and logging should be customized and standardized for each deposit, such that the information logged is actually relevant and consistent among the different exploration campaigns and geologists involved. Detailed discussion of this process is beyond the scope of this paper.

In the context of the exploration of a mineral deposit, the geologic information gathered is analyzed to determine which are the most important mineralization controls. Tools used at this stage include genetic models for ore occurrence, testing of geologic characteristics (including grade itself), and statistical analyses of the quantifiable properties. This stage results in the definition of a few geologic variables that need to be spatially modeled.

The geologic variables that are usually modeled depend on the type of deposit and the level of exploration at any given stage of the project development process. The spectrum of possibilities is wide:

some simpler cases include the definition of only one geologic attribute, and occasionally of none. There are instances where the only attribute available is grade, which is used to define zones within the deposit. More commonly, at least lithology is available for modeling and used to constrain grade interpolation. In some large-tonnage, porphyry copper type deposits several variables are recognized as mineralization controls, including lithology, type of mineralization, and alteration. Structural blocks or structures sets are also modeled as mineralization controls.

GEOLOGIC MODELS FOR RESOURCE ESTIMATION

The geologic models applied to support resource estimation should be simplified and more focused versions of the available geology gathered from detailed exploration work.

Certain geologic aspects are of more consequence to resource estimation than others. Specifically, and since we are interested in building a model that will predict as accurately as possible tonnages and grades extracted from a mining operation, we need to describe and model the geologic variables that defined or controlled the deposition of mineralization. These variables ("mineralization controls") should be the focus of all geologic investigation and modeling related to resource and reserve estimation.

Therefore, to obtain adequate models of mineralization controls, two important factors define the difference between the deposit geology and the resource model geology:

Not all mapped geologic information will be a direct or indirect mineralization control, and thus it will not aid in defining the estimation units to be used in the block model¹; and,

The level of geologic detail that can be realistically input into the block model is limited. Sometimes too much detail is undesirable, since it creates geologic populations with little data representation. However, it is usually the case that a resource model with no geologic support is an inadequate one.

Therefore, abundance of geologic information does not necessarily entail a more accurate grade estimation and resource model and, in some cases, it may be a hindrance. This concept helps define the variables to be interpreted and modeled.

A "deterministic geologic model" is obtained by direct interpretation of the geologic variable of interest based on drill hole information. The amount of information available, in addition to other geologic knowledge, allows the geologist to draw, with an acceptable degree of confidence, two- and three-dimensional continuous shapes that represent the position in space of the variable being modeled.

The interpreted geologic model is based on two-or three-dimensional interpretations, generally performed on a set of cross sections. The resulting polygons that represent the interpreted shapes are (or should be) refined on a second set of sections (longitudinal), and finally refined again on plan views.

The order in which the interpretation proceeds depends in part of the geometry of the deposit. For disseminated-type deposits, the final stage should be interpretation on plan, because mine planning

is typically done on benches. For vein-type deposits, it is likely that the most important views will be cross and long sections.

Three-dimensional solid modeling: in this case interpretation occurs also using two-dimensional views, but the available information is not projected onto a plane, but rather the interpreted shapes are tied (“snapped”) to the true three-dimensional location of the drill hole intercept. A three-dimensional solid is then built along the original view planes (cross sections, for example), and then intersected with the second interpretative plane (longitudinal sections). The same solid-building procedure is repeated, from the second view plane, and then intersected again by the third interpretative plane (plan view). The final model is then a three-dimensional solid built from the final view.

The final “deterministic” geologic model is used as input into the subsequent steps in resource estimation. Typically, the resource block model is created and coded with the geologic information according to the solids described above. The geologic model thus becomes an integral part of the resource model, for which no uncertainty is allowed. The interpreted model is coded face value into the block model.

It can be shown that the grade estimation domains defined mostly determine the available mineralized tonnage above cutoff. Since the grade estimation domains are typically based on the geologic variables modeled, then it follows that the geologic model is in itself the most important control on the resources and reserves tonnage above cutoff.

CHECKING FOR BIASES OF GEOLOGIC MODELS

Geologic interpretation and models are subject to errors of different types. The process of interpretation is subjective, and is usually controlled by the amount of drill hole data information, and the conceptual geologic model of the deposit. The interpretation depends on the geologist(s) performing the interpretation, their knowledge about the deposit and potential data shortcomings, and their consistency in applying interpretative criteria in the process. Two different geologists will provide different interpretations, and even, in the experience of this author, two different geologists working in different sectors of the same deposit will probably come up with interpretations that are not easily reconciled.

Besides the inherent subjective nature of the process, there are also potential errors due to the implementation itself, and to accuracy of the tie ups of the interpreted polygons to the drill hole data.

Further discussion on the potential sources of uncertainty of geologic models is beyond the scope of this paper. It should suffice to say that geologic models are oftentimes taken for granted by the ore resource estimator and the mining engineers, with little allowance made for its uncertainty, as if they were as if they were error-free.

This paper suggests that there are at least two additional steps that should be performed to improve the geologic models themselves, and to incorporate its uncertainty into the resource estimation process:

Each geologic variable of the model should be checked for potential biases against the original drill hole information; and,

Geostatistical conditional simulations of geological properties should be used to incorporate the uncertainty of geologic boundaries and domains into the resource and reserve model.

As examples of 1) above, two different comparisons can be implemented to validate the geologic model. These verify that the intended modelling procedure is executed correctly, and also to check the effect of the each modelling step on the resulting overall volumes for each geologic variable.

Areas of Interpreted Polygons

The first check is to compare the areas of the interpreted perimeter with the areas corresponding to the coded blocks, in m². Table 1 illustrates some of the differences encountered for the main Lithology units at the Lince-Estefanía mine² (see the Case Study below). Relative differences of 10% or less are generally deemed acceptable.

Table 1: Comparison between Areas from Polygons in Cross Sections and Blocks, Lithology.

Lithology	Code	Area (m ²)		% Dif
		Polygons	Blocks	
<i>Volcanic Breccia</i>	1	36,493,500	39,328,125	7.8%
<i>Andesite</i>	2	48,213,500	45,987,500	-4.8%
<i>Intrusives</i>	3	12,969,800	14,148,000	9.1%

Back-Coding of Drill Hole Data

The second check is to compare the total length of the original logging (either at an assay or at a composite level) to the total length of the drill hole data when they are “back-coded” with the information contained in the block model, and/or using the interpreted geologic model. This check evaluates how faithfully the original drill holes are reflected in the final geologic model. The basic assumption here is that the relative percentages of the geologic attributes should be more or less maintained after interpretation, i.e., attributes that are present in the drill hole database in a given proportion should also be as present in similar proportions after modelling. Although this is not necessarily true, since the representation of geologic attributes in the database may be itself biased, the check still provides an indication of reasonableness of the geologic model.

Table 2: Comparison of Number of 15m Composites with Discrepancies between the Original Logged Lithology and the “back-coded” Lithology from the Block Model.

Lithology	CODE	Total	Miss-Code	Miss-code/Total (%)
<i>Volcanic Breccia</i>	1	15539	1401	9.0%
<i>Andesite</i>	2	9078	1013	11.2%
<i>Intrusives</i>	3	776	144	18.6%

The column “Miss-code” in Table 2 is the number of 5m composites (in this case) that would receive a different geologic code using the original logged attributes, compared to the “back-coding” from the geologic codes in the block model. As before, differences within 10% are deemed acceptable.

The two checks described above are not the only ones that can be implemented, but they are the basic checks that should provide a first indication of the quality of the geologic model. Further refinement of the checking process, including the use of the uncertainty of geologic models, can be accomplished using geostatistical conditional simulations.

¹ Yet there will be certain geologic variables that need to be interpreted, modeled, and carried into the block model, although they have little relevance from a grade estimation standpoint. These may include variables needed to build metallurgical and geotechnical models, and are not discussed here.

² All numbers presented in this paper have been factored to protect confidentiality.

A CONDITIONAL SIMULATION MODEL: THE MICHILLA CASE STUDY

An implementation of the Sequential Indicator Simulation method is described here, which is used to characterize the uncertainty of the lithology model routinely used to aid in the estimation of resources and reserves at the Minera Michilla copper (Cu) operation.

The simulation model is constructed to assess the resource risk and its impact on the mine plan, as well as the predicted uncertainty of the official resource and reserve statement of the company, incorporating both the uncertainty due to the geologic interpretation, and the uncertainty attached to the grade estimation process.

The Lince-Estefanía mine is located within the district of the same name, some 120 km to the north of Antofagasta. The mine is currently operated by Minera Michilla S.A., and produces approximately 50,000 tons of cathode Cu per year from both an open pit (Lince, using a 10m bench height) and an underground mine (Estefanía, mostly cut-and-fill with 5m lifts). The mine is located at 900m above sea level. Figure 1 shows the location of the Michilla district in northern Chile.

The Lince-Estefanía resource is distributed in various zones at different depths, and includes all drill-indicated oxide, mixed, and sulfide resources to date. The deposit has an upper portion amenable to open pit methods (Lince), and a lower portion, extracted by underground methods (Estefanía). In addition, within the open pit mine there are several distinct geologic zones, which are grouped in areas called Lince, D4 Zone, and Hilary. Within the underground mine, zones are limited by the mining extraction sequence, and are named using letters and numbers, such as A1, B2, D3, and so forth. There are at least 17 areas of interest within the open pit and underground mines. Resources are classified following the AusIMM standards (JORC code), as adopted by Anaconda Chile, and result in approximately 21% of the total resources being classified as measured, 64% classified as indicated, and the rest classified as inferred.

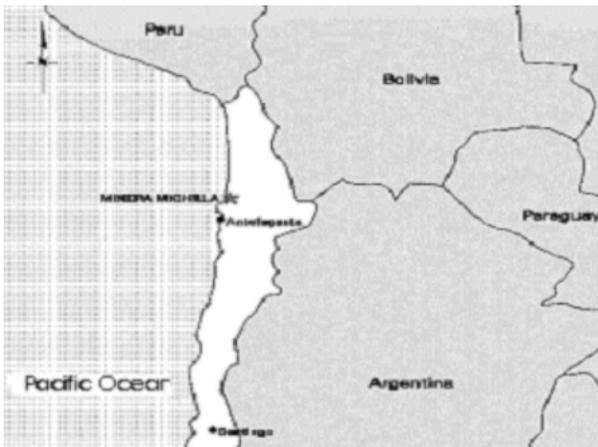


Figure 1: Location Map of the Michilla District.

The geology of the area is characterized by a thick, well-known volcanic sequence, known as La Negra Formation, regionally dipping 30° to the NW, and composed of a stratified series of andesites and volcanic breccias of different characteristics. The andesitic sequence varies from afanitic to porphyric, with intercalated volcanic breccias. Mineralization is hosted in this volcanic sequence, where breccias

are the most favorable hosts. For a more detailed description, the reader is referred to Ferraris and Di Biase (1978).

Genetic models to date suggest that copper (Cu) mineralization has been deposited in small high-grade bodies, according to the porosity of the strata. Within the district, mineralization is hosted around smaller dioritic intrusives (stocks), themselves barren, but that are thought to have contributed Cu mineralization to the host volcanic sequence. The lithology units of interest are three: Volcanic Breccias, Andesites, and Intrusives; these are shown to be the main control on the Cu grade distribution. It is important to note that the presence of volcanic breccias is a necessary, but not sufficient condition for significant Cu mineralization ("mantos") to occur.

The small mineralized bodies ("mantos") are generally ellipsoidal in shape, of variable dimension and grades, and generally concordant with stratification. It is difficult to predict the existence and the size of each manto, as well as its grade distribution. Generally, the mantos are small, 4 to 5m thick, with length and widths of up to 40 or 50m, but many are less than 25m. Cu minerals include mostly Atacamite, with some Chrysocolla ("green" oxides), as well as mixed and sulphide Cu mineralization at depth (mainly chalcocite, covellite, chalcopyrite, and occasional bornite). Grades within the mantos are typically 1 to 5% Total Cu (TCu). Grades over 10% are commonly reported, with individual 1m samples reaching as much as 25% Total and Soluble Cu (TCu and SCu). In addition to the lithology controls, mineralization is also strongly controlled by a series of important structures, principally the Muelle fault, striking N45°E/N60°E, and its conjugate set.

The motivation for simulating geologic units at Minera Michilla stems from the difficulty in accurately defining the transition from better-grade ore bearing, more porous breccias, to poorly mineralized, less porous afanitic andesites, as they occur in the stratigraphic sequence. The lithology transitions are smooth, the thickness of each type of rock being highly irregular. There is little lateral correlation of the units because often the sequence has been displaced by high-angle faults. Given this geologic setting, traditional methods used to interpret and model the lithology sequence implicitly carry a high degree of uncertainty.

Since lithology is the single-most important Cu grade control, it is necessary to assess the quality of the geologic model used to condition grade estimation. A conditional simulation model was developed soon after the Updated 2000 Resource Block Model (interpolated using Multiple Indicator Kriging, Journel 1986) was completed. The simulation model was also based on indicator kriging techniques, so that both the kriged and the simulation models are based on the same basic Random Function model.

The simulation model was built in the volume corresponding to some key sectors and mining phases for the upcoming 5 years of production, both from the open pit mine and for the underground mine. The lithology units were simulated at nodes on a small grid using an indicator (categorical) sequential algorithm, as implemented in the GSLIB software (Deutsch and Journel, 1998), but with a few necessary modifications to the code. The simulated geology was then used to condition the uncertainty model for Cu grade simulation.

Drill Hole Database

There were 1,901 drill holes available at Minera Michilla at the time, including conventional rotary (which are older holes), reverse circulation, and diamond drill holes. The mixture of drill hole types is a significant contribution to the uncertainty in mapping lithology, because the smooth transitions that occur from afanitic andesites to volcanic breccias in the stratigraphic column are much more difficult to accurately identify from cuttings than from core. This difficulty, in addition to other characteristics in mapping, have led to several re-mapping campaigns of existing drill holes, itself an indication of the

intrinsic difficulties associated with mapping lithology in the Michilla district.

The sequence of steps required to obtain the lithology model is:

- The geologic codes incorporated into the database are checked and validated. These checks include identification of cases where the Cu grade for any given interval falls within an expected range. For example, it is extremely unusual to have grades in afanitic andesites above 2% TCu. These unusual intervals are flagged, and re-checked, both for mistakes in drill hole mapping and database coding, and for laboratory errors.
- The different lithology units are then plotted and modeled in cross sections, using geologic and mining software to record the polygons that represent each unit within the section. The cross sections are spaced every 25m, and orientated along the main axis of mineralization, according to the rotated coordinate system.
- The solids corresponding to each perimeter are obtained by extrusion of the polygons half way to the next section in each direction.
- Several plan views of the modeled solids are obtained, which are used to assess continuity of the lithology units across sections, and to validate the sectional interpretation.

The resulting solids are the basis for the block model used to estimate resources. The block model uses a basic block size of 12.5 x 12.5 x 5m, defining sub-blocks at lithology contacts down to a 3.125 x 3.125 x 2.5m block size. The solids representing the lithology units are used to flag each sub-block and to calculate the majority lithology for each main block. Cu grade is then estimated into the block model using the modeled lithology to condition estimation parameters, including using different indicator variogram models and different kriging plans for each unit.

The model described does not allow for uncertainty, and assumes that the polygons on section describe precisely the limits of the different lithology units. Figure 2 shows an example of a cross section, showing the main modeled lithology units.

SIMULATING GEOLOGIC UNITS

The purpose of simulating geologic units in a mining setting is to obtain an uncertainty model that includes both the uncertainty due to geologic interpretation and due to grade interpolation. This uncertainty model can be used in several ways to evaluate, optimize or control a mining operation. The characteristics of the simulated geologic model are dictated thus by its application, as is not necessarily intended to faithfully reproduce geologic details at a very small scale.

Using Sequential Indicator Simulation

There are several algorithms that can be used to simulate categorical variables. They can be object-based (or "Boolean") stochastic methods (Ripley, 1987, Deutsch, 2002), or grid-based methods, such as the sequential simulation discussed here (Journel, 1989, Alabert, 1986), or single or multiple truncations of a Gaussian field (Matheron et al, 1987, Xu and Journel, 1993). There are also other simulation methods that have not been used in mining applications.

The Sequential Indicator method (SIS) is well suited for simulating lithology units at Michilla (as opposed to truncated Gaussian fields) because the smooth transition from porous to non-porous rocks in the stratigraphic sequence is complicated by structural displacements of the units (faults and dikes). These structures incorporate a high degree of variability in the sequence, adding significant short-scale variability, and making the transition much less predictable. In addition, the Lince-Estefanía resource model uses Multiple Indicator Kriging to estimate grades into the block model,

which is important because each component of the uncertainty and derived risk models be internally consistent with the "base case", or resource block model, in this case.

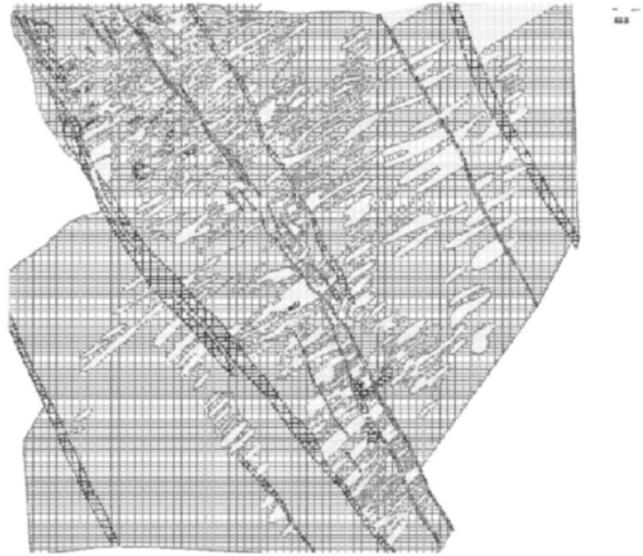


Figure 2: Cross Section of Lithology Polygons and block model with sub-cells. Andesites are modeled as background lithology, Volcanic Breccias are shown in light gray and Intrusives are shown in darker gray, cross-cutting the sedimentary sequence.

It is important to note that all uncertainty models are model-dependent, meaning that choices about the algorithms used in the simulations, about selecting conditioning data, and about other model parameters will impact the final uncertainty and risk model (Goovaerts, 1998, Rossi and Camacho, 2001, Rossi, 2003). Therefore, if a risk model is built from several components (simulated geology plus simulated grades, for example), and is to be applied to a base-case estimate (such as a resource block model), then its components must share as many of the basic assumptions as possible.

Defining the Units and Sub-Zones to be Simulated

The definition of the geologic units to be simulated was done based on a combination of geologic criteria and constraints derived from the simulation study itself and its objectives. Recall that the simulation of the geologic sequence is only a step in a major study that included simulating copper grades (Total and Soluble), and then using the simulation model to assess different aspects of mining risks and resource uncertainty. The sub-zones simulated were determined by the following main factors:

- Geologic knowledge from the district and the operating mines (on a local scale, open pit and underground), in addition to prior statistical studies that demonstrate the relationships between geologic units and copper grades.
- Previous geologic studies (J. Hunt, J. Camacho, and P. Sepulveda, personal communications, 1997-1999) and statistical analysis done by this author noted that a "mineralized envelope" could be defined in the district at a 0.1% TCu cutoff. This "envelope" is in essence a geochemical Cu background threshold for the district, and defines volumes within which mineralization can occur.

- Sub-zones of interest within the Lince-Estefanía deposit where defined based on the sequence derived from the mine plan, rather than by geologic differences. This was done to match the simulated volumes to provide an assessment of mine plan risk for the different production years, both for mining phases in the open pit mine (OP, Lince), and mining blocks in the underground mine (UG, Estefanía).

The three lithology units simulated are shown in Figure 2, and are: a) Volcanic Breccias, including a porous andesite (“amygdaloidal”); b) Andesites and un-mineralized (“dry”) breccias; and c) Intrusives and tectonic breccias.

The geochemical envelope discussed above has important practical implications at Michilla. The underlying assumption is that there is zero probability of finding mineralization outside the 0.1% TCu envelope; on the other hand, there is no assurance that significant or economic mineralization will be found within the envelope. This assumption, which is a key component of both the resource and the simulation models, can be expressed using a mineralization indicator as:

$$Ind_{Cu=0.1\%} = \begin{cases} 1, & \text{if } Cu \geq 0.1\%, P_{min} > 0\% \\ 0, & \text{if } Cu < 0.1\%, P_{min} = 0\% \end{cases} \quad (1)$$

Where the Geochemical Copper Grade Indicator takes a value of 1 if the expected grade is greater or equal than 0.1%, implying a non-zero probability of finding mineralization (P_{min}), and takes a value of 0 if the expected grade is less than 0% Cu, and thus P_{min} is equal to zero.

Definition of the Simulation Grid and Plan

The grid that defined the nodes to be simulated was, for both the geologic and the grade simulation, the same, having the same origin coordinate and rotation than the Resource Block Model at Michilla, so that comparisons and evaluations on a block by block were easily done.

The total number of grid nodes defined is 27.874.000. Not all these nodes receive a simulated value, because two conditions were imposed on the simulation: a) that the node existed inside the 0.1% TCu grade envelope (as discussed above), and b) that at least two composites (hard data) exist within the search neighborhood. Given these conditions, the actual number of simulated nodes was close to 7M.

The simulated models were obtained using a modified version of the SIS routine of the GSLIB software (Deutsch and Journel, 1998). The modifications introduced were related to the handling of the input and output data, simulation parameters, and definition of the nodes to be simulated. The algorithm itself was not modified.

Some of the basic parameters of the simulation plan were as follows:

- The search neighborhood was defined according to the main orientation of the stratigraphic sequence, using a 25m-radius ellipse in the main plane of anisotropy, dipping 30° and with an azimuth N30°W. The search distance in the plane normal to dip was 18.75m.
- To simulate a node, a minimum of two composites was required, with a maximum of 10 composites (hard data) and 10 previously simulated nodes. Also, an octant condition was imposed, accepting a maximum of 3 conditioning data per octant (composites plus nodes).

The use of the mineralization envelope deserves further discussion. As mentioned above and described in Equation (1), mineralization can only occur inside the volume defined by the geochemical

threshold of 0.1%TCu. Two different approaches were used to model this envelope and define the available nodes for simulation.

The first approach was the more traditional, deterministic modeling. Polygons representing the 0.1% TCu were drawn on section by Michilla geologists, based on the available drill hole data, and then used to model in three dimensions the potentially mineralized volume.

The second approach is stochastic, simulating, based on the same drill hole data information, the indicator of Equation (1). The simulation results in a probability of each node being inside the envelope. By applying an arbitrary rule to the simulated probability value, the node can be defined to be inside or outside the envelope. In the case of Michilla, a 0.50 cutoff was chosen, such that if the probability for any node of being inside the envelope was 50% or greater, then the node was defined as inside.

Both approaches were compared in terms of resulting volumes and also in terms of its spatial distribution. The main differences were found at the definition of the edges of the envelope, and in areas where little drill hole information exists. These differences were found to be of little consequence to the final objective of the study, which was risk assessment of the upcoming 5 years production. For simplicity, the deterministic envelope was then chosen to represent the volume of potentially mineralized material.

Applications of the Simulated Lithology Model

There are several possible practical applications of a conditionally simulated model. To illustrate the place of a geologic model simulation in the context of more complete simulation studies, a brief description of the some of these applications follows.

Uncertainty of the Ore Resources

As with most other mining projects, Minera Michilla relies on a Resource Block Model to predict Cu grades for the Lince-Estefanía deposit. This block model is built based on the original drill hole information and geologic mapping, from which a geologic model is built, as well as the copper grades interpolated.

A series of simulated models, regularized to match the exact same geometry and block size of the resource block model, can be interpreted to provide possible grade ranges on a block-by-block basis. This is the “uncertainty model” discussed elsewhere, and can be valuable in assessing possible biases, errors, or simply weaknesses of the resource model.

The “uncertainty model” will be more “realistic” if all possible sources of uncertainty are accounted for. In particular, the geology model (or lithology in this case) is one of the most significant sources of errors, along with grade interpolation. Therefore, incorporating the simulated geology into the uncertainty model will result in a better assessment of possible grade ranges.

Once an uncertainty model is available, several useful sub-products can be derived. For instance, in the mining industry certain resource classification schemes need to be followed for publicly reporting resources, and depending on the authorities involved. In all cases, the resource classification scheme has an implicit assessment of uncertainty, such as “measured” means well-known, “indicated” not as much, and “inferred” quite uncertain”. A simulated uncertainty model can be used to quantify, on a block-by-block basis, on a sub-zone basis, or deposit-wide, what is meant by “measured”, “indicated”, and “inferred” in terms of confidence intervals (Rossi and Camacho, 2001).

Another practical use of the uncertainty model is to define areas within the deposit that have less information than desired. These areas can be found by analyzing their level of uncertainty. If the range of possible values simulated is too large for comfort, then these areas should be drilled more to increase the level of knowledge about their geologic and grade distribution.

Mine Risk Analysis by Sector

A natural follow-up to the uncertainty model is to transform it into a risk model, usually through the application of a mine plan.

If using an existing mine plan, the risk analysis is done by processing the simulated grade models through the specified mine plan, by sectors and according to the existing schedule. Thus, the risk of not achieving production goals can be assessed.

If assessing whether an optimal mine plan has been developed, then the simulated models are processed on an individual basis, just like any other resource block model is normally processed. This includes determining the optimal pit shell or underground mining sectors, and then defining an optimal extraction sequence for the material. Processing all the available simulated models results in possible variations of production from the mine, and thus a complete risk analysis on the initial prediction.

Finally, even before the mine opens, a complete simulation of the mining operation is possible. This includes simulating the extraction sequence based on the grade simulation model, including the ore/waste selection process. This can be useful in predicting future dilution and ore loss, based on a given level of geologic knowledge.

RESULTS

Twenty lithology simulations were obtained and statistically and graphically validated and compared against the drill hole dataset (5m composites). Three were discarded because they did not reproduce adequately the proportions of each lithology, or their arrangement in space was not “realistic”.

Of the remaining 17 simulated models, only one was kept as the final product (Figure 3), see discussion below. The decision to discard the other 16 models was subjective, given that all of them complied with pre-defined statistical criteria. The final decision was made based on visual inspections, and comparisons of simulated geology with known geology in areas where past production information was available (open pit and underground workings).

The most significant difference between the interpreted and the simulated lithology models is the representation of the continuity of the sub-vertical intrusives that cross cut the stratigraphic sequence. This is visually obvious (compare Figures 2 -a cross section- and 3 -a perspective view-), but is also reflected in the statistical analysis shown in Table 1 and from the statistical validation of the simulation, not shown here in detail. The interpreted intrusives are given more continuity than the actual data reflects, mostly due to the geologist’s interpretative model, which requires less data support to give these dikes and tectonic breccias continuity. Instead, the conditional simulation reflects more faithfully the actual proportion of drill hole data available that has been coded as intrusives. The decision as to which model is closer to the “truth” is subjective, since it depends on how much weight is given to the intrusives’ model of continuity as interpreted by the geologist.

There are several alternative methods that can be used to incorporate a simulated lithology model into a simulated grade model, and eventually a risk analysis study. The most laborious option is to apply each simulated lithology model as direct conditioning information on the simulated grade model, much like a traditional lithology model is used to define domains and constrain grade interpolation. This requires that a simulated lithology model be obtained and validated for each simulated grade model desired.

A second alternative is to obtain the most likely lithology using, for example, a majority rule to determine which of the three lithologies is more likely at any given point in space. Then, this “secondary” simulated model would be used to constrain all simulated grade models.

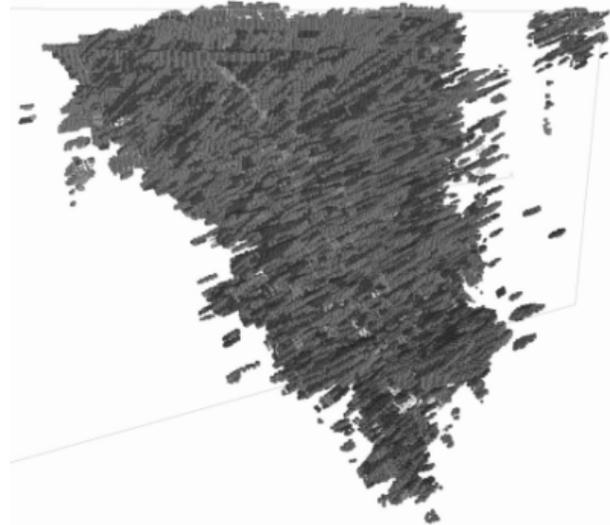


Figure 3: Perspective View of the Final Output Lithology Simulation. Note the gently dipping pseudo-stratigraphic sequence. In light gray Volcanic Breccias; in dark gray Andesites; and in lighter gray Intrusives. Compare to Figure 2.

A third alternative, applied in this case study, is to use a single lithology simulation, and transform it to a series of “soft indicators” (Alabert, 1987). These soft indicators are in fact transformations of the simulated lithology into a conditional cumulative distribution function (ccdf) at each node. The idea is to quantify through these soft indicators statements about volcanic breccias being “more mineralized” than andesites, for example. The process requires definition of the lithology-grade relationship, based on original drill hole data, and done on a local basis (by sectors or sub-zones), to avoid mixing the local grade controls over the whole deposit. To ensure consistency, the same indicators defined to obtain the grade simulations need to be used in this step.

Table 3 shows the probabilities (“soft indicators”) used defined for the central-upper portion of the deposit (“Lince-Low”). Note how the volcanic breccias show a higher probability of being mineralized. Consider, for example, the 1.0% TCu indicator: there is a 24.2% probability that the grade will be higher than 1.0% if the lithology is a breccia, but only 7% probability for andesites and a 5.6% probability for intrusives of ever exceeding 1.0% TCu.

Table 3: “Soft Indicators” used to condition TCu grade simulations, “Lince-Low” Sub-Zone. The probabilities shown are taken from the simulated CCDF.

Grade Indicators →	0.2% TCu	0.5% TCu	0.8% TCu	1.0% TCu	1.2% TCu	1.5% TCu	2.0% TCu	3.0% TCu	5.0% TCu
Volcanic Breccias	52.5%	67.5%	73%	75.8%	78.2%	81.1%	84.9%	90.2%	95.4%
Andesites	60.5%	83.7%	92.2%	93.0%	94.6%	96.4%	97.9%	99.2%	99.5%
Intrusives and Tectonic Breccias	73.5%	89.0%	93.2%	94.4%	96.1%	97.3%	98.2%	99.1%	99.5%

Simulation Model Comparison and Validation

Several methods were used to validate the lithology simulations described. These included statistical comparisons of the resulting global (deposit-wide) and local (by sub-zones) proportions of each lithology against the existing lithology proportions in the database,

and also comparing with the proportions resulting from the deterministic model.

There is always a degree of "bias" between the information as provided by the drill hole data and the geologic model constructed, whether deterministic or stochastic. This bias can be by the process of interpreting and assigning spatial influence to each composite, see discussion above. For a relatively complicated deposit such as Michilla, "modeling error rates" (Tables 1 and 2) of 10% or less are deemed acceptable. This level of "acceptable" bias also provides a guideline for the simulated model. However, because the simulation always honor the conditioning data point, this comparison has to be done on a larger volume, regularizing the original cells to a block (typically the same size as the block of the resource model), and assigning its lithology based on a majority rule, for example.

Also, it is important to visually compare the interpreted (deterministic) lithology units on cross sections and plan views, with the various simulated images. This comparison provides an assessment of the "reasonableness" of the simulated models, and, if needed, is also an important component on convincing the local geologists as to the merits and characteristics of the simulated model. In particular, the characteristics of the simulated lithology should be analyzed in "problematic" areas, where specific concerns may need to be addressed. Finally, the lithology model should be validated against actual production information, such as blast hole and underground mine workings mapping. Assuming that this information has not been used to obtain the simulation itself, it is important to check what are the error rates ("misclassification") of lithology codes on a block-size level compared to observed (logged) data. If, as is commonly the case, production data is to be used as conditioning data in the simulation model itself, then it is advisable to run a smaller lithology simulation model on a sub-zone where production data is available, using only exploration drill hole data. This area can be used to "calibrate" the simulation model under the assumption that, if acceptable error rates are achieved in the calibration area, then the simulation model should behave similarly well elsewhere within the deposit.

CONCLUSIONS

This paper illustrates the application of indicator variables to the simulation of geological properties, or, more generally, categorical variables.

Deterministic geologic models are typically taken for granted in the context of resource estimation, with little or no understanding of their limitations. Basic checks for potential biases are often neglected, and little validation, other than the overall reasonableness of the geologic model, is done.

Conditional simulation techniques can be used to assess the uncertainty of interpreted geologic boundaries or zones, which is particularly relevant when a model of uncertainty for the resources and reserves is sought. The inherent difficulties in modeling deterministically the pseudo-stratigraphic sequence at the Lince-Estefanía mine provides a good example of such a case.

The Sequential Indicator method has been the most common approach used to date in a mining setting mostly because it is reasonably simple and easily understood by practitioners. Additionally, it provides several alternatives to input the geologic uncertainty

model into the grade uncertainty model, principally through the indicator formalism.

The use of soft indicators at Michilla allowed representing the lithology control on copper grades on a local basis (by sub-zones), ensuring that the posterior grade uncertainty model incorporates the uncertainty related to the deterministic lithology modeling.

Comparisons and validations between the interpreted geologic model and the simulation model ensure consistency of these models, providing also indications of the appropriateness of the overall resource model.

REFERENCES

- ¹ Alabert, F.G., 1987, "Stochastic Imaging of Spatial Distributions using Hard and Soft Information", MSc. Thesis, Stanford University, Stanford, California, USA.
- ² Deutsch, C.V., 2002, "Geostatistical Reservoir Modeling", Oxford University Press, New York, 376p.
- ³ Deutsch, C.V. and Journel A.G., 1992, "Annealing Techniques Applied to the Integration of Geological and Engineering Data", In Report 5, Stanford Center for Reservoir Forecasting, Stanford, California, USA.
- ⁴ Deutsch, C.V. and Journel A.G., 1998, "GSLIB: Geostatistical Software Library and User's Guide", Second Edition, Oxford University Press, New York, 340 p. plus CD.
- ⁵ Ferraris, F., and Di Biase, 1978, "Hoja Antofagasta", Carta Geológica de Chile, Instituto de Investigaciones Geológicas, Santiago, Chile.
- ⁶ GeoSystems International, July 1999, "Informe Simulaciones Condicionales, Lince-Estefanía", Cía. Minera Michilla, S.A, 105p. plus Appendices, Unpublished Internal Report.
- ⁷ GeoSystems International, May 1999, "Informe Actualización Cálculo de Recursos, Lince-Estefanía", Cía. Minera Michilla, S.A., 85p. plus Appendices, Unpublished Internal Report.
- ⁸ Goovaerts, P., 1997, Geostatistics for Natural Resources Evaluation, Oxford University Press, 483p.
- ⁹ Journel, A.G., 1986, "Constrained Interpolation and Qualitative Information", Mathematical Geology, Vol. 18, No.3, 269-286.
- ¹⁰ Ripley, B.D., 1987, Stochastic Simulation, John Wiley and Sons, New York, 237p.
- ¹¹ Rossi, M.E., 2003, "Practical Aspects of Large-Scale Conditional Simulations", Proceedings of the 31st International Symposium on Applications of Computers to the Mineral Industry (APCOM), Cape Town, South Africa.
- ¹² Rossi, M.E., and Camacho V., J., 2001, "Applications of Geostatistical Conditional Simulations to Assess Resource Classification Schemes", Proceedings of the 102nd Annual Meeting of the Canadian Institute of Mining, Metallurgy, and Petroleum (CIM), Quebec City, Canada.
- ¹³ Xu, W., and Journel, A.G., 1993, "Gtsim: Gaussian Truncated Simulation of Lithofacies", in Report 6, Stanford Center for Reservoir Forecasting, Stanford, California, USA.