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Quantifying Uncertainty in Mineral Resources by Use of Classification Schemes and Conditional Simulations[1]

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Mineral inventory determination consists of estimating the amount of mineral resources on a block-by-block basis and classifying individual blocks into categories with increasing level of geologic confidence. Such classification is a crucial issue for mining companies, investors, financial institutions, and authorities, but it remains subject to some confusion because of the wide variations in methodologies and the lack of standardized procedures. The first part of this paper considers some of the criteria used to classify resources in practice and their impact through a sensitivity study using data from a Chilean porphyry copper deposit. Five classification criteria are compared and evaluated, namely: Search neighborhoods, absolute and relative kriging variances, absolute and relative conditional simulation variances. It is shown that some classification criteria either favor or penalize the high-grade areas if the grade distribution presents a proportional effect. In the second part of the paper, conditional simulations are used to quantify the uncertainty on the overall mineral resources. This approach is promising for risk analysis and decision-making. Unlike linear kriging, simulations allow inclusion of a cutoff grade in the calculation of the resources and also provide measures of their joint uncertainty over production volumes.

KEY WORDS: resource classification, mineral inventory, geostatistics, kriging, conditional simulations, proportional effect.

INTRODUCTION

The investments and development of mining projects depend on the quantity (tonnage) and quality (grades) of the mineral resources in the deposit (Vallée, 1999, 2000). Mineral inventories are based on assessing the grades and tonnages through an estimation procedure such as ordinary kriging. This allows the construction of a model where block grades are estimated, usually from exploration data. Logically,

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this leads to block estimates with different precisions, depending on the number and configuration of the neighboring samples used to estimate each block, as well as on the spatial continuity of the grades and their local values (Diehl and David, 1982). This observation has led the mining industry to define several categories of mineral resources, to reflect the degree of uncertainty on the estimated grades. Classification of mineral resources and ore reserves is important because reliable information is required by financial institutions, investors, and authorities for fixing royalties and taxations, and for strategic decisions and investment planning.

Several international classification systems have been developed in the past decades (Rendu and Miskelly, 2001), the main ones being the American USGS Circular 831 (USGS, 1980) and SME Guide (SME, 1999), the South-African SAMREC Code (SAMREC, 2000), the Canadian CIM Guidelines (CIM, 2000) and National Instrument 43-101 (CSA, 2001), the European Code (EURO, 2002), and the Australasian JORC Code (JORC, 2004). All these codes are broadly similar, although some differences in their definitions remain. The JORC code is with little doubt the one that has found wider acceptance in countries that do not have their own code. The following definitions are taken from the JORC code:

- A *mineral resource* is accepted as a concentration of material of intrinsic economic interest such that there are reasonable prospects for eventual economic extraction. The characteristics of a mineral resource (location, tonnage, grade, continuity, etc.) are estimated or interpreted from geologic evidence and knowledge, such as exploration samples from drill holes. Mineral resources are subdivided into *measured*, *indicated*, and *inferred* categories, in order of decreasing geologic confidence.
- An ore *reserve* is defined as an economically mineable part of a measured and/or an indicated mineral resource. Its assessment includes mining, metallurgic, economic, legal, environmental, social, and governmental considerations, such that the extraction can be reasonably justified. Ore reserves are subdivided into *proven* and *probable*, in order of decreasing financial confidence.

The previous categories combine the uncertainty that stems from several sources, the first one being the inherent geological uncertainty of the phenomenon. Indeed, the modeling of the deposit is nothing but an interpretation based on scarce information. The expert appreciation of the available data (samples, analyses, maps, etc.) allows one to construct a model of the main geological units of the deposit, that is, an interpretation of their extent, location, and characteristics. However, the geologic information and interpretation are subject to error. In any case, the mineral resources should be automatically classified as *inferred* if the geological model is deemed unconfident: Geological considerations always prevail over any mathematical measure of uncertainty. A second source for errors is the grade variability, which can be quantified through structural tools such as the variogram. Geostatistical methods can be used to generate estimates of the block grades using this information, but this requires assumptions of homogeneity of the grades over each geological unit (stationarity decision) as well as the knowledge of the model parameters. Finally, there are "modifying factors," including technological factors (mining, metallurgic, environmental) and external factors (economic, legal, social, and governmental).

Codes for mineral inventory classification and reporting aim at accounting for all these uncertainties through the definition of confidence classes (Wober and Morgan, 1993). For instance, *measured resources* are defined as those for which the data locations are spaced closely enough to confirm geologic and grade continuity, while for *indicated resources*, there must be enough information to reasonably assume geologic and grade continuity, although this continuity is not confirmed. The definitions of the various categories remain somewhat vague and are left to the judgment of a specialist called "competent" or "qualified" person.

In this work, we focus on the evaluation and classification of mineral resources and do not examine the definition of ore reserves. This study compares five criteria that are currently used in Chilean copper mining companies, based on geometrical or geostatistical considerations, and stresses the pros and cons of each criterion. In the last section, an alternative approach based on stochastic simulations is proposed for quantifying the uncertainty on mineral resources.

PRESENTATION OF THE DEPOSIT AND THE DATA

The concepts and results will be illustrated through a case study of a porphyry copper deposit exploited by open pit, located in the Central Andes in Chile and owned by Codelco Chile (Andina Division). We focus on a single estimation domain central to the deposit. The implementation in a full-scale study would require investigating the geological unit definition, the treatment of the boundaries between these units, and the use of cutoff grades to distinguish ore from waste, which are beyond the scope of this application.

The available data are the copper grades determined for a set of 2376 twelve-meter composites from diamond drill holes in a volume of 400 m $\times$ 600 m $\times$ 130 m. The drill hole spacing is about 40 m along the north and east coordinates, with several infill drill holes in the center of the sampled area (Fig. 1A). Sampling and sample preparation errors are kept under standard levels, ensuring the quality of the grade values. Their histogram has a lognormal shape with a mean grade of approximately 1.00% Cu and a coefficient of variation of 0.63 (Fig. 1B). Three main rock types can be distinguished in the area (Serrano and others, 1996): (1) Cascade granodiorite, which is one of the host rocks of the breccia complex and is located in the eastern and southern sides of the area; (2) tourmaline breccia, located in the central part of the area; most of the mineralization lies in this rock type, which is constituted of granodiorite clasts surrounded by matrix cement

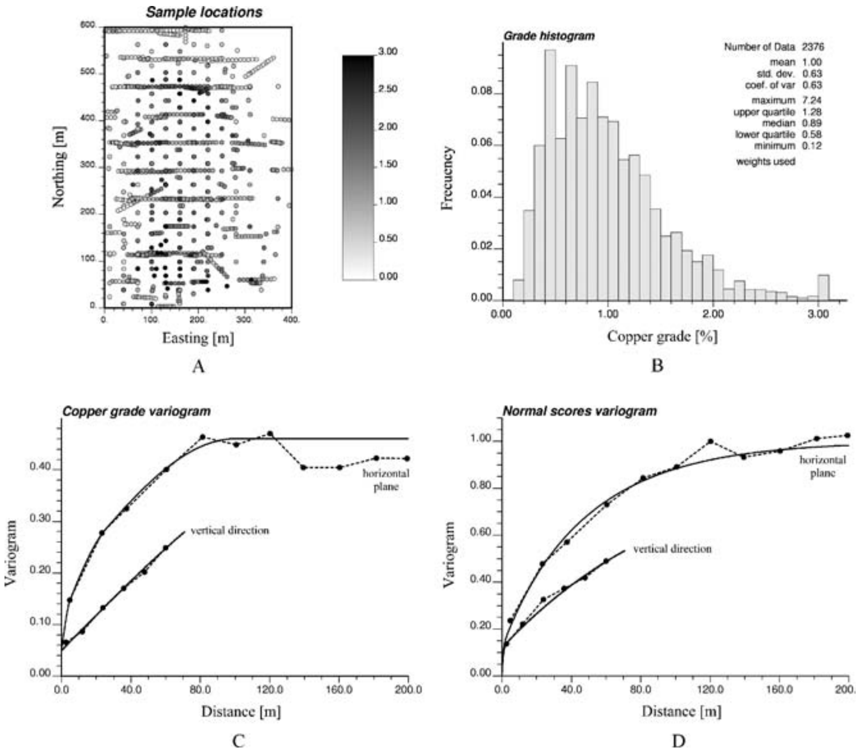

Figure 1. (A) Location map of drill hole samples; (B) declustered histogram of the copper grades for the studied area; experimental and modeled variograms along the main anisotropy directions for (C), the copper grades and (D), their normal scores transforms.

dominated by tourmaline and sulfides; and (3) minor breccias, principally located in the western and southern parts of the area under study. The variogram analysis shows a greater spatial continuity along the vertical direction than in the horizontal plane, for both the copper grades and their normal scores transforms (Table 1 and Fig. 1C and D). Selective mining units are 15 m $\times$ 15 m $\times$ 12 m in size, which is also the size of the blocks in the models that will be used to represent the grade distribution; each of these models contains 15,644 blocks that cover the sampled area.

Two block models are constructed: The first one by ordinary kriging of the grades (Fig. 2A), the second one by averaging a set of 49 conditional simulations (Fig. 2B) obtained by applying the turning bands method (Matheron, 1973, p. 461). In each case, additionally to the grade estimates, one also has a measure of uncertainty: Kriging variance (Fig. 2C) and conditional variance of the simulations (Fig. 2D). Notice that the maps of block grade estimates are slightly different,

Table 1. Parameters for the Models of the Copper Grade and Normal Scores Variograms

Model type	Sill	Range (north direction) (m)	Range (east direction) (m)	Range (vertical) (m)
Copper grades				
Nugget	0.05			
Spherical	0.135	20	20	180
Spherical	0.285	100	100	180
Normal scores transforms				
Nugget	0.14			
Exponential	0.05	20	20	50
Exponential	0.81	135	135	400

Note. The models are isotropic in the horizontal plane, but have a greater range along the vertical direction.

particularly at the edges of the estimated domain. These differences are due to the use of ordinary kriging in the first case, where the mean changes locally from one kriging neighborhood to another one, whereas the second model corresponds to an average of simulated fields, where a stronger assumption of stationarity is required and a single global mean is used to adjust the estimates over the domain. Much more different are the maps of block grade variances. From the one corresponding to the kriging variances, it can be seen the dependency between this measure of uncertainty and the local configurations of the data, while for the map of conditional variances (local variances of the simulated block grades), a strong dependency between the estimated grades (local mean) and the measure of uncertainty is evident. The consequences of this difference in classification are discussed in the next section.

MINERAL RESOURCE CLASSIFICATION

In this section, we consider several criteria for classifying the estimated resources and comment on their pros and cons.

Criteria for Classifying

Neighborhood Restrictions (Applied to the Kriged Resources)

This first criterion consists of classifying the blocks according to geometrical constraints, that is, the number and configuration of data located in a given neighborhood. In this application, the block grades estimated by ordinary kriging (Fig. 2A) are classified using two auxiliary estimation runs, corresponding to two kriging neighborhoods with different search constraints. The blocks estimated by

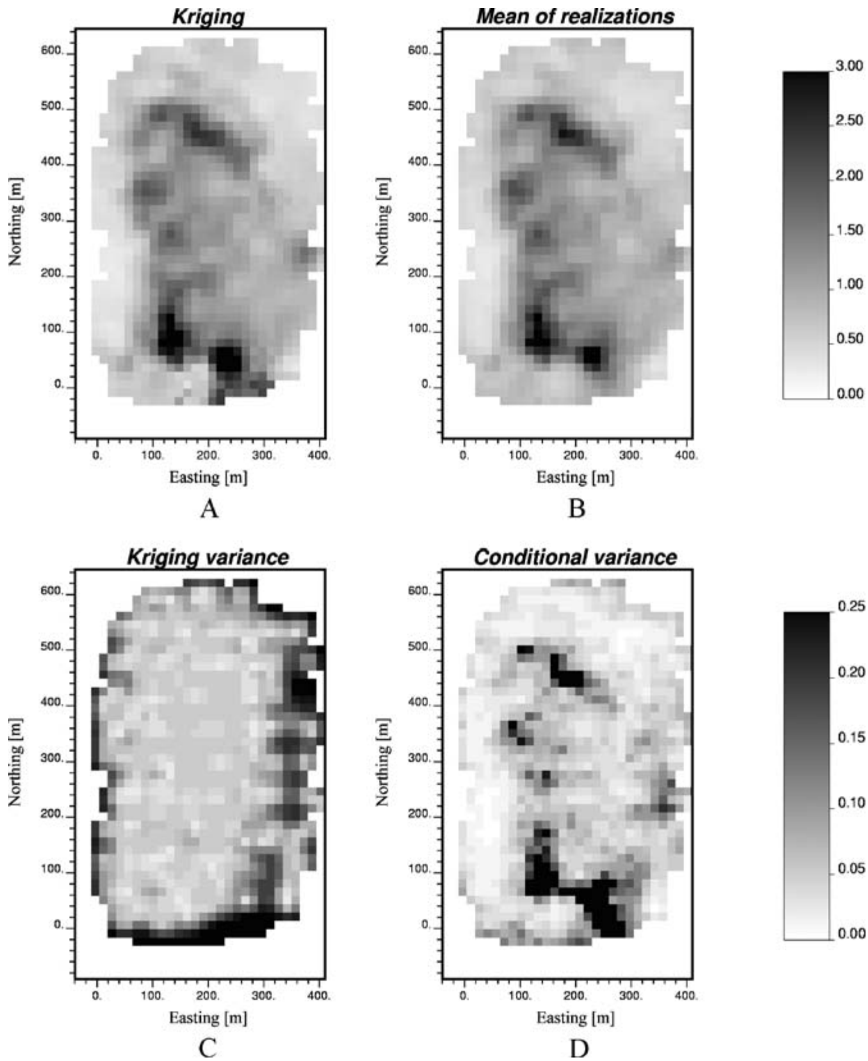

Figure 2. Block models with the estimated copper grades obtained by (A) ordinary kriging, and (B) conditional simulations. Uncertainty models corresponding to (C) ordinary kriging variances, and (D) conditional simulation variances. Representation of a single bench.

using the most restrictive neighborhood are classified as measured resources, the blocks estimated with the second neighborhood but not the first one are classified as indicated resources, whereas blocks within the study volume not estimated by either of these runs are classified as inferred resources. Beware that the grades

Table 2. Parameters of the Kriging Neighborhoods Used for Classifying the Mineral Resources

	First test		Second test		Third test	
	Measured resources	Indicated resources	Measured resources	Indicated resources	Measured resources	Indicated resources
Radius along east direction	50 m	90 m	50 m	90 m	50 m	90 m
Radius along north direction	50 m	90 m	50 m	90 m	50 m	90 m
Radius along vertical direction	90 m	90 m	90 m	90 m	90 m	90 m
Minimum number of data	4	4	4	4	4	4
Maximum number of adjacent empty octants	2	3	2	3	2	3
Maximum distance without data	15 m	20 m	20 m	25 m	25 m	30 m

estimates are obtained from the original kriging run shown in Figure 2A. The two auxiliary runs are done only to define the volumes corresponding to measured, indicated, and inferred resources, but the estimated grades of these two runs are not kept. In particular, the estimated amount of measured resources would be imprecise and conditionally biased if it were calculated after the most restrictive neighborhood, which has a small search radius and may contain few samples.

In the present case, three tests are performed. The parameters that define the neighborhoods are given in Table 2. The search radius in the horizontal plane is smaller or equal to the radius in the vertical direction, so as to account for the greater continuity of the grades along the vertical direction than in the horizontal plane. The three tests only differ on the maximum distance without data.

Kriging Variance (Applied to the Kriged Resources)

Here, each block is classified according to its kriging variance, which accounts not only for the quantity and configuration of the neighboring data, but also for the spatial continuity of the grades measured by their variogram. In this respect, the kriging variance combines both geometric and geological knowledge (through geostatistical parameters). In practice, the criterion requires defining a threshold variance between the categories (Royle, 1977; Sabourin, 1984; Froidevaux, Roscoe, and Valiant, 1986; Snowden, 2001). For instance, one can compute the kriging variance of a block located at the center of a given sampling mesh, which is taken as the upper bound of the category (the calculation of this threshold variance can be made once the grade variogram is modeled, since the kriging variance does not depend on the data values). Again three tests are performed with the parameters given in Table 3. Different mesh sizes, based on experience in this type of deposits, define the threshold variances for classification.

Table 3. Definition of the Sampling Meshes and Threshold Variances for Classifying the Blocks into Measured, Indicated, or Inferred Resources

	First test		Second test		Third test	
	Measured resources	Indicated resources	Measured resources	Indicated resources	Measured resources	Indicated resources
Sampling mesh (east direction)	30 m	60 m	60 m	120 m	75 m	150 m
Sampling mesh (north direction)	30 m	60 m	60 m	120 m	75 m	150 m
Sampling mesh (vertical direction)	12 m	12 m	12 m	12 m	12 m	12 m
Maximum kriging variance	0.081	0.233	0.233	0.366	0.293	0.389

Conditional Variance (Applied to the Average Simulated Resources)

This criterion is similar to the previous one, except that the kriging variance is replaced by the conditional variance calculated from the realizations conditioned to the available data. Since the values of the kriging and conditional variances lie in a similar range [between 0.0 and 0.5 $(\%\mathrm{Cu})^2$], the same threshold variances are applied to define the three categories. However, results are expected to differ since, as previously mentioned, the conditional variance strongly depends on the local mean while the kriging variance only depends on the spatial configurations and is independent of the data values, thus also independent of the local mean.

Relative Kriging Variance (Applied to the Kriged Resources)

This criterion relies on the kriging variance of each block divided by the square of its estimated grade, providing a standardized and dimensionless measure of uncertainty that is used to define whether a block is classified as a measured, indicated, or inferred resource (David, 1988, p. 203). Blackwell (1998) suggests threshold relative variance values for porphyry copper deposits; however, here we choose more restrictive values that are closer to the ones commonly used in Chilean copper deposits (Table 4).

Table 4. Definition of the Relative Kriging Variance Thresholds for Classifying the Blocks into Measured, Indicated, or Inferred Resources

	First test		Second test		Third test	
	Measured resources	Indicated resources	Measured resources	Indicated resources	Measured resources	Indicated resources
Relative standard deviation	15%	25%	20%	30%	25%	35%
Relative kriging variance	0.0225	0.0625	0.04	0.09	0.0625	0.1225

Relative Conditional Variance (Applied to the Average Simulated Resources)

The classification is performed according to the values of the relative conditional variance (variance of the simulated block grades over all the realizations divided by the square of the average simulated block grades); the same threshold variances as in the previous criterion are used to define the resource categories. This standardization can be understood as removing the effect of the local mean grade in the measure of uncertainty, making it similar to the kriging variance.

Results and Comments

For each criterion and each test, the tonnages and metal quantities of the three categories are calculated. The results, presented in Figures 3 and 4 and summarized in Tables 5 and 6, call for several comments. First of all, great differences are observed when changing the criterion that defines the categories, or when the values of the parameters that rule a given criterion are modified. It is important to mention that all these methods can be considered *valid* methods in the current framework defined by international codes. Therefore, we can conclude that results from mineral resource evaluation are still very dependent on the way the uncertainty is modeled and how it is taken into account (absolute versus relative variances). The classification is always subjective and should be clearly documented so as to be reproducible by an external auditor. Although the sensitivity

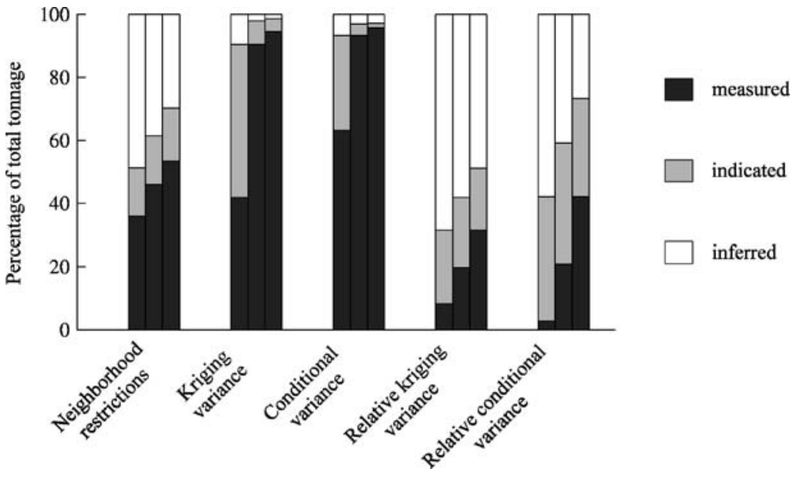

Figure 3. Percentage of the total tonnage per category corresponding to five different classification criteria. For each criterion, three tests are performed and represented by three vertical bars.

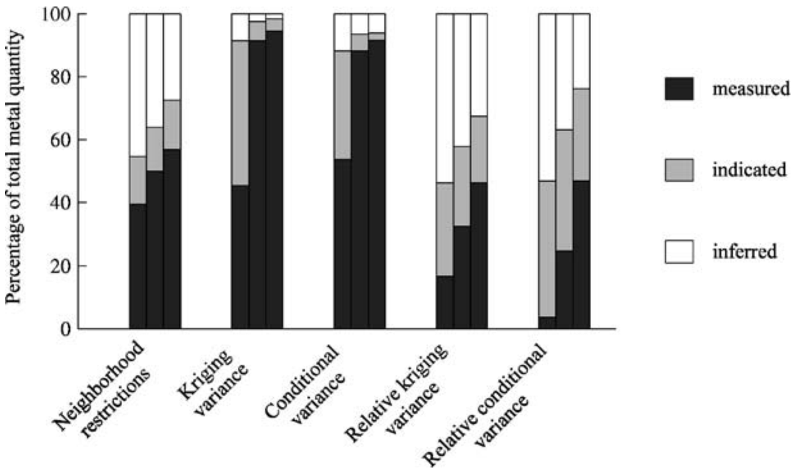

Figure 4. Percentage of the metal quantity per category corresponding to five different classification criteria. For each criterion, three tests are performed and represented by three vertical bars.

study is not presented, the authors have also noted that the classification strongly depends on the block size of the resource models: When this size increases, the kriging variance and conditional variance decrease due to the *support effect*, so the quantity of measured resources is likely to increase, as pointed out by David (1988, p. 194). This observation raises the question of determining which block size is appropriate for resource classification. For instance, larger blocks may be considered in the first stages of the project, when the drill hole spacing is important and the uncertainty about the grades on small supports is of great magnitude.

By examining the mean grade per category (Table 7), one notes that the relative kriging variance criterion favors the high grades and that the conditional variance criterion favors the low grades: For these criteria, the measured resources have a mean grade equal to 2.01 and 0.85%Cu, respectively, whereas the overall mean grade is 1.00%Cu. This can be explained by a property of the grade spatial distribution known as *proportional effect*, according to which the high-grade areas have a greater variability than the low-grade areas. For lognormal distributions (which is almost the case for the deposit under study), theory even states that the local dispersion is proportional to the square of the local mean, i.e., the local standard deviation is proportional to the local mean (Journel and Huijbregts, 1978, p. 187; Chilès and Delfiner, 1999, p. 56). This effect appears in deposits of metals for which the grades have a positively skewed distribution (copper, gold, silver, etc.); the higher variability affects the low grades instead of the high grades for negatively skewed grade distributions (e.g., for iron deposits).

Table 5. Percentage of the Total Tonnage Per Category, Corresponding to the Five Tested Classification Criteria

	First test			Second test			Third test		
	Measured	Indicated	Inferred	Measured	Indicated	Inferred	Measured	Indicated	Inferred
Neighborhood restrictions	35.9	15.4	48.7	45.9	15.6	38.5	53.4	16.8	29.8
Kriging variance	41.8	48.6	9.6	90.4	7.4	2.2	94.5	4.2	1.3
Conditional variance	63.2	30.1	6.7	93.3	3.7	3.0	95.7	1.5	2.8
Relative kriging variance	8.3	23.1	68.6	19.8	22.0	58.2	31.4	19.7	48.9
Relative conditional variance	2.8	39.2	58.0	20.9	38.3	40.8	42.0	31.3	26.7

Note. The total tonnage is 114 million tonnes.

Table 6. Percentage of the Metal Quantity per Category, Corresponding to the Five Tested Classification Criteria

	First test			Second test			Third test		
	Measured	Indicated	Inferred	Measured	Indicated	Inferred	Measured	Indicated	Inferred
Neighborhood restrictions	39.4	15.2	45.4	49.9	14.0	36.1	56.8	15.8	27.4
Kriging variance	45.3	46.1	8.6	91.4	6.1	2.5	94.6	3.8	1.6
Conditional variance	53.7	34.4	11.9	88.1	5.4	6.5	91.5	2.4	6.1
Relative kriging variance	16.7	29.5	53.8	32.4	25.4	42.2	46.2	21.3	32.5
Relative conditional variance	3.6	43.2	53.2	24.8	38.4	36.8	46.8	29.4	23.8

Note. The total metal quantity is 1.14 million tonnes for both the kriged and the simulated block models.

Table 7. Mean Grades Per Category (% Cu) Corresponding to the Five Tested Classification Criteria

	First test			Second test			Third test		
	Measured	Indicated	Inferred	Measured	Indicated	Inferred	Measured	Indicated	Inferred
Neighborhood restrictions	1.10	0.98	0.93	1.09	0.90	0.94	1.06	0.94	0.92
Kriging variance	1.08	0.95	0.90	1.01	0.83	1.16	1.00	0.91	1.20
Conditional variance	0.85	1.15	1.77	0.94	1.47	2.13	0.96	1.62	2.18
Relative kriging variance	2.01	1.28	0.78	1.64	1.16	0.72	1.47	1.08	0.66
Relative conditional variance	1.28	1.10	0.92	1.19	1.00	0.90	1.11	0.94	0.89

Note. The overall mean copper grade is 1.00% for both the kriged and the simulated block models.

The kriging variance does not depend on the data values and therefore does not account for the proportional effect (Journel and Huijbregts, 1978, p. 308), hence it underestimates the "true" grade uncertainty in the high-grade areas. However, this underestimation compensates the request of the geologists and mining engineers to allow a greater estimation error for the high grades than for the low grades (the reliability in the mineral resources is rather defined in terms of *relative* errors instead of *absolute* errors), hence the criterion is "neutral," i.e., neither favorable nor detrimental to high or low grades. In contrast, the relative kriging variance divides the kriging variance by the squared grades and turns to be favorable to the high-grade areas: The richer portions of the deposit tend to be declared as measured, which explains why the proportion of measured metal quantity is greater than the proportion of measured tonnage with this criterion. This situation would be acceptable if the sampling were denser in the high-grade areas. However, this is not really the case for the present study (the declustered mean grade is 1.00%, whereas the arithmetic data mean is 1.05%) and the differences between the proportions of measured tonnage and measured metal prove that the relative kriging variance favors the high-grade areas in the classification.

Contrary to the kriging variance, the variance of the realizations is conditioned to the data values and therefore accounts for the proportional effect. A classification based on this parameter penalizes the high-grade areas, which tend to be declared as "indicated" or "inferred" resources. In this case, the proportion of measured metal quantity is much smaller than the proportion of measured tonnage, which is quite unsatisfactory. Finally, the relative conditional variance measures a relative error and appears as a neutral criterion, i.e., it does not penalize nor favor the high- or low-grade areas. It performs similar to the kriging variance criterion in terms of being neutral.

In conclusion, the criterion chosen to establish the resource classification should be suited to the requirements of the geologists, mining engineers, authorities, and investors, so as not to favor nor penalize the high- or low-grade areas. The measures of uncertainty can incorporate different levels of information:

- The use of neighborhood constraints only accounts for geometrical considerations and loses all structural information about the phenomenon.
- In addition to the geometrical information, the kriging variance allows one to include the global properties of the grade distribution, in particular the spatial continuity of the grades measured by the variogram.
- The relative conditional variance derived from a set of conditional simulations constitutes a more complete measure of uncertainty, as the simulations reflect the local properties of the grade distribution such as a proportional effect arising in high-grade areas.

The results let us foresee that standardization of the criterion for classification and reporting will be difficult, and most likely, national codes will remain as subjective as they are now in this matter: Expert judgment will always be required for classifying and reporting mineral resources and ore reserves.

QUANTIFYING UNCERTAINTY BY SIMULATIONS

In this section, we propose an alternative approach that quantifies the overall uncertainty on the mineral resources by means of conditional simulations of the grades and that can also be used to classify each block as measured, indicated, or inferred resource. More precisely, for each of the 49 realizations used to construct the block model in Figure 2B, the tonnage-cutoff and metal-cutoff curves are computed, assuming an average rock density of 2.7 t/m^3 (Fig. 5).

Ideally, each realization constitutes a plausible scenario for the real deposit, so that the true tonnage and metal curves are likely to lie within the set of simulated curves. We now have an estimate of the uncertainty on the total amount of mineral resources: Risk analysis can be performed with the simulated curves in order to assess the worst and the best scenarios, with no need for classifying. Furthermore, one can assess the uncertainty on the mineral resources after applying a cutoff without drawing biased conclusions, whereas the approaches presented in the previous section are limited to the total resources (or equivalently, at zero cutoff) because of the smoothing effect of the estimators based on kriging or averaging realizations.

The simulation approach is promising for quantifying the uncertainty on mineral resources, but it requires attention to three points:

1) The available data should be representative of the whole deposit. The practitioner must look over the sampling strategy, check the sample quality, and beware of preferential samplings that may lead to an overestimation of the resources. This is not peculiar to the simulation approach; it is valid for any resource estimation and classification (Annels and Dominy, 2003). Declustering techniques for inference of the histogram and variogram for Gaussian simulation have been proposed by the authors (Emery and Ortiz, 2005).
2) The geostatistical model used to simulate the grades should describe accurately their spatial distribution. In particular, the model must include structural features like anisotropies, trends, proportional effect, destructuring effect of the extreme grades or, on the contrary, connectivity of the high-grade values (Goovaerts, 1997, p. 401; Chilès and Delfiner, 1999, p. 460; Emery, 2002, 2005). If need be, the deposit should be divided in several domains, each with a homogeneous grade distribution, based on geological features such as rock type, mineral type, alteration, etc.
3) The boundaries of the ore zone to be simulated should be clearly defined by geologic, economic, and mining considerations. Indeed, if the ore zone

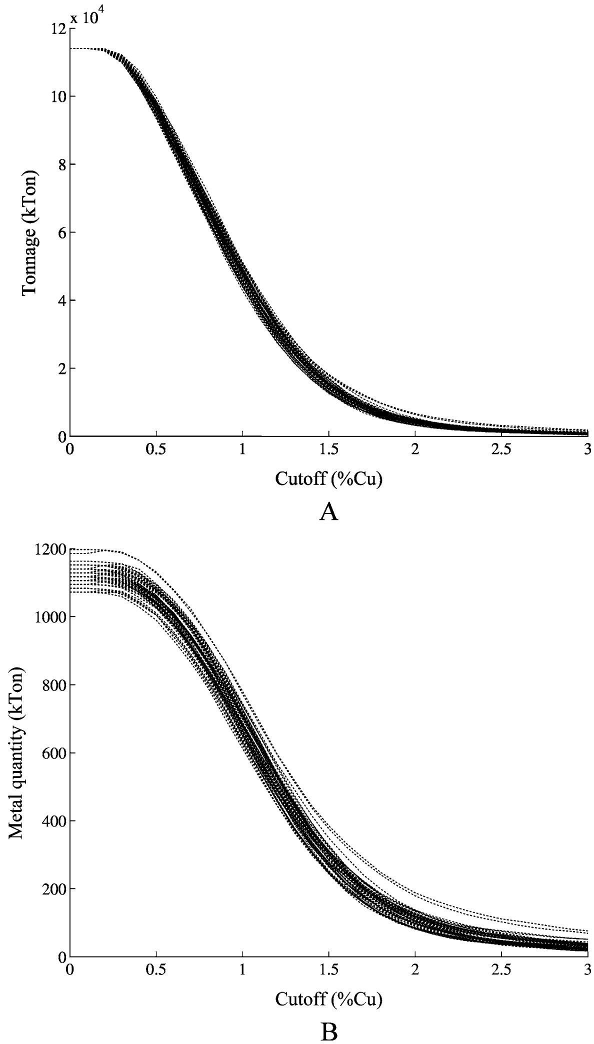

Figure 5. (A) tonnage-cutoff curves and (B) metal-cutoff curves obtained from a set of conditional simulations of the copper grades.

is wrongly defined and its extent is overestimated, because of the stationarity assumption in simulation, on average there will be an overstatement of the amount of ore and the quantity of resources will increase unrealistically: The principle of geostatistical simulation is to draw grade values according to a specified model, so it "creates" non-existing resources if the simulated domain increases too much. To the authors' opinion, the correct delimitation of the deposit is the most crucial issue for the simulation approach to be successful. This delimitation is inherent to the problem at hand: The definition of the resources implicitly refers to a specific spatial domain, and a modification of this domain alters the values of the mineral resources (tonnages, metal quantities, mean grades) (Sinclair and Blackwell, 2000). Expert judgment is once again necessary.

Conditional simulations can also help to classify mineral resources. We suggest three possible approaches.

- Classify each block on the basis of a measure of local uncertainty, for instance the relative conditional variance or the selectivity index (Gini coefficient), which is the ratio between the dispersion indicator and the mean and belongs to the interval [0,1) (Matheron, 1984, p. 431; Chilès and Delfiner, 1999, p. 424).
- Classify each block according to a confidence level (Snowden, 2001). For instance, a block corresponds to a measured resource if the relative difference between its simulated grade and its estimated grade (average of all the realizations) is less than 10% nineteen times out of twenty. It is an indicated resource if this relative difference is less than 20% nineteen times out of twenty. Otherwise, it is an inferred resource.
- Classify each block according to a confidence level considering a production volume. The idea is to consider the error on the grade over the expected quarterly and annual production. For instance the measured resources can be defined as the set of quarterly production volumes whose simulated grades have a relative difference with their estimated grades (average of the realizations) less than 10% nineteen times out of twenty. Indicated resources can be defined similarly, but considering an annual production volume. This methodology is similar to the ones proposed by Dominy, Noppé, and Annels (2002, p. 93) and Dohm (2005). Some of the issues of this approach are how to define the production volume, which in principle relates to ore reserves. This requires assuming (anticipating) the size of the operation and the production rate.

One advantage of such approaches is to provide a classification in which the expected amount of resources depends on the cutoff, a characteristic that cannot be obtained from the traditional approach based on a kriged block model because of the smoothing effect of kriging. A second advantage is that these approaches are easily interpretable and provide an intuitive measure of uncertainty, accounting for the amount of conditioning data and for their grade values. Naturally, implementing conditional simulations requires time, knowledge about the details of the method, and post-processing effort. However, it is worthwhile since these models provide a much richer information that can be used to answer many more questions than the ones discussed in this article. As a final comment, we should state that subjectivity has not and cannot be removed from the classification procedure.

CONCLUSIONS

Classification of mineral resources into measured, indicated, and inferred is always subjective and strongly depends on the criteria chosen by the competent person, hence it should be clearly documented and justified. It is also important to be aware that some criteria penalize and others favor the high-grade areas, e.g., classification based on the conditional variance or the relative kriging variance. Other criteria are more neutral, such as the relative conditional variance or the absolute kriging variance. The former is more complete than the latter as it accounts for the local features of the grade distribution like a proportional effect; it could also constitute a standard criterion applicable to any deposit of the same type since it just requires defining percentage bounds for the relative error.

Conditional simulations enable to calculate a set of simulated selectivity curves and constitute an alternative (or a complement) to the traditional classification framework. This approach offers greater flexibility such as the possibility to quantify the uncertainty on the total amount of resources at a given cutoff, a feature that the classification on a kriged block model cannot provide due to the smoothing effect of kriging. Several points should be taken care of to make the simulation approach successful, in particular the choice of the geostatistical model and its parameters, the division of the deposit into homogeneous geological units, and the correct delimitation of the ore zone. All these points may be considered as additional sources of uncertainty and be included in the simulation paradigm.

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REFERENCES

Annels, A. E., and Dominy, S. C., 2003, Core recovery and quality: Important factors in mineral resource estimation: Trans. Inst. Min. Metall. Sect. B Appl. Earth Sci., v. 112, no. 3, p. 305–312.

Blackwell, G. H., 1998, Relative kriging errors—A basis for mineral resource classification: Explor. Min. Geol., v. 7, no. 1–2, p. 99–106.

Chilès, J. P., and Delfiner, P., 1999, Geostatistics: Modeling spatial uncertainty: Wiley, New York, 695 p.

CIM, 2000, CIM standards on mineral resources and reserves—Definitions and guidelines. Prepared by the CIM Standing Committee on Reserve Definitions: CIM Bull., v. 93, no. 1044, p. 53–61.

CSA, 2001, Standards of disclosure for mineral projects: National Instrument 43–101, Canadian Securities Administration, 22 p.

David, M., 1988, Handbook of applied advanced geostatistical ore reserve estimation: Elsevier, Amsterdam, 216 p.

Diehl, P., and David, M., 1982, Classification of ore reserves/resources based on geostatistical methods: CIM Bull., v. 75, no. 838, p. 127–136.

Dohm, C., 2005, Quantifiable mineral resource classification-A logical approach, *in* Leuangthong, O., and Deutsch, C. V., eds., Geostatistics Banff 2004: Springer, Dordrecht, v. 1, p. 333–342.

Dominy, S. C., Noppé, M. A., and Annels, A. E., 2002, Errors and uncertainty in mineral resource and ore reserve estimation: The importance of getting it right: Explor. Min. Geol., v. 11, no. 1–4, p. 77–98.

Emery, X., 2002, Conditional simulation of nongaussian random functions: Math. Geol., v. 34, no. 1, p. 79–100.

Emery, X., 2005, Conditional simulation of random fields with bivariate gamma isofactorial distributions: Math. Geol., v. 37, no. 4, p. 419–445.

Emery, X., and Ortiz, J. M., 2005, Histogram and variogram inference in the multigaussian model: Stochastic environmental research and risk assessment, v. 19, no. 1, p. 48–58.

EURO, 2002, Code for reporting of mineral exploration results, mineral resources and mineral reserves (the European code): Report prepared by the Institution of Mining and Metallurgy Working Group on Resources and Reserves in conjunction with the European Federation of Geologists and the Institute of Geologists of Ireland, 34 p.

Froidevaux, R., Roscoe, W. E., and Valiant, R. I., 1986, Estimating and classifying gold reserves at Page-Williams C zone: A case study in nonparametric geostatistics, *in* David, M., Froidevaux, R., Sinclair, A. J., and Vallée, M., eds., Proceedings of the Symposium on Ore reserve estimation—Methods, models and reality: Canadian Institute of Mining, Metallurgy and Petroleum, Montreal, p. 280–300.

Goovaerts, P., 1997, Geostatistics for natural resources evaluation: Oxford University Press, New York, 480 p.

JORC, 2004, Australasian Code for reporting of exploration results, mineral resources and ore reserves (the JORC Code, 2004 Edition): Report prepared by the Joint Ore Reserve Committee of the Australasian Institute of Mining and Metallurgy, Australian Institute of Geoscientists and Minerals Council of Australia, 21 p.

Journel, A. G., and Huijbregts, C. J., 1978, Mining geostatistics: Academic Press, London, 600 p.

Matheron, G., 1973, The intrinsic random functions and their applications: Adv. Appl. Probab., v. 5, p. 439–468.

Matheron, G., 1984, The selectivity of the distributions and the "second principle" of geostatistics, *in* Verly, G., David, M., Journel, A. G., and Maréchal, A., eds., Geostatistics for natural resources characterization: Reidel, Dordrecht, v. 1, p. 421–433.

Rendu, J. M., and Miskelly, N., 2001, Mineral resources and mineral reserves: Progress on international definitions and reporting standards: Trans. Inst. Min. Metall. Sect. A Min. Technol., v. 110, p. 133–138.

Royle, A. G., 1977, How to use geostatistics for ore reserve classification: Eng. Min. J., v. 30, p. 52–55.

Sabourin, R., 1984, Application of a geostatistical method to quantitatively define various categories of resources, *in* Verly, G., David, M., Journel, A. G., and Maréchal, A., eds., Geostatistics for natural resources characterization: Reidel, Dordrecht, v. 1, p. 201–215.

SAMREC, 2000, South African Code for Reporting of Mineral Resources and Mineral Reserves (The SAMREC Code): Report prepared by the South African Mineral Resource Committee SAMREC under the auspices of the South African Institute of Mining and Metallurgy, 38 p.

Serrano, L., Vargas, R., Stambuk, V., Aguilar, C., Galeb, M., Holmgren, C., Contreras, A., Godoy, S., Vela, I., Skewes, M. A., and Stern, C. R., 1996, The late Miocene to early Pliocene Río Blanco-Los

Bronces copper deposit, Central Chilean Andes, *in* Camus, F., Sillitoe, R. H., and Petersen, R., eds., Andean copper deposits: New discoveries, mineralizations, styles and metallogeny: Society of Economic Geologists, Special Publication no. 5, Littleton, Colorado, p. 119–130.

Sinclair, A. J., and Blackwell, G. H., 2000, Resource/reserve classification and the qualified person: CIM Bull., v. 93, no. 1038, p. 29–35.

SME, 1999, A guide for reporting exploration information, resources, and reserves: Report prepared by SME Resources and Reserves Committee, Society for Mining, Metallurgy and Exploration, 17 p.

Snowden, D. V., 2001, Practical interpretation of mineral resource and ore reserve classification guidelines, *in* Edwards, A. C., ed., Mineral resource and ore reserve estimation—The AusIMM Guide to Good Practice: The Australasian Institute of Mining and Metallurgy, Monograph 23, Melbourne, p. 643–652.

USGS, 1980, Principles of a resource/reserve classification for minerals: U.S. Geological Survey Circular 831, 5 p.

Vallée, M., 1999, Resource/reserve inventories: What are the objectives?: CIM Bull., v. 92, no. 1031, p. 151–155.

Vallée, M., 2000, Mineral resource + engineering, economic and legal feasibility = ore reserve: CIM Bull., v. 93, no. 1039, p. 53–61.

Wober, H. H., and Morgan, P. J., 1993, Classification of ore reserves based on geostatistical and economic parameters: CIM Bull., v. 86, no. 966, p. 73–76.