



Mineral Resources Evaluation with Mining Selectivity and Information Effect

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Abstract

The most common approach used in the mining industry for mineral resources modeling is to estimate the grades using ordinary kriging and report the recoverable resources based on this deterministic estimated model. Mineral resources calculated with kriging are a smooth representation of the actual distribution of grades and do not provide an assessment of uncertainty. Unlike kriging, simulation reproduces the variability of the grades in the mineral deposit and provides an assessment of uncertainty. Reporting mineral resources directly on high-resolution simulation results would assume perfect knowledge of the grade at the time of mining and selectivity at the scale of the data. There will always be uncertainty left at the time of mining, so assuming perfect knowledge of the grade in the future is incorrect. There are two concerns when geostatistical simulation is used for resources modeling: the information and the mining selectivity effects. A new framework for resource estimation is proposed with two separate modules to address those concerns. The information effect is accounted for by anticipating the additional production data that will be available at the time mining to guide the destination for the mined material. The mining selectivity effect is addressed by mimicking the grade control procedure to get mineable dig limits at a chosen selectivity, represented by a minimum mineable unit size. In addition to a prediction of recoverable resources that will be closer to the material mined in the future, the framework proposed provides an assessment of local and global uncertainty for risk management.

Keywords Resources · Simulation · Geostatistics · Selectivity

1 Introduction

There are three main complementary and sequential tasks that are essential to any mining project: long-term mineral resources and reserves modeling, mine planning, and grade control. They are performed at different stages of the mine life, in different contexts, and with distinct objectives and techniques. They must be successfully integrated in order to achieve balance between what has been planned and the material that is actually mined. Each company has a different procedure for updating those models, but they must be updated with a certain regularity for accurate forecasting. There is a variety of geostatistical

techniques available; Isaaks and Srivastava [11], Goovaerts [10], Deutsch and Journel [4], Sinclair and Blackwell [20], and Rossi and Deutsch [19] describe the many different geostatistical techniques available for grade estimation and evaluation of mineral resources and reserves.

The context of this paper is on recoverable resources evaluation. Mineral resources and reserves evaluation are done to predict tonnage and grade of ore that may be mined. The grade, location, and tonnage of material must be forecasted with the greatest accuracy possible to justify the large investment associated with a mining project. The recoverable resources and reserves tabulations are done by adding up blocks of different tonnages—due to different specific gravities of the host rocks—to obtain total tonnes and grades based on a tonnes-weighted average of different grades. The calculations are generally done within deposit subsets or for different types of material and for different destinations for the mined material, such as different processing routes.

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2 Current Practice in Mineral Resources Evaluation

The traditional approach used in the mining industry for mineral resources evaluation is to estimate the grades of all variables of interest within blocks through a deterministic block model and report the recoverable resources on those estimates. Long-term resources are typically reported directly from numerical models built from delineation drilling, with no special post processing. The most used estimation technique is ordinary block kriging, but inverse distance interpolation is also popular. Rossi and Deutsch [19] present details on minimum, good, and best practices for estimating, managing, and reporting ore resource models under a deterministic approach. The estimated results provided by kriging are a smooth representation of the actual distribution of grades on the estimated blocks [13]. The use of restricted searches in kriging is a common approach in the mining industry in a tentative of controlling its smoothing effect. The local accuracy provided by block kriging is fundamental for final selection at the time of mining/grade control, when it is necessary to minimize misclassification of ore and waste blocks. On the other hand, the resources obtained from estimation are not the correct representation of the grades at block scale [13]. Moreover, this approach does not assess the uncertainty related to the mineral resource.

In addition to the deterministic approach, there are alternatives to evaluate recoverable resources, such as probabilistic estimation and geostatistical simulation. Probabilistic estimation techniques, such as multi-gaussian kriging [12] and Uniform Conditioning (UC), directly predict the variability and uncertainty in grade variables using a probability distribution model. We compute conditional distribution functions from which we can extract a range of possible values for the estimated grade [19]. Gaussian-based probabilistic estimation is the most commonly applied due to the simplicity of the Gaussian distribution. Neufeld and Deutsch [16] provide a summary of some of the main features of Uniform Conditioning and can be further referred. The disadvantage of probabilistic estimation is that, by not accounting for the variability from one location to another, it does not provide a joint model of uncertainty.

The third and more complete approach is geostatistical simulation. As opposed to the deterministic approach through estimation, simulation is particularly useful because it includes an assessment of joint multiple-location uncertainty. Multiple “realizations” are drawn for all locations simultaneously to allow the transfer of local uncertainty through large-scale resource uncertainty. Simulation could be thought of as the process of generating realizations; some references refer to realizations as simulations. Building a long-term resource model using geostatistical simulation provides a way of assessing a complete model of uncertainty for the mineral

deposit. Even though the application of simulation has been subject of extensive research, its use is still limited in the mining industry, and its results are not typically used for resources reporting and mine planning. Accounting for the uncertainty assessment in a resources evaluation workflow and transferring this uncertainty to further engineering calculations, such as mine planning and production scheduling, is fundamental to the understanding of a mineral deposit. It is highly recommended to adopt an approach where the mineral resource report accounts for the degree of uncertainty.

Simulation provides a joint model of uncertainty between multiple locations. Upscaled simulated grades are assigned to each block representing a selective mine unit. Simulation attempts to reproduce the data histogram and variogram model [13]. At the time of assessing the recoverable resources and reserves, it is important that the histogram of estimated block values shows the same proportion of ore as the histogram of the true grades that could be achieved at the time of mining. Unlike the traditional estimation approach, simulation provides block grades that are not smoothed [13].

The common practice when geostatistical simulation is used to assess the recoverable resources is to summarize the simulated realizations into one model, but the simulated grade distribution should be summarized as late as possible. All resource and reserve calculations that can be computed on a single block model can also be computed on a number of realizations of the same block model. After performing the necessary calculations over all realizations and not over one particular realization or a summary model, the response variables could be summarized [5]. At the end, the expected value of all realizations can be retained as a single value. The probability to be within a 15% interval of the expected value is also a value that is commonly retained in mining. Resources reported on an average model or on one specific realization are different from the average resource. Resources reported on one single model do not carry the underlying uncertainty in grade and tonnage. One should always go back to realizations to perform other calculations, instead of calculating directly on expected values.

Post-processing the simulation results is critical because of the point scale resolution at which the realizations are computed, that is, the data scale. The concept of a Selective Mining Unit (SMU) is necessary to report resources from the high-resolution simulated geostatistical realizations. When simulation is performed, the traditional approach is to average the grades at high resolution to the chosen SMU scale. Many factors are considered when choosing the SMU block size. The paradigm conventionally adopted is that the SMU block size must be related to the selectivity of the mining equipment, the availability of grade control data that is used to classify the material as ore or waste, the geological boundaries of the deposit, and, in the context of an open pit mining

operation, the practicality of the dig limits that will be generated from these blocks [19, 20].

Direct block simulation is an alternative to computing high-resolution simulated realizations and averaging up to the chosen SMU scale. Journel and Huijbregts [12] first proposed a direct block simulation approach where the conditioning would happen at the block support after computing the simulated realization. This approach would be valid for properties that average linearly from point to block support, such as grade. Additional applications and algorithms are also discussed and implemented in Benndorf and Dimitrakopoulos [1], Emery [7], and Emery and Ortiz [8]. The problem with direct block simulation is that assumptions have to be made to build a local change of support model. The point support is recommended because it assures consistency between the simulated high-resolution grades and the block-averaged values at any larger support [13].

Volume-variance correction methods can also be used to create a target SMU grade distribution in the resources evaluation workflow [11, 12, 15, 19]. They provide a quick assessment of the recoverable resources. By applying a change of support model to drill hole information, it is possible to calculate grade-tonnage curves to check and calibrate the resource models. The most common change of support models are the Affine Correction, the Indirect Lognormal, and the Discrete Gaussian methods; where the latter is considered the most robust option because it provides a realistic prediction of the change in shape of the variable distribution. The references mentioned above provide further details on each volume-variance correction method.

3 Problem and Motivation

Resource models are constructed at specific times in the mine life and consider the information available at that time. Geostatistical simulation is normally calculated at high resolution and quantifies the uncertainty in the truth at the scale of the data used, not at the scale that mining will take place. Reporting resources directly on high-resolution simulation results would assume selectivity at the scale of the data and perfect knowledge of the grade at the time of mining. The resources reporting and the determination of ore and waste limits must consider the selectivity of future mining and the information available at the time of mining.

Even though the uncertainty reduces as more or better information becomes available during the exploration and mining processes, there will still be remnant uncertainty that is not fully resolved at the time of mining because even the grade control sampling is incomplete and imperfect. The remnant uncertainty can be explained by small scale geological variability, mining practice, location errors, among other factors. The decrease in uncertainty from the resources model to the

time of mining can be referred to as the information effect. The information effect reflects the potential for misclassification of ore/waste material because the long-term resource model does not account for future information that will be available at the time of mining. Anticipating future information to correctly predict ore/waste classification errors is critical. The economic performance of any mining operation will be impacted by misclassification of material.

The other concern when evaluating recoverable resources is referred to as the mining selectivity effect. The maximum profit available in a mining project would be given by free selection of small-scale blocks of ore and waste, without accounting for any mining inefficiency and equipment limitations. The mining selectivity effect can be defined as how selective the resource model can be to incorporate both mining practice and equipment selectivity restrictions and geological characteristics of the deposit, while trying to retain most of the profit available at free selection of small-scale blocks of ore and waste. The mining selectivity effect reflects the fact that the resources evaluation is done at a scale orders of magnitude larger than the core sample data used to estimate the grades [13].

In the traditional framework for resource estimation, the SMU size alone accounts for the information effect, mining selectivity considerations (e.g., the mining practice and equipment limitations and geological variability), and remnant uncertainty at the time of mining. The traditional framework combines the information effect, remnant uncertainty, and mining selectivity considerations into an SMU size that is larger than the final grade control data spacing [14]. It is assumed that there is no remnant uncertainty in the SMU size at the time of mining.

Deraisme and Roth [3] stated that there were no significant advances towards trying to address the information effect for estimating recoverable reserves despite being widely discussed in geostatistical theory. Even 18 years later, not much has changed. In the latest version of software ISATIS, Geovariances [9] released a new tool called “Information Effect for Simulations.” This tool helps optimize grade control sample spacing by evaluating its impact on grade-tonnage curves, but it can also be applied to mimic ore loss/dilution at the time of mining. The idea is similar to what is proposed here to assess the information effect: sample high-resolution simulated grids at the anticipated grade control spacing and use the samples to re-estimate the grades. Nevertheless, the entire workflow proposed here is different because it includes an additional module to address the mining selectivity effect.

Some advances have been made in research. Journel and Kyriakidis [13] discuss the information effect and propose a simulation approach to anticipate the production data. This approach is also similar to the one implemented in the latest release of software ISATIS. In addition, Journel and Kyriakidis [13] proposed to address the difference in the data

quality from the long-term resources modeling and grade control. For example, if the present data (resources modeling) is drill hole data and the future data (grade control sampling) is blast hole data, according to Journel and Kyriakidis [13], the possible error in the future data should be modeled. The statistics between the two types of data and the correlation between the error and the present data should be inferred by prior experience on similar mining operations.

Leuangthong et al. [14] and Neufeld, Leuangthong, and Deutsch [17] also proposed the sampling of simulated realizations and re-estimation of the grids using those samples. Leuangthong et al. [14] proposed this simulation approach to determine the optimal SMU size that would give ore and waste tonnages and grades of ore to match the actual production at the time of mining. Neufeld et al. [17] compared the results of the simulation approach with a change of support model. In the change of support approach, the information effect is accounted for by reducing the variance of the block scale distribution. In the change of support model, as the block size increases and the block variance decreases, the block distribution becomes smoother (less selective) and the final profit decreases. In the simulation approach, the ore and waste classification quality decreases as the grade control sample spacing increases resulting in less profit. The results of both approaches can be combined to help choose the SMU size for resources and reserves evaluation. Both papers mix the concepts of information and mining selectivity effects. This research develops a framework to specifically account for the information and mining selectivity aspects separately.

Cuba, Boisvert, and Deutsch [2] propose a framework to model the evolution of the degree of knowledge of a deposit and its dynamic behavior due to the acquisition of new data in the design of the long-term mine plan. The mining sequence is continuously adapted to information sampled from simulated realizations. The goal of here is to calculate directly the final resources/reserves that would be obtained.

The remnant uncertainty at the time of mining must be considered for long-term mineral resource reporting and the information and mining selectivity effects must be anticipated at the time of resources modeling. A methodology is proposed to correctly predict recoverable resource estimates by explicitly accounting for the information and mining selectivity effects. The recoverable resources forecast will be closer to the material actual mined in the future. A framework consisting of separate modules to address these two concerns is proposed.

4 Proposed Methodology

This paper proposes a framework to address the two concerns in long-term models for probabilistic resources reporting: (1) the information effect, that is, anticipating the additional data that will be available in the future to direct the choice of

destinations of the mined material, and (2) the selectivity effect, that is, how selective the model can be to incorporate both mining equipment and practical selectivity restrictions considering the geological characteristics of the deposit. The steps of the proposed procedure are described below:

1. Simulate high-resolution realizations of all necessary variables considering the data available. Parameter and data uncertainty could also be taken into account. This step is no different from the traditional simulation paradigm.
2. (a) Sample the realizations at the anticipated production data spacing to mimic the grade control data planned in the future. (b) Interpolate all variables of interest that are required for grade control for every set of sampled final data. Use a larger block size than for the simulations and the best possible set up for ordinary kriging. Sampled data from each realization and the existing exploration data are considered in the estimation. This step will account for the information effect.
3. (a) Calculate expected profit values for every block in the estimated grade control grids for at least two different destinations (i.e., ore and waste), depending on the final estimated grade. (b) Apply the mining selectivity calculations for each estimated grade control model at a chosen selectivity to anticipate future mining. This step mimics the grade control practice to get a different mineable dig limit for each estimated grade control grid of anticipated grade control data.
4. (a) Transfer the mineable dig limits at the desired selectivity resulted from the previous step to the high-resolution reference simulated model from the first step. (b) Estimate the probabilistic resources using these dig limits for the long-term model to be reported, that is, available as the distribution over all realizations from the original reference simulated model.

By following the proposed workflow, recoverable resources are estimated accounting for the information and mining selectivity effects explicitly and assessing the degree of uncertainty associated with it. Any summary models required for mine planning can be calculated on the long-term resources model including the probability to be above or below the cutoff grade, the average grade above the cutoff grade, the tonnes of ore and waste, and the grade of ore. The kriging estimates done in step two are exclusively for determining the destinations of mined material; all resources are estimated based on the original simulated realizations.

5 Methodology—Information Effect

The uncertainty reduces as more information becomes available during the exploration and mining process. However,

there will still be remnant uncertainty that is not resolved at the time of mining because even the final sampling is incomplete. There are many factors that contribute to the remnant uncertainty at the time of mining, including small scale geological variability, mining practice, incomplete grade control sampling, and location errors. The decrease in uncertainty from the resources model to the time of mining is referred to as the information effect. Figure 1 illustrates the information effect.

There will be classification errors of ore and waste due to incomplete information during the mining process. There are two types of classification errors: type I and type II. The type I error refers to the material that is classified as ore, but in fact is waste, that is, a false positive, while the type II error is a false negative, the material that is thought to be waste but is actually ore [19]. Both of these errors reduce the profit of an area being mined. These ore/waste classification errors should be minimized.

The remnant uncertainty at the time of mining should be considered for long-term model reporting and the information effect should be anticipated. The distribution of grades represented in geostatistical realizations for resources reporting relates to the distribution of the true values, not the values at the time of mining. Calculating resources directly on the simulated realizations would be too optimistic. Reporting resources from geostatistical realizations simulated with widely spaced exploration data is only reasonable because we use the concept of a production volume or SMU that is larger than the final grade control data spacing [14]. Choosing an SMU size that is larger than the final data spacing results in a small remnant uncertainty at the SMU scale. The large SMU size would account for the remnant uncertainty at the time of mining.

The proposed workflow to account for the information effect starts by sampling each of the realizations at the anticipated production data spacing. The goal of this step is to mimic the production data planned in the future. Then, it is necessary to

estimate all variables that are required for grade control for every set of sampled final data. As shown by Vasylychuk [21], the recommended grade control grid resolution is 25 to 40% of the (anticipated) production data spacing to minimize the amount of misclassified ore and waste on the grade control model.

Anticipating the information that will be available at the time of mining by sampling the reference simulation realizations is a critical step of the proposed procedure. The existing exploration data could be considered together with the sampled data from each realization in the estimation. Sampled data that is too close to the original drill holes from delineation/exploration campaigns can be rejected because production sampling is of lower quality than exploration sampling in practice.

By sampling each high-resolution realization at the anticipated final grade control data spacing, we will have a different dataset for each realization. This is the case unless the exploration drilling is at the final production data spacing and there will be no additional grade control sampling forthcoming. The majority of mining operations gather additional production data. Sampling the realizations from geostatistical simulation will provide an approximation of the final data that will be acquired at the time of mining.

An important detail to consider is the expected quality of grade control data that will be available in the future. Dedicated grade control drilling samples would have higher quality and better precision than regular production sampling coming from blast holes. The practitioner can make a decision on whether or not to add some reasonable error to the grade values sampled from the reference simulation realizations [13].

6 Methodology—Mining Selectivity Effect

During the mining process, the material is classified and sent to a destination that could include a processing plant, waste

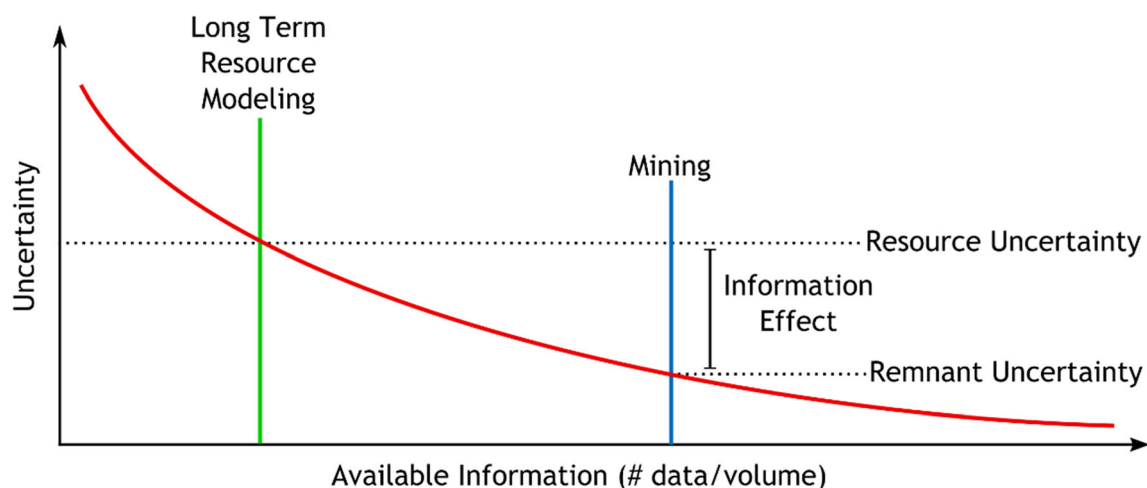


Fig. 1 The information effect: the decrease in uncertainty from the resources model to the time of mining

dump, leach pad, or stockpile. Depending on the complexities of the mining process and of the deposit itself, there can be many other different destinations. The scale at which material can be separated during the mining process is referred to as mining selectivity and represents a key feature for long-term resources reporting, mine planning, and design. Mining selectivity depends on a series of factors intrinsic to the deposit type and operation. It depends on the amount of information available at the time of mining, geological variability of the deposit, mining equipment and mining practice constraints, and other factors. Concepts and solutions for mining selectivity applied to the open pit mining context will be presented and discussed.

Selectivity can be represented by a number of different approaches in practice. Conventionally, in open pit mining, dig limit polygons are drawn using information from blast hole samples, that maybe refined by adding information of visual inspections made on-site. In the approach developed here, selectivity is represented by a minimum mineable size unit, instead of dig limits polygons. Research has been done towards assessing the final selectivity for grade control models and determining the exact dig limits for actual mining. Vasylychuk and Deutsch [22] developed a system called “Intelligent Grade Control” to automate the grade control practice (selection of ore/waste) while maximizing the total profit given by a mine bench, requiring a minimum level of user input. This approach has a different context than the research presented here. It is aimed at drawing/calculating the exact dig limits for the actual mining practice. Here, the concern is to accurately predict the recoverable resources by accounting for the information and mining selectivity effects at the time of resources modeling.

Calculating the profit assuming free selection of small-scale blocks of ore and waste, without accounting for any mining practice and equipment limitations, would overstate achievable profit. The ore/waste selection process should not be free, and each small-scale block should not be selected as ore or waste independently of other locations in the surrounding area. Geometrical or mining constraints may limit access to a specific location. The volumes considered should incorporate mining practice, equipment selectivity restrictions, and geological characteristics of the deposit and, at the same time, try to retain the maximum profit possible. The actual profit realized at the time of mining will be less than the maximum profit available with free selection of small scale blocks.

As discussed above, following the standard practice of choosing an SMU size that is larger than the final data spacing results in a small remnant uncertainty at the SMU scale. It is the normal approach to increase the SMU size to account for the fact that there will not be perfect information in the future. Assigning a fixed dilution factor in the hope to account for the information effect and selectivity of mining practice and equipment is also a common approach [17]. Figure 2

illustrates a typical situation in hard rock mining where resources reporting is normally done using a large block size to account for the remnant uncertainty and for the fact that there will not be perfect information in the future and the operational grade control model is constructed at the scale that the actual mining will take place, that is smaller than the block size used for resources reporting. This concern is part of the selectivity effect. The mining limits must, at the same time, capture geological variations in grade and keep the practicality of the mining volumes for the mine operation. On the other hand, considering a block size smaller than the final grade control data spacing and assuming no remnant uncertainty will likely provide too optimistic resource estimates. The practitioner must target estimates in the grade control model and in the long-term resources model that reconcile.

Consider two or more destinations d for the mined material within the grade control grid A ; at a minimum, ore and waste. Every block in the grade control grid corresponds to a location \mathbf{u} . Calculate the expected profit value associated with each different destination d for each location \mathbf{u} within the grade control grid A as:

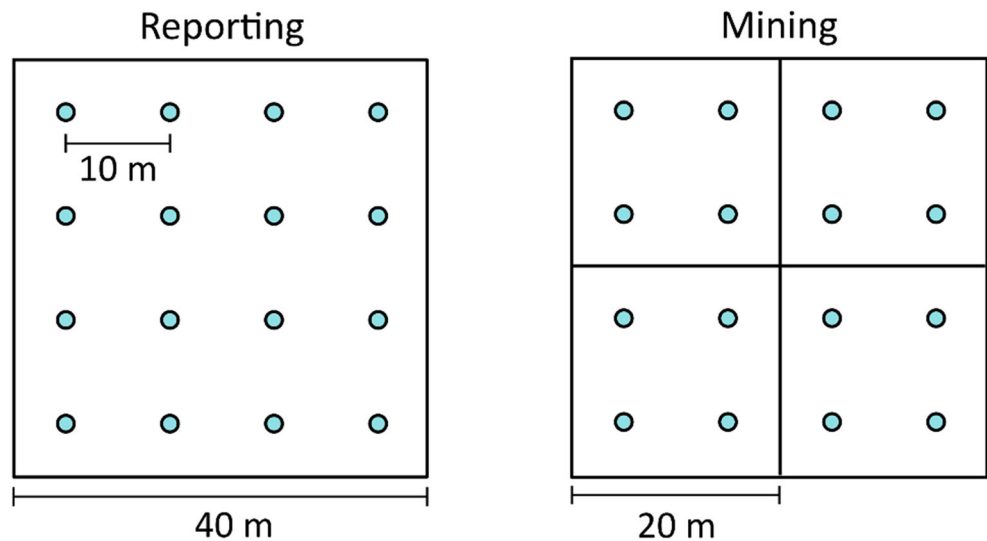
$$EP(\mathbf{u}; d), \quad d = 1, \dots, D, \quad \mathbf{u} \in A$$

One can consider as many factors as necessary for the definition and calculation of the expected profit values. Normally, these values depend on the destination and are generally a function of the grade of the material, recovery and value (selling price), and all costs associated with it: mining, processing, selling, and overhead. The maximum total profit for the entire grade control grid would be given by free selection of small-scale blocks of ore and waste (and any other destination being considered in the scenario) based on their expected profit values that would maximize the total profit.

For practical purposes, we will define a square or rectangular minimum mineable unit size to represent the mining selectivity. Note that the aforementioned minimum mineable unit size (MMUS) is different than the selective mining unit (SMU). In this paper, the concept of the SMU refers to a long range regular block size that is intended to match the results of short-term grade control in the future. The concept of the MMUS, on the other hand, simply refers to a floating selection frame intended to match equipment minimum widths during the creation of dig lines. The developed algorithm considers the MMUS dimension and visits the set of blocks in the locations \mathbf{u} that falls inside this chosen selectivity scale. The iteration occurs in the entire grade control grid A . Based on the expected profit values calculated earlier, $EP(\mathbf{u}; d)$, the most profitable destination is assigned to the set of blocks in the locations \mathbf{u} within the chosen mineable unit size as:

$$d_{\max EP}(\mathbf{u}) = \max_{dof} (EP(\mathbf{u}; d), \quad d = 1, \dots, D), \quad \mathbf{u} \in A$$

Fig. 2 Contrasting block size used for resources reporting (left) and SMU size used for the operational grade control model (right). The anticipated final grade control data spacing is presented in blue



where $d_{\max EP}(\mathbf{u})$ is the most profitable destination for each location \mathbf{u} within the grade control grid A , d is the two or more destinations for the mined material, and $EP(\mathbf{u}; d)$ is the expected profit value associated with each different destination d .

The total profit is calculated as the sum of the expected profits of all maximum profit destinations at the chosen selectivity (MMUS) over the grade control grid:

$$P_{\max EP} = \sum EP(\mathbf{u}; d_{\max EP}(\mathbf{u})), \mathbf{u} \in A$$

where $P_{\max EP}$ is the total profit over the grade control grid A and $EP(\mathbf{u}; d_{\max EP}(\mathbf{u}))$ is the sum of the expected profits of all maximum profit destinations at the chosen selectivity (MMUS) for each location \mathbf{u} within A .

The mineable unit (MMUS) is translated over five different origin points of the block model. The procedure described above is followed multiple times considering different origins. Finally, the most profitable case in terms of total profit over the grade control grid A is chosen and the final destinations are assigned to each block in the locations \mathbf{u} within A and the mineable dig limits are calculated.

The idea behind this algorithm is very similar to the one developed by Deutsch [6]. The algorithm developed by Deutsch [6] will assign the maximum profit destination onto locations that meet the mineability criteria from the beginning and will flag the locations that do not attend the mineability criteria. By revisiting the problematic locations and enforcing the mineable unit size onto them, the mineability criteria are almost guaranteed to be met over the entire grid. There could be areas that do not satisfy the mineable constraint because of interactions between problematic locations. The main concern involved with this algorithm is the computational time. At the time of long-term resources modeling, it is not crucial to have the exact locations of ore/waste blocks, since this

classification will inevitably change at the time of mining. Rather, it is necessary to have a faster procedure that will anticipate the expected profit given the mining selectivity.

The algorithm developed in this paper is faster than the one mentioned previously within relatively small blast volumes. It will not be exact given interactions between the five different origin offsets mentioned above: adjacent mineable areas/units do not necessarily need to have the same origin and small volumes may be created between the mineable ones. Nevertheless, it is reasonable and practical to support the probabilistic resources workflow proposed here. The developed algorithm is also flexible with the edges of the block model. There will be cases where the edges do not meet the mineability criteria. This is not a concern. In a real situation, there would not be ore close to the limits of the block model. The limits would be large enough to include all profitable areas within the bench that will be mined.

Developing an algorithm in a full optimization fashion would be recommended for final grade control procedures and classification of ore/waste blocks. The tools developed by Vasylychuk and Deutsch [22] and presented here are examples of what should be applied in the context of final classification. The algorithm developed in this research is a less time-demanding alternative appropriate to anticipate the mining selectivity at the time of recoverable resources modeling. An example of an implementation of the algorithm is presented in the following section.

7 Combined Workflow and Case Study

Figure 3 summarizes the steps in the proposed framework in a flowchart. Note that the SMU scale is not incorporated in the workflow. Instead, the proposed workflow applies the concept of the MMUS in its selectivity module. In the case study,

ordinary kriging at the SMU scale is performed as representative of the traditional long-term resources evaluation for comparison with the resources evaluated by the proposed methodology.

The proposed methodology to evaluate long-term mineral resources is demonstrated through an example that represents one bench of an open pit metallic deposit. This synthetic example provides access to the “truth,” that is, the reference model created to generate a dataset. The truth can be used for comparisons that can help validate the proposed framework. Since one bench is being considered, the example is 2-D. A reference model is generated via one unconditional simulated realization. The variogram model $\gamma(\mathbf{h})$ for all lag vectors \mathbf{h} is arbitrary and its maximum continuity direction is along azimuth 45° with the following model:

$$\gamma(\mathbf{h}) = 0.05 + 0.45 \cdot Sph_{ah_{max} = 400, ah_{min} = 200}(\mathbf{h}) + 0.5 \cdot Sph_{ah_{max} = 500, ah_{min} = 300}(\mathbf{h})$$

Note that *Sph* is short for the common spherical variogram function and the variogram ranges are in the subscripts. The

reference model is 1000×1000 cells and each cell is $1 \times 1 \times 5$ m. The cell height is equivalent to a nominal bench height of 5 m. A positively skewed distribution is used for back transformation of grades from Gaussian to original units. Figure 4 presents the reference grade distribution and the reference grade grid model generated.

In order to mimic exploration data, the reference unconditional simulated realization is sampled at a 100×100 m spacing. The exploration dataset created has 100 drill holes. The traditional long-term resources evaluation paradigm is to simply estimate the grades by ordinary kriging at a SMU scale. Experimental variograms were calculated for the exploration dataset created in original units. The major direction of anisotropy is at 45° azimuth. A variogram model was fitted and ordinary kriging was used to estimate the grades at $20 \times 20 \times 5$ m cells. The variogram model $\gamma(\mathbf{h})$ fitted is as follows:

$$\gamma(\mathbf{h}) = 0.05 + 0.95 \cdot Sph_{ah_{max} = 500, ah_{min} = 150}(\mathbf{h})$$

As above, *Sph* is short for the common spherical variogram function. These estimates and the resources assessed by them will be used for comparison with the resources evaluated by

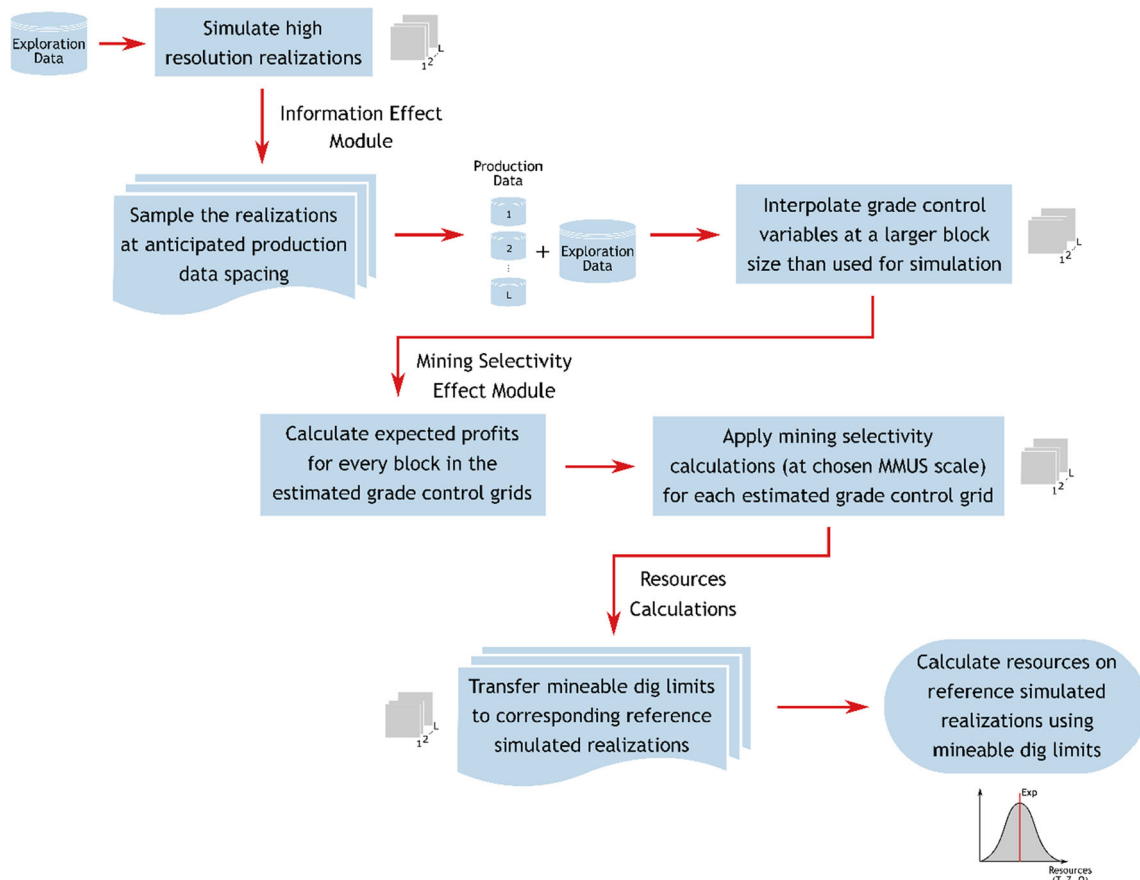


Fig. 3 Flowchart that illustrates the steps in the proposed framework

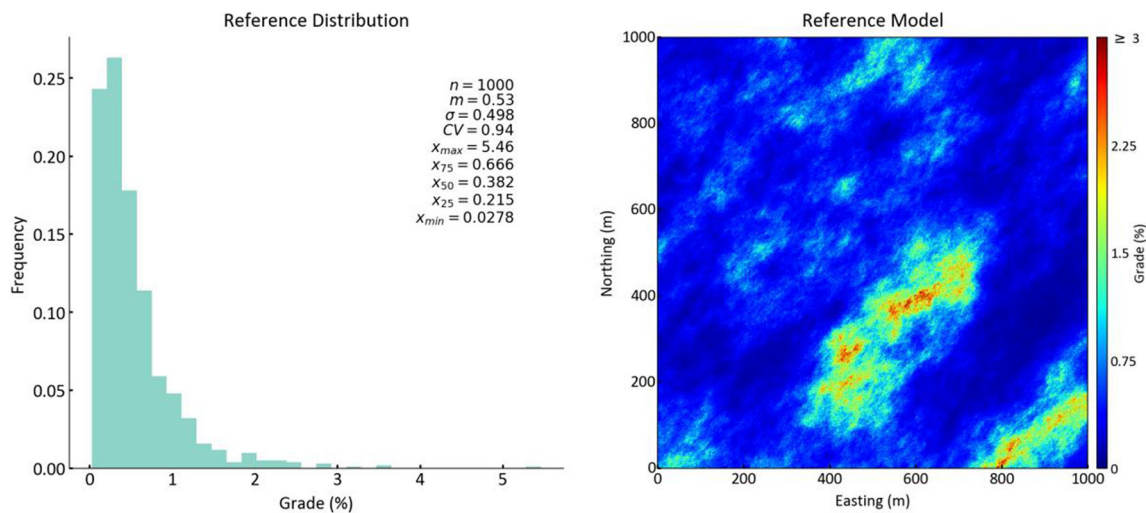


Fig. 4 Reference grade distribution (left) and reference gridded model (right)

following the proposed methodology. Figure 5 presents the exploration data sampled from the simulated realization in original units and their estimates by ordinary kriging.

The first step in the proposed workflow is to generate high-resolution simulated realizations of grade using the exploration data. The exploration data was transformed to normal scores to simulate a hundred realizations. Normal score experimental variograms were calculated following the major direction of anisotropy at 45° azimuth and perpendicular to it, 135°. The normal score variogram model fitted to perform the simulation is:

$$\gamma(\mathbf{h}) = 0.05 + 0.95 \cdot Sph_{ahmax = 420}(\mathbf{h})$$

$$ahmin = 160$$

In order to account for the information effect, the simulated realizations are sampled at the anticipated production data

spacing at the time of mining. To mimic a typical hard rock deposit, where the production data (dedicated grade control drilling or blast holes) is usually done at a closely spaced grid, the simulated realizations are sampled at 10 × 10 m. The one hundred datasets generated consist of 100 drill holes and 9701 data that mimic production data. Figure 6 shows one simulated realization of exploration data and a location map of the production data sampled from the same realization.

Still in the information effect module of the workflow, the next step is to interpolate the grade control grades. Blast hole sampling is normally of lower quality than exploration drilling and the exploration data is the only actual data available at the time of resources modeling. The production data too close to the exploration data is, then, rejected. The remaining production data and the existing exploration dataset are used in the estimation. Following the recommendation to minimize the amount of misclassified ore and waste on the grade control

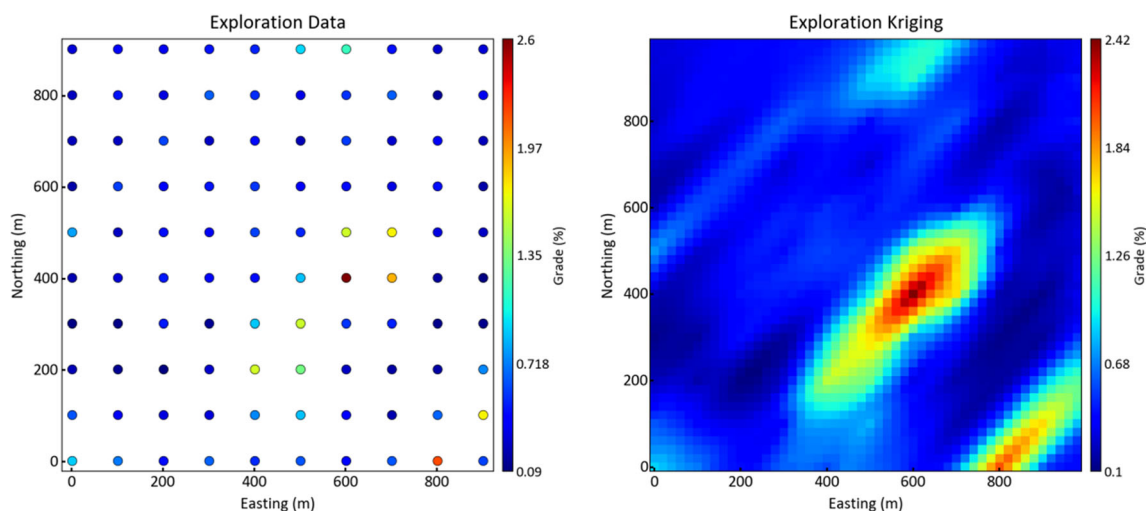


Fig. 5 Location map of exploration data (left) and kriging estimated grid (right)

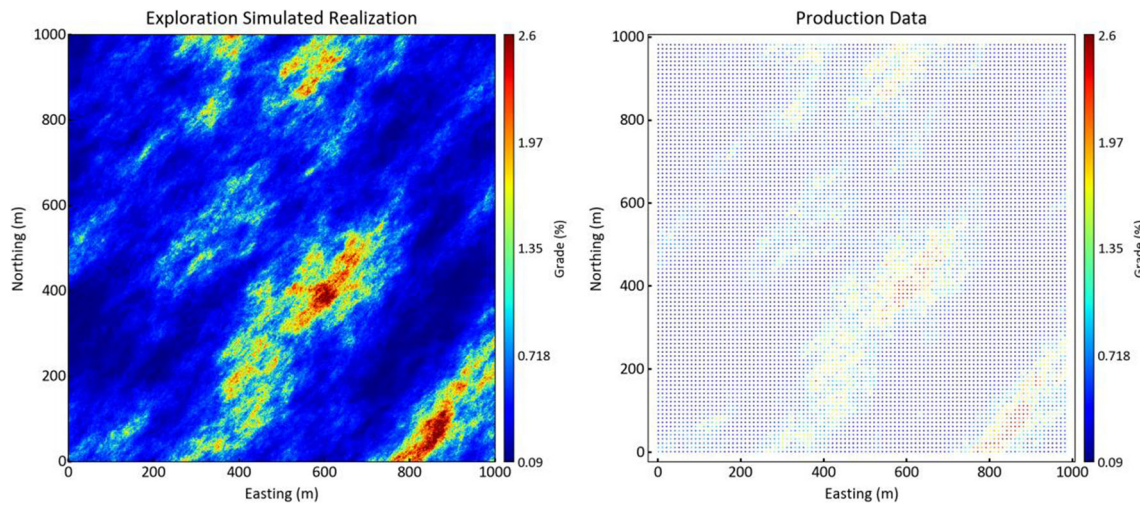


Fig. 6 Simulated realization with exploration drill holes (left) and blast holes sampled from it (right)

model proposed by Vasylchuk [21], the grade control block size is $4 \times 4 \times 5$ m, that is, 40% of the anticipated production data spacing.

Experimental variograms were calculated for each dataset consisting of exploration and sampled production data. The major direction of anisotropy is at 45° azimuth. Variogram models were automatically fit and ordinary kriging was used to estimate the grades of the grade control blocks. The experimental variograms calculated and the fitted variogram model for one dataset are shown in Fig. 7 together with the estimated grade control grid.

Proceeding to the mining selectivity module of the proposed framework, the expected profit values $EP(\mathbf{u}; d)$ were calculated for two different destinations for the mined material, ore and waste, for all blocks in the locations \mathbf{u} on the bench. Expected profits were calculated for each block in the estimated grade control grids. If the final destination for a block is ore, its expected profit is calculated as:

$$EP(\mathbf{u}; d) = \alpha \times \text{grade}(\mathbf{u}) + C_0 \text{ (/t)}, \quad d = \text{ore}, \quad \mathbf{u} \in A$$

where α is the slope of the grade \times profit graph and C_0 is the cost of sending material at zero grade to the processing plant. In this example, $\alpha = 30$ and $C_0 = -15$ \$/t, which yields a cutoff grade of 0.5% between ore and waste. The expression to calculate expected profit if the final destination of a block is waste does not depend on the grade value, it is a fixed cost of \$2/t:

$$EP(\mathbf{u}; d) = -2 \text{ (/t)}, \quad d = \text{waste}, \quad \mathbf{u} \in A$$

Expected profit calculations are done using a specified cutoff grade. A precise calculation could include all costs and prices associated with the final product. The profits calculated for both destinations for each block of estimated final grade control data will be used to calculate the maximum profit destinations at high resolution and at the chosen selectivity.

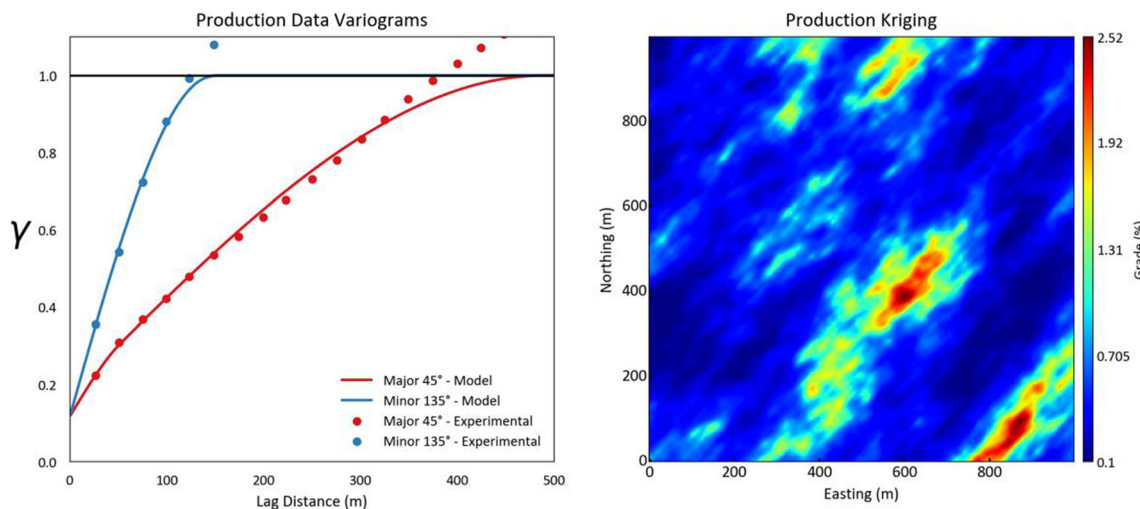


Fig. 7 Experimental variograms calculated with production data and fitted variogram model (left) and their estimates (right)

Moving forward to the mining selectivity module of the proposed workflow, the next step is to get mineable dig limits at a chosen mining selectivity (MMUS). The idea of this step is to mimic the actual grade control practice. The minimum mineable unit size (MMUS) considered for this example is 12×12 m, which seems to be a reasonable dimension for the deposit type represented here. The developed algorithm for mining selectivity is used to calculate the most profitable destination for each mineable unit. The mining selectivity calculations are applied to each estimated grade control grid. A small block size ore and waste map of the same estimated grade control grid shown in Fig. 7 is shown in the left side of Fig. 8. This map is purely the maximum profit destination available for each small-scale block without accounting for selectivity at the time of mining. The mineable ore and waste map are showcased in the right side of Fig. 8, after applying the selectivity calculations using the algorithm developed.

The proposed workflow is completed by transferring the mineable dig limits calculated in the mining selectivity module to the high-resolution realizations simulated with exploration data only. This step is needed to ensure that all resources estimations are done over the simulated grid that uses the actual data available at the time of resources modeling. The resampling from the simulated realizations and re-estimates of final grade control data are exclusively for determining the destinations of the mined material. No final resource tabulations are done on the re-estimated models.

Finally, the probabilistic mineral resources can be evaluated. They are available as the distribution over all realizations from the original simulated grid with exploration data and considering the mineable dig limits. For comparison, the resources were also tabulated directly on the high-resolution simulated results, without applying selectivity considerations, on the reference model that was used to generate the exploration data and on the kriged model with exploration data. A

fixed density value of 2.7 g/cm^3 was considered. The tonnage is calculated as the volume of each block multiplied by the density. Figure 9 shows the probabilistic resource distributions.

The cutoff grade is lower than the average grade on the bench. The smoothing effect of kriging leads to ore tonnes that are greater than the truth—represented by the reference model (black solid lines in the graphs)—in the kriged exploration data (orange solid lines). The larger support of the model following the proposed workflow (blue dashed lines) leads to ore tonnes that are greater than the ore tonnes calculated from the high-resolution simulated realizations. The average ore tonnes given by the model that follows the proposed workflow is closer to the true value. Regarding the total profit calculated, note that high-resolution simulated realizations yield a maximum profit that is not attainable at the time of mining. The selectivity and the data available at the time of mining must be considered to report the recoverable resources.

Note that a carefully implemented kriging can be tuned to perform very good from a global perspective. If the kriging is allowed to use a large number of samples, then the estimates will be quite smooth and the tonnage, grade, and metal will not likely match the future (reference). The mismatch would depend on where the cutoff falls on the distribution. A low cutoff (compared with the mean of the grade distribution) would lead to kriging overstating the tonnes and metal. A high cutoff would lead to kriging understating the tonnes and metal. A second approach would be to use ordinary kriging and severely limit the number of samples and smoothing. This would lead to locally poor estimates and an overstatement of selectivity. Some practitioners tune kriging to perform well for global predictions despite conditional bias and poor local predictions (further discussion on this matter can be found in Nowak and Leuangthong [18]). In summary, although the

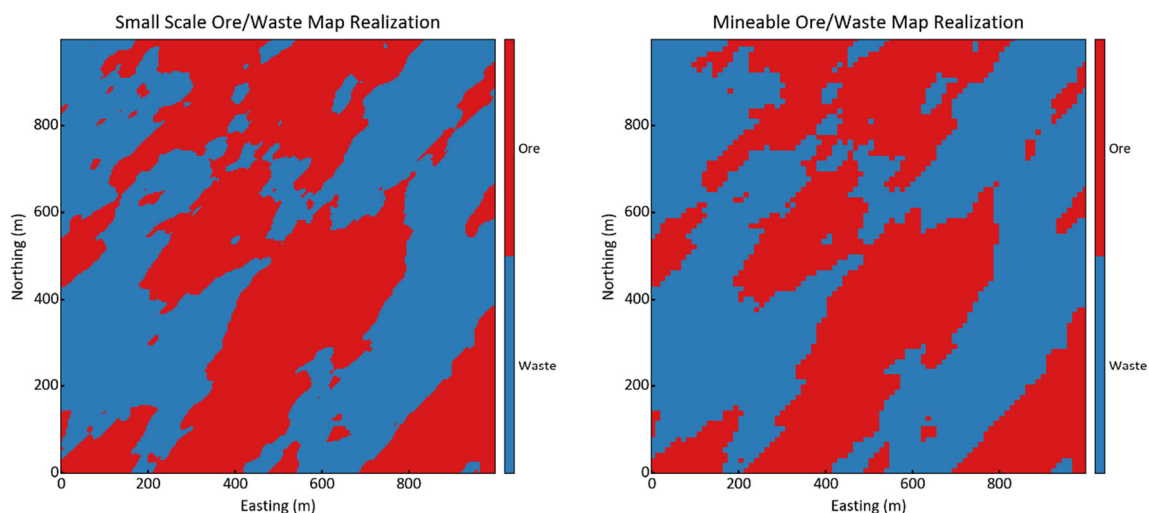


Fig. 8 Maximum profit destination maps at small-scale blocks (left) and considering mining selectivity (right)

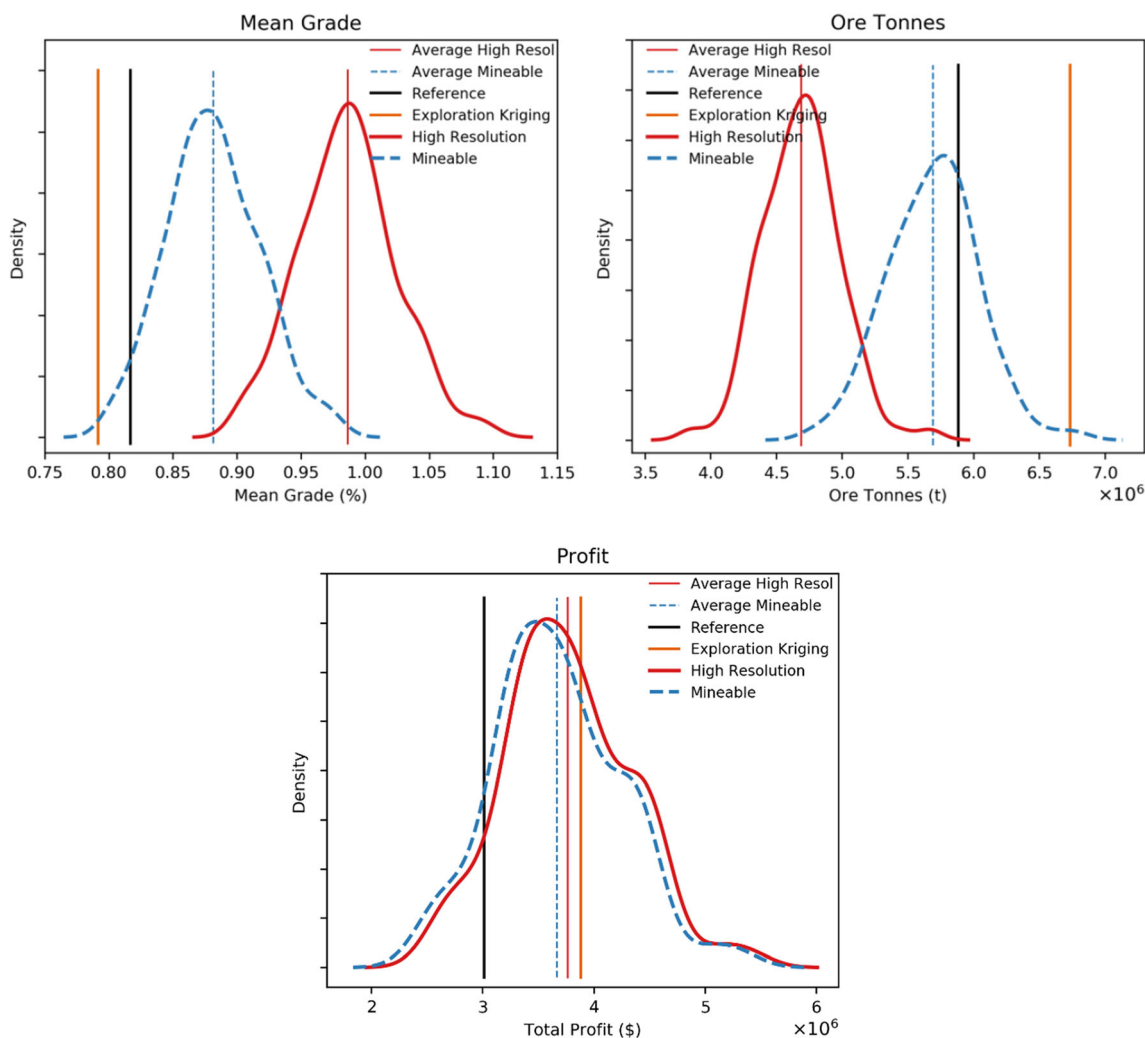


Fig. 9 Distributions of resources calculated on the reference model (black), the kriged estimates of exploration data (orange), the high-resolution simulated realizations (red), and going through the proposed workflow (blue)

kriging can look to perform well globally, it is not recommended. Kriging applied with a reasonable search and number of data would perform better locally, but not as good globally.

Regarding the apparent bias in the expected value of the high-resolution simulated realizations, it is the result of one reference. In other cases, the expected could be low or, coincidentally, exactly right. The theoretical expectation is that the uncertainty predicted by the proposed methodology would represent the truth in an accurate manner; being below the reference half the time, above the reference half the time and so on. Table 1 is presented to help understand these differences. The variations between the summary statistics indicate the significant uncertainty attributable to incomplete sampling.

Ore and waste location maps were generated for the reference model and ore loss and dilution maps were generated for the kriged exploration data and for all realizations going through the proposed workflow. The results are shown in Fig. 10. As mentioned before, the precise location of ore and

waste blocks is not known at the time of resources modeling. The ore and waste classification and decision will change at the time of mining based on real production data. One goal here is to minimize the classification errors to have more accurate resources reporting.

Summary probabilities models can also be calculated following the results of this workflow. For example, the

Table 1 Comparison of summary statistics in different datasets related to example

	Mean	Std	Min	Max
Reference model	0.504	0.396	0.033	5.981
Exploration data	0.537	0.464	0.095	2.591
Exploration data kriging	0.530	0.383	0.079	2.490
High-resolution realizations	0.538	0.472	0.095	2.591

probability of a grid cell to be above the cutoff grade, that is, to be ore, is shown in Fig. 11.

Figure 12 shows an overview of all steps and results of the proposed workflow for the case studied.

8 Discussion

There are a large number of factors that can influence the estimation of recoverable resources and the results of this workflow. The exploration data variogram, the grade control data spacing, the mining selectivity, and the cutoff grade relative to the grade distribution are examples of the factors that could be important for the estimation of recoverable resources of the bench. In practice, a sensitivity study could be carried out to understand the influence of each factor as well as the interactions between them. Nevertheless, the importance of anticipating the information and mining selectivity effects at the time of resources modeling with exploration data only is shown.

Besides a prediction of recoverable mineral resources closer to what will be mined in the future, the results of the workflow provide assessments of both local and global uncertainty on the resources. The local model of uncertainty is represented by ore probability maps, as shown in Fig. 11. The global model of uncertainty is represented by the uncertainty in the global recoverable resources. The distribution of resources calculated using the mineable dig limits resulted from the workflow is shown in Fig. 9. These results can be used to support resource/reserve classification and the uncertainty implicitly considered in the chosen classification scheme. Public disclosure of uncertainty should not be considered. There is a danger that reported low probability results could be adopted by the marketplace and unfairly punished advanced technical work. Additionally, the uncertainty should be used for internal evaluation of reconciliation results as mining takes place.

Using the mineable dig limits to calculate the resources would be equivalent to using an economic cutoff grade in a traditional approach. Then, the global resources are presented

in terms of tonnes of ore and ore grade. Table 2 shows an example of how the uncertainty could be internally disclosed in a mineral resources evaluation. It consists of the average value of each element calculated and other two values that correspond to the P10 (10th percentile) and P90 (90th percentile) of the distribution derived from the realizations and represent low and high “boundaries” for the resources. Although these percentiles are most commonly used in the petroleum industry, they provide a valuable understanding of the distribution of uncertainty as they represent the tails of the uncertainty distribution given by the realizations.

Other values could also be retained to assess the uncertainty in the overall resources, such as the probability of the reported values to be within the plus or minus 15% interval of the average value. The important point here is that, in the proposed approach, by not summarizing the simulated realizations into one model, the uncertainty can be assessed.

9 Conclusion

The main contribution of this paper is a framework that will properly forecast recoverable resource estimates by explicitly accounting for the information and mining selectivity effects. By following the proposed framework, the prediction of recoverable resources at the time of resources modeling will be closer to the material that will be actually mined in the future. In order to explicitly address these two concerns, the proposed framework consists of two separate modules. The first module is designed to account for the information effect and the second for the mining selectivity effect.

The information effect is accounted for by anticipating the additional production data, represented by blast holes or dedicated grade control drilling, which will be available at the time mining to guide the destination for the mined material (i.e., ore or waste). The selectivity effect is addressed by mimicking the grade control procedure to get mineable dig limits at a chosen selectivity, represented by a minimum mineable unit size (MMUS). The proposed methodology does not introduce

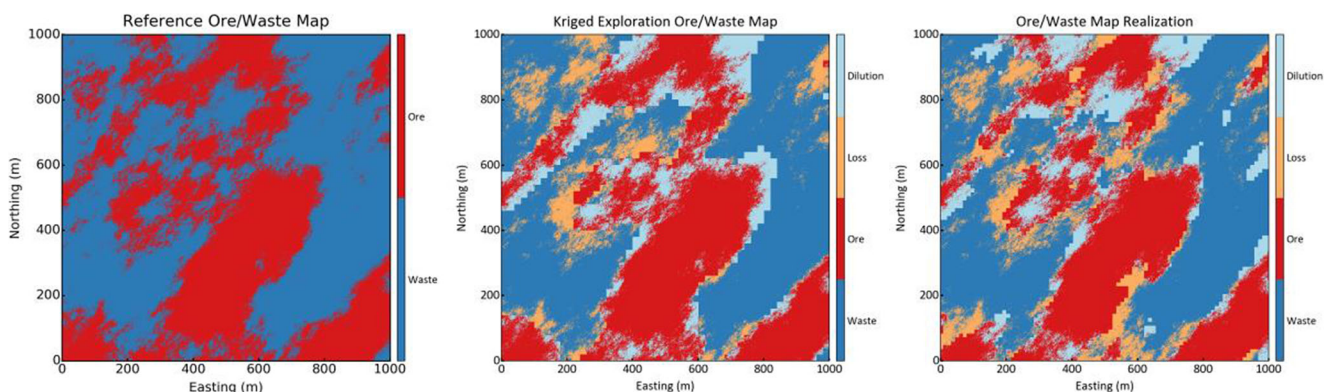


Fig. 10 Ore, waste, ore loss, and dilution location maps

Fig. 11 Ore probability map of simulated model going through the proposed workflow

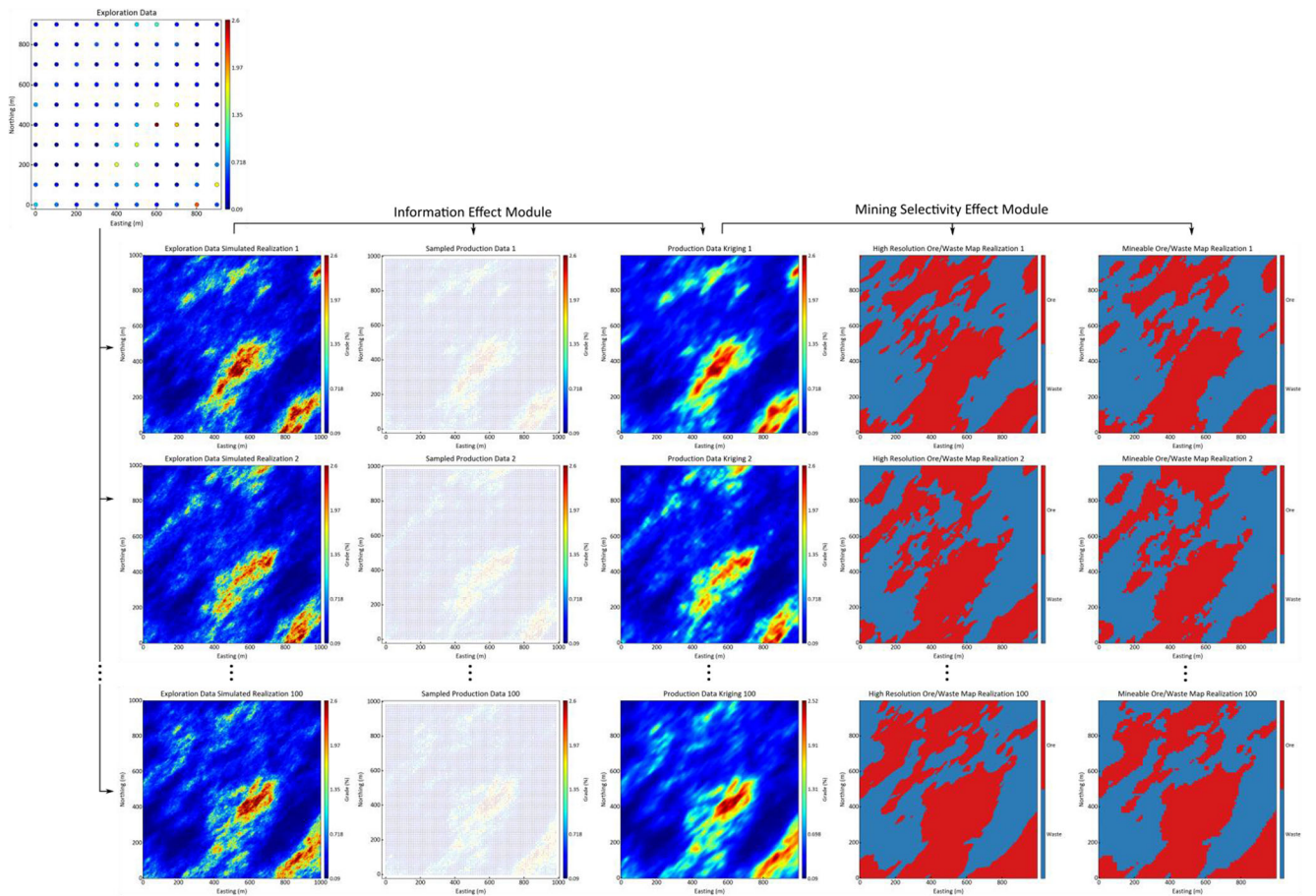
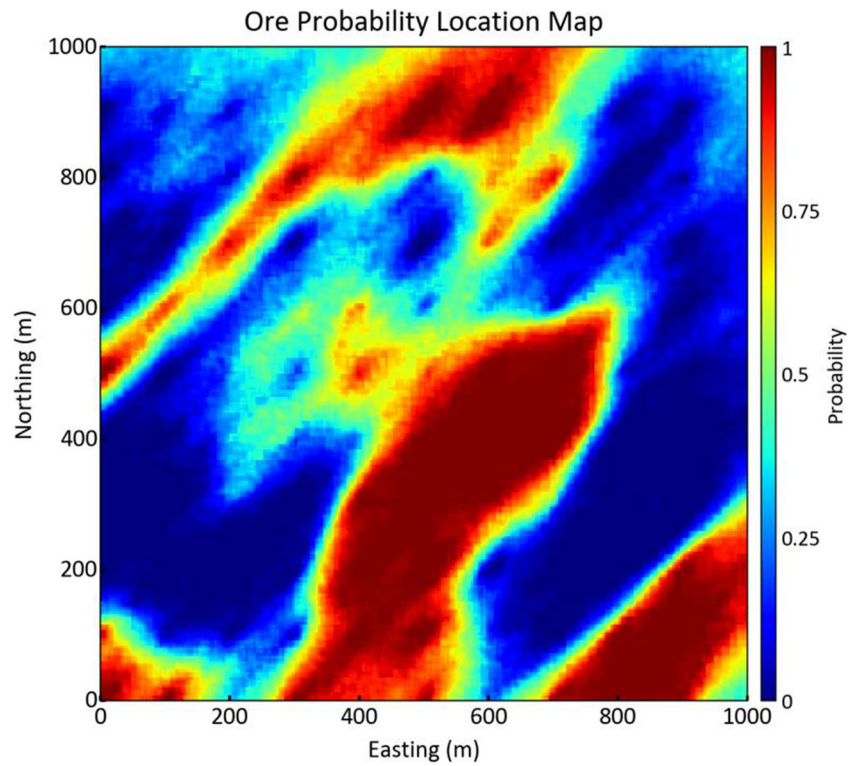


Fig. 12 Overview of steps and results of the proposed workflow for the case studied

Table 2 Overall mineral resources of the bench studied and the uncertainty on it

Tonnes		Grade	
(000 t)		(%)	
5692.2		0.88	
5263	6098	0.83	0.93
P10	P90	P10	P90

any bias in the resources estimations, is effective at anticipating information and selectivity considerations, and can be straightforwardly applied as a resources modeling workflow.

Another important result of the proposed methodology is a model of uncertainty in the recoverable mineral resources assessed. In addition to a prediction of long-term resources that will be closer to the mined material in the future, there is an uncertainty assessment for risk management by following the framework proposed. The case study presented follows the complete framework for open pit mining and shows how the uncertainty is assessed by successfully accounting for the information and mining selectivity effects in the long-term resources evaluation. The multiple realizations generated at the beginning of the proposed framework are used as an ensemble; they are not summarized into one model as with the traditional approach. The workflow is set in a way that each step is repeated for each realization and uncertainty is carried all the way to the end.

The proposed framework allows the practitioner to assess local and global uncertainty. The local model of uncertainty is represented by ore probability maps, which are easily achievable using the results of the workflow. Ore probability maps are generated by visiting one location at a time over all realizations to determine local distributions of uncertainty. The average value of the ore and waste flags (1 or 0, respectively) is then calculated for the location. This is done at all locations. A map of probabilities of ore can then be plotted. The same technique could also be used for classification of resources. For example, one could decide what should be the minimum probability of a grid cell to be ore for it to be considered measured resource and so on. The global model of uncertainty is represented by the uncertainty in the global recoverable resources assessed in the workflow. The global resources are calculated for each realization of the workflow using the mineable dig limits resulted that are equivalent to using an economic cutoff grade in a traditional approach. The global resources can be presented in terms of ore grade, tonnes of ore, and profit. After calculating the recoverable resources for each realization, the uncertainty in the resources can be found.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

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