Mineral Resources Evaluation with Mining Selectivity and Information Effect

by

Ana Paula Chiquini

A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in

Mining Engineering

Department of Civil and Environmental Engineering
University of Alberta

ABSTRACT

Long term mineral resources modeling is done to predict tonnage and grade of ore that may be mined and represents a key feature in the development of any mining project. The most common approach used in the mining industry 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 they do not provide an assessment of uncertainty. Other approaches include probabilistic estimation and geostatistical simulation, that provide an assessment of uncertainty. Unlike kriging, simulation reproduces the variability of the mineral deposit. 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, without considering mining practice constraints. There will always be uncertainty left at the time of mining because even the grade control sampling is imperfect, so assuming perfect knowledge of the grade in the future is not correct. In addition, mineral resources are evaluated at a specific time considering only the information available at that time. There are two concerns when geostatistical simulation is used for resources modeling: the information and the mining selectivity effects. The information effect is the decrease in uncertainty from the resources model to the time of mining, as more or better information becomes available. The mining selectivity effect is the selectivity or scale that would match future mining practice and geological constraints. The determination of ore (and mineable dig limits) must consider mining selectivity and the information available at the time of mining. A new framework for resource calculations 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. The proposed methodology is mainly designed for open pit mining. An adaptation to underground mining, more specifically to sublevel stoping of a tabular vein deposit, is also developed. 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.

ACKNOWLEDGMENTS

I would first like to thank my supervisor, Dr. Clayton Deutsch. Clayton's extraordinary teaching abilities along with a comprehensive experience and incredible patience offered guidance through the tricky research path and made this research and thesis possible. His brightness and contagious passion for geostatistics are motivating. His dedication and respect devoted to all students are certainly an example to be followed.

I would like to thank the Centre for Computational Geostatistics (CCG) and sponsors from the industry for the financial support. In addition, I want to thank all colleagues at CCG for their friendship, assistance and all great times together during these two years in Canada. I also want to thank all students from the MIN E 310 course (2017 and 2018) for the stimulating and challenging experience of teaching it and for the friendships built there. May we cultivate these friendships for many years to come.

A huge thanks to all great new friends (and renovated old friendships) made in Canada. Being so far away from home is definitely easier when surrounded by these beloved people. To the old friends/extended family in Brazil and abroad: I feel blessed to be able to count on your companionships and laughter throughout my life. Despite the physical distance, I know you all have my back and I will always have yours. A special thank you to my late friend Jorge (Fofão): your bright spirit, generosity and incredible knowledge in geostatistics have blessed all of us who were lucky enough to have had you in our lives during your (so brief) passage through Earth. Your memory will continue to inspire us. Thank you, my dear friend, colleague and mentor.

This challenging experience would not have been possible without the love and support of my husband, Dhaniel. His encouragement and admiration pushed me through the most difficult times. His ability to recognize the goodness and greatness in life gave me the strength to keep going. Last but not least, I would like to thank my parents and my sister for their unconditional love and support. You are my foundation and represent everything it is worth fighting for.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

CSA	Canadian Securities Administrators
EP	Expected Profit
IGC	Intelligent Grade Control
IGC-BM	Intelligent Grade Control - Blast Movement
IGC-DL	Intelligent Grade Control - Dig Limits
IGC-EP	Intelligent Grade Control - Expected Profit
JORC	Australasian Joint Ore Reserves Committee
MSHA	U.S. Department of Labor's Mine Safety and Health Administration
NI 43-101	National Instrument 43-101: Standards of Disclosure for Mineral Projects
SEC	Securities and Exchange Commission
SMU	Selective Mining Unit

Chapter 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 to maintain the integration between the plan and the result. There is a variety of geostatistical techniques available; it is the practitioner's responsibility to identify the appropriate one in each context. To name a few, Isaaks and Srivastava (1989), Goovaerts (1997), Deutsch and Journel (1998), Sinclair and Blackwell (2002) and Rossi and Deutsch (2014) present an overview of the many different geostatistical techniques available for grade estimation and evaluation of mineral resources and reserves.

The context and focus of this research is on recoverable resources evaluation. Mineral resources and reserves evaluation is done to predict tonnage and grade of ore in the ground and that may be mined. The grade, location and tonnage of material must be forecast with the greatest accuracy possible to justify the large investment associated with a mining project. The recoverable resources and reserves calculations are done by adding up blocks of different tonnages – due to different specific gravities of the host rocks – to get total tonnes and grades. It is 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 treatment options.

Section 1.1. Current Practice in Mineral Resources Evaluation

The most 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 calculated 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 (2014) present details on minimum, good, and best practices for calculating, managing and reporting ore resource models under a deterministic approach. Although its use is widespread, the estimated results provided by kriging are a smooth representation of the actual distribution of grades on the estimated blocks (Journel & Kyriakidis, 2004). 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 computed with estimation are not the correct representation of the grades at block scale (Journel & Kyriakidis, 2004). Moreover, this approach does not assess the uncertainty related to the mineral resource.

In addition to the deterministic approach, there are alternatives to calculate recoverable resources, such as probabilistic estimation and geostatistical simulation. Probabilistic estimations techniques 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 (Rossi & Deutsch, 2014). Gaussian-based probabilistic estimation is the most commonly applied due to the simplicity of the Gaussian distribution. 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 between multiple realizations.

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 uncertainty. 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. Realizations from geostatistical simulation are constructed at high resolution and grades (or a distribution of grades) are assigned to each block. Simulation attempts to reproduce the data histogram and variogram model, so the spatial variability of the deposit is going to be represented by the simulated realizations (Journel & Kyriakidis, 2004). 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. This can be achieved by simulation. Unlike the traditional estimation approach, simulation provides estimated block grades that are not smoothed (Journel & Kyriakidis, 2004). On average, the results from simulation are close to the values provided by estimation, with the addition of uncertainty assessment.

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 (Deutsch, 2015). At the end, the expected value of all realizations can be retained as a single value. Resources calculated on an average model or on one specific realization is different from the average resource. Resources calculated 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 for expected values. All realizations should be used all the time (Deutsch, 2015), as well as in mineral resource reporting.

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 application of 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 practicality of the dig limits that will be generated from these blocks and the geological boundaries of the deposit (Sinclair & Blackwell, 2002; Rossi & Deutsch, 2014).

Direct block simulation can be an alternative to computing high resolution simulated realizations and averaging up to the chosen SMU scale. Journel and Huijbregts (1978) 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. Gómez-Hernández (1992) proposed a different approach, in the context of hydraulic conductivity simulation in hydrogeology and petroleum engineering, a property that do not average linearly. This approach uses synthetic point and block training images to characterize the joint spatial variability model of the property. Gómez-Hernández (1992) provides implementation details. The problem with direct block simulation is that assumptions have to be made to compute 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 (Journel & Kyriakidis, 2004).

Volume-variance correction methods can also be used to create a target SMU grade distribution to be computed in the resources evaluation workflow (Journel & Huijbregts, 1978; Isaaks & Srivastava, 1989; Rossi & Deutsch, 2014). They provide a very 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 does not make any assumption of permanence of the shape of the variable distribution. The references mentioned above provide further details on each volume-variance correction method.

Section 1.2. Current Practice in Mineral Resources and Reserves Reporting

Public mining companies have the obligation to regularly inform their investors, government and regulators about their assets through annual reports and others means of communication. Professional regulating codes were developed to set minimum standards for public reporting and guidance for the public disclosure of mineral resources and mineral reserves. The mineral resources reporting formats generally adopted by the mining industry do not include any information with respect to the uncertainty in the evaluated resources. Besides assessing uncertainty during the mineral resources evaluation and transferring this uncertainty to further engineering calculations, disclosing it is fundamental. The requirements for mineral resources reporting demanded by three of the main regulating codes, NI 43-101, JORC and Industry Guide 7, were investigated and are presented here.

The National Instrument 43-101: Standards of Disclosure for Mineral Projects (NI 43-101, 2011) was developed by the Canadian Securities Administrators (CSA) to establish standards and guidelines for all public disclosures of mineral properties and projects of companies listed on exchanges within Canada. Similarly, the JORC Code (JORC, 2012) is a product of the Australasian Joint Ore Reserves Committee that provides a mandatory set of standards for public reporting of exploration targets, mineral resources and ore reserves for companies listed in Australia and New Zealand stock exchanges. The SEC Industry Guide 7 (SEC, 2016), contained in the Securities Act Industry Guides and published by the United States Securities and Exchange Commission, is the equivalent of those documents in the United States and provides a set of instructions on disclosure of "significant mining operations".

The NI 43-101 and the JORC Code state specific requirements for disclosure of any information about ore resources and reserves; alternatively, the SEC Industry Guide 7 foresees exclusively the report of reserves; resources reporting is not allowed under its guidelines. The NI 43-101 and the JORC Code were reviewed to identify the main requirements for resources reporting.

The NI 43-101 and the JORC Code make explicit requirements on the resources categories that must be reported, namely: inferred, indicated and measured –

considering an increasing level of geological knowledge and confidence. In addition, both documents state that each of these categories must be reported individually, clearly indicating the grade (or quality) and the quantity existent in each category. The issuer must also indicate the key assumptions, parameters, and methods used in the mineral resources estimate.

Neither of those documents state any recommendation towards the need for a deterministic resources model for reporting. In fact, they encourage a discussion regarding the uncertainty involved in the resources estimation, including geostatistical procedures to quantify it. Table 1.1, extracted from the JORC Code, shows guidelines on how this discussion can be approached by the issuer.

Table 1.1 – Guidelines on the discussion of uncertainty (modified from the JORC Code, 2012)

Criteria	Explanation
Discussion of relative accuracy/ confidence	• Where appropriate a statement of the relative accuracy and confidence level in the Mineral Resource estimate using an approach or procedure deemed appropriate by the Competent Person. For example, the application of statistical or geostatistical procedures to quantify the relative accuracy of the resource within stated confidence limits, or, if such an approach is not deemed appropriate, a qualitative discussion of the factors that could affect the relative accuracy and confidence of the estimate. • The statement should specify whether it relates to global or local estimates, and, if local, state the relevant tonnages, which should be relevant to technical and economic evaluation. Documentation should include assumptions made and the procedures used. • These statements of relative accuracy and confidence of the estimate should be compared with production data, where available.

Geostatistical simulation will be used to obtain the final probabilistic resources in the workflow that will be proposed in this thesis. Including the uncertainty assessment in the resources report is straightforward. This information is substantial to further evaluations of every project and extremely valuable to shareholders.

Section 1.3. Problem and Motivation

The resource model is constructed at a specific time of the mine life and considers only 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 the mining process 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 information effect. The information effect reflects the potential for misclassification of ore/waste material because the long term resource models do not account for future information that will be available at the time of mining. Anticipating information to try and minimize ore/waste classification errors is critical. The economic performance of any mining operation will be impacted by misclassification of material.

The other concern when calculating recoverable resources is referred to as the mining selectivity effect. The maximum profit available in a mining project would be the one given by free selection of high resolution blocks of ore and waste, without accounting for any mining practice 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 high resolution 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 (Journel & Kyriakidis, 2004).

In the traditional framework for resource calculation, 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. All these factors are normally combined into one parameter: the SMU size. The traditional framework combines information effect, remnant uncertainty and mining selectivity considerations, trying to address all factors by using an SMU size that is larger than the final grade control data spacing (Leuangthong, Neufeld, & Deutsch, 2003). In the conventional geostatistical simulation approach for long term resource modeling, by using a large SMU size, it is being assumed that there is no remnant uncertainty at the time of mining, resulting in a long term model that carries a profit that is not attainable.

In the practice of mainstream mining industry procedures, Deraisme and Roth (2000) had already anticipated that there are no significant advances towards trying to address the information effect for estimating recoverable reserves, even though the information effect has been widely discussed in geostatistical theory. Even eighteen years later, not much have changed from the above statement. In the latest version of software ISATIS, Geovariances (2018) released a new tool called "Information Effect for Simulations". This tool helps optimize the grade control sampling 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 of this new tool is similar to what will be proposed in this thesis to assess the information effect: sample high resolution simulated grids at the anticipated grade control spacing and use the samples to re-estimate the grids. Nevertheless, the entire workflow proposed here is different because it includes an additional module to address the mining selectivity effect in resources modeling.

Some advances have been made in research. Journel and Kyriakidis (2004) identified the concern on the evaluation of mineral reserves due to the information effect and proposed 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 (2004) 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 (2004), 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. (2003) and Neufeld, Leuangthong, and Deutsch (2007) also proposed the sampling of simulated realizations and re-estimation of the grids using those samples. Leuangthong et al. (2003) 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. The framework is somewhat similar since the actual production is simulated by sampling simulation realizations at the production sampling spacing and using this information to predict the recoverable resources/reserves. Neufeld et al. (2007) proposed it to account for the information effect in recoverable resources and reserves estimation. Neufeld et al. (2007) compared the results of the simulation approach to incorporating an assumption about the information effect into 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. The change of support model and the simulation based approach showed the predicted results. 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 sampling increases resulting in less profit. The results of both approaches can be combined to help choosing the SMU size for resources and reserves evaluation. Both papers are important because, besides raising awareness towards the effect of information on recoverable resources estimation, they both present the simulation approach to account for it. Nonetheless, there is still a mix of concepts between information and mining selectivity effects. This thesis develops a framework to specifically account for the information and mining selectivity aspects separately.

Cuba, Boisvert, and Deutsch (2012) used a similar framework to target the evolution of the degree of knowledge of a deposit and its dynamic behaviour due to the acquisition of new data in the design of the long term mine plan. In the proposed paradigm, the mining sequence is continuously adapted to information sampled from simulated realizations.

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. The goal of this research is to correctly predict recoverable resource estimates by explicitly accounting for the information and mining selectivity effects. By doing so, the recoverable resources forecast at the time of resources modeling will be closer to the material actual mined in the future. A framework consisting of separate modules to address these two concerns is proposed.

Section 1.4. Proposed Methodology

This thesis 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 practice selectivity restrictions and geological characteristics of the deposit, while trying to retain most of the profit available at free selection of high resolution of blocks of ore/waste. 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 production 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 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) Assign expected profit values to every grid cell of estimated final data for at least two different destinations (i.e. ore and waste), depending on its grade. (b) Simulate the mining selectivity considerations by applying the mining selectivity calculations for each estimated grid of final data at a chosen selectivity. An algorithm is developed to flag each set of grid cells within the chosen minimum mineable unit size to its most profitable destination. This algorithm visits the set of grid cells that falls inside the mineable block size and assigns the most profitable destination to it. The idea of this step is to mimic the grade control practice to get mineable dig limits at a chosen selectivity.

4. (a) The mineable dig limits at the desired selectivity resulted from the previous step are transferred to the high resolution reference simulated model from the first step. (b) Based on these dig limits, we can now calculate the probabilistic

resources 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 calculated 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: the probability to be above or below the cutoff grade, the average grade above the cutoff grade, the tonnes of ore and waste, the grade of ore, and so on. The estimates done in step two are exclusively for determining the destinations; all resources are calculated based on the original simulated realizations.

Section 1.5. Thesis Outline

Chapter 2 defines and illustrates the information effect on mineral resource modeling, discusses its impact on resource evaluation and presents with examples the module to account for the information effect of the proposed framework. In Chapter 3 the module designed to address the mining selectivity effect is presented and illustrated with practical examples. An algorithm developed to assess different mining selectivities in ore/waste classification is also described in Chapter 3. In Chapter 4 an implementation of the complete workflow in open pit mining is presented and different factors that influence on the mineral resource assessment are discussed, such as the variogram, grade control data spacing, mining selectivity and the cutoff grade relative to the grades distribution. Chapter 5 presents an adaptation of the proposed workflow to underground mining, specifically to sublevel stoping of a tabular vein deposit. The underground mining application is illustrated with a case study from a real data set in the same chapter. The conclusion and other remarks, such as possible avenues of future work, are presented in Chapter 6.

Chapter 2. Methodology – Information Effect

Section 2.1. Introduction

In the context of mineral resources and reserves modeling, probabilistic estimates and geostatistical realizations are constructed at a specific time of the mine life and consider the information available at that time. Geostatistical simulation leads to high resolution block models and quantifies uncertainty at the scale of the data used. Assessing and reporting recoverable resources directly on high resolution simulated realizations would assume perfect knowledge of the grade at the time of mining and perfect selectivity at the scale of drilling.

In the simplest context of resources and reserves evaluation, the mined material is classified as ore or waste. Sinclair and Blackwell (2002) define the term ore as the material that is "mined at a profit", and waste, that contains "insufficient value to earn a profit". Ore and waste are separated from each other in mining practice by a cutoff grade.

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 2.1 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 (Rossi & Deutsch, 2014). Both of these errors reduce the profit of an area being mined. These ore/waste classification errors should be minimized.

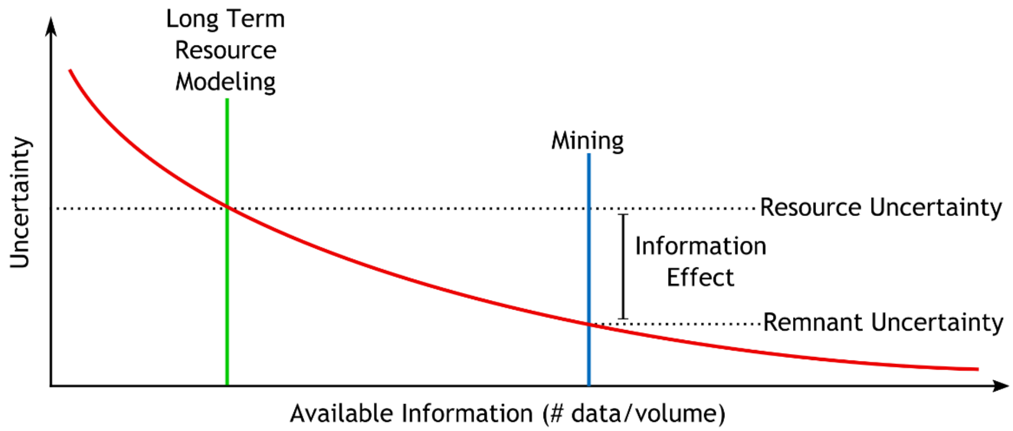

Figure 2.1 – The information effect: the decrease in uncertainty from the resources model to the time of mining.

Even though more data is available at the time of mining, the true grade within a production volume is not known; only an estimate of that grade is calculated using the grade control sampling (Deraisme & Roth, 2000). The ore and waste selection is imperfect because there will always be an estimation error. Some misclassification of ore and waste blocks will inevitably happen. As mentioned in Deraisme and Roth (2000), the amount of misclassification can be due to, along with other reasons, the lack of complete sampling before mining takes place.

The remnant uncertainty at the time of mining should be considered for long term models 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. The conventional geostatistical simulation approach used for long term modeling and resources reporting uses only the data available at the time of modeling, pending including more or better information that will be available in the future. Thus, there is no remnant uncertainty included in the modeling. The traditional simulation framework results, then, in a long term resource model that carries a profit that is not achievable. 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 Selective Mining Unit (SMU) that is larger than the final grade control data spacing (Leuangthong et al., 2003). 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. It is common to increase the SMU size to account for imperfect information in the future. It is also a common approach to assign a fixed dilution factor that would account for the information effect and selectivity of mining practice and equipment on the recoverable resources evaluation (Neufeld et al., 2007). Both solutions combine the information effect and selectivity considerations into one general parameter, but the information effect in long term resources evaluation is related to the smoothing effect of kriging with widely spaced exploration data, while the selectivity and SMU size are closely related to dilution (internal, contact and operational). Combining these considerations into one general parameter is not the best approach.

Section 2.2. Proposed Framework for Information Effect

Addressing these concerns in probabilistic resources modeling requires two separate modules to be added to the traditional simulation workflow. The first module is designed to address the information effect by anticipating the additional production data that will be available in the future to direct the choice of destinations for the mined material. This module is presented in detail later in this section. The second module accounts for the mining selectivity effect and will be presented in the next Chapter.

Prior to applying the proposed workflow, high resolution realizations of all necessary variables using the available exploration data are simulated. This is no different from the traditional simulation paradigm. Parameter and data uncertainty could be considered in order to more fully assess the uncertainty.

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 Vasylchuk (2016), 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 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 (Journel & Kyriakidis, 2004).

A small example is used to illustrate the information effect impact on the evaluation of a mineral deposit. In this example, exploration data is sampled from a dense grid of production data. The full set of production data will be the future information we would get at the time of mining. The dataset used in the example consists of 2,278 blast holes on one bench of an open-pit disseminated gold deposit. The blast holes dataset contains the X, Y, and Z locations of each blast hole collar and gold grades.

The exploration data would be the only data available at the time of resources modeling, that is, the "now". To mimic it, the production data was sampled at an exploration data spacing of 30 x 30 m. The gold grades histograms of the sampled exploration data (the "now") and the actual production data (the "future") are then compared. The histograms are very similar: both show a highly positively skewed lognormal-like distribution, characteristic of gold grades. The average gold grade on the exploration dataset is 0.626 with a variance of 1.64, while the average gold grade on the production dataset is 0.615 with a variance of 1.96. Figure 2.2 shows the sampled exploration data and the bench production dataset as well as their gold grades histograms.

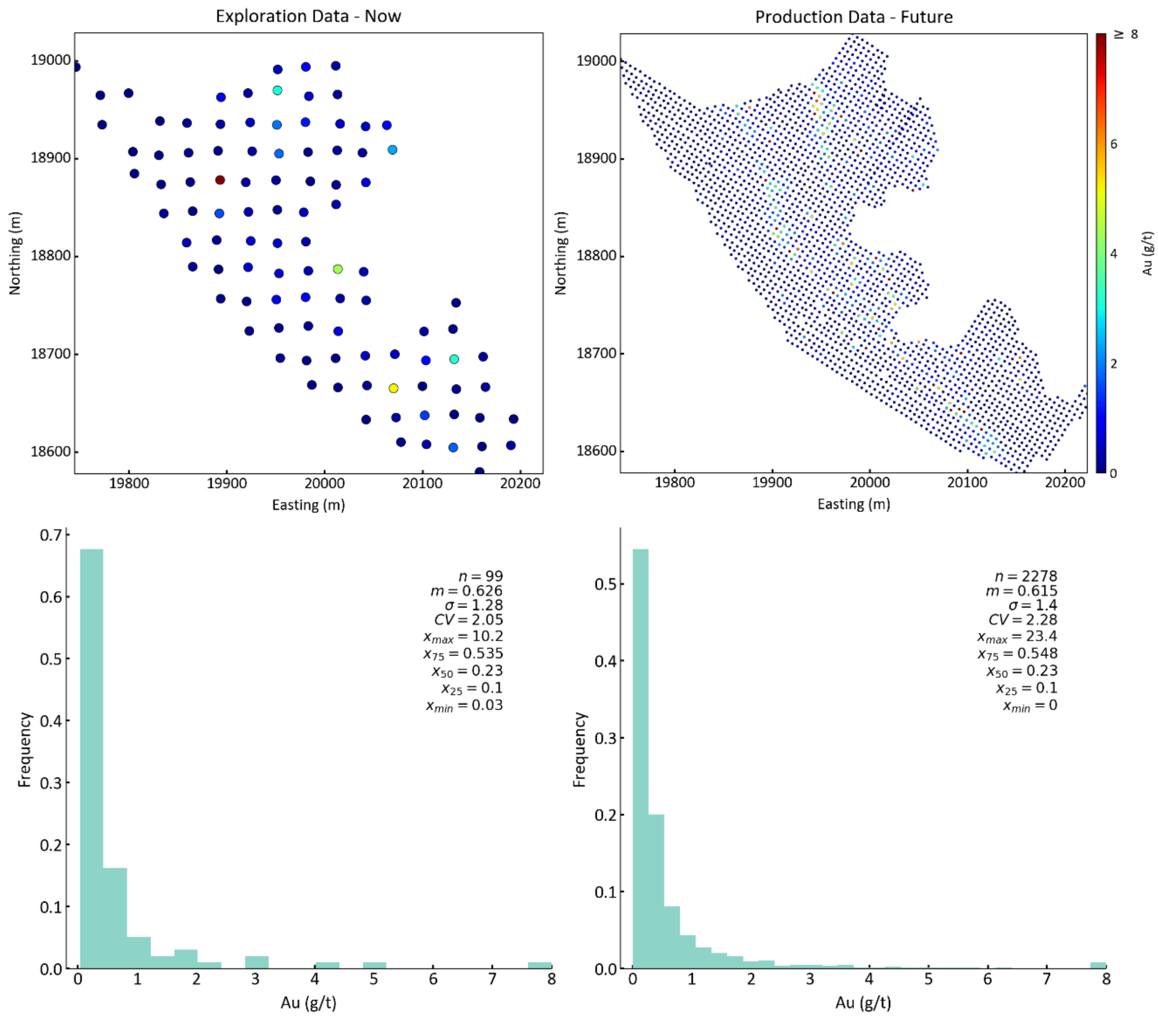

Figure 2.2 – Sampled exploration data (top left) and bench production dataset (top right) and their gold grades histograms (bottom).

Following the proposed workflow to assess the information effect, the gold grades were estimated by ordinary kriging using the best possible set up. First, considering only the exploration data sampled from the production data, and later, using the full set of actual blast holes. The variograms used for ordinary kriging were calculated along the azimuth 150° and perpendicular to it, 60°, for both cases. The variogram models fitted are as follows:

1. Exploration data:

$$\gamma(\mathbf{h}) = 0.1 + 0.25 \cdot Sph_{\substack{ahmax=50\\ahmin=20}}(\mathbf{h}) + \ 0.65 \cdot Sph_{\substack{ahmax=145\\ahmin=68}}(\mathbf{h})$$

2. Production data:

$$\gamma(\mathbf{h}) = 0.1 + 0.45 \cdot Sph_{\substack{ahmax=12\\ahmin=9}}(\mathbf{h}) + \ 0.45 \cdot Sph_{\substack{ahmax=45\\ahmin=15}}(\mathbf{h})$$

Figure 2.3 presents the kriged estimates for both data sets and their histograms. The data sets histograms from Figure 2.2 and estimates histograms are different because of the change of support from the raw data to the estimated grid (i.e., from points to blocks) and the smoothing effect of kriging. We can expect a decrease in the variance of the estimates compared to the data histograms. On the other hand, the limited information at the time of resources modeling leads to an excessive smoothing of the exploration data estimates. The information effect is reflected on the histograms of the estimated exploration data (dashed red line on the bottom of Figure 2.3) and the estimated blast holes data (dashed blue line), that has a higher variance.

The information effect influence can also be seen on the classification of ore and waste blocks. A cutoff grade of 0.6 g/t of gold was used to separate ore and waste on the exploration data estimates and blast holes estimates. The two ore and waste maps generated were then compared (Figure 2.4). Final classification will be based on the estimated production data. The precise location of ore and waste predicted from the exploration model is not critical since the assignment will be changed at the time of mining. The errors and smoothing are still relevant on the overall resources in the large production volume. Every grid cell misclassified as ore with the exploration data will be dilution during the mining practice and every grid cell misclassified as waste on the estimated exploration data grid will be an ore loss. The cutoff grade plotted on the estimates histograms in Figure 2.4 illustrates that the proportion of exploration data estimates above the cutoff grade is larger than the proportion of production data estimates above the cutoff grade. Considering a fixed density value of 2.7 g/cm^3, the total ore tonnage calculated on the exploration data estimates is 603,450 t while the total ore tonnage calculated on the production data estimates is 490,134 t. The ore tonnes calculated only with exploration data are not attainable at the time of mining. This result is sensitive to the cutoff grade relative to the grade distribution on the specific case, but the smoothing of kriging with widely spaced exploration data will always have an impact. The ore tonnes are over estimated in this case because the cutoff grade is below the mean and the excessive smoothing places more material closer to the mean, that is, above the cutoff grade.

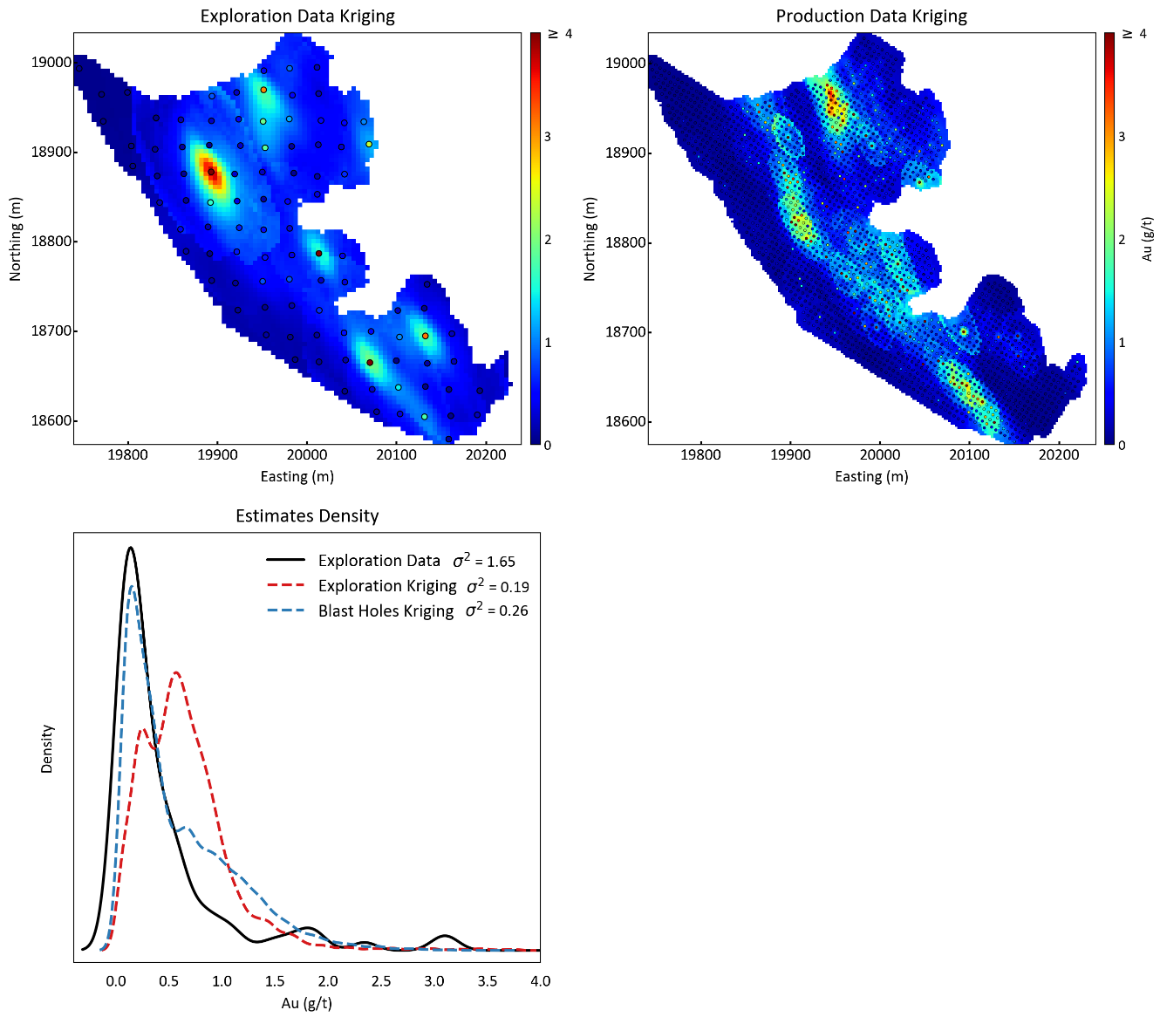

Figure 2.3 – Estimated exploration (top left) and blast holes (top right) datasets and histograms of the estimates (bottom).

The long term model and the grade control model show significant differences. The change is mainly due to the acquisition of new information at the time of mining. There is still remnant uncertainty at the time of mining due to incomplete grade control sampling. The grade control model still has potential for misclassification because of the imperfect production sampling. Nevertheless, the significant differences shown between the two models justify the need for anticipating this change at the time of resources modeling through a framework that will account for the information effect.

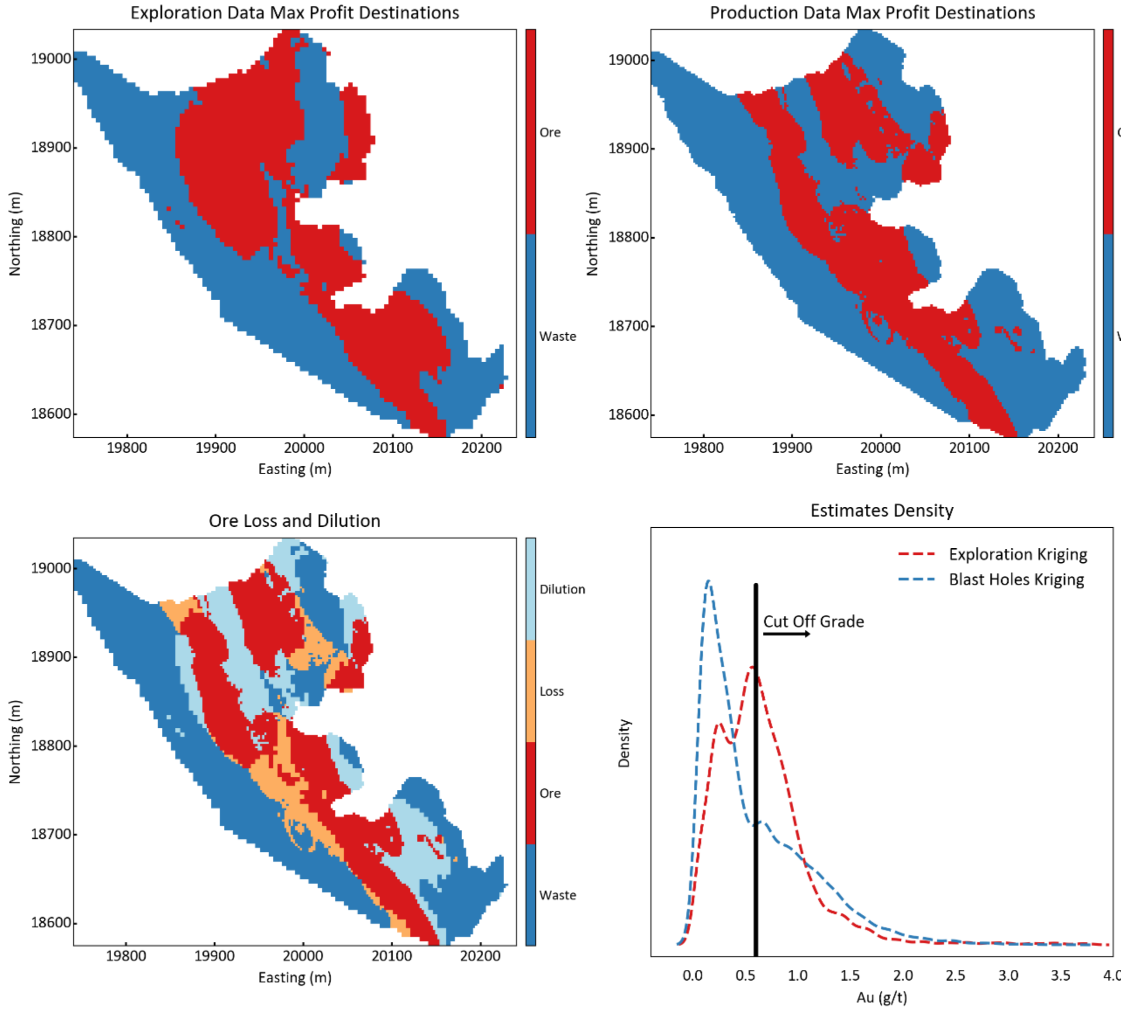

Figure 2.4 – Ore and waste maps on the exploration (top left) and production data (top right) estimates, ore loss and dilution map (bottom left) and estimates histograms (bottom right).

Section 2.3. Implementing the Proposed Framework for Information Effect

A 2-D example of the proposed methodology to account for the information effect in resources modeling is presented. Unlike the previous example, where we had access to the final grade control sampling for comparison, the current example illustrates exactly the proposed procedure at the time of resources modeling, when only exploration data is available. This 2-D example represents one bench of an open pit gold deposit. A reference gold grade model was generated through one realization of an unconditional simulation. The major direction of anisotropy is along the azimuth 90° and the following variogram model was used to simulate:

$$\gamma(\mathbf{h}) = 0.0 + 0.5 \cdot Sph_{\substack{ahmax=150 \\ ahmin=100}}(\mathbf{h}) + \ 0.5 \cdot Sph_{\substack{ahmax=300 \\ ahmin=200}}(\mathbf{h})$$

The unconditional simulated realization was transformed to original units following a positively skewed reference distribution characteristic of gold deposits. The reference model is 500 x 500 blocks and each block is 2.5 x 2.5 x 1 m. This 2-D reference model will be sampled to mimic exploration drilling. The maximum total profit in the bench will be calculated on this reference model as well as reference ore and waste maps for comparisons and total resources in terms of grade, ore tonnage and quantity of metal. Figure 2.5 shows the reference grade distribution used for transformation to original units and the reference gold grade model.

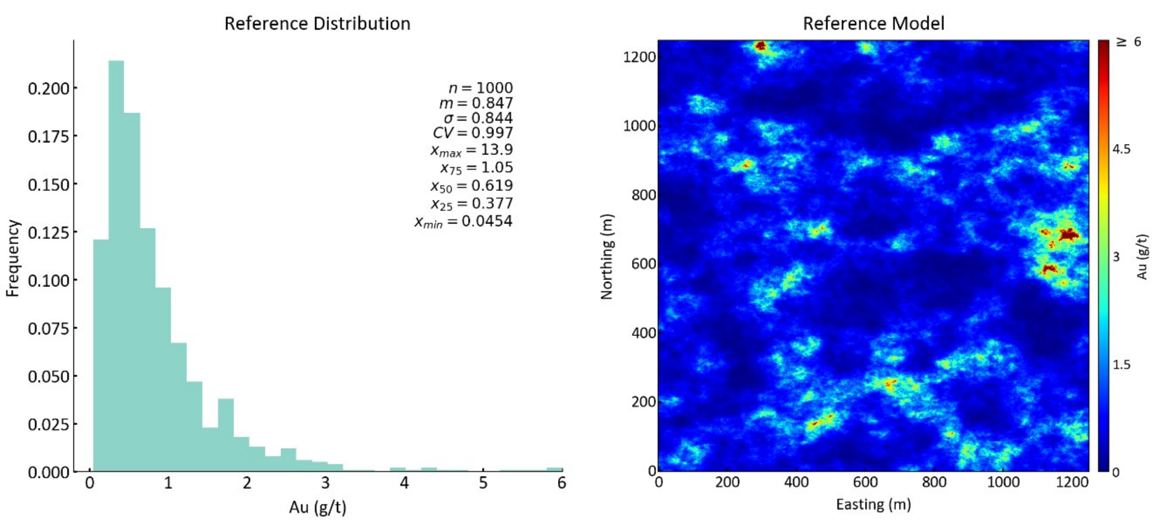

Figure 2.5 – Reference grade distribution (left) and reference gold model (right).

The only information available at the time of resources modeling would be the exploration drilling. To mimic this situation, the reference model was sampled at a 100 x 100 m spacing, generating 169 "drill holes". The traditional resources modeling approach is to estimate the grades by ordinary kriging, so the gold grades were estimated using only the exploration dataset to compare with the proposed workflow. Figure 2.6 shows the sampled exploration data from the reference model and the estimated grades by ordinary kriging.

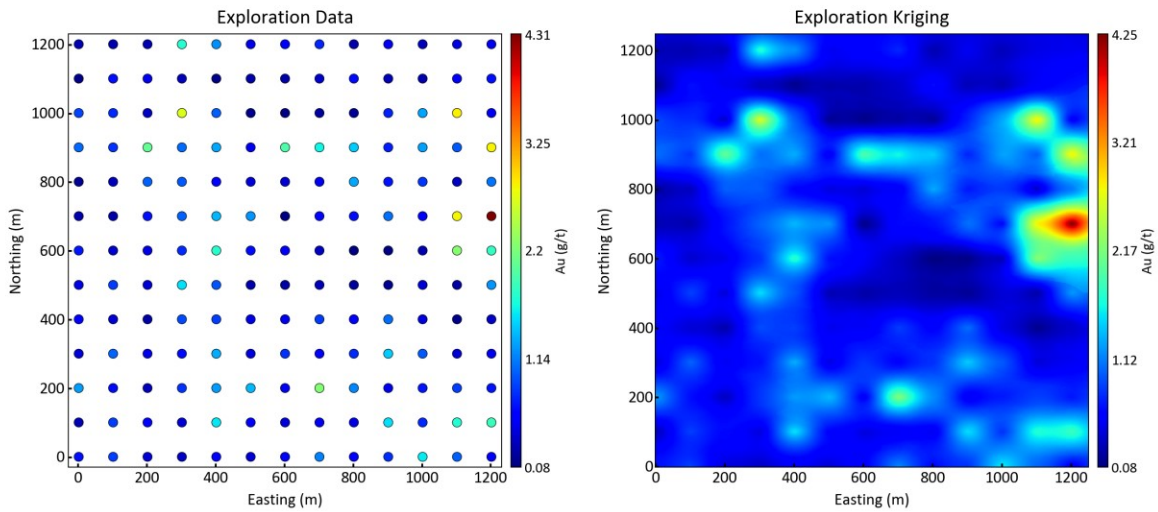

Figure 2.6 – Exploration data sampled from reference model (left) and estimates (right).

The exploration dataset is also used to simulate a hundred high resolution realizations of gold grades. No parameter and data uncertainty are considered in this example. Each realization is sampled at the anticipated production data spacing to mimic the production data planned in the future. In this example, a typical hard rock mining data configuration is considered, where the blast holes sampling is normally done at a closely spaced grid, so there will be a significant number of additional data available at the time of mining compared to the time when the long term model was constructed. For this reason, a production data spacing of 10 x 10 m was used. One hundred unique datasets are sampled consisting of 169 drill holes and 15,207 production data. Figure 2.7 shows one simulated realization of the exploration data and the production dataset sampled from the same realization.

The next step is to estimate the gold grades using the sampled production datasets. The existing exploration data was considered in the estimation with the production data. The sampled production data too close to the exploration drilling were rejected because the exploration data is the only actual data available and production sampling is of lower quality in practice. Experimental variograms were calculated for each dataset along azimuth 90º and perpendicular to it. Variogram models were automatically fit. Ordinary kriging was used to estimate the grades. Figure 2.8 shows the experimental variogram calculated and the fitted variogram model as well as the production data estimates for the same sampled realization shown in Figure 2.7. Although the computational effort to perform the estimation of a hundred grids seems demanding, by setting up a simple Jupyter notebook embedded with a Python script the workflow is straightforward.

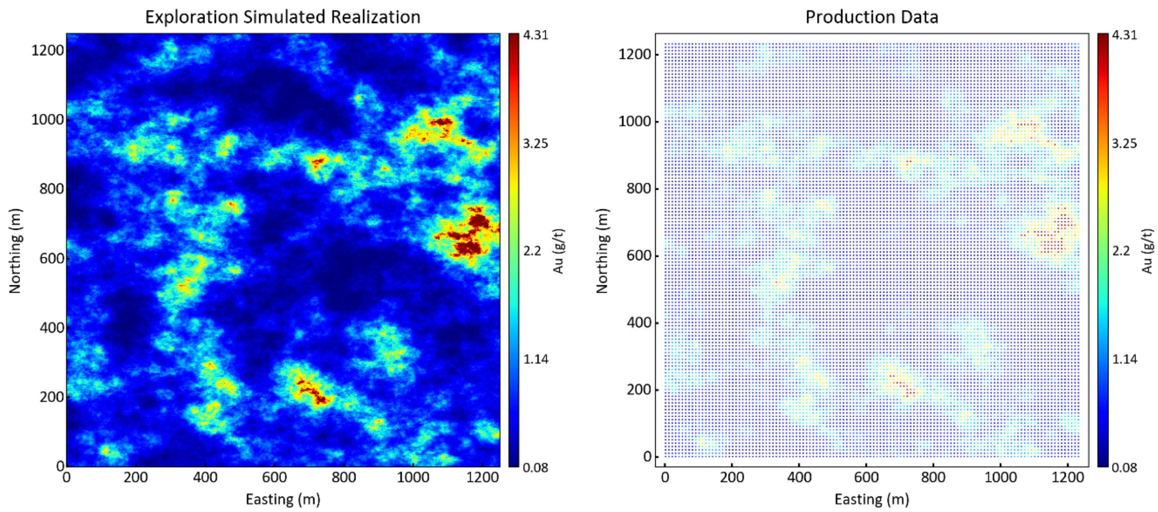

Figure 2.7 – One exploration simulated realization (left) and the sampled production dataset (right).

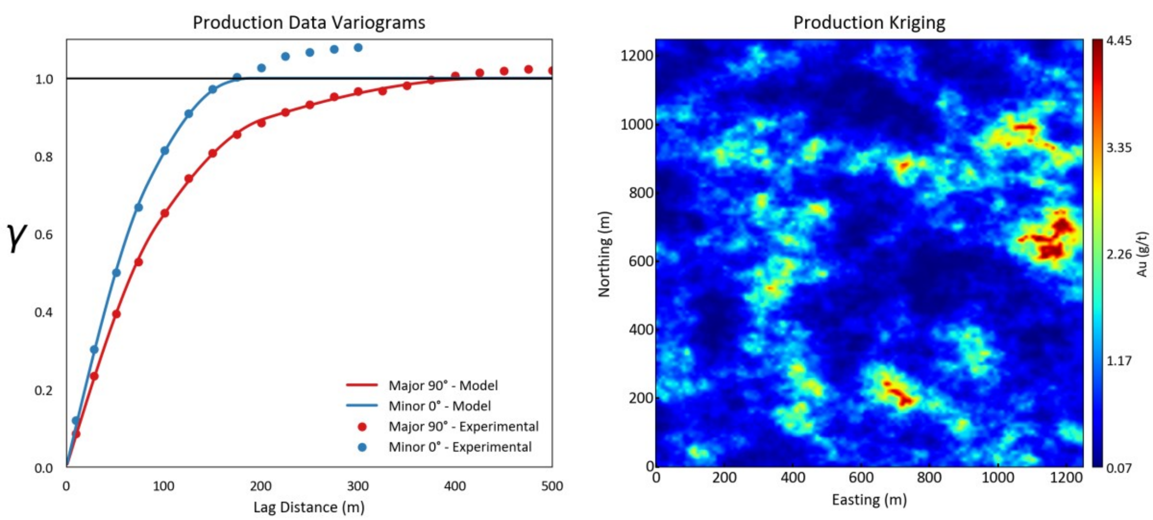

Figure 2.8 – Production data variograms and their estimates.

The results of the proposed workflow will be compared with the reference model and the kriging estimates calculated only with exploration data. The comparisons will be done in terms of total profit given by the bench, ore and waste maps, lost profit due to misclassification of ore and waste and total resources (grade, ore tonnage and quantity of metal). It is important to mention that selectivity at the time of mining is not yet being accounted for. The idea is to isolate the information effect and its impact on the overall resources. The total profits shown here assume high resolution mining selectivity and free selection of blocks of ore and waste.

The profit of each grid cell was calculated as:

$$\begin{cases} EP_{ore}(\mathbf{u}) = \propto * grade\ (\mathbf{u}) + \ C_0\ (\$/t) \\ EP_{waste}(\mathbf{u}) = \ -2\ (\$/t), \qquad \mathbf{u} \in A \end{cases}$$

Where EP refers to expected profit if that grid cell is classified as ore or waste for all locations **u** within the area to be mined A, $\propto$ is the slope of the grade x profit graph and C_0 is the cost of a material at zero grade to the processing plant. If available, all costs could have been considered on the expected profit calculation: costs of mining ore, mining waste, processing ore, gold price and recovery and so on. The total profits that will be used for comparison are the sum of each grid cell profits within the models. The values used for expected profit calculations are usual for current open pit mining: $\propto$ = 30 and C_0 = - 15 \$/t. The cutoff grade to separate ore and waste is straightforwardly calculated from the expected profits formulas given above. When EP_{ore} = 0, the cutoff grade is 0.5 g/t.

The total profit given by the reference model, that is, the "truth", is 2.61 million dollars. Without considering ore/waste classification errors, the total profit given by the kriged exploration data is 90% of the reference model, 2.35 million dollars. The average total profit calculated for the production data grids going through the proposed framework is 99.50% of the reference model, 2.60 million dollars. Neither of these profits will be attainable at the time of mining without considering the mining selectivity. The interesting point here is that, even though actual data is not being acquired by mimicking production sampling on the proposed workflow, the average total profit assessing the information effect is closer to the reference total profit. Similarly, we can compare the profit distribution given by the simulated realizations with exploration data only and with resampling and reestimation of the grids. Figure 2.9 compares both profit distributions and the reference and kriged values. This comparison shows that there is no bias being introduced by following the proposed workflow, with resampling and reestimation. No new real data is added with resampling, so the results are still unbiased.

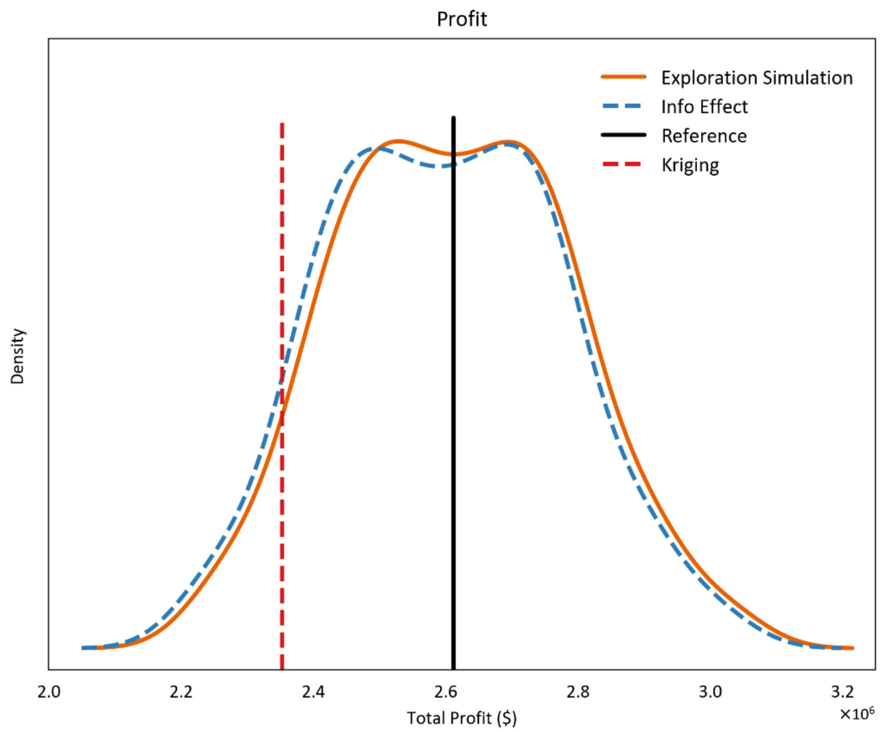

Figure 2.9 – Profit distributions from the simulated realizations with exploration data and following the proposed workflow, the reference and kriged values.

Each grid cell was classified as ore or waste by applying the cutoff grade (0.5 g/t) to generate ore and waste maps on the reference model, the kriged exploration data and blast holes estimates. Figure 2.10 illustrates the ore and waste maps generated. The last two models were then compared to the reference model and lost ore and dilution were calculated. Every grid cell misclassified as ore will be processed in the processing plant with the actual ore and will end up costing $EP_{ore} = alpha * grade + C_0\ (\$/t)$. Every grid cell misclassified as waste will end up costing the waste mining cost, EP_{waste}. The lost profit due to misclassification of ore and waste cells was then calculated. The exploration data model estimated by ordinary kriging has a lost profit of 798 thousand dollars, that represents 30% of the total profit given by the reference model. The average lost profit of the production data models in the proposed workflow is 589 thousand dollars, that represents 22% of the total reference profit. The ore and waste classification errors will be minimized by sampling the simulated realizations and anticipating the production data because of the excessive smoothing associated with the exploration data kriging. The exact location of ore and waste blocks is not relevant at the time of resources modeling because the classification will be changed at the time of mining. On the other hand, minimizing the classification errors translates to more accurate resources reporting.

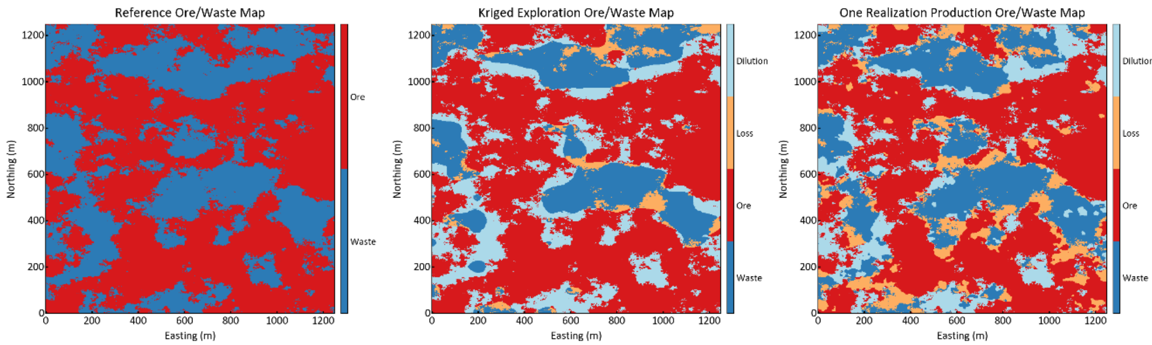

Figure 2.10 – Ore and waste maps calculated on the reference model (left), exploration data kriged estimates (center) and one realization of production data estimates (right).

The mineral resources were calculated for the bench studied in the three cases: the reference model, the exploration data kriged model and the resources distribution given by the proposed workflow to account for the information effect. A fixed density value of 2.7 g/cm^3 was considered and the volume of each grid cell is 6.25 m^3. The metal content is calculated in troy ounces by multiplying the tonnage of each grid cell by its gold grade and dividing everything by 31.10345. Figure 2.11 presents the resources calculated. The dashed blue line represents the distribution of resources assessed by the proposed workflow, the dashed red line corresponds to the results from the exploration data kriging and the solid black line is the reference model. We can see that the smoothing effect associated with kriging widely spaced exploration data impact the overall resources of the bench. The errors and smoothing are critical to the overall resources in the large production volume. The results are sensitive to the position of the cutoff grade relative to the original grade distribution: due to the smoothing effect of kriging and because the cutoff grade is lower than the average grade of the bench, the ore tonnes given by kriging and by the proposed workflow are greater than the truth. In this example, the total profit (bottom right graph in the figure) can also be greater than the reference profit (that is the maximum profit and it is not attainable in the mining practice) because we are not yet considering the selectivity at the time of mining.

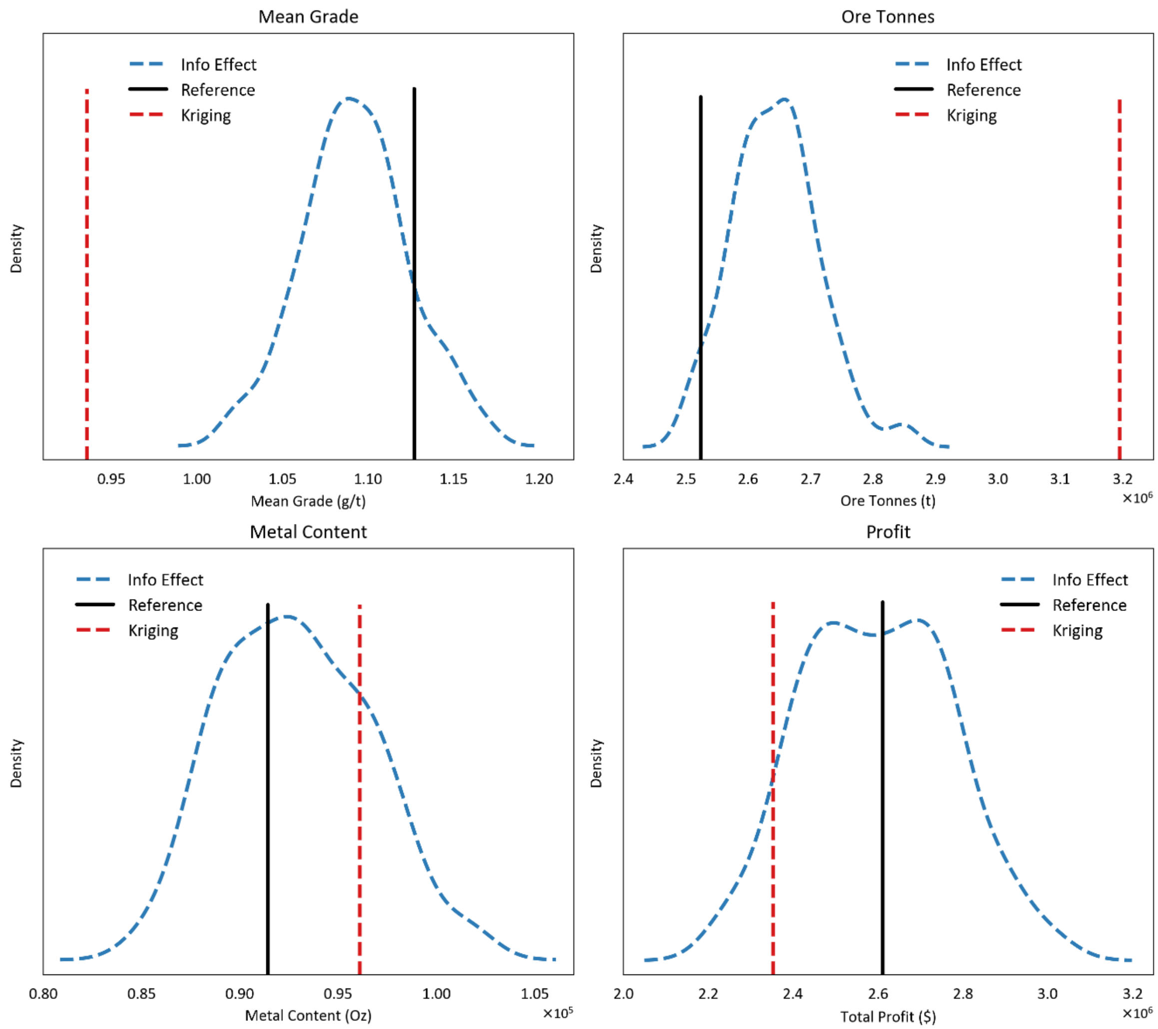

Figure 2.11 – Mineral resources for the entire bench: mean grade (top left), tonnes of ore (top right), metal content (bottom left) and total profit (bottom right).

Provided that additional information will almost always be available at the time of mining, the key idea of the proposed approach to account for the information effect is to show that, by resampling a set of realizations at the anticipated grade control data spacing, there will be a more accurate prediction of the resources. In the figure shown above, the reference values are always within the distribution of resources given by the proposed workflow, which is not true for the kriged model. The proposed workflow also carries a measure of uncertainty for risk management, that is available as the resources distribution calculated. It is also important to mention that none of the realizations within the framework is locally accurate; in fact, the kriged model with exploration data only is locally more accurate than any of the resampled and reestimated models, regardless of its smoothing, because kriging minimizes the error variance (as discussed in many classic geostatistics references, such as Journel and Huijbregts (1978) and Isaaks and Srivastava (1989)).

In the next Chapter, the mining selectivity effect will be presented, as well as the developed code to account for this factor in mineral resource evaluation.

Chapter 3. Methodology – Mining Selectivity Effect

Section 3.1. Introduction

During the mining process, the material is classified and sent to a destination that could include a processing plant, waste 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, such as stockpiles of different grade groups, different processing types and so on. 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. In this Chapter, concepts and solutions associated with open pit mining will be presented and discussed; underground mining will be explored in Chapter 5.

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 used 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. Vasylchuk and Deutsch (2017) 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. The IGC system consists of three modules: the Expected Profit module (IGC-EP), the Blast Movement module (IGC-BM) and the Dig Limits module (IGC-DL). The last module, IGC-DL, delineates the dig limits polygons on a bench that will maximize profit, based on the results provided by the previous modules. Maptek (2017) released a new grade control optimizer tool within Vulcan software. This tool evaluates thousands of scenarios and chooses the one with the optimized mineable polygons in terms of economic value. As opposed to having a single dig limit digitised by an engineer, that generally is not easily reproducible or auditable, this process of generating optimized mineable dig limits is fully repeatable. These two approaches shown have different contexts than the research presented in this thesis. They are both 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.

In addition, the concept of a Selective Mining Unit (SMU) is commonly used to determine the mining selectivity in an operation. Sinclair and Blackwell (2002) define the SMU as "the smallest block on which selection as ore or waste is commonly made". The decision on the SMU size is traditionally based on restrictions and conditions derived from the chosen mining method and the scale of operations (Sinclair & Blackwell, 2002), but other factors must also be taken into account when deciding the SMU size. Rossi and Deutsch (2014) commented on the importance of anticipating the grade control practices and the data available at the time of mining for the SMU size selection.

Leuangthong et al. (2003) defined the SMU as "the block model size that would correctly predict the tonnes of ore, tonnes of waste, and diluted head grade that the mill will receive with anticipated grade control practice". They developed a framework for choosing the optimal SMU size that would give ore and waste tonnages and grades of ore to match actual production at the time of mining. Likewise the framework to assess the information effect proposed in the previous Chapter of this thesis, in the procedure proposed by Leuangthong et al. (2003), the actual production is also simulated by sampling simulated realizations at the anticipated production sampling spacing and using this information to predict the recoverable resources/reserves.

Calculating the profit assuming free selection of high resolution 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, each high resolution 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 high resolution 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 (Neufeld et al., 2007). Both solutions combine the information effect and selectivity considerations into one general parameter. In this thesis, both factors are accounted for separately.

A large SMU size can also impact the construction of the operational grade control model. The grade control model is generally constructed at a much higher resolution than the SMU size used for long term resources reporting because the actual mining typically occurs with dig lines at a much more detailed scale than the SMU size used in the long term model. Figure 3.1 illustrates a typical situation in hard rock mining where resources reporting is normally done using a large SMU 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 SMU 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 practically of the mining volumes for the mine operation. On the other hand, considering an SMU 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 high resolution grade control model and in the long term resources model that reconcile.

Selectivity is also closely related to dilution. There are three basic types of dilution associated with a resources block model (Rossi & Deutsch, 2014): internal dilution, contact dilution and operational dilution. The internal dilution is related to the support difference between the composites used to estimate blocks and the actual blocks. The contact dilution is related to the mining that occurs near geological contacts and will result in mixing of grade populations. The operational dilution is the one that will inevitably happen during the mining practice. The choice of SMU size needs to reflect future dilution. In general, the larger the SMU, the larger the expected dilution.

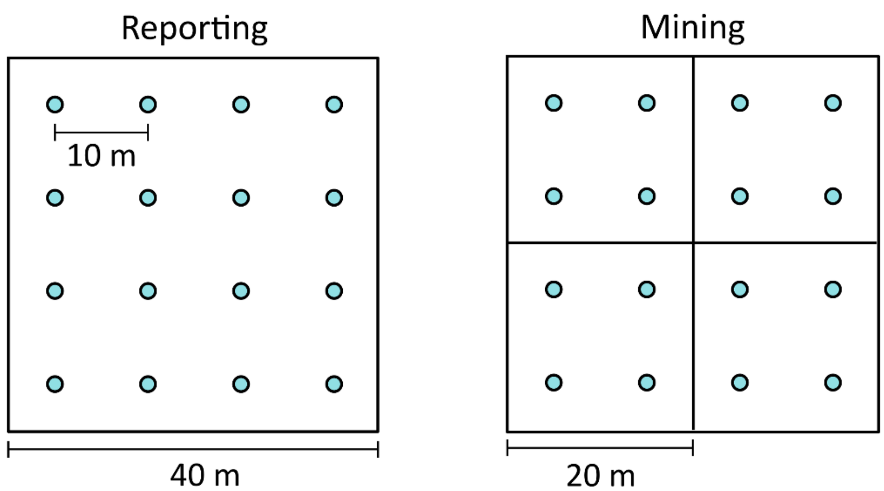

Figure 3.1 – Contrasting SMU sizes used for resources reporting (left) and operational grade control model (right). The anticipated final grade control data spacing is presented in blue.

Calculating resources directly on high resolution simulation results with no post processing would assume selectivity at the scale of the data, that is, free selection, not considering the mining equipment and practical limitations. The determination of ore must consider the information available at the time of mining, as presented in the previous Chapter, and the mining selectivity. However, anticipating the mining selectivity is a step not directly considered in long-range resource modeling. The mining selectivity effect can be assessed by mimicking the grade control practice and getting mineable dig limits for the anticipated selectivity. The algorithm developed for anticipating mining selectivity is described in the following section.

Section 3.2. Proposed Framework for Mining Selectivity Effect and Developed Algorithm

Consider two or more destinations *d* for the mined material within an area *A*; at a minimum, ore and waste. Calculate the expected profit value associated with each different destination *d* for each location **u** within the area to be mined *A* as:

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

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 area to be mined would be given by free selection of high resolution 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.

In reality, free selection of high resolution blocks should not be assumed. There are operational limitations that are intrinsic to the mining practice. It is unfeasible for the mining equipment to mine small isolated blocks. The cost associated with mining at a high resolution is generally impractical. There is a nominal selectivity that is inherent to the deposit type and operation. Mineable dig limits, based on a minimum mineable unit size, should be defined. The main concern addressed here is identifying and managing isolated or narrow areas surrounded by different destination(s) material that would not match the required selectivity.

For practical purposes we will define a square or rectangular minimum mineable unit size to represent the mining selectivity. The developed algorithm considers this size and visits the set of grid cells that falls inside this chosen selectivity scale. Based on the expected profit expecs calculated earlier, $EP\ (\mathbf{u}; d),$ the most profitable destination is assigned to the set of grid cells within the chosen window size as:

$$d_{maxEP}(\mathbf{u}) = \max d\ of\ (EP\ (\mathbf{u}; d), \qquad d = 1, \ldots, D), \qquad \mathbf{u} \in A$$

The total profit is calculated as the sum of the expected profits of all maximum profit destinations at the chosen selectivity over the area mined:

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

The mineable unit is translated over five different origin points of the block model. The procedure described above is followed five times considering five different origins. Finally, the most profitable case is chosen and the final block destinations are assigned to the grid cells and the mineable dig limits are calculated.

The idea behind this algorithm is very similar to the one developed by Deutsch (2017). The algorithm developed by Deutsch (2017) 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 is almost guaranteed to be met over the entire grid. 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 thesis is remarkably fast compared to algorithms intended for final grade control within relatively small blast volumes. It will not be exact given interactions between the different origin offsets. 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 Vasylchuk and Deutsch (2017) and Maptek (2017) and presented here are examples of what should be applied in the context of final classification. The algorithm developed in this thesis is a less time-demanding option appropriate to anticipate the mining selectivity at the time of recoverable resources modeling. In the following section, an example of an implementation of the algorithm is presented.

Section 3.3. Implementing the Proposed Framework for Mining Selectivity Effect

Building on the example shown in Section 2.3 on the previous Chapter, the proposed module to account for the mining selectivity effect is demonstrated. The 2-D example represents one bench of an open pit gold deposit. A reference gold grade model was generated with an unconditional simulation. One hundred high resolution realizations of grade were simulated. An anticipated grade control data spacing of 10 x 10 m was considered to sample the simulated realizations. The gold grades were estimated using a set of sampled final data and the original exploration data. Figure 3.2 shows two production data estimated grids from Chapter 2. Up to this step, the workflow has accounted for the information effect only. Section 2.3 on the previous Chapter can be referred for details on each step followed to assess the information effect.

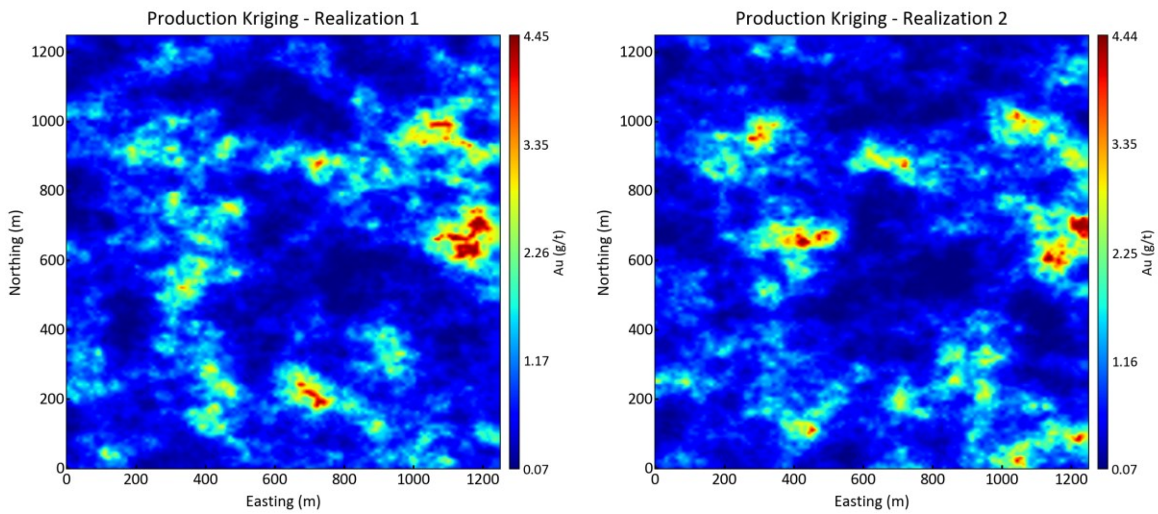

Figure 3.2 – Two realizations of production data estimated grids.

In this example, there are two possible destinations for the mined material: ore or waste, but others could be considered. The first step in the proposed framework to account for the mining selectivity effect in resources evaluation is to calculate the expected profit value *EP* for each different destination *d* for all locations **u** within the area to be mined *A*, in this case, the bench. This is done for the estimated grids with the production data sampled from each realization. A simple expression to calculate the expected profit is being used here, but, if available, all costs would be considered: costs of mining ore, mining waste, processing ore, gold price and recovery. If the final destination of the grid cell is ore, its expected profit is calculated following the expression below:

$$EP(\mathbf{u};d) = \propto * grade\ (\mathbf{u}) + C_0\ (\$/t), \qquad d = ore, \qquad \mathbf{u} \in A$$

Where $\propto$ is the slope of the grade x profit graph (Figure 3.3) and C_0 is the cost of sending material at zero grade to the processing plant. The values used for expected profit calculations are usual for current open pit mining: $\propto$ = 30 and C_0 = - 15 \$/t. If the final destination of the grid cell is waste, the expected profit is a fixed cost of \$2/t and it does not depend on the grade value:

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

Figure 3.3 illustrates the expressions used to calculate the expected profits. Mining companies set a cutoff grade with the intent that material above the cutoff grade is ore and material below the cutoff is waste. Additionally, the intent is that ore will generate a profit. The notch in the profit response is to be consistent with the conventional usage of cutoff grades in the mining industry, even though, numerically, material that will lose less money than the waste mining cost should be called ore. The profits of each grid cell will be used to calculate the maximum profit destinations at the chosen selectivity.

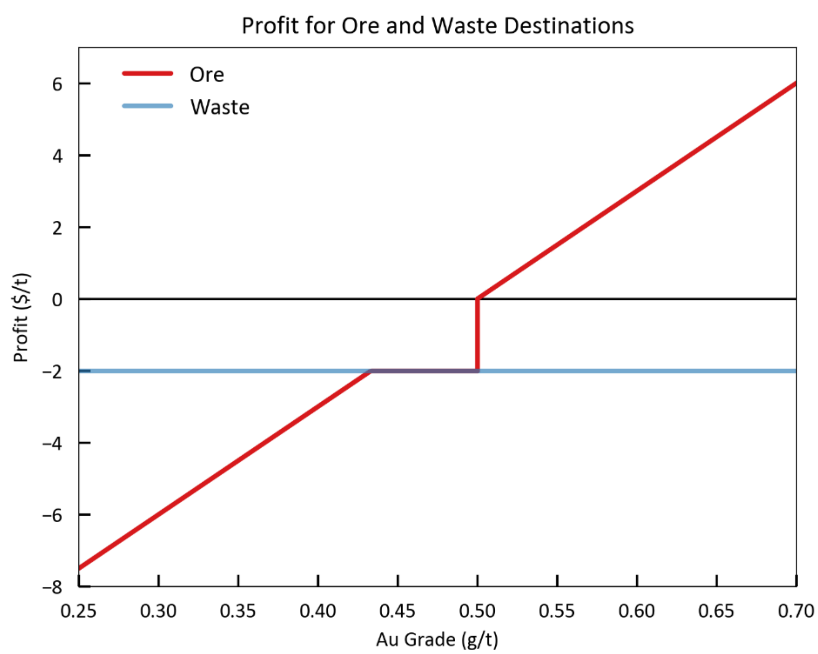

Figure 3.3 – Expected profits for ore and waste grid cells.

After calculating the expected profits for both destinations, the next step is to mimic the grade control practice and get mineable dig limits at the chosen selectivity. The mining selectivity calculations are applied to each estimated grid of final data. The minimum mineable unit size considered for this example is 15 x 15 m. The developed algorithm is used to calculate the most profitable destination for each mineable unit:

$$d_{maxEP}(\mathbf{u}) = \max d\ of\ (EP\ (\mathbf{u}; d), \qquad d = ore/waste), \qquad \mathbf{u} \in A$$

Figure 3.4 shows the maximum profit destinations for the same realizations of production data estimates shown on Figure 3.2 at high resolution and after going through the proposed mining selectivity module.

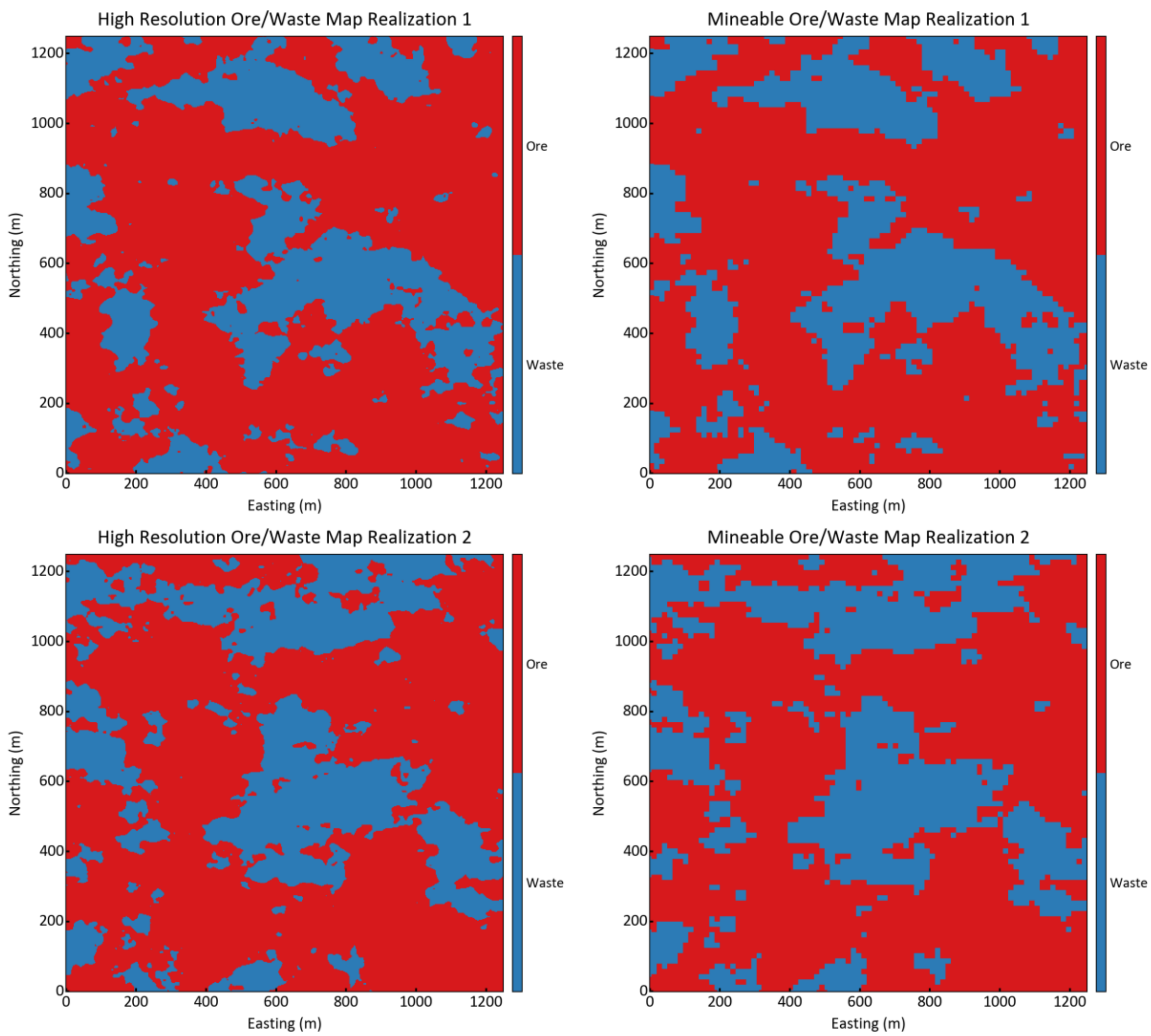

Figure 3.4 – High resolution maximum profit destinations (left side) and mineable destinations maps (right side).

In order to calculate the probabilistic resources for the long term resources model, we need to transfer the mineable dig limits at the desired selectivity from the previous step to the high resolution simulated realizations with only exploration data. This is necessary because the actual data available at the time of resources modeling is the exploration data only. The resampling from the simulated realizations and reestimates of production data done in Chapter 2 are exclusively for determining the destinations; all resources must be calculated on the original simulated realizations to honour the actual data, not the resampled data that mimic production data. The mine will achieve the "true" grade from the deposit and not the estimated.

Based on the dig limits transferred to the high resolution simulated realizations with only exploration data, the probabilistic resources for the long term model to be reported can be calculated, that is available as the distribution over all realizations from the original simulated model. For comparison, the total resources were also calculated directly on the high resolution simulated results, without applying selectivity considerations, and on the reference model that was used to generate the data in the first place. Figure 3.5 illustrates the distributions of resources calculated. The distributions of profits calculated prove that high resolution simulated realizations deliver a maximum profit that is not attainable at the time of mining. The total profit distribution calculated as a result of the framework proposed is the actual mineable profit; both the information and mining selectivity effects are being accounted for. The selectivity at the time of mining must be considered to report the recoverable resources. Reporting resources directly on high resolution simulated results would be too optimistic.

Any summary models required for mine planning can be calculated on the final resource models: the probability to be above or below a cutoff grade, the average grade above the cutoff grade and so on. In the example, the probabilities of grid cells to be ore have been calculated. The mineable dig limits were used in this calculation, so the probabilities are achievable at the time of mining. Figure 3.6 shows the probability map calculated. The probability map on the right presents the grid cells where the probability to be ore is greater than 60%. This summary is very useful for mine planning. It can also be applied to mineral resources classification purposes. Different confidence thresholds for a grid cell to be ore could be assumed for each mineral resource category: measured, indicated and inferred.

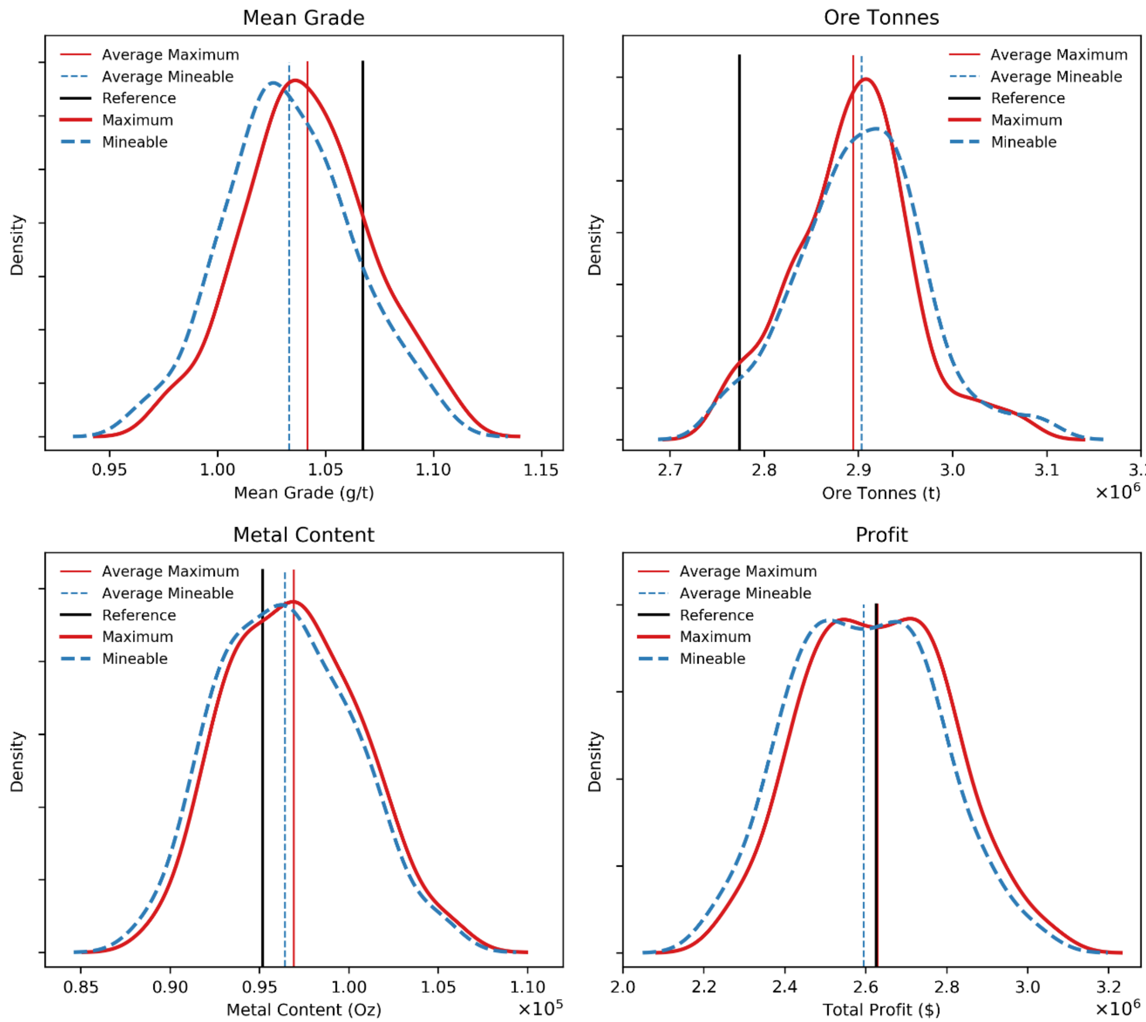

Figure 3.5 – Distributions of maximum, mineable and reference resources.

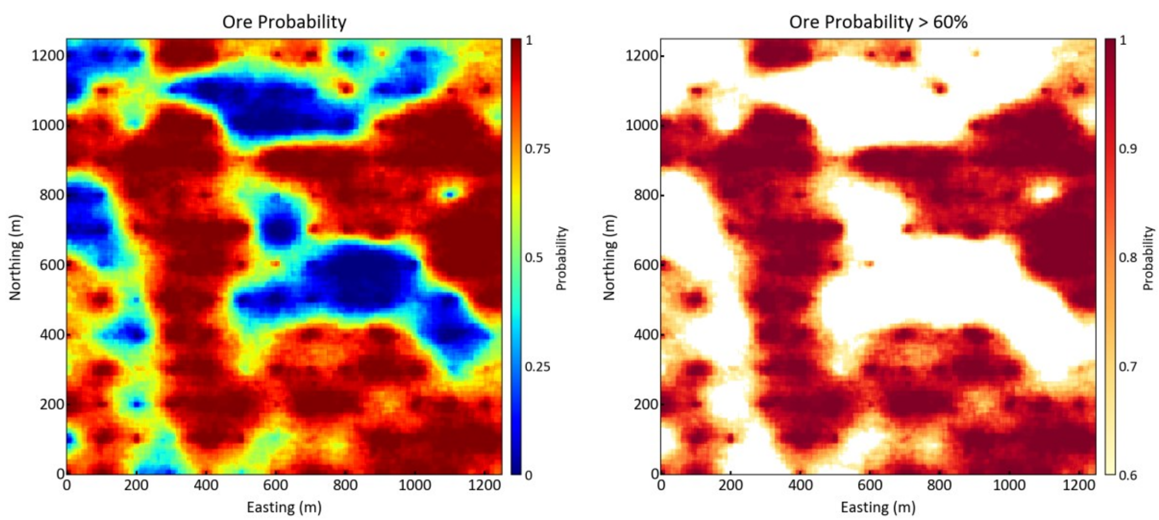

Figure 3.6 – Ore probability map (left) and the grid cells where the ore probability is greater than 60% (right).

By following the proposed framework, long term recoverable resources are calculated explicitly accounting for the information and mining selectivity effects and assessing the degree of uncertainty. The sensitivity of the resources on different mining selectivities and different grade control data spacing will be explored in the next Chapter, as well as other factors that can influence the recoverable resources evaluation.

Chapter 4. Implementation

Section 4.1. Introduction

This thesis proposes a framework to address two concerns in long term mineral resources evaluation: the information effect and the selectivity effect. The steps proposed to address each concern have been presented individually so far. In this Chapter, the combined workflow will be presented and implemented in a case study. First, the information effect will be addressed by anticipating the final grade control data that will be available at the time of mining to direct the choice of destinations of the mined material. Afterwards, the selectivity at the time of mining will be anticipated, trying to retain the most profit with a practical mining plan. The steps of the proposed procedure are as follows:

1. Simulate high resolution realizations using the exploration drilling available at the time of resources modeling. This step corresponds to the traditional simulation paradigm.

2. (a) Sample the realizations at the anticipated production data spacing to mimic the production data planned in the future. (b) Interpolate the variables required for grade control for every set of sampled final data, using the best possible set up for ordinary kriging. Consider the sampled data from each realization and the existing exploration data in the estimation. This step accounts for the information effect.

3. (a) Calculate expected profit values for every grid cell for at least two different destinations of the mined material (i.e. ore and waste), depending on the final estimated grade. (b) Apply the mining selectivity calculations for each estimated grid 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 grid of anticipated final data.

4. (a) Apply each mineable dig limit at the anticipated selectivity from the previous step to the corresponding high resolution simulated realization from step one. (b) Calculate the probabilistic resources for the long term model using these mineable

dig limits, that is available as the distribution over all realizations from the original reference simulated model.

The expected profits calculated on step three of the workflow are a way of summarizing a value for each grid cell for different destinations of the mined material to provide a quantification for mineable dig limits calculation. These values do not necessarily reflect the actual profit that the mining practice will process at the time of mining. The actual profit calculation should involve more variables than the ones considered here.

Figure 4.1 summarizes the steps in the proposed framework in a flowchart:

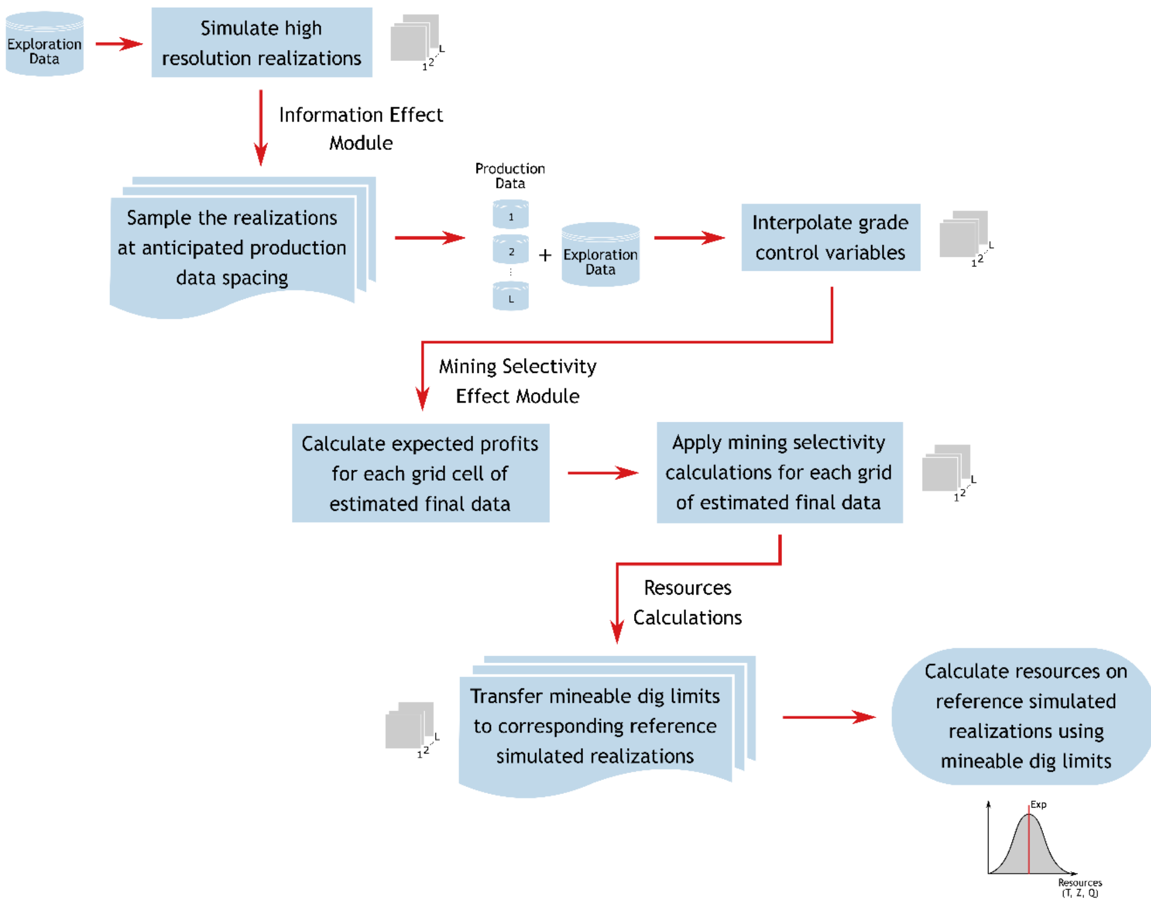

Figure 4.1 – Flowchart that illustrates the steps in the proposed framework.

Section 4.2. Combined Workflow

The proposed methodology to evaluate long term mineral resources is demonstrated through an example that represents one bench of an open pit gold 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 is arbitrary and its maximum continuity direction is along azimuth 45° with the following model:

$$\gamma(\mathbf{h}) = 0.05 + 0.45 \cdot Sph_{\substack{ahmax=400 \\ ahmin=200}}(\mathbf{h}) + 0.5 \cdot Sph_{\substack{ahmax=500 \\ ahmin=300}}(\mathbf{h})$$

The reference model is 1000 x 1000 blocks and each block is 1 x 1 x 5 m. The block height is equivalent to a nominal bench height of 5 m. A positively skewed distribution characteristic of gold deposits is used for back transformation of grades from Gaussian to original units. Figure 4.2 presents the reference grade distribution and the reference gold grade grid model generated.

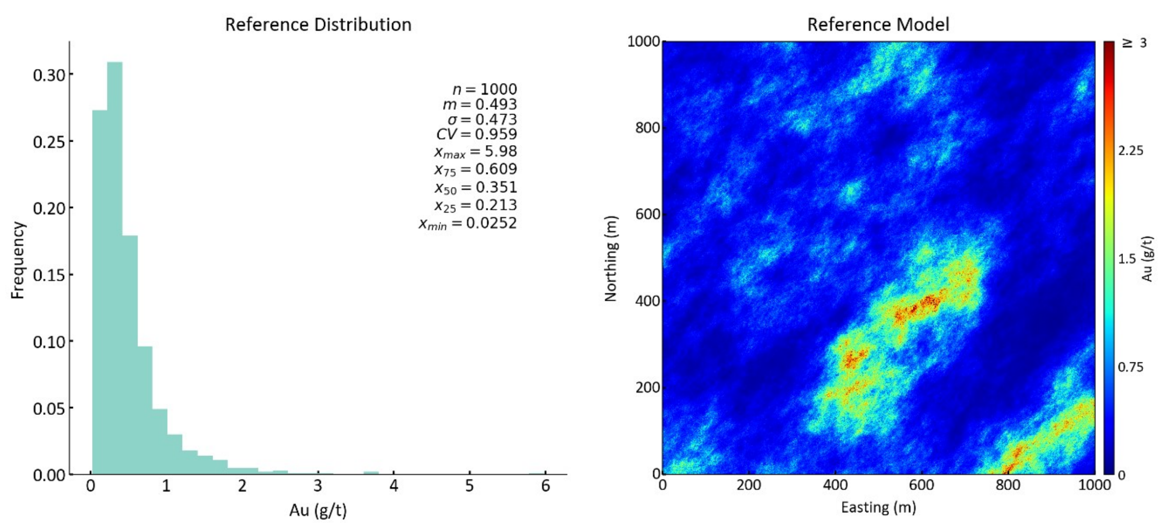

Figure 4.2 – Reference grade distribution (left) and reference gold gridded model (right).

In order to mimic exploration data, the reference unconditional simulated realization is sampled at a 100 x 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. 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. The variogram model fitted is as follows:

$$\gamma(\mathbf{h}) = 0.05 + 0.95 \cdot Sph_{\substack{ahmax=500 \\ ahmin=150}}(\mathbf{h})$$

These estimates and the resources assessed by them will be used for comparison to the resources evaluated by following the proposed methodology. Figure 4.3 presents the exploration data sampled from the simulated realization in original units and their estimates by ordinary kriging.

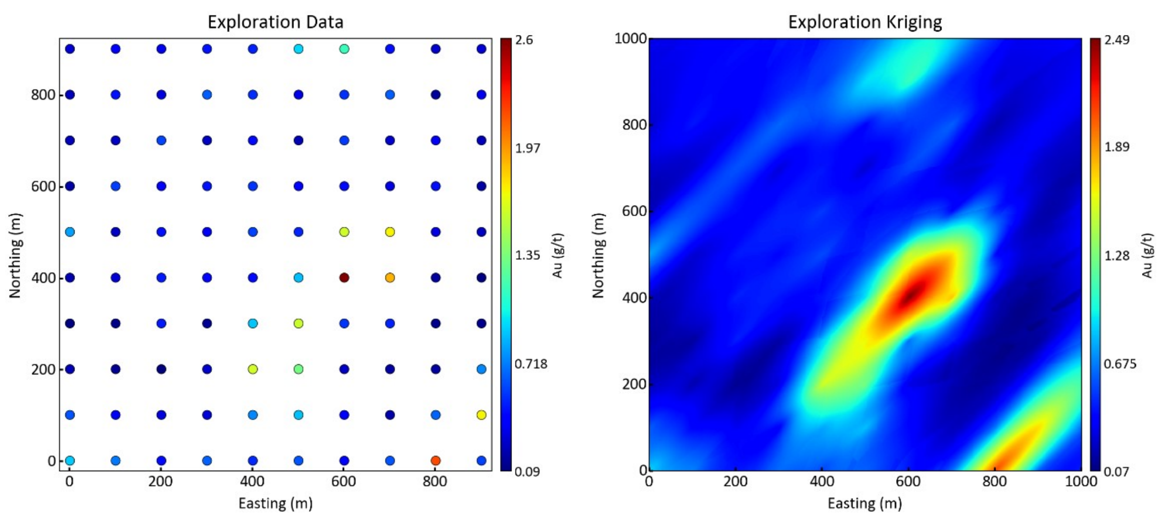

Figure 4.3 – Location map of exploration data (left) and kriging estimated grid (right).

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 scores experimental variograms were calculated following the major direction of anisotropy at 45° azimuth and perpendicular to it, 135°. The normal scores variogram model fitted to perform the simulation is:

$$\gamma(\mathbf{h}) = 0.05 + 0.95 \cdot Sph_{\substack{ahmax=420 \\ ahmin=160}}(\mathbf{h})$$

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 gold 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 x 10 m. The one hundred datasets generated consist of 100 drill holes and 9,701 data that mimic production data. Figure 4.4 shows one simulated realization of exploration data and a location map of the production data sampled from the same realization.

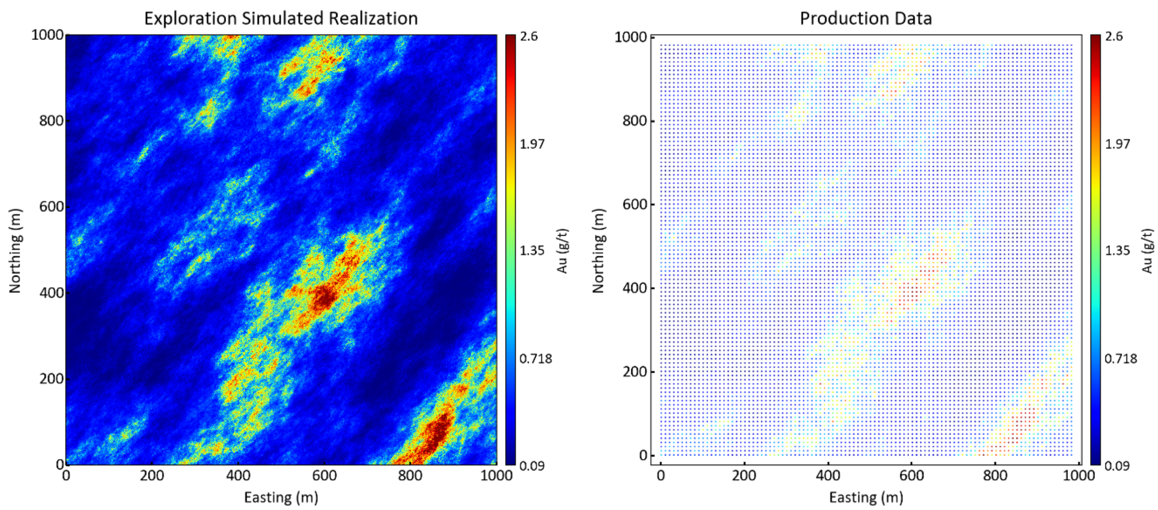

Figure 4.4 – Simulated realization with exploration drill holes (left) and blast holes sampled from it (right).

Still in the information effect module of the workflow, the next step is to interpolate the gold 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 gold grades estimation. Following the recommendation to minimize the amount of misclassified ore and waste on the grade control model proposed by Vasylchuk (2016), the grade control grid resolution is 4 x 4 x 5m, 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. The experimental variograms calculated and the fitted variogram model for one dataset are shown on Figure 4.5 together with the estimated grid.

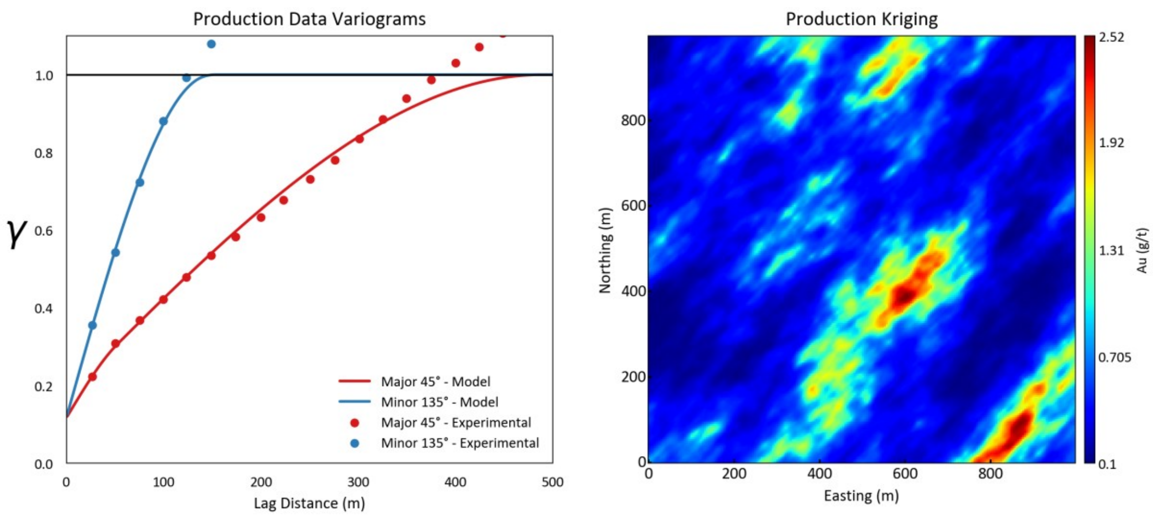

Figure 4.5 - Experimental variograms calculated with production data and fitted variogram model (left) and their estimates (right).

Proceeding to the mining selectivity module of the proposed framework, the expected profit values *EP* were calculated for two different destinations for the mined material, ore and waste, for all locations **u** on the bench. Expected profits were calculated for each grid of final data estimated previously. If the final destination for a grid cell is ore, its expected profit is calculated as:

$$EP(\mathbf{u}; d) = \propto * \, grade\ (\mathbf{u}) + \ C_0\ (\$/t), \qquad d = ore, \qquad \mathbf{u} \in A$$

Where $\propto$ is the slope of the grade x profit graph and C_0 is the cost of sending material at zero grade to the processing plant. In this example, $\propto$ = 30 and C_0 = - 15 \$/t. The expression to calculate expected profit if the final destination of a grid cell is waste does not depend on the grade value, it is a fixed cost of \$2/t:

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

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

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. The idea of this step is to mimic the actual grade control practice. The minimum mineable unit size considered for this example is 12 x 12 m, that seems to be a reasonable dimension for the deposit type represented here. The developed algorithm for mining selectivity explained in Chapter 3 is used to calculate the most profitable destination for each mineable unit. The mining selectivity calculations are applied to each estimated grid of final data. A high resolution ore and waste map of the same estimated grid of final data shown on Figure 4.5 is show in the left side of Figure 4.6. This high resolution map is purely the maximum profit destination available for each grid cell without accounting for selectivity at the time of mining. The mineable ore and waste map is showcased in the right side of Figure 4.6, after applying the selectivity calculations using the algorithm developed in this thesis.

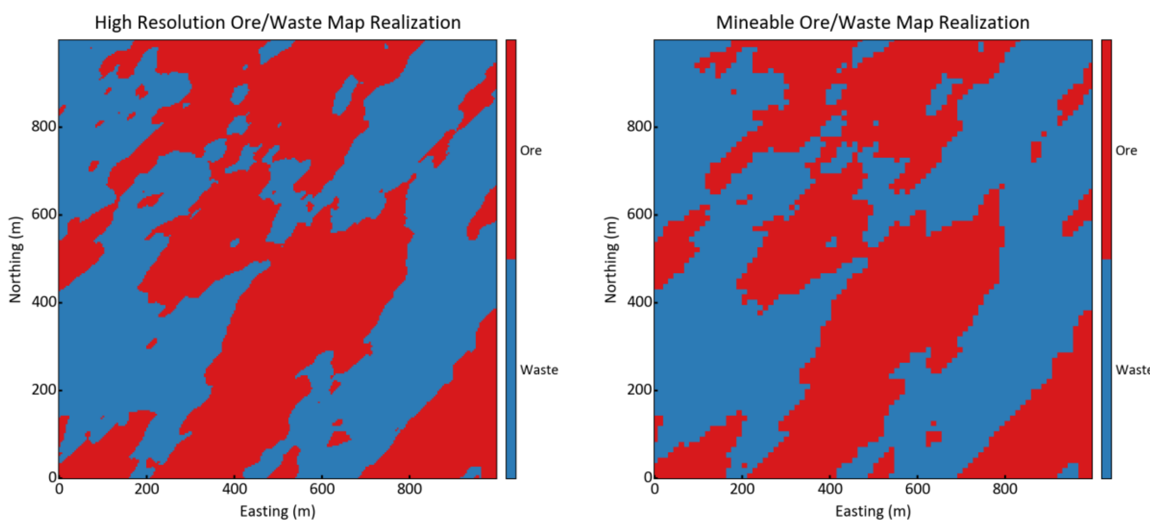

Figure 4.6 – Maximum profit destinations maps at high resolution (left) and considering mining selectivity (right).

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 calculations 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 reestimates of final data are exclusively for determining the destinations of the mined material. No final resources calculations are done on the reestimated grids.

Finally, the probabilistic mineral resources can be calculated. 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 calculated 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 grid with exploration data. A fixed density value of 2.7 g/cm^3 was considered. The tonnage is calculated as the volume of each grid cell multiplied by the density. The metal content is calculated in troy ounces by multiplying the tonnage of each grid cell by its gold grade and dividing everything by 31.10345. Figure 4.7 shows the probabilistic resources distributions calculated.

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.

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 on Figure 4.8. As mentioned before, the precise location of ore and waste blocks is not relevant 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.

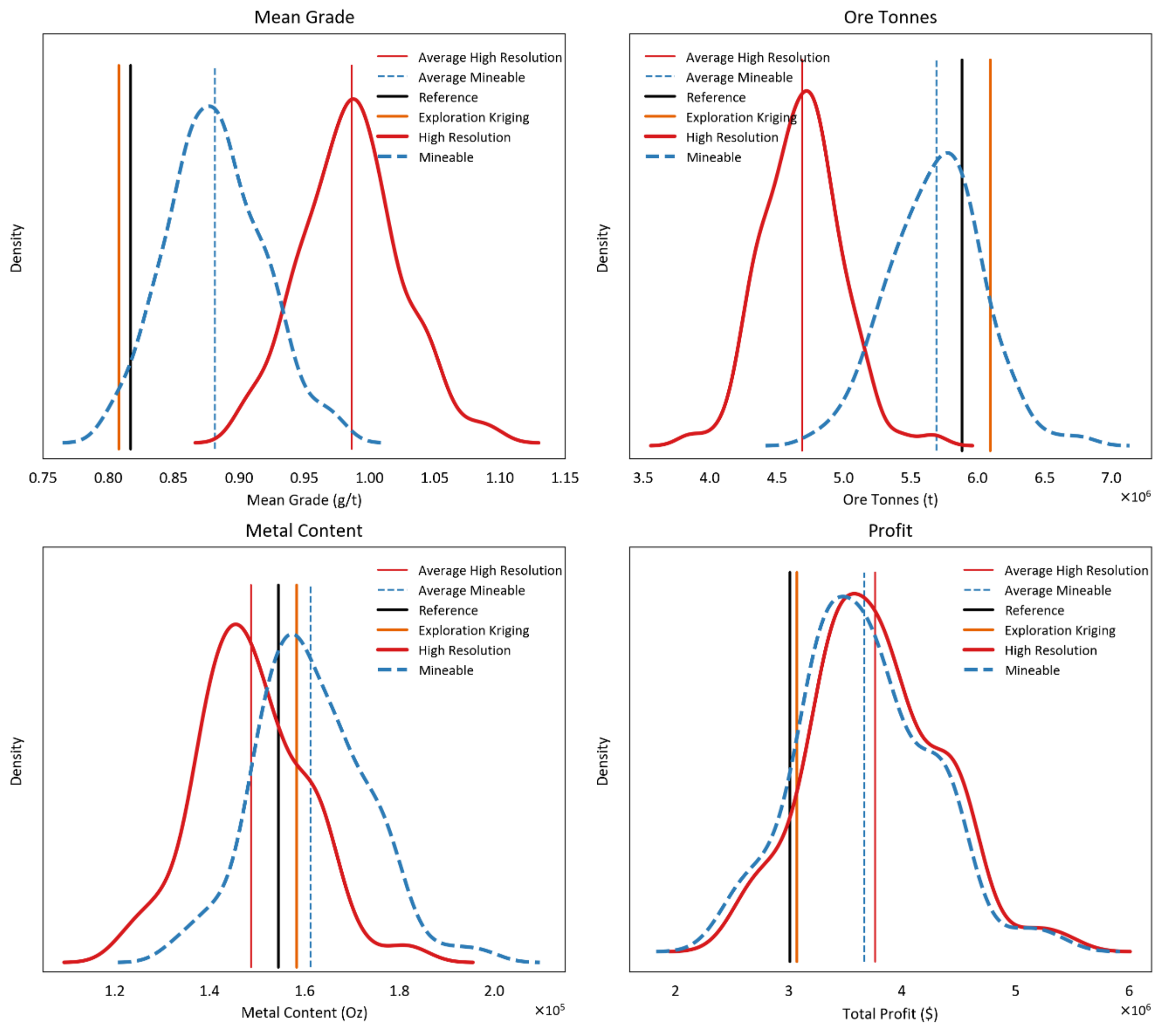

Figure 4.7 – Distributions of resources calculated on the reference model (black), the kriged estimates of exploration data (orange), the high resolution simulated realizations (red) and going through the proposed workflow (blue).

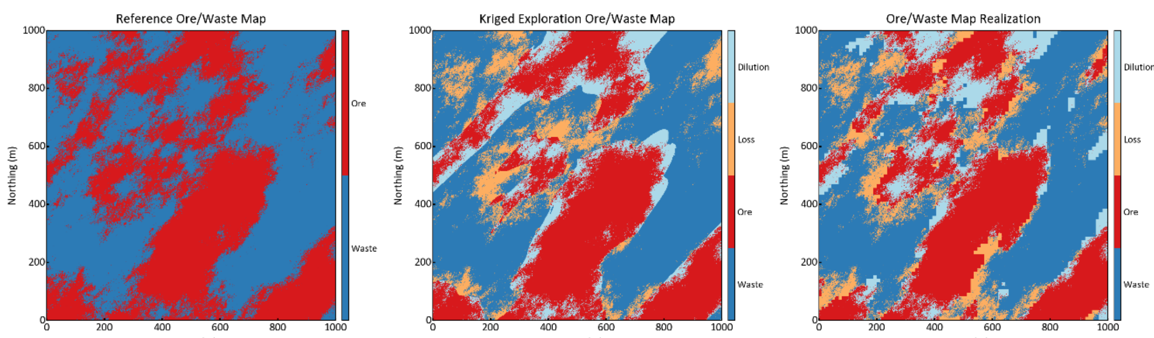

Figure 4.8 – Ore, waste, ore loss and dilution location maps.

Summary probabilities models can also be calculated following the results of this workflow. For example, the probability of a grid cell to be above the cutoff grade, that is, to be ore, is shown on Figure 4.9.

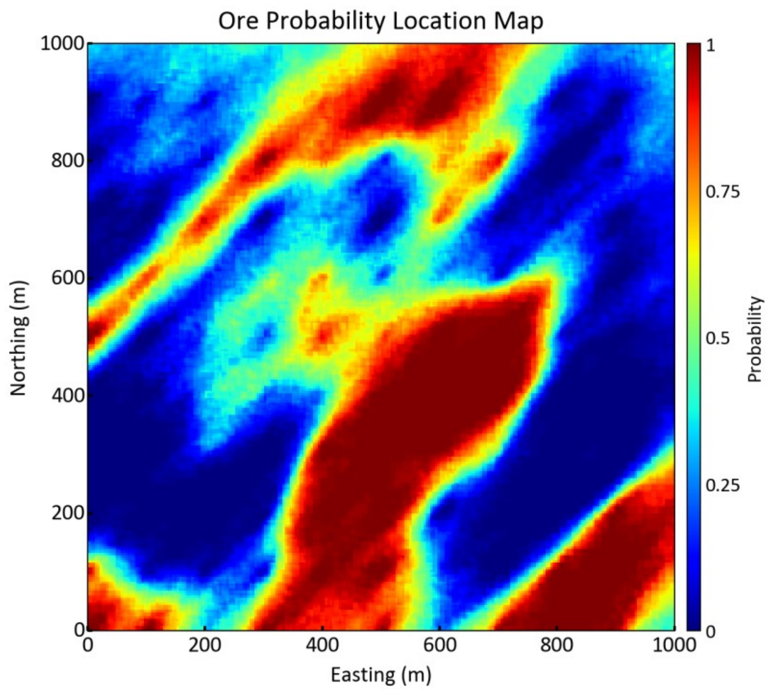

Figure 4.9 – Ore probability map of simulated model going through the proposed workflow.

Figure 4.10 shows an overview of all steps and results of the proposed workflow for the case studied.

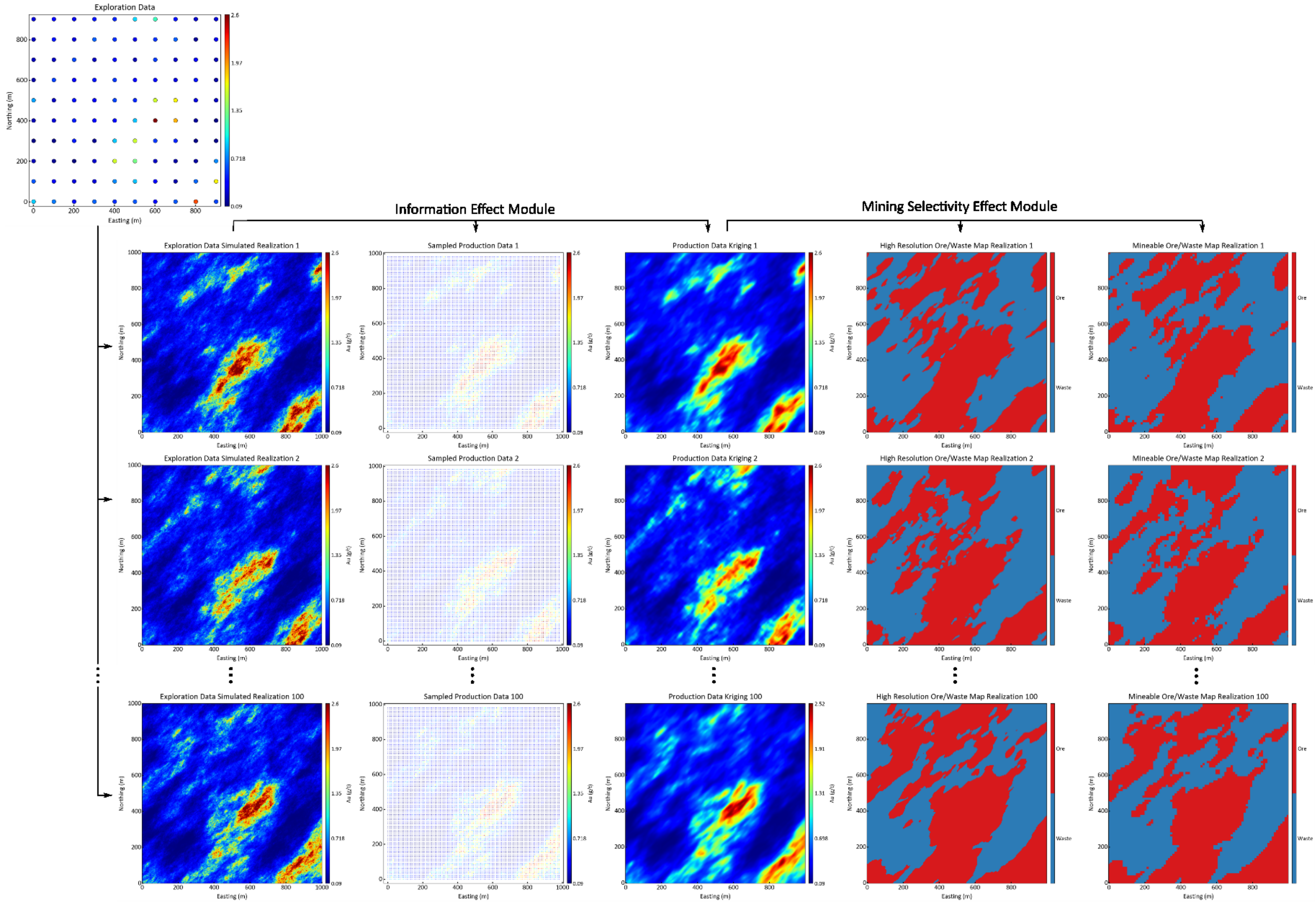

Figure 4.10 – Overview of steps and results of the proposed workflow for the case studied.

Section 4.3. Sensitivity Analysis

4.3.1. Production Sampling Spacing

In open pit mining, grade control data generally consists of blast holes or dedicated grade control drilling. At the time of mining, there will also normally be other types of additional data available to direct the choice of destinations of the mined material, such as face mapping of the bench being mined. In order to understand how the final data change the recoverable resources, the simulated realizations with exploration data were sampled at varied anticipated production data spacing: 10 x 10 m, 15 x 15 m, 20 x 20 m, 25 x 25 m, 30 x 30 m, 40 x 40 m and 50 x 50 m. This grade control data is then used to interpolate the grade variable and generate estimated grids to go through the mining selectivity effect module of the framework. Figure 4.11 presents ore, waste, ore loss and dilution location maps of one realization of the workflow for increasing final data spacing to illustrate the exercise realized.

The deposit is subject to more ore/waste classification errors with wide production data spacing, increasing ore loss and dilution. The cumulative distributions of the percentages of ore loss and dilution for all realizations in the proposed workflow are shown in Figure 4.12 for varying production data spacing. This graph shows the increasing degree of misclassification of ore and waste blocks for decreasing information. There will always be a certain amount of uncertainty left at the time of mining because the grade control sampling is imperfect and the selection of ore and waste will always be done with limited information. Nevertheless, the ore and waste classification errors are minimized by sampling the simulated realizations at finer grids. The ore and waste selection errors are critical to the overall resources in the large production volume. The information effect is related to the spacing of grade control data: closely spaced blast hole drilling provides more information about the deposit and improved selection, and widely spaced production sampling results in worse classification, compromising the mineral resources assessment.

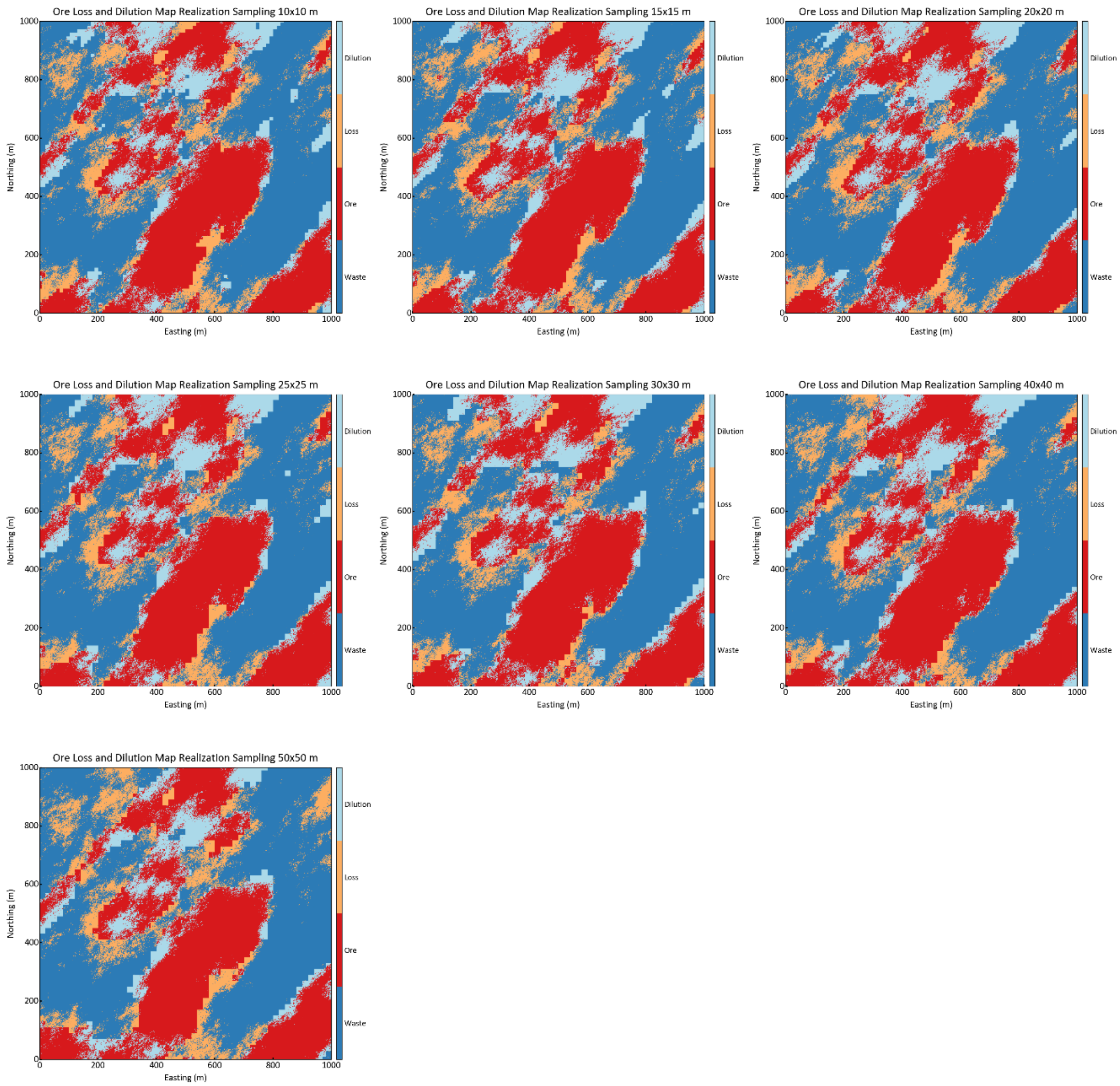

Figure 4.11 – Ore, waste, ore loss and dilution location maps of one realization of the workflow for increasing grade control data spacing.

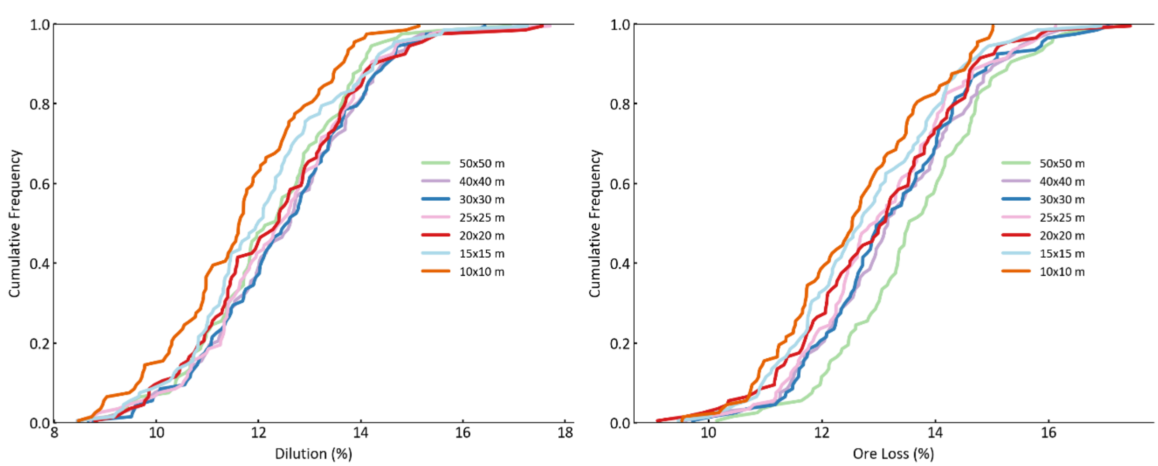

Figure 4.12 – Percentages of dilution and lost ore for varying production data spacing.

The total profit of all realizations for each grade control data spacing is calculated and compared to the maximum profit. The maximum profit is with high resolution simulated realizations with exploration data. As an effect of increasing misclassification of ore and waste, profit decreases as less information is available. Figure 4.13 shows the decrease in the profit that is achievable at the time of mining for widely spaced production sampling as a proportion of the maximum profit. The actual cost of acquiring the information is not being considered here. How the information available changes the resources and profit are being assessed.

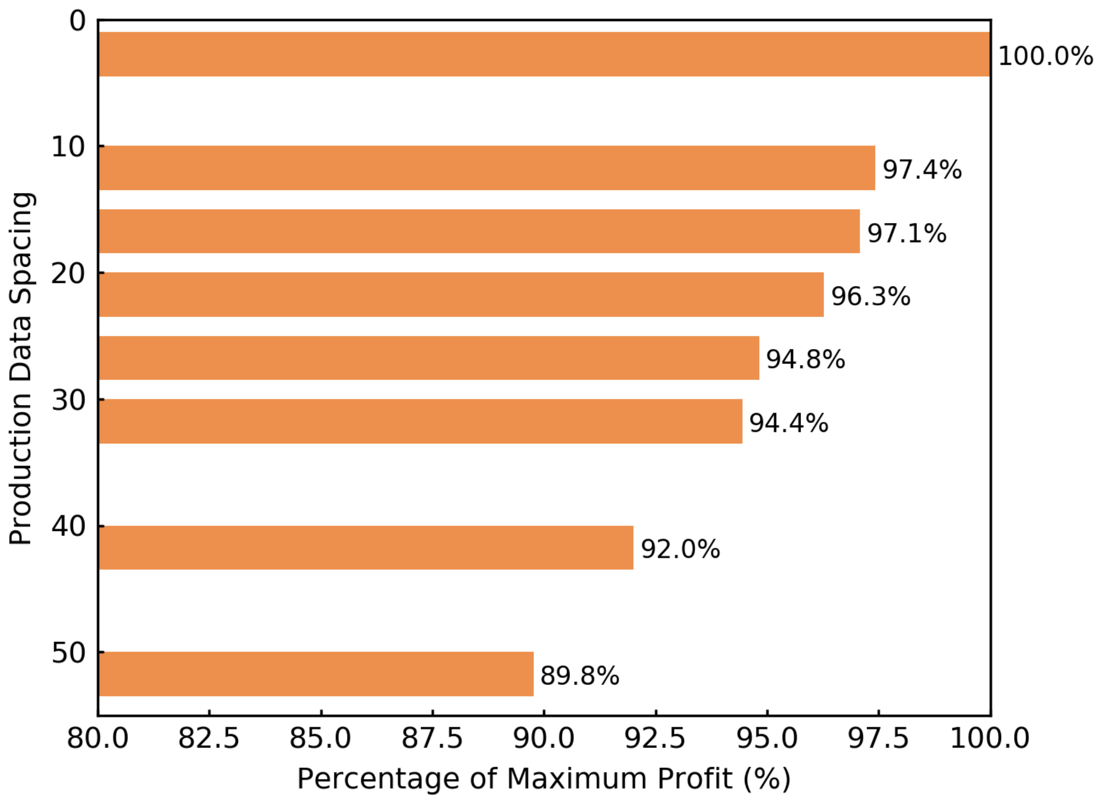

Figure 4.13 – Decrease in total profit for widely spaced production data.

4.3.2. Mining Selectivity

The anticipated selectivity at the time of mining is represented by a mineable size unit in the proposed workflow. In practice, selectivity depends on a series of factors that can include, but are not limited to: the equipment dimensions, mining practice, other operational factors and the geological variability of the deposit. The influence of changing anticipated mining selectivity on the overall resources of the bench studied is analyzed. The base case scenario shown on Section 4.2 considers a minimum mineable unit size of 12 x 12 m. Six increasing minimum mineable unit sizes were tested: 20 x 20 m, 28 x 28 m, 36 x 36 m, 44 x 44 m, 52 x 52 m and 60 x 60 m. The selectivity along the height of the mineable unit is the bench height, 5 m, and is not changed in this study. Figure 4.14 presents the mineable ore and waste location maps for the selectivities tested. A high resolution ore and waste map of the same estimated grid of final data is also shown in Figure 4.14.

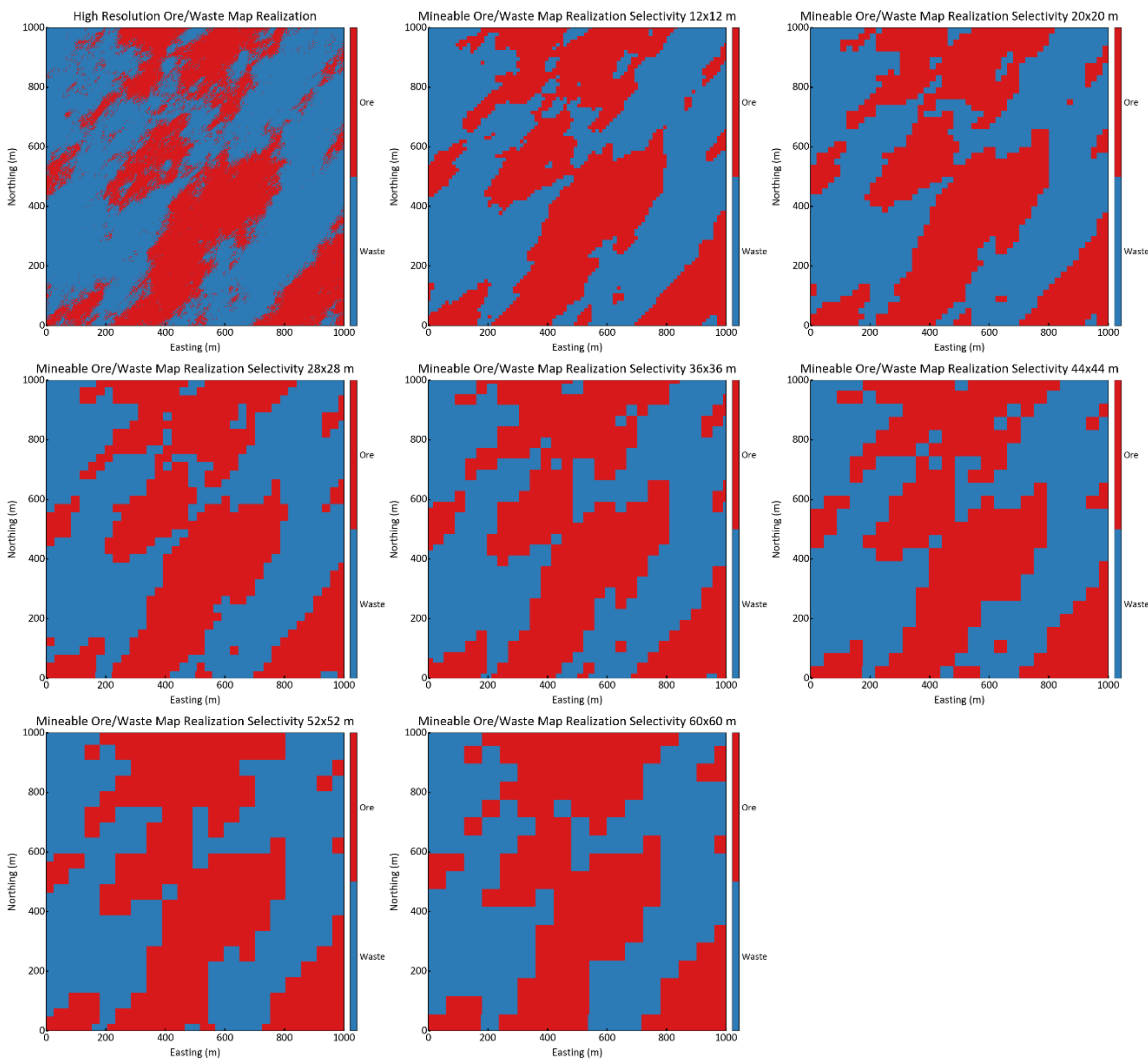

Figure 4.14 – Ore and waste location maps for one realization for increasing minimum mineable unit size.

In general, increasing the mineable unit size leads to an increase of lost ore and dilution at the time of mining. In order to mine larger volumes, the mining operation is forced to take more waste together with ore or to leave more ore as waste. Figure 4.15 presents cumulative distributions of the percentages of dilution and ore loss for a hundred realizations generated in the selectivities evaluated. Dilution and ore loss are larger for larger volumes mined. It is also interesting to point out that the common practice of assigning a fixed dilution factor in the hope to account for the information effect and selectivity of mining practice does not represent the truth. In reality, the dilution can vary a lot and the choice of a minimum mineable size needs to incorporate this variation and the allowable dilution at the time of mining.

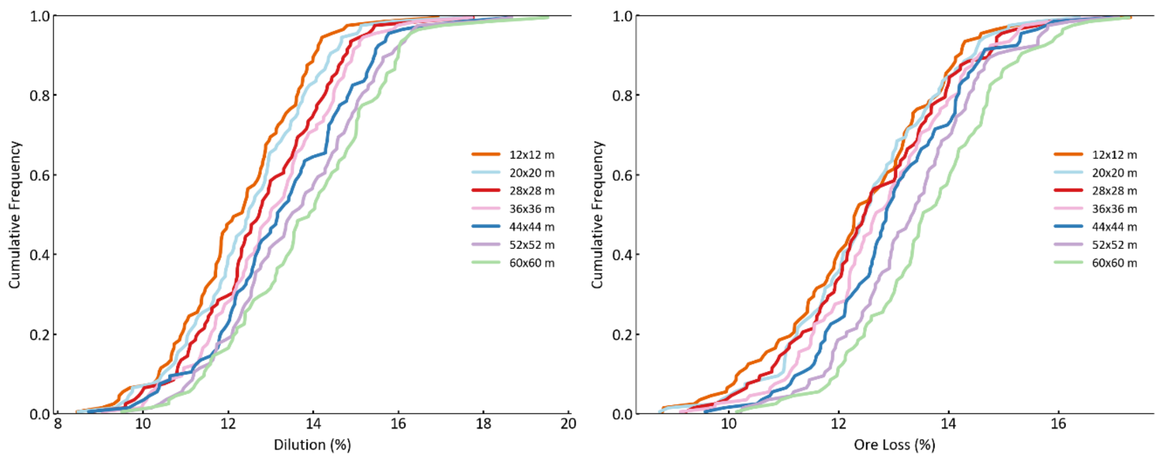

Figure 4.15 – Percentages of dilution and lost ore for varying mineable unit sizes.

The larger percentages of dilution and ore loss reflect on the total profit given by the bench. The total expected profit given by all realizations for each mining selectivity was calculated compared to the maximum profit. The maximum profit is given by the high resolution simulated realizations with exploration data. Figure 4.16 presents the percentages of the maximum profit that is achievable at the time of mining for each mineable unit size analyzed. This shows that calculating the profit assuming free selection of high resolution blocks of ore and waste, without accounting for any mining practice and equipment limitations, overstates the profit achievable at the time of mining.

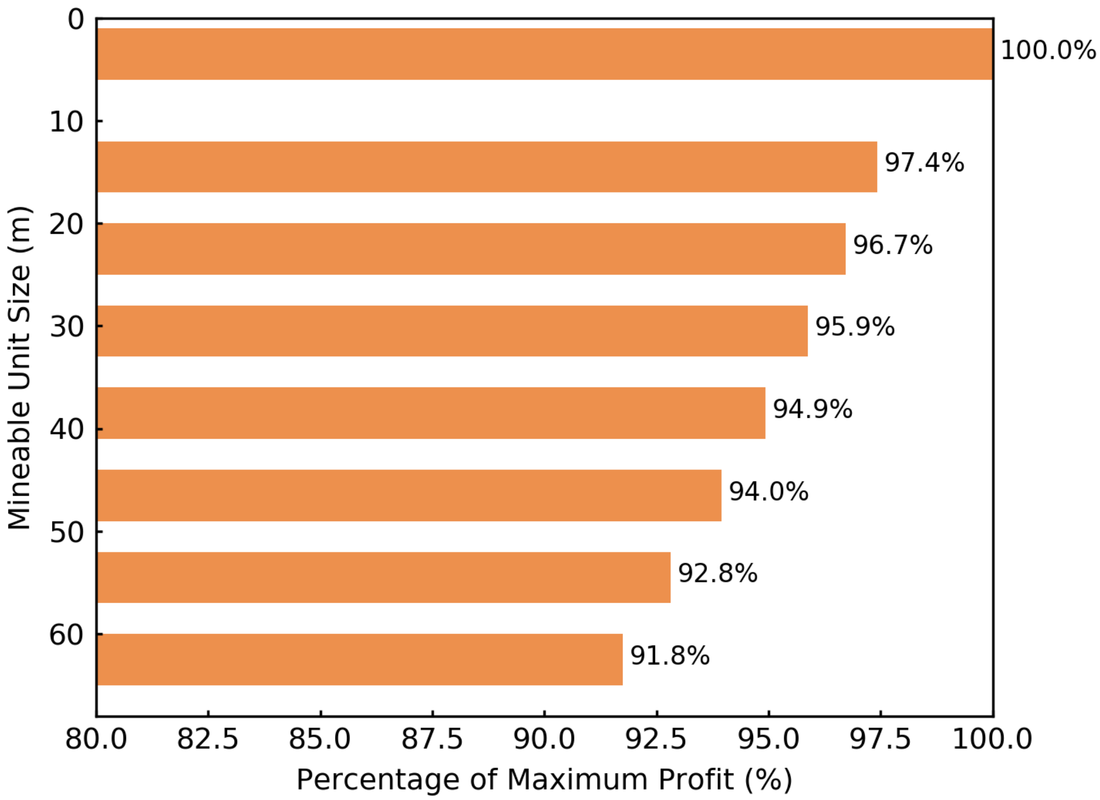

Figure 4.16 – Percentages of maximum profit achievable at the time of mining and the minimum mineable unit sizes.

By anticipating the final data spacing and the selectivity at the time of mining, it is possible to predict and quantify the percentage decrease relative to the maximum profit that can be expected at the time of mining. The approximate actual profit that will be attainable at the time of mining given the final production data spacing and the future selectivity can be calculated and the mineral resources can be assessed and reported accordingly.

4.3.3. Exploration Data Variogram

The ore and waste classification is also sensitive to the normal scores exploration data variogram used in simulation. Using the same data histogram as before, the entire workflow was tested for three different configurations of the normal scores exploration data variogram model. The exploration data and production data spacing are the same as the base case scenario being used for this exercise (100 x 100 m and 10 x 10 m respectively) as well as the mineable unit size, 12 x 12 m. The exploration data variogram models are isotropic and have one spherical structure, with varying ranges and nugget effect. A range three times the exploration data spacing, that is 300 m, considered a long range and zero nugget effect; a range twice the exploration data spacing, 200 m, that is a short range, and no nugget effect, and, finally, a short range and 50% of nugget effect. The variogram models are presented in the equations below and in Figure 4.17.

$$\gamma(\mathbf{h}) = 0.0 + 1.0 \cdot Sph_{ah=300}(\mathbf{h})$$

$$\gamma(\mathbf{h}) = 0.0 + 1.0 \cdot Sph_{ah=200}(\mathbf{h})$$

$$\gamma(\mathbf{h}) = 0.5 + 0.5 \cdot Sph_{ah=200}(\mathbf{h})$$

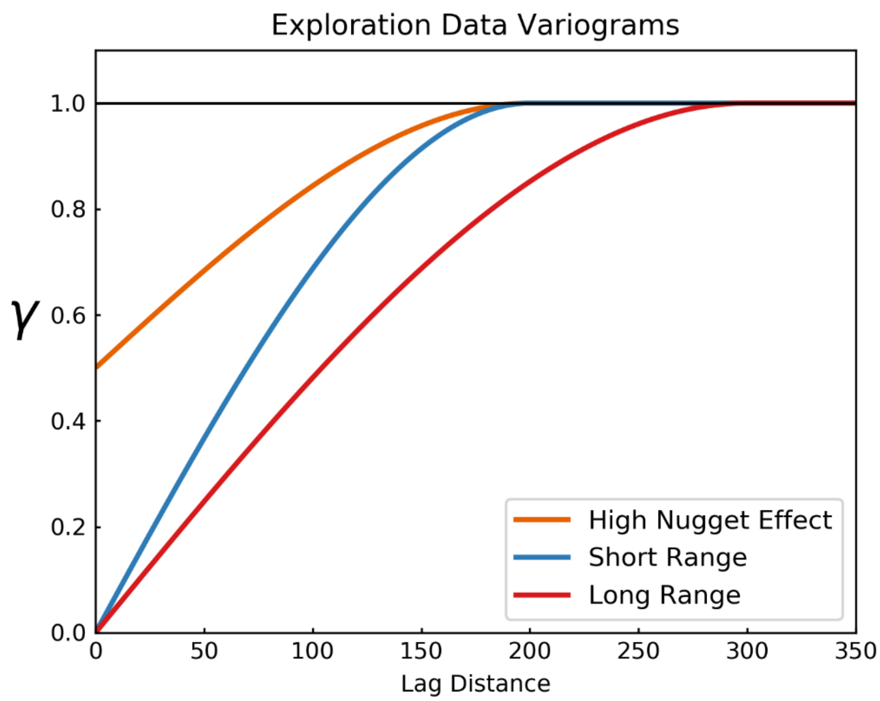

Figure 4.17 – Exploration data variogram models used in the workflow.

In order to understand the behaviour of the ore and waste classification for different exploration data variograms, histograms and location maps of the probabilities of a grid cell to be ore after going through the entire workflow were generated for the three exploration data variograms tested. Figure 4.18 presents the ore probabilities location maps and distributions.

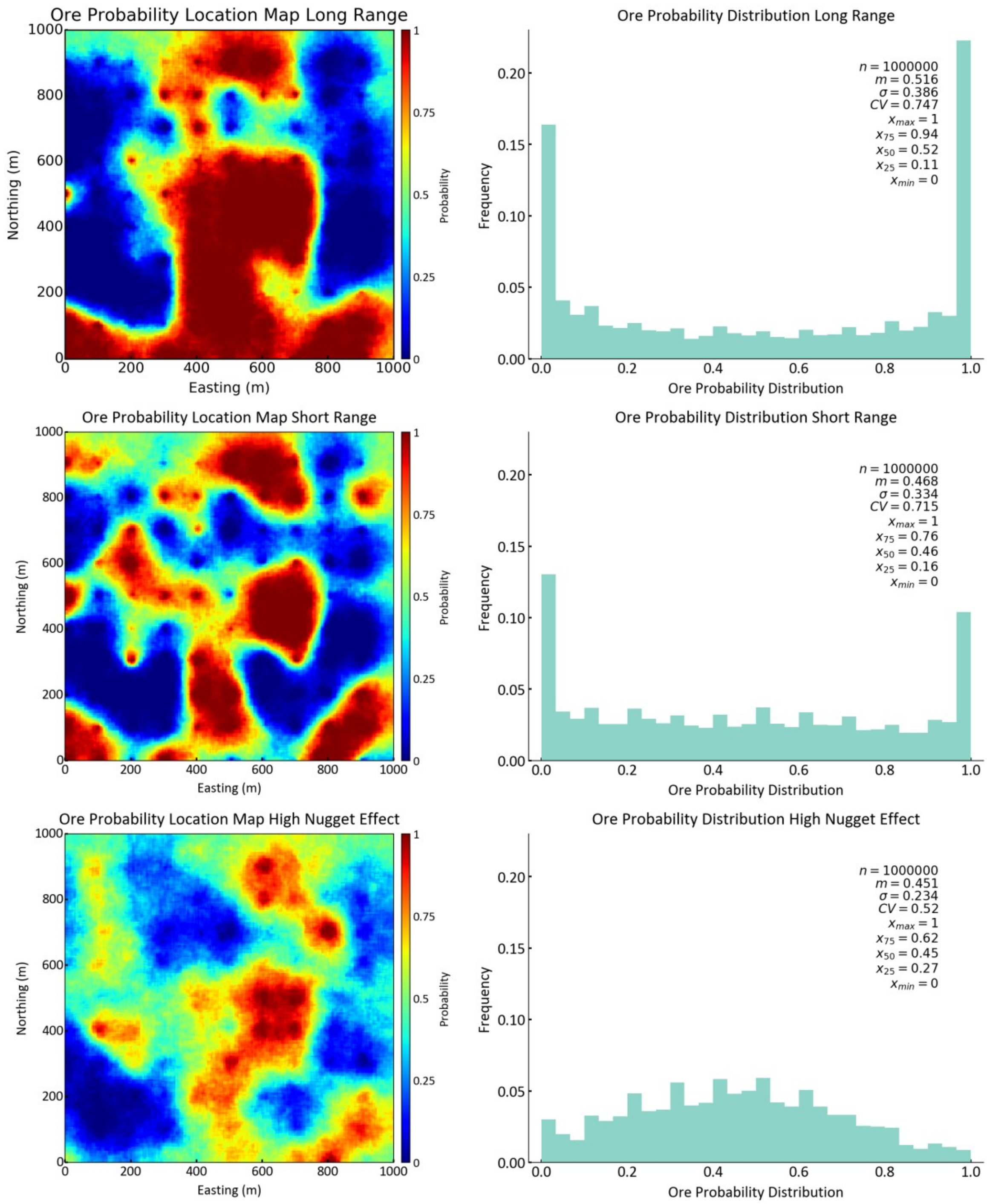

Figure 4.18 – Ore probabilities locations maps and histograms for three different exploration data variogram models: long range variogram (top), short range variogram (center) and high nugget effect variogram (bottom). Note that the Y axis scale is the same for all histograms of ore probabilities to showcase their differences.

Figure 4.18 shows how the ore and waste classification changes as the exploration data variograms change for a fixed data histogram. It is possible to note, especially in the histograms of ore probabilities, that there is more material being mixed for higher nugget effects, whereas for long range variograms it is easier to correctly classify the material. These results are expected. The more continuous the variogram, the more certainty there is in the ore and waste selection process. The higher the nugget effect, there is more uncertainty in the definition of ore and waste contacts.

The ore and waste selection affects the total profit of the bench. Figure 4.19 shows how much the total profit is being affected by the changes in the exploration data variograms relative to the maximum profit available as high resolution blocks. It is possible to notice that the high nugget effect situation is especially critical to the bench profit. In fact, realizations show only loss, no profit is being achieved by mining the bench. Knowing the characteristics of the exploration data variogram, it is possible to anticipate how hard the selection process of ore and waste can be at the time of mining and to more correctly evaluate the long term resources.

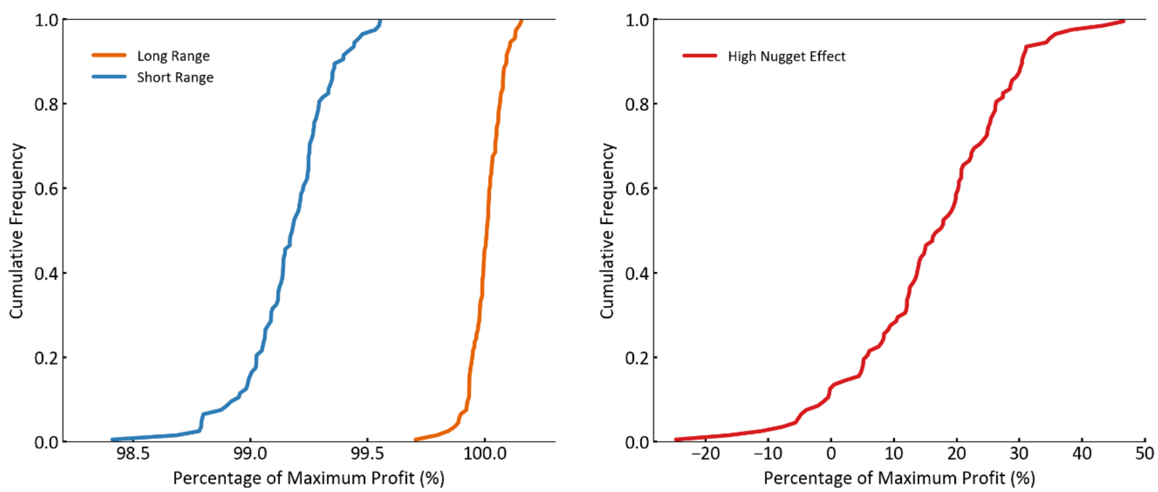

Figure 4.19 – Percentages of maximum profit achievable at the time of mining for changes in the exploration data variogram.

4.3.4. *Cutoff Grade Relative to the Grades Distribution*

The impact of the cutoff grade relative to the estimated grades distribution on the overall resources for the bench is also investigated. The same reference distribution is used with a mean grade of 0.493 g/t. The workflow was adapted for a cutoff grade above the reference distribution mean grade, 0.73 g/t. Figure 4.20 illustrates the reference grade distribution and the expressions used to calculate the expected profits giving a cutoff grade of 0.73 g/t.

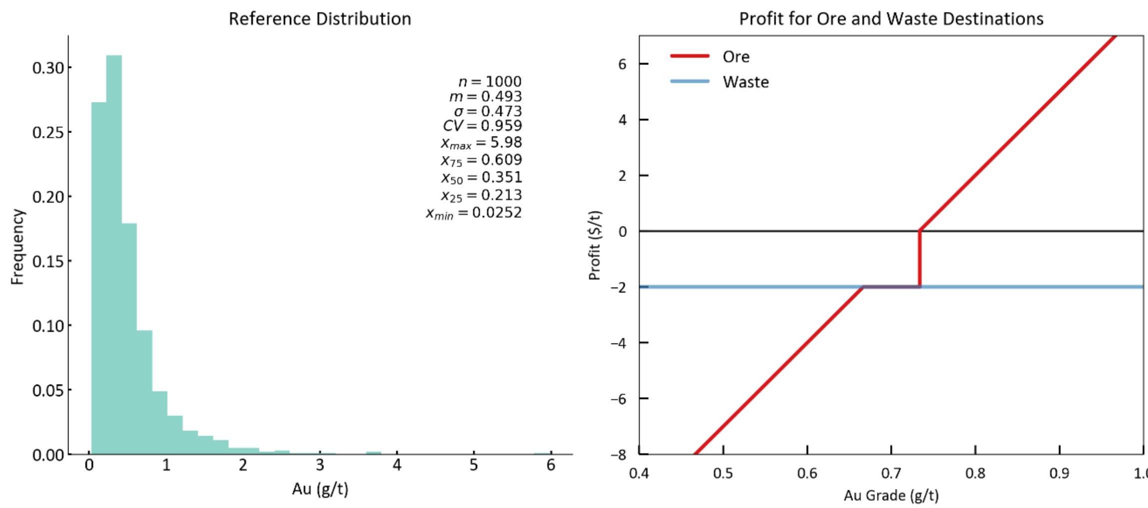

Figure 4.20 – Reference grade distribution (left) and expected profits for ore and waste.

The recoverable mineral resources in the bench are sensitive to the cutoff grade relative to the grade distribution, combined with the smoothing effect present in the production data kriging. Figure 4.21 presents the resources calculated in the base case scenario, where the cutoff grade is below the mean grade of the bench, and the resources calculated in this scenario, where the cutoff grade is above the mean grade of the bench. The smoothing associated with kriging the production data places more material closer to the mean, that is, below the cutoff grade. Because the cutoff grade in this case is above the mean grade, the mineable ore tonnes are less than the base case scenario, but the mean grade is higher. That is, less ore tonnes may be mined, with a higher mean grade.

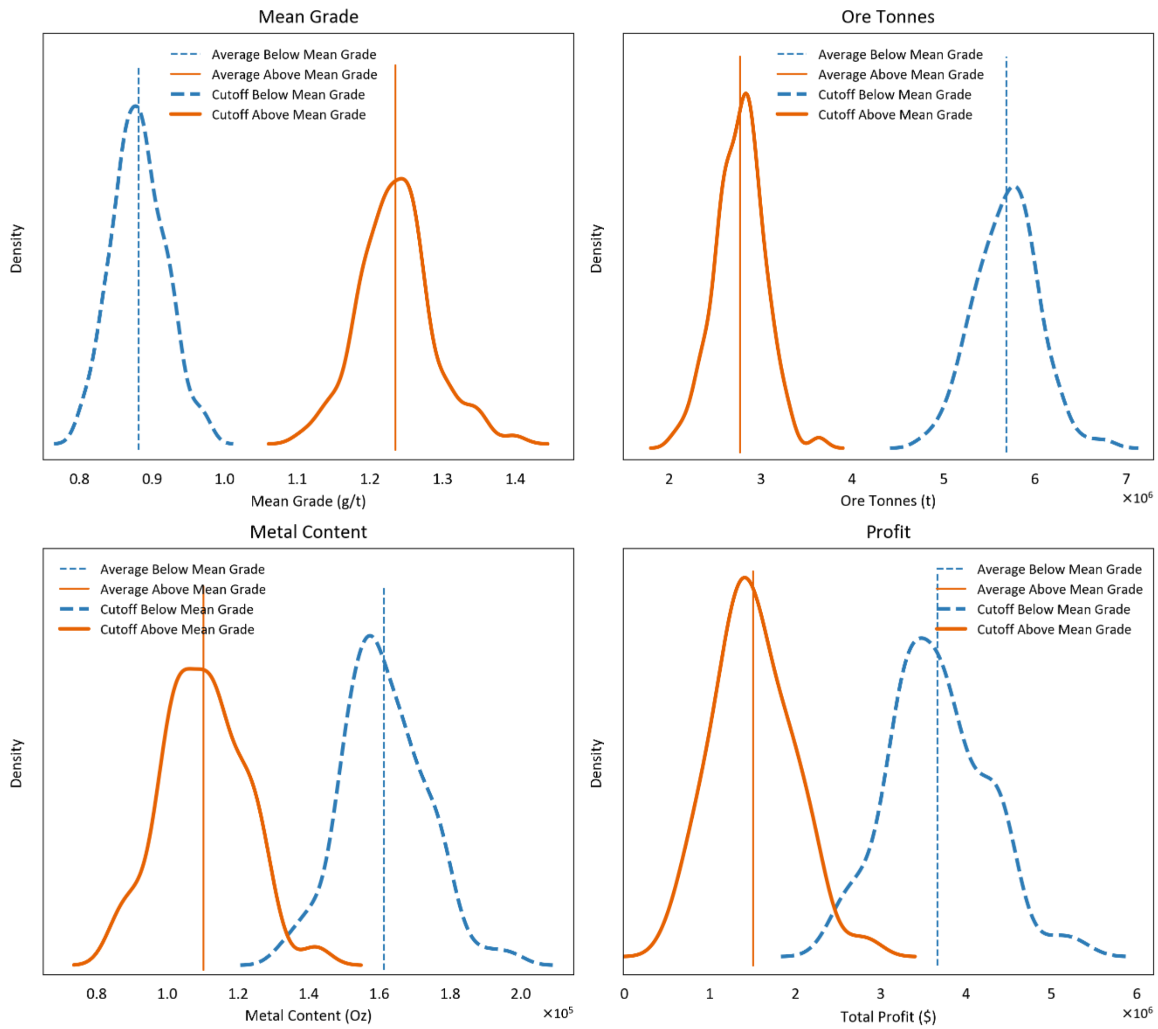

Figure 4.21 – Distributions of resources calculated on the base case scenario (cutoff below mean grade of the bench – blue) and for the cutoff above the mean grade (orange).

Section 4.4. Conclusion

There are a large number of factors that can influence the calculation of recoverable resources and the results of this workflow. The factors shown here represent a few that could have a large impact on the recoverable resources of the bench. In practice, a sensitivity study is not straightforward and should include the interactions between the isolated factors chosen here. Nevertheless, the importance of the assessment of the impact of these factors on the resources is clearly shown, as well as the importance of anticipating their impact at the time of resources modeling with exploration data only.

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, easily achievable using the results of the workflow, as shown in Figure 4.9. The global model of uncertainty is represented by the uncertainty in the global recoverable resources assessed in the workflow. The distribution of resources calculated using the mineable dig limits resulted from the workflow were shown in Figure 4.7. These results can be used for reporting purposes, disclosing a degree of uncertainty, as recommended by the JORC Code (Table 1.1). 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, ore grade and metal content. Table 4.1 shows an example of how the uncertainty could be 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 field, they provide a valuable understanding of the distribution of uncertainty.

Table 4.1 – Overall mineral resources of the bench studied and the uncertainty on it.

Tonnes (000 t)		Grade (g/t Au)		Contained Metal (000 Oz Au)	
P10	P90	P10	P90	P10	P90
5,692.2		0.88		161.3	
5,263	6,098	0.83	0.93	148	176

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.

Chapter 5. Underground Mining Considerations

Section 5.1. Introduction

According to the "Mine Employment" report from the U.S. Department of Labor's Mine Safety and Health Administration (MSHA, 2016), in 2015, of all employees within the mining industry in the United States territory, there were approximately 78% employees working in surface mining operations (excluding office workers) compared to 22% in underground mining. These numbers can be extrapolated to mining operations worldwide: the majority of operations is within a surface mining context. The lower costs and lesser safety constraints compared to underground mining make surface mining generally more attractive to mining companies. On the other hand, as large lower grade and low cost operations become more rare and environmental constraints more strict, the proportion of underground mining operations will likely increase in the future. The framework developed to account for the information and mining selectivity effects in long term mineral resources evaluation could be extended to an underground mining context.

There are a large number of underground mining methods available. A specific deemed representative underground mining method was chosen for the application of the framework proposed in this thesis. Consider the context of sublevel conventional stope mining of a tabular vein deposit. Sublevel stoping is a mining method where ore is extracted and the stope is, generally, left empty. It is applied to vertical or steeply dipping regular-shaped orebodies composed by competent rock that require little or no support (Gertsch & Bullock, 1998; Haycocks, Aelick, & Hartman, 1992). In large orebodies, there can be two or more stopes separated by part of the ore that is left in place to serve as support and prevent the stopes from collapsing (Gertsch & Bullock, 1998). In some cases, these pillars can be partially or fully recovered at the final stage of the mining operation. The actual mining takes place at levels at predetermined vertical intervals, hence the name *sublevel* stoping. The ore is drilled and blasted from the sublevels, falling to the bottom of the stope, where it is transported out of the mine (Gertsch & Bullock, 1998). Typically, stoping mining starts at the bottom of the stope and moves upwards to facilitate the ore flow in the stope and transportation.

Underground mines present a different challenge in grade control than open pits; the production drilling spacing is usually less than in open pit mining (blast holes) and the ore/waste decision is typically made under larger uncertainty. The production drilling in sublevel stoping consists of longhole drilling. The longholes can be drilled as ring drilling from sublevels, where the entire cross section of the stope is drilled following a ring pattern. In narrow orebodies/veins, parallel holes or fan drilling is normally used instead of ring drilling (Gertsch & Bullock, 1998). Longhole blasting is more efficient for orebodies at least 6 m wide (Haycocks et al., 1992). The concept of an SMU cannot be applied to sublevel stoping; the ore/waste selection process happens at the scale of the stope. The stope boundaries must be regular, since there is no easy way of avoiding dilution caused by waste inclusions and irregular orebodies in sublevel stoping (Haycocks et al., 1992). The production drilling data is the basis to define which stopes are going to be mined and normally the entire stope is classified as ore or left as waste.

The most common approach used for resource calculation in sublevel stoping is to design the stopes on an estimated deterministic model and to assign a fixed dilution factor to account for the selectivity of the mining practice (Neufeld et al., 2007). As discussed in Chapter 2, this approach combines information and selectivity considerations into one general parameter. This is known to be optimistic. Another approach could be to use geostatistical simulation with exploration data to assess the uncertainty in the grades, design a fixed stope and report the resources inside this fixed stope. This would consider the uncertainty only on grade values, but not on the stope location, that depends essentially on the grade values and on the orebody location and would yield a pessimistic resource assessment. A third approach could be to adapt perfectly each stope location to a simulated grade/vein realization. By not considering the influence of future information on the stope location, this would be too optimistic. The framework proposed in this research addresses the information and the mining selectivity effects.

The framework developed for long term resources reporting in underground mining also consists of two modules, one designed to address the information effect and the other to account for the mining selectivity effect. As in open pit mining, the only information available at the time of resources modeling is exploration drilling. For the application of the proposed framework in the context of underground mining, anticipating the final data configuration that will be available at the time of mining to guide the ore/waste classification is also necessary. The final data available for sublevel stoping is summarized into two categories in this research: openings (or sublevels) for stope development and additional drilling. The selectivity aspect of the framework, since the concept of an SMU cannot be applied to sublevel stoping, is represented entirely by the configuration of the stope itself, its size and orientation. Figure 5.1 presents schematic cross section views that illustrate typical initial and final data configurations of a region to be mined by sublevel stoping in a tabular vein deposit. The extension of the framework to the sublevel stoping context considers one stope at a time and predicts the recoverable resources within that stope individually, accounting for the information and mining selectivity effects. Interactions between the mineable areas within the mineralized vein are not considered and represent an area of future work.

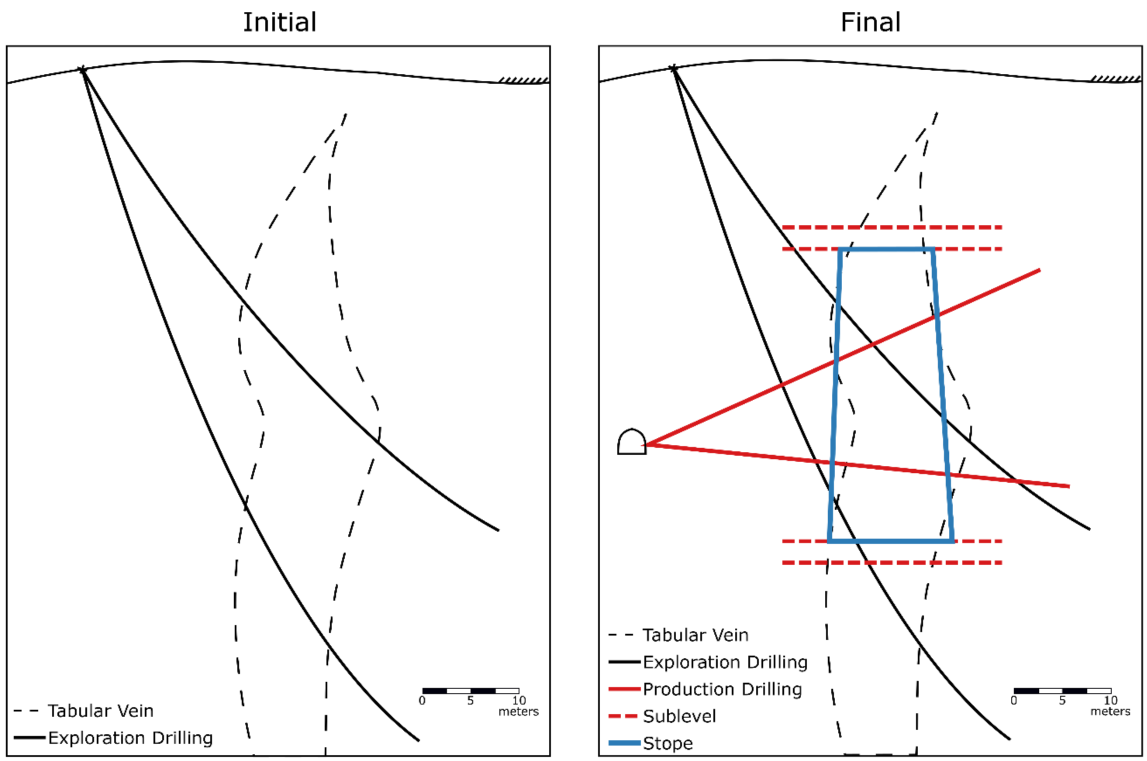

Figure 5.1 – Schematic cross section views illustrating typical initial (left) and final (right) data configurations of a subvertical tabular vein deposit.

In order to characterize the uncertainty in the geological representation of a tabular vein, the workflow for vein geometry modeling under uncertainty developed by Carvalho and Deutsch (2017) is used here. This work consists on computing multiple simulated realizations of vein boundaries and surfaces. The methodology starts by creating a local coordinates system to match the vein geometry and anisotropy to the Cartesian grid system. Geometry data need to be imputed where inclined drill holes make it difficult to correctly calculate the vein thickness. Then, surface simulation is carried out using an unstructured tetrahedron grid that produces accurate surfaces to efficiently match the vein geometry. This workflow for vein geometry modeling creates multiple realizations of the vein geometry (hangingwall and thickness) and grade. Carvalho and Deutsch (2017) can be referred to for further details on the implementation of the modeling workflow. The results from this workflow are the starting point of the underground application of the framework developed in this thesis. The multiple realizations of vein surfaces and boundaries generated by the workflow proposed by Carvalho and Deutsch (2017) will serve as the input data in this thesis.

Section 5.2. Proposed Framework for Information Effect in Sublevel Stoping

Prior to applying the proposed workflow, multiple realizations of surfaces and boundaries of a mineralized tabular vein were generated through the workflow proposed by Carvalho and Deutsch (2017). These realizations use only the exploration drilling data that is available at the time of modeling. The next step is to choose a location of the vein that has a potential to be mined, that is, a location where a stope could be placed. The stope dimensions need to be specified: the length along the strike of the orebody, the height between sublevels and the elevations of the sublevels. These parameters are based on dimensions that would be chosen based on other engineering studies.

With these parameters fixed, to account for the information effect, it is necessary to sample one vein realization at a time, from the ones computed through the vein uncertainty workflow, at the stope location chosen before. The sampling takes place at the anticipated production drilling spacing to mimic the production data planned in the future. Typically, the production drilling will follow a ring or fan-shaped pattern. The openings/sublevels provide additional information at the time of mining.

The intersections from the production (drilling and openings) and exploration data with the vein surface in each surface realization are used to account for the information effect. New vein surfaces will be interpolated using all data in the area being studied. This step is equivalent to kriging the anticipated production data in benches of open pit mining. This will provide a different vein surface for each realization with anticipated final data at the location considered. Figure 5.2 presents schematic cross section views of a subvertical vein deposit illustrating the intercepts acquired by sampling one surface simulated realization and the interpolation of those intercepts.

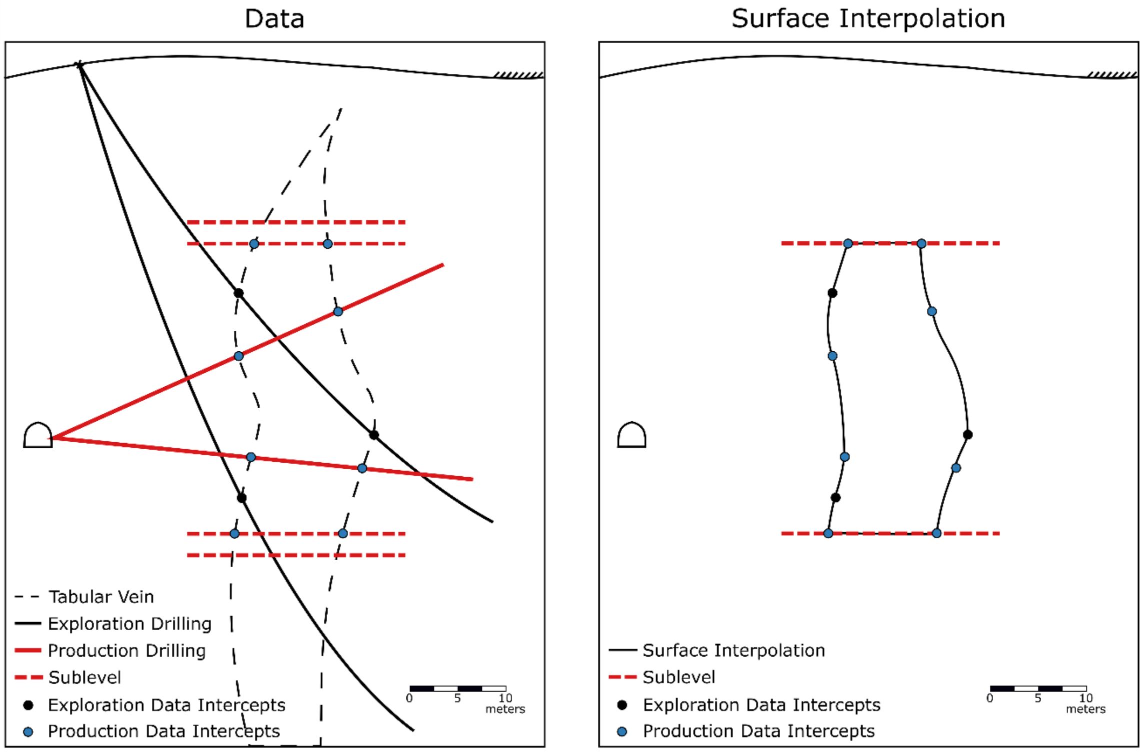

Figure 5.2 – Schematic cross section views of a mineralized vein illustrating the data intercepts with a vein surface realization (left) and the interpolated vein surface (right).

Sampling the surface realizations and interpolating the sampled data will provide an approximation of the final vein geometry that would be found at the time of mining. The key idea of the proposed application in underground mining is to show that, by resampling a set of surface realizations at the final data spacing, there will be a more accurate prediction of the resources extracted and dilution for the stope parametrization. Additionally, the proposed workflow provides a measure of uncertainty for risk management.

Section 5.3. Proposed Framework for Mining Selectivity Effect in Sublevel Stoping

As explained above, the concept of an SMU is not normally applied to sublevel stoping. Typically, the ore/waste classification takes place at the scale of the stope, that is, the entire stope is classified as ore or left as waste. Thus, the configuration of the stope itself, its size and orientation, defines the selectivity aspect of the framework proposed in this thesis. The mining selectivity module on this variation of the resources modeling framework consists, then, in optimizing the boundaries of the stope. The stope must be parameterized in a way that will minimize ore loss and dilution.

Because neither stope sequencing nor the interactions between the mineable areas within the mineralized vein are being considered, part of the dimensions/locations that define a stope are predefined. They are the length along the strike of the orebody, the height between two sublevels and the elevations of the sublevels. The stope boundaries must be regular given drilling and blasting constraints, that is, the longholes are drilled for the entire stope height at once. A stope is defined, then, by eight 3-D location points. Figure 5.3 presents a schematic perspective view of a stope in a steeply dipping vein and illustrates the specified dimensions of the stope (L - length along the strike, H - height between two sublevels, Z_{upper} and Z_{bottom} - sublevels elevations) and the eight 3-D points that define it, numbered from 1 to 8.

It is convenient to discretize the interpolated vein in grid cells for a regular volume surrounding the vein, the bounding box in Figure 5.3. The grid cells inside and outside the vein are assigned an indicator value (i.e. 1 is inside the vein and 0 is outside). The starting point of the stope configuration is a determination of points 1 to 8. The grid cells inside and outside this stope configuration are identified. The goal of the stope optimization is to minimize ore loss and dilution. That is, the objective is to maximize the proportion of grid cells inside the vein and inside the stope and to minimize, at the same time, the proportion of grid cells inside the vein and outside the stope and outside the vein and inside the stope. These categories of material are illustrated in Figure 5.4.

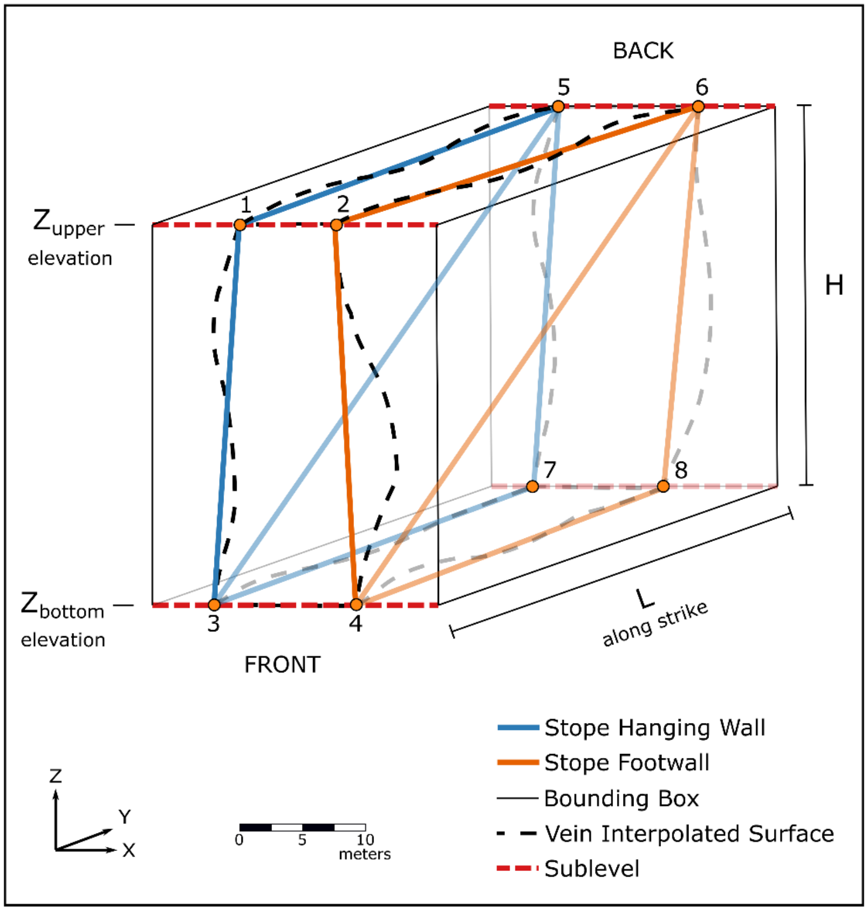

Figure 5.3 – A schematic perspective view of a stope in a steeply dipping mineralized vein.

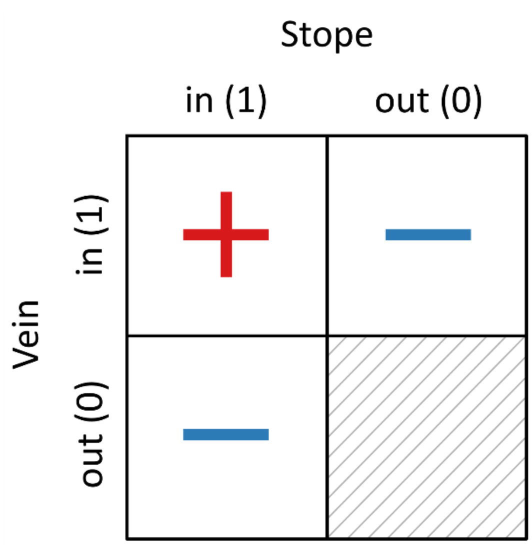

Figure 5.4 – Categories of material identified for stope optimization. The plus sign indicates the category that needs to be maximized and minus signs indicate categories to be minimized.

Since the sublevel elevations and the stope height and length are fixed, the optimization varies the location of the key eight points along the vein thickness. The only locations being varied are perpendicular to the vein. Figure 5.5 shows a schematic perspective view of a stope that illustrates a case where the stope orientation is consistent with the original coordinates system.

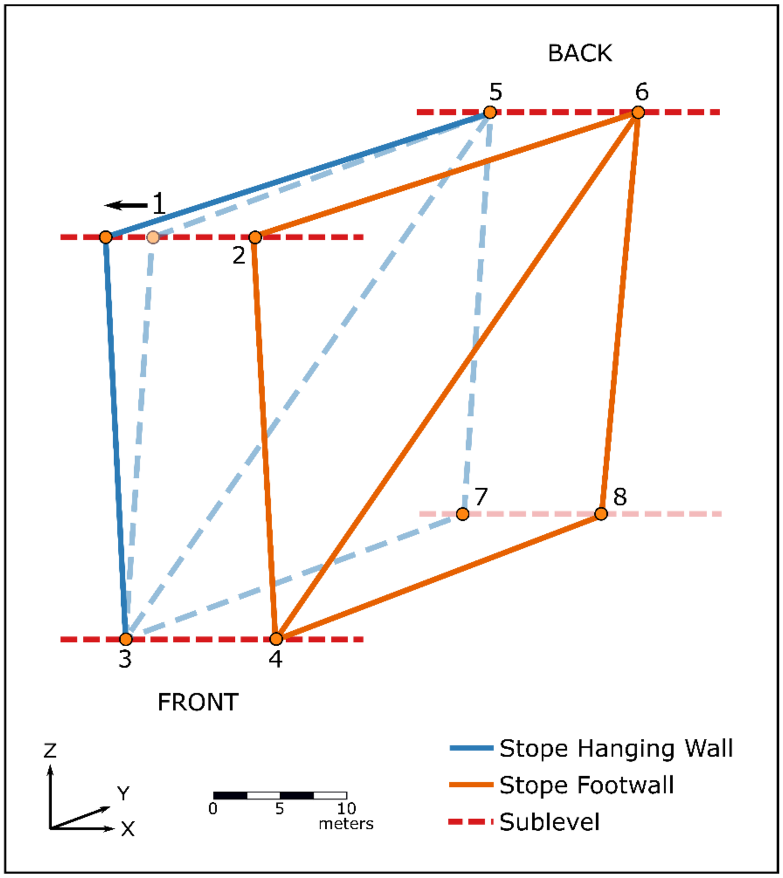

Figure 5.5 – A schematic perspective view of a stope optimization where the stope orientation is consistent with the original coordinates system. The key eight points that define the stope vary along the X axis only.

In this case, the eight points vary along the X axis only, Y and Z locations are fixed. Consider small increments (i.e. the size of the grid resolution) in the location of each point, from 1 to 8, in the X axis. For each change in a point location, the stope hangingwall and footwall are triangulated again, as shown in Figure 5.5. After each new stope triangulation, the value of the objective function is recalculated as:

$$O = P_{in,in} - P_{in,out} - P_{out,in}$$

Where the subscript follows the format stope/vein and $P_{stope,vein}$ is the proportion of grid cells inside or outside the stope and the vein. The recalculated value of the objective function is stored every time it is larger than the last one stored. Due to the impractical number of possible combinations between the possible locations of each of the eight points, a maximum number of iterations is chosen to retriangulate the stope and recalculate the value of the objective function.

At the end of this workflow, there will be L optimized stope boundaries, L being the number of surface realizations generated as the input of the workflow. The extension of the framework to the sublevel stoping context considers one stope at a time and predicts the recoverable resources within that stope individually, accounting for the information and mining selectivity effects. Interactions between the mineable areas within the mineralized vein are not considered and represent an area of future work.

Section 5.4. Implementing the Proposed Framework in Sublevel Stoping

An example is used to illustrate the proposed framework to account for the information and mining selectivity effects in sublevel stope geometry. The example consists of an epithermal vein mineralization of a silver deposit. The orebodies in this deposit are characterized for being largely confined to sub-vertical structures, which correspond to a typical use of sublevel stope mining. For convenience, a local coordinates system that matches the vein geometry is used. The dataset consists of 14 exploration drillholes that intersect the main vein structure. The drillholes dataset contains the X, Y, and Z locations of each drillhole collar, survey measurements of the sampled intervals and silver grades. Figure 5.6 shows perspective and section views of the main vein structure and the exploration data.

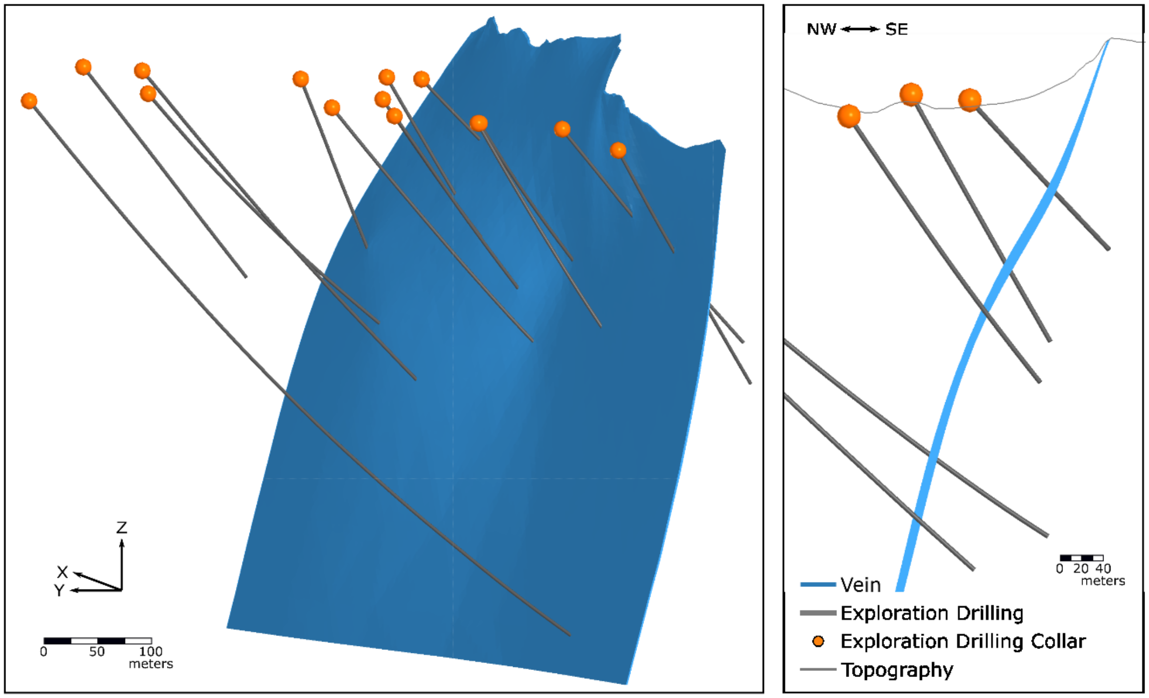

Figure 5.6 – Perspective (left) and section (right) views of the vein and exploration data.

Following the workflow for vein geometry modeling proposed by Carvalho and Deutsch (2017), a hundred realizations of surfaces and boundaries of the tabular vein were generated. These realizations use only the exploration drilling data that is available now, at the time of modeling. The application of the workflow proposed in this thesis is particularly interesting for deposits in an exploration stage and with little exploration data such as the one used in this example. A region of the vein that has a potential to be mined and where a stope could be placed was chosen. Based on typical stope dimensions for tabular vein deposits, the stope dimensions were defined as: 50 m along the vein strike, 30 m height between the two sublevels with sublevel elevations of 720 m and 750 m. Figure 5.7 shows cross section views of two surface realizations generated and the area chosen for stope placement in perspective. The region chosen for stope placement does not have any exploration data that intersects it. This region of the vein is associated with a large uncertainty, so it is of particular interest to have the framework applied to help understand the possible stope variations in geometry and volume.

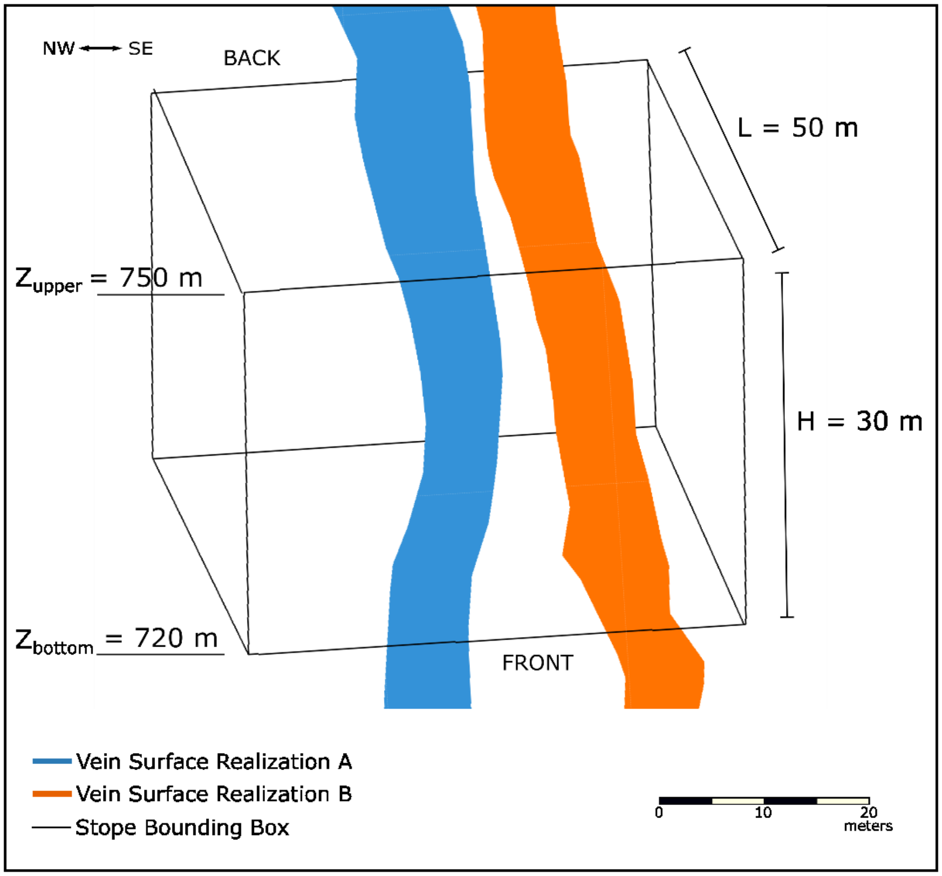

Figure 5.7 – Cross section views of two surface realizations and stope bounding box in perspective.

The next step is to sample a vein surface realization at the anticipated production data spacing to mimic the production drilling and openings for stope development planned in the future. The sampling takes place at the front face and at the back of the possible stope location. Three production drillholes were "drilled" following a fan-shaped pattern and the openings for stope development, the sublevels, are horizontal. One hundred unique datasets are sampled consisting of the intersections between the production (drilling and openings) and exploration data with the hangingwall and footwall of the vein surface in each surface realization. The hangingwall and footwall intercepts were then interpolated to form new vein surfaces. Following these steps, there will be a different vein surface for each simulated realization with anticipated final data at the location considered. Figure 5.8 presents a perspective view of one production dataset sampled from a vein surface realization and the interpolations of the hangingwall and footwall for the same realization.

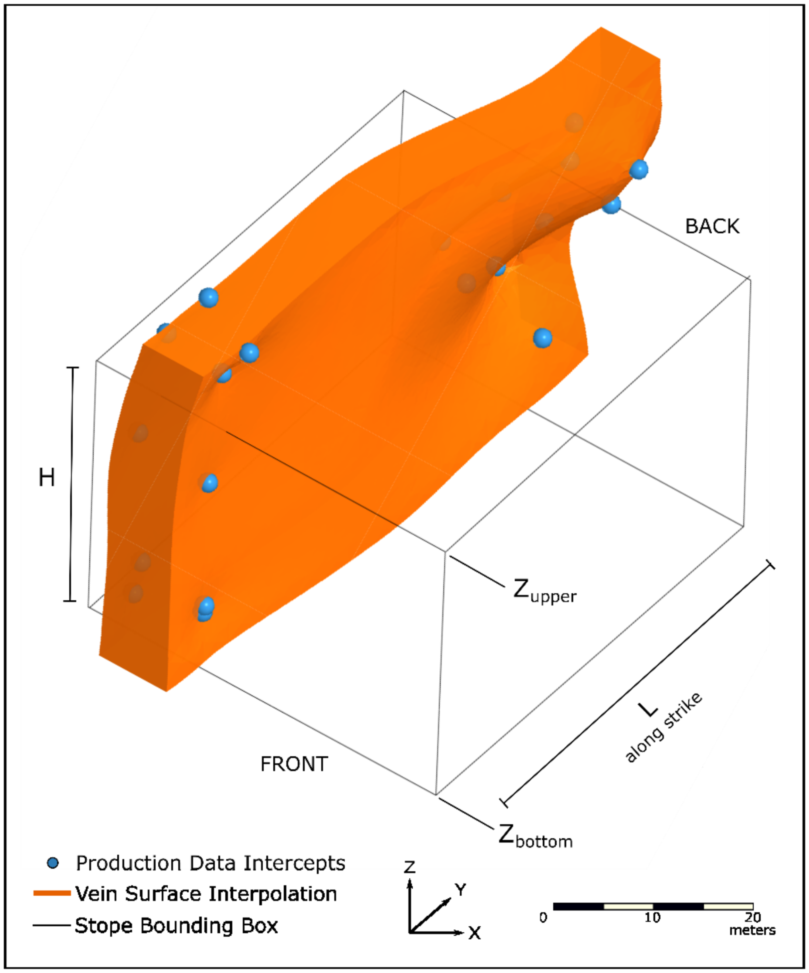

Figure 5.8 – Perspective view of production data intercepts and vein surface interpolation.

The intersections between the sublevels and the vein hangingwall and footwall surfaces were identified. There are four points at the stope front and four points at the back. A bounding box surrounding the vein volume was generated and its volume was discretized with high resolution grid cells of 1 x 1 x 1 m. An indicator column was created to identify the grid cells inside the vein (1) and the grid cells outside the vein (0). Another indicator column was created to identify the grid cells inside (1) and outside (0) the stope. The first stope configuration tested is the one formed by triangulating the eight intersection points between the sublevels and the vein hangingwall and footwall. The goal is to minimize ore loss and dilution, that is, to maximize the proportion of grid cells inside the vein and inside the stope (both indicator columns with a value of 1) and to minimize the proportion of grid cells inside the vein (vein indicator column as 1) and outside the stope (stope indicator column as 0) and outside the vein and inside the stope. A fixed value is assigned to the grid cells inside both the vein and the stope, in this example 10 units, whereas the grid cells inside the vein and outside the stope or vice versa are assigned a value of -1 units. These values are arbitrary and their only role is to quantify the value of the objective function. They are equivalent to the expected profit value of different destinations for the mined material assigned to the grid cells in the open pit mining application of the framework. As mentioned before, the problem of stope placement is related to geometrical constraints derived from the vein shape and not to a minimum mineable unit size, so the expected profit values are not applied for sublevel stoping in this research. An area of future research would be to directly account for the value of the ore and the costs incurred by taking dilution.

Keeping the sublevel elevations and the stope height and length fixed, small increments on the size of the grid resolution were applied to the location of each stope definition point along the vein thickness. The only dimension being varied is perpendicular to the vein. For each change in a point location, the stope hangingwall and footwall are retriangulated. Following each new stope triangulation, the new value of the objective function is calculated. The final objective function value is updated every time it is larger than the last one stored. A maximum number of iterations and increments for the points locations is chosen as 6000 to maintain reasonable computational time. The stope configuration that returns the largest value for the objective function among the 6000 iterations is the optimized stope for that realization. Figure 5.9 shows a graph of the objective function value every time it is updated versus the iteration number for two realizations. It is possible to see that the number of iterations chosen achieves a stable high value of the objective function.

The stope optimization is done individually for each reinterpolated vein surface with the anticipated production data. At the end, there are a hundred optimized stope boundaries. Figure 5.10 shows a perspective view and a cross section of one final stope configuration for a reinterpolated vein surface. As shown by this stope configuration, the stope optimization is a compromise between avoiding dilution and leaving behind as little ore as possible. Depending on the complexity of the vein shape, this compromise is more easily achieved or not.

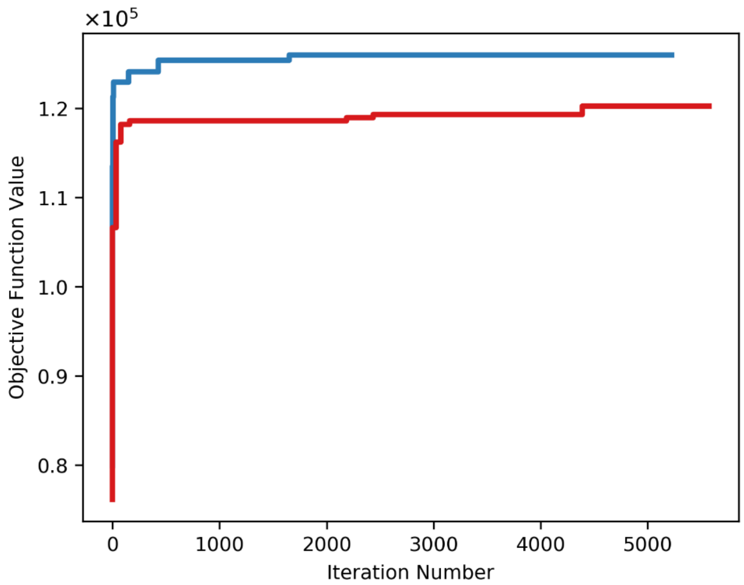

Figure 5.9 – Objective function value versus iteration number for two realizations.

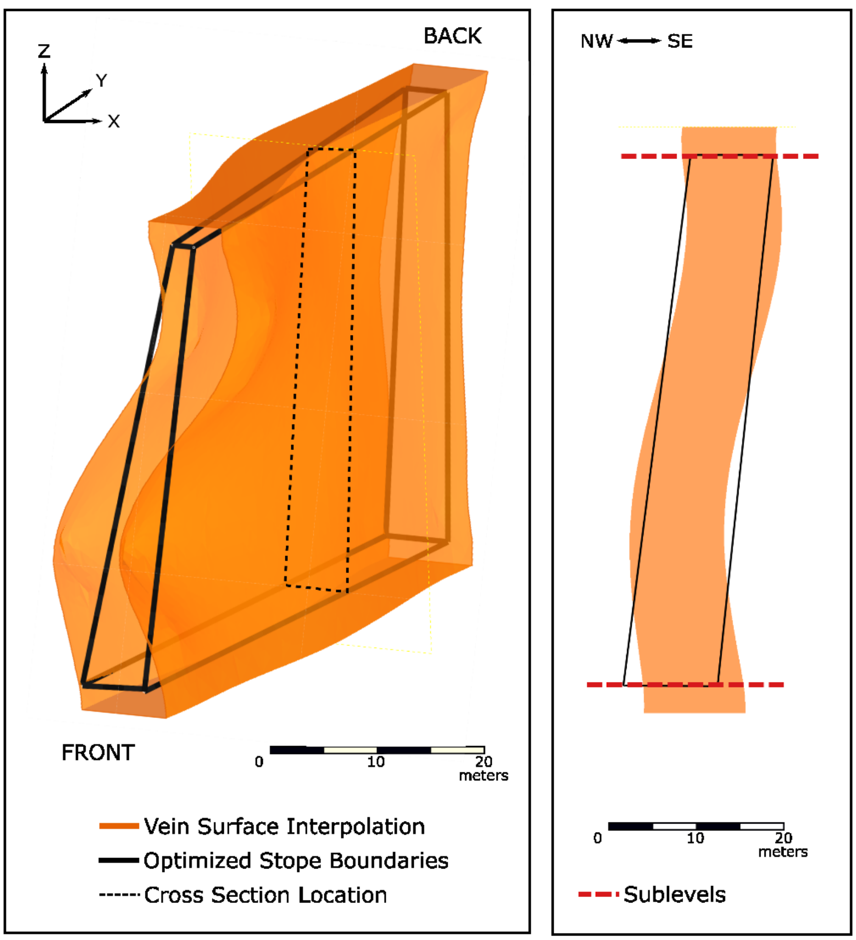

Figure 5.10 – Perspective view (left) and cross section (right) of optimized stope boundaries for one reinterpolated vein surface.

The volumes of the optimized stopes vary depending on the reinterpolated vein surface. This variation corresponds to the degree of uncertainty in the stope volumes. In order to quantify it, the tonnage of each stope is calculated, considering a fixed density value of 2.7 g/cm^3. Figure 5.11 presents the stopes tonnage distribution for all reestimated vein surfaces. The stope tonnage can be as low as 14,400 t and as large as 86,100 t. The average tonnage of the stopes is 34,600 t.

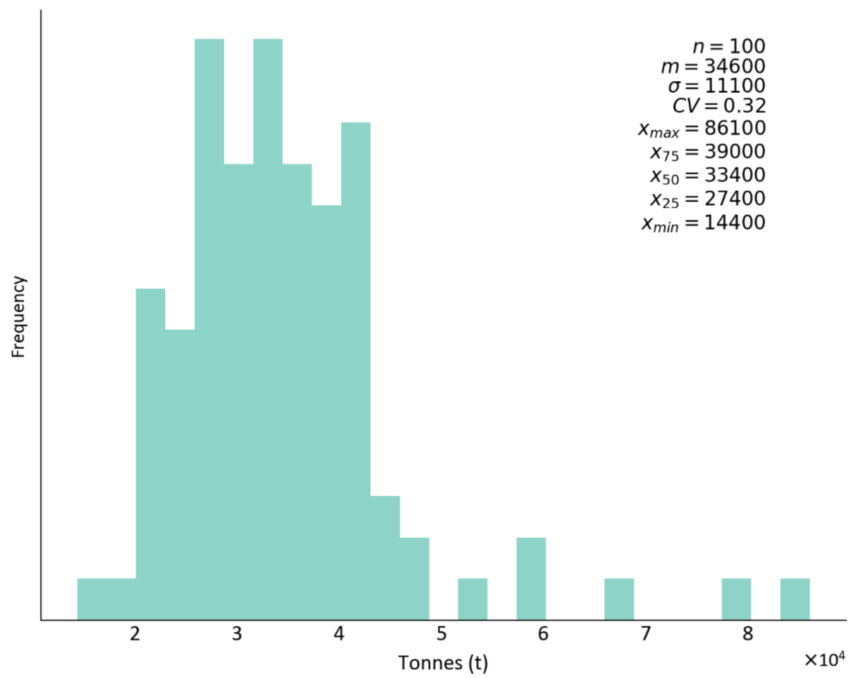

Figure 5.11 – Stopes tonnage distribution for all reestimated vein surfaces.

A summary of all expected ore loss and dilution within the optimized stopes is also calculated. Ore losses and dilution are calculated as a proportion relative to the total volume of the optimized stope for each realization, so the values are expressed as percentages of stope volume. Figure 5.12 presents the distributions of proportions of ore loss and dilution relative to the stopes volume. This calculation can assist the identification and minimization of ore loss and dilution at the time of mining.

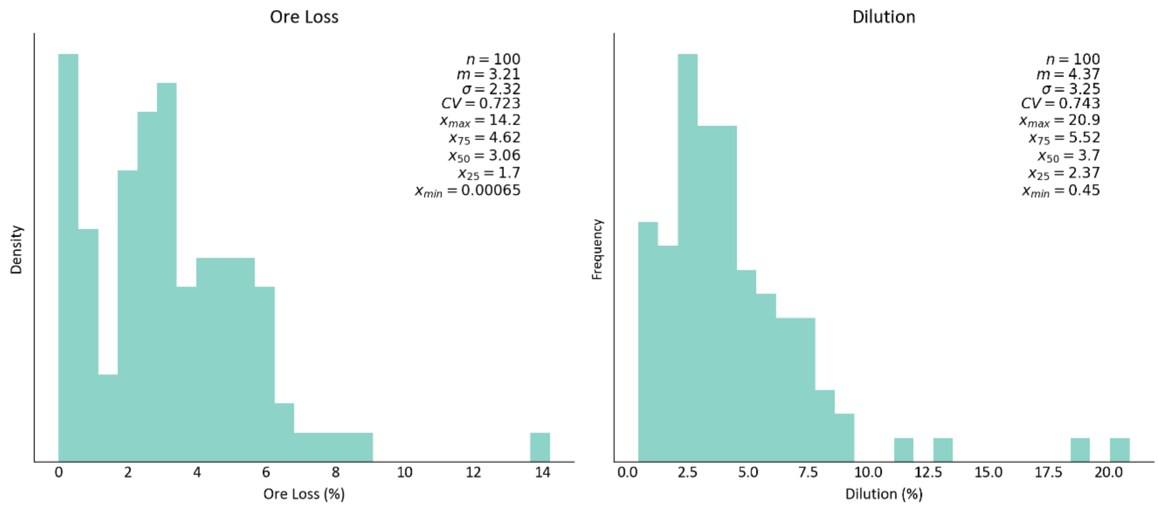

Figure 5.12 – Ore loss (left) and dilution (right) relative to the optimized stope volume for each realization.

The probability of a grid cell to be within the optimized stopes generated is also calculated. Figure 5.13 shows perspective and cross section views of the probabilities of every grid cell of being inside the optimized stopes generated for each realization of the proposed framework. In general, the probabilities are low. The maximum value is 0.35. This is expected due to the scale dependency of uncertainty. The region being studied is a small portion of the entire mineralized vein. This summary is useful for mine planners to identify critical areas that require further investigation (i.e. more data) before placing a stope.

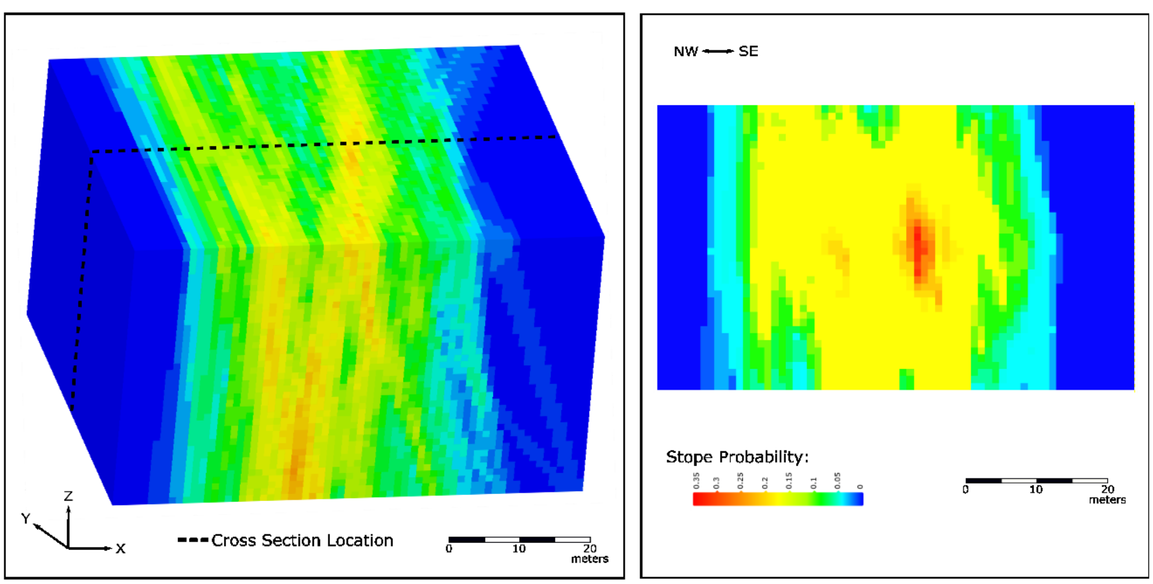

Figure 5.13 – Perspective (left) and cross section (right) views of the probability of a grid cell to be inside the optimized stopes for a hundred realizations.

The large variability in the tonnages of the stopes generated and presented in Figure 5.11 indicates that the stope height used for this exercise is probably not the most appropriate choice considering the configuration of this deposit at this specific location. Further investigation is suggested in order to make a final decision, but this constitutes an important measure of uncertainty for any mineral deposit, especially tabular veins in exploration stages. As with the open pit mining implementation, this workflow is not intended for final grade control. The ore losses and dilutions assessed here are not final. The framework is proposed to assess the uncertainty in the resources at the time of resources modeling, when only exploration data is available. In most cases, this is the time when crucial decisions generally need to be made, such as the continuation (or not) of investment in a mining asset.

Chapter 6. Conclusions and Future Work

Section 6.1. Problem Review

The most common approach used in the mining industry to evaluate mineral resources is to estimate the grades at a block scale using ordinary kriging and report estimates from this deterministic model. Kriging is locally accurate, which is fundamental for final selection during grade control. At the time of mining, there must be a minimization of misclassification of ore and waste blocks. However, the mineral resources calculated with kriging are a smooth representation of the actual distribution of grades at block scale (Journel & Kyriakidis, 2004). Besides, there is no uncertainty assessment on resource models reported with kriging.

Geostatistical simulation is an alternative to kriging. It provides a complete model of uncertainty, but its use is still not widespread in the mining industry. Unlike kriging, simulation reproduces the variability of the mineral deposit (Journel & Kyriakidis, 2004). In order to properly assess the recoverable resources and reserves, the block estimates should show the same tonnes of ore, tonnes of waste and grade of ore as will be encountered at the time of mining. The common practice when simulation is used is to summarize the simulated realizations into one model, but the uncertainty is lost by following this approach. To account for resource uncertainty, it has been proposed (Deutsch, 2015) that the simulated realizations be summarized as late as possible.

Simulated realizations are calculated at high resolution and quantify the uncertainty at the data scale, not at the actual mining scale. Mineral resources are evaluated at a specific time considering only the information available at that time. Selectivity at the scale of the data and perfect knowledge of the grade at the time of mining would be assumed by reporting resources directly on high resolution simulated realizations. The assumption of perfect knowledge of the grade in the future is not correct because there will always be uncertainty left at the time of mining since even the grade control sampling is imperfect. As more or better information becomes available at the time of mining, the uncertainty reduces. The decrease in uncertainty from the resources model to the time of mining is known as the information effect. In addition to the anticipated information that will be available at the time of mining, a well calibrated long term mineral resources model should account for the selectivity of future mining. The mining selectivity effect can be defined as the scale or support that would match future mining practice and geological constraints. The greatest profit is available with free selection of high resolution blocks of ore and waste, but this is unrealistic.

The traditional framework for mineral resources evaluation considers the SMU size alone to account for the information effect, the selectivity of future mining and the remnant uncertainty at the time of mining. It is a common practice to increase the SMU size to account for imperfect final data and to assume no remnant uncertainty in the future (Leuangthong et al., 2003). The long term model generated as a result of using a large SMU size and assuming no remnant uncertainty at the time of mining may be too optimistic. In contrast, if the actual mining practice can achieve higher selectivity, the model may be too pessimistic. Assigning a fixed dilution factor is also common to try to account for selectivity of future mining and imperfect future information (Neufeld et al., 2007). The problem is that both solutions combine the information effect and selectivity of future mining into one general parameter. This is not the best approach because the information effect is closely related to the smoothing effect of kriging with widely spaced exploration data and the selectivity and SMU size strongly depends on dilution.

Reconciliation between the long term resources model and the grade control model will be a key feature at the time of mining. It should be considered when generating the long term resources model. Reporting resources using a large SMU size creates a disconnection between the two models. The actual mining takes place at a more detailed resolution than the large SMU size normally used for resources reporting. The motivation behind this research is the fact that anticipating the information available at the time of mining and the selectivity of future mining is not directly considered in mainstream long term recoverable resources modeling.

Section 6.2. Contributions

The main contribution of this thesis 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, that will be available at the time mining to guide the destination for the mined material (i.e. ore or waste). Further details on the steps of this module of the methodology are presented in Chapter 2. 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. This module is presented in Chapter 3, including a description of the algorithm developed for mining selectivity calculations in open pit mining. The proposed methodology does not introduce any bias in the resources calculations, is effective at anticipating information and selectivity considerations and can be straightforwardly applied as a resources modeling workflow.

The proposed methodology was mainly designed for open pit mining. Nevertheless, underground mining has become increasingly relevant in worldwide mining. For this reason, the proposed methodology was adapted to underground mining in Chapter 5, more specifically to sublevel stoping of a tabular vein deposit. This extension also consists of two modules to account for the information and mining selectivity effects. The final data to be anticipated in the context of sublevel stoping are openings (or sublevels) for stope development and additional drilling. The selectivity aspect is represented by the configuration of the stope itself, defined by its size and orientation relative to the mineralized vein. Then, the mining selectivity module consists of optimizing the boundaries of the stope in a way that will minimize ore loss and dilution. Details of the procedure are presented in Chapter 5. An application of the methodology for sublevel stoping for a real data set of a tabular vein deposit is shown in Chapter 5.

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 in Chapter 4 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, that 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, metal content, tonnes of ore and profit, as shown in Chapter 4. After calculating the recoverable resources for each realization, the uncertainty in the resources can be found. The mineral resources can then be reported as an expected resource (the average value of each relevant measure calculated) with uncertainty (plus or minus an interval).

Section 6.3. Limitations and Future Work

Applying the proposed probabilistic resources workflow can be computationally expensive. As the final grid spacing becomes tighter when anticipating the grade control data or the minimum mineable unit size increases in the mining selectivity module, there are larger computational costs. Although, the gain in knowledge of the recoverable resources in place is a reasonable trade off. It is, indeed, possible to keep the computer time manageable by choosing reasonable combinations of mineable unit sizes and production data sampling spacing. Nonetheless, in the future, improvements could be made to the algorithms used in the workflow to make them less computationally costly.

Even though this research targets probabilistic resources evaluation and the ore and waste selection is not final as it would be in the actual grade control practice, it would be useful to have an algorithm that would optimize the selection of ore and waste blocks based on different minimum mineable unit sizes as well as different levels of anticipated grade control information. The workflow is pending an algorithm that would find the optimal configuration of grade control data and minimum mineable unit size to retain the most possible profit from the high resolution reference model. This algorithm could also consider the cost to obtain the final data information. This is an avenue of future research.

A certain degree of free selection is still being assumed in the mining selectivity module. Blocks of ore or waste are selected without fully accounting for geometrical or mining practice constraints that may limit the access to a specific location. This module also assumes a fixed origin for blocks of adjacent mineable areas/units that do not necessarily need to have the same origin; small volumes could be created between the mineable ones. These details could be added to the algorithm for mining selectivity calculation.

The applications shown in this thesis consider two destinations only for the mined material, ore or waste. Reality is often more complex. There can be multiple stockpiles of different grade ranges, multiple processing options and so on. This workflow could be extended to consider multiple destinations. The calculation of expected profits itself could consider all costs associated: costs of mining ore, mining waste, processing ore, gold price and recovery. This calculation could also consider the grades of contaminants that could interfere in the value of the commodity being mined.

In the open pit application, because the problem is being dealt with essentially as 2-D, data from upper or previous mined benches are not being considered. These data can be important, especially for steeply dipping structures.

The underground mining extension is a demonstration of how the same concepts applied to the open pit context can be expanded to underground mining. This extension of the framework to sublevel stoping considers one stope at a time and predicts the recoverable resources within that stope individually, accounting for the information and mining selectivity effects. Interactions between the mineable areas within the mineralized vein and stope sequencing are not considered. Parameters such as minimum allowable dip and minimum stope width are also not being considered. Accounting for variations of grade within each optimized stope, together with the other factors described, represent areas of future work.

In the stope optimization procedure described in Chapter 5, the same value is being considered for ore loss and dilution. Another area of future research would be to directly account for the value of ore losses and the costs related to dilution. It is common in metal mining to have a higher cost associated with sending ore to the waste dump as opposed to processing waste material. This is expected because small volumes of ore generally have a high value. In contrast, there can be cases where the opposite is true (especially in high-volume open pit mining). High costs associated with shipping, for example, can lead to dilution having a higher cost than ore loss. These nuances can be incorporated to reflect each specific case.

Section 6.4. Conclusion

A framework to properly forecast recoverable resources by individually accounting for the information and mining selectivity effects was developed. By following the proposed framework, the prediction of long term recoverable resources will be closer to the material mined in the future. In addition, by not summarizing the simulated realizations into one model, the framework proposed provides an assessment of local and global uncertainty for risk management. The importance of assessing the impact of different factors on mineral resources evaluation was also shown, as well as the importance of anticipating their impact at the time of resources modeling with exploration data only. These factors include: the exploration data variogram, grade control data spacing, mining selectivity and the cutoff grade relative to the grades distribution. There are a few avenues of future research to improve the mineable dig limits calculation in the proposed workflow. Nevertheless, the proposed workflow is reasonable to anticipate the information effect and selectivity at the time of mining for long term resources evaluation.

References

Carvalho, D., & Deutsch, C. V. (2017). Developments on Tabular Vein Geometry Modeling. *CCG Annual Report 19*. Retrieved from http://www.ccgalberta.com

Cuba, M. A., Boisvert, J., & Deutsch, C. V. (2012). Simulated Learning Model for Mineable Reserves Evaluation. *CCG Annual Report 14*. Retrieved from http://www.ccgalberta.com

Deraisme, J., & Roth, C. (2000). The information effect and estimating recoverable reserves. *Geovariances.*

Deutsch, C. V., & Journel, A. G. (1998). *GSLIB: geostatistical software library and user's guide.* 2nd ed. New York: Oxford University Press.

Deutsch, C. V. (2015). All Realizations all the Time. *CCG Annual Report 17*. Retrieved from http://www.ccgalberta.com

Deutsch, C. V. (2017). IGC-DL: Intelligent Grade Control - Dig Limits (Version 0.1). *CCG Annual Report 19*. Retrieved from http://www.ccgalberta.com

Geovariances. (2018, April 1). What's new in ISATIS 2018? Retrieved May 3, 2018, from https://www.geovariances.com/wp-content/uploads/2018/04/isatis-v2018-new-features.pdf

Gertsch, R. E., & Bullock, R. L. (Eds.). (1998). *Techniques in underground mining: Selections from Underground mining methods handbook*. Littleton, CO: Society for Mining, Metallurgy, and Exploration.

Gómez-Hernández, J. J. (1992). Regularization of hydraulic conductivities: A numerical approach (A. Soares, Ed.). *Geostatistics Tróia '92, 1*, 767-778.

Goovaerts, P. (1997). *Geostatistics for natural resources evaluation*. New York: Oxford University Press.

Haycocks, C., & Aelick, R. C. (1992). Sublevel stoping. In H. L. Hartman (Ed.), *SME mining engineering handbook* (2nd ed., Vol. 2, pp. 1717-1731). Littleton, CO: Society for Mining, Metallurgy, and Exploration.

Isaaks, E. H., & Srivastava, R. M. (1989). *Applied geostatistics*. New York, NY: Oxford University Press.

JORC. (2012). Australasian code for reporting of exploration results, mineral resources and ore reserves (The JORC Code). Retrieved from www.jorc.org

Journel, A. G., & Huijbregts, C. (1978). *Mining geostatistics*. London: Academic Press.

Journel, A. G., & Kyriakidis, P. C. (2004). *Evaluation of mineral reserves: a simulation approach*. Oxford University Press.

Leuangthong, O., Neufeld, C., & Deustch, C. V. (2003). Optimal Selection of Selective Mining Unit (SMU) Size. *CCG Annual Report 05*. Retrieved from http://www.ccgalberta.com

Maptek. (2017, September). Vulcan - New grade control optimizer. Retrieved July 11, 2018, from https://www.maptek.com/forge/september_2017/vulcan_new_grade_control_optimiser.html

MSHA. (2016, December). Mine Employment and Coal Production - Historical MIWQ Employment and Production. Retrieved July 17, 2018, from https://www.msha.gov/sites/default/files/Data_Reports/Charts/Average_Number_of_mine_employees._mine_employee_hours_worked._and_coal_production_1978-2015.pdf

Neufeld, C., Leuangthong, O., & Deustch, C. V. (2007). A Simulation Approach to Account for the Information Effect. *CCG Annual Report 09.* Retrieved from http://www.ccgalberta.com

NI 43-101 (2011). National Instrument 43-101: Standards of Disclosure for Mineral Projects. Retrieved from www.cim.org

Rossi, M. E., & Deutsch, C. V. (2014). *Mineral resource estimation*. Berlin, Germany: Springer.

SEC (2016). Securities and Exchange Commission's Industry Guide 7. Retrieved from www.sec.gov

Sinclair, A. J., & Blackwell, G. H. (2002). *Applied mineral inventory estimation*. Cambridge University Press.

Vasylchuk, Y. V. (2016). *Integrated system for improved grade control in open pit mines* (Master of Science dissertation). Retrieved from https://library.ualberta.ca/catalog/7646899

Vasylchuk, Y. V., & Deutsch, C. V. (2017). Intelligent Grade Control – Overview. *CCG Annual Report 19.* Retrieved from http://www.ccgalberta.com