COMPARATIVE ANALYSIS OF 3D DOMAIN MODELLING ALTERNATIVES:
IMPLICATIONS FOR MINERAL RESOURCE ESTIMATES

by
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ABSTRACT

Domain modelling is a fundamental component of contemporary mineral resource estimation. There exist four major modelling techniques that are distinct with respect to method complexity, time and effort. A Comparative analysis is presented in this document constituting estimation of resources using 3D estimation domains generated with four different modelling approaches; (i) explicit modelling, (ii) implicit modelling, (iii) indicator kriging, and (iv) conditional simulation. Furthermore, identical grade estimation method and parameters are considered in order to demonstrate the discrepancies arising only from the choice of the domain modelling approach and underlying assumptions.

Comparison of the outcomes indicated the significance of the domain modelling decision on resource estimates of a polymetallic massive sulfide deposit located in western Turkey. Economic implications are demonstrated in the form of range of outcomes for the extends of the ultimate pit, ore tonnages (min:37.0 Mt, max: 46.7Mt), waste tonnages (min:201.2 Mt, max: 251.2 Mt), stripping ratios (min:5.18, max: 5.71), and total pit values (min: $1.05B, max: $1.45B).

The study showed that indicator kriging and simulation results are largely consistent with each other due to similar estimation criteria considered. Moreover, these two techniques resulted in notably larger volumes particularly for highly mineralized estimation domains compared to the ones generated with explicit and implicit modelling techniques. Examination of solid models as well as cross-sections revealed that major discrepancies are observed beyond outlying drillholes. Therefore, it has been proposed that assumptions regarding extrapolation distance is the main source of mentioned dissimilarities.
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CHAPTER 1
INTRODUCTION

Mineral resources are the primary assets of mining companies, and estimation of resources is an important task forming the basis of capital intensive investment decisions. It is apparently a challenging process calling for extensive expertise and input from several sources each of which introducing its related uncertainties. In this perspective, quantification of uncertainties associated with each component of estimation process is critical.

In the last decades, substantial role of quantitative analysis of geological risk and uncertainty in evaluating projects’ upside potential and downside risks has been realized. Studies indicated that mining companies have been severely impacted because of not meeting project expectations. As noted by Vallee (2000) “… in the first year of operation after start-up, 60% of mines surveyed had an average rate of production less than 70% of designed capacity”. Several other studies on mining projects also revealed that uncertainties related with the resource model are the one of the major contributors of mentioned shortfalls.

Identification of mineralization controls and subsequent three-dimensional geological modelling is an essential component of resource estimation. It is a complex process involving many unknowns and assumptions. Furthermore, geological modelling is important process having pronounced economic implications for the resource estimates.

There exists a variety of 3-D geological modelling alternatives representing differences in terms of complexity, time and effort involved. Traditional methods of geological modelling are those involving time-consuming manual digitization of geological boundaries. On the other hand, recent modelling techniques significantly reduce time and effort. The quality of the geological model is clearly important because it influences downstream mining practices. Selection of the modelling approach should involve consideration of not only complexity, time and effort but also the potential influences of the method on subsequent steps in the mining process.
1.1. Problem Statement

A typical resource modeling routine involves construction of stationary estimation domains which are representing statistically homogenous volumes ideally guided by knowledge about major mineralization controls. If we assume following ellipses represent alternative geological interpretations all honoring the drill hole intercepts, it is clear that uncertainty of geologic contacts, that is a natural outcome of our limited information, has a great potential to have profound implications on mineral resource estimates.

The problem can simply be illustrated as in Figure 1.1. DH-1 and DH-2 are two vertical drillholes for which mineralized intercepts are indicated with red. On the particular cross-section in Figure 1.1a, continuous blue line and dashed brown lines represent the two alternative geological interpretations both of which honor the mineralized intercepts observed in the drillholes but having certain differences in term of the area (and volume in third dimension) shown as green (A) and orange (B) colored portions in the figure above. Figure 1.1b illustrates an even more severe case where the two mineralized intercepts are interpreted to be belonging to en échelon veins.

In this perspective, decision of the geological modeling approach has a high potential to control the tonnage of the deposit. Moreover, slight variations in the mineralization geometry might significantly impact unplanned dilution. In cases where there exist pronounced differences in terms of metallurgical and geotechnical characteristics across geological domains, different geological interpretations might result in significantly different outcomes for the downstream
mining practices. Therefore, geological modeling efforts that are not capturing the geological variability of the deposit are likely to be suboptimal.

This study aims to address the question that how does domain modeling method utilized may influence mineral resource estimates. It involves consideration of identical grade estimation method and parameters with an objective to demonstrate the discrepancies arising only from the choice of the domain modelling approach and underlying assumptions.

1.2. Thesis Goal and Objectives

The primary objective of this thesis is to execute a comparative analysis of domain modelling alternatives. It is further aimed to document implications of each modelling routine on mineral resource estimation outputs of a polymetallic massive sulfide deposit located in western Turkey. Following are the goals set to achieve the objectives of the thesis:

- Identification of the major geological controls on mineralization
- Execution of modelling alternatives to generate three-dimensional representations of the deposit
- Estimation of mineral resources for each alternative scenario
- Comparison of resource estimates
- Address inconsistencies among outputs of different scenarios
- Quantify major risks arising from geological uncertainty
- Provision of conclusions

1.3. Thesis Structure

For ease of reference, the remainder of the thesis is divided into following major sections:

- Chapter 1 introduces the subject of the thesis and provides thesis goal and objectives as well as its outline
- Chapter 2 presents a literature review of various resource estimation techniques together with description of modelling alternatives
- Chapter 3 introduces the study area and describes the regional and local geology of the deposit
- Chapter 4 involves statistical and geostatistical characterization of the data and identification of the major mineralization controls
Chapter 5 covers the details of implementation of explicit modeling, implicit modeling, indicator kriging and conditional simulation in geological modelling of the deposit.

Chapter 6 deals with the aspects regarding resource estimation and classification.

Chapter 7 involves comparison of the outcomes and discussions.

Chapter 8 addresses the conclusions.
CHAPTER 2

BACKGROUND: GEOSTATISTICAL RESOURCE ESTIMATION

Mineral resource estimation is a challenging task calling for extensive expertise and contribution from several disciplines. It involves execution of a sequence of steps in construction numerical models using limited amount of data available about the deposit. Although there exists a variety of resource estimation techniques ranging in complexity, principle steps included in construction of resource models are common. It involves collection and validation of data, definition of geological constraints on mineralization, delineation of estimation domains, statistical and geostatistical analysis of the data, grade assignment using an appropriate estimation technique, and resource classification. Assessment of the uncertainty and validation of the results are also fundamental components of a typical resource modelling.

There are numerous unknowns and assumptions involved in modelling practice. Therefore, it is thought to be valuable to revisit and briefly summarize the primary steps and widely accepted techniques in terms of their application and limitations.

2.1. Data Validation

Data validation is the first and most crucial step in resource modelling because quality of the outcomes is directly related with that of the data. Therefore, validation of the data is needed to ensure the data to be used for resource estimation is clean, useful and consistent. The checks should ideally start in the field and generally cover sampling collection and preparation procedures, topographic and down the hole surveying as well as quality control and quality assurance practices. On the other hand, validation of resource database involves identification of numerical inconsistencies with basic validation routines and constraints. Some of the automated validation routines include from-to checks, stoichiometric checks and values within range checks.

2.2. Geological Constraints on Mineralization

Ore genesis is strongly controlled by complex geological processes. Thus, sound understanding of geology is an essential component in mineral resource estimation. It should also be emphasized that “a resource model with no geologic support is inadequate …” (Rossi &
Deutsch, 2014). Geological data gathered in different forms namely drillhole logs, products of geophysical investigations, surface and underground maps can be utilized in construction of 3D models representing geological characteristics of the deposit. This kind of models may also be particularly valuable in delineation of distinct geotechnical and metallurgical zones. Traditional method of constructing 3D geological models from input geological variables which relies on interpretation and manual digitization of cross-sections is known as explicit modeling. On the other hand, use of 3D interpolation functions in construction of geological surfaces forms the basis of implicit modeling techniques. Implicit modeling has several advantages over explicit modeling. For instance, three dimensional models of complex deposits can be generated in both time and cost-effective manner. Furthermore, larger datasets can be incorporated and data from various sources can be used in generation of a single model. However, none of these advancements eliminate the vital role of geologist in modeling practice.

Stationary is a property of random functions (Isaaks & Srivastava, 1989), and also the key condition for validity of the geostatistical models. Stationarity is also a requirement to make inference. In its simplest sense, it represents statistically homogenous populations (Rossi & Deutsch, 2014). Delineation of geostatistical stationary estimation domains is one of the challenging tasks of a resource geologist that necessitates understanding of deposit geology and statistical data characteristics. It is an iterative process calling for consideration of reasonable combinations of geological attributes and assessment of defined domains to assure representation of major mineralization controls.

An integral step of stationary domain definition is characterization of mineralization contacts. Sharp and gradational contacts are the two primary contact types. Sharp contacts are characterized by abrupt changes in mineralization grades across contact (Figure 2.1). On the other hand, gradual change of grades represents gradational contacts (Figure 2.1).

![Figure 2.1 Sketch illustrating sharp and gradational contacts (Abzalov, 2016)](image-url)
Contact analysis is performed with construction of diagrams representing grade distribution profiles as a function of distance from contact. The ultimate objective of contact analysis is to determine the estimation strategy. Hard boundary approach is usually applied to deposits that are characterized by sharp contacts. On the other hand, soft boundary approach is preferred for deposits with gradational contacts.

Estimation of dilution and mining losses calls for quantification of uncertainty associated with the contacts. Conditional simulation techniques enable generation mathematically equiprobable contact models which was not possible with deterministic models. Outputs of conditional simulation capture the original variability of input data hence a better representation of the reality.

Spatial data availability compounded with intrinsic variability usually results in higher uncertainty along contacts as illustrated in Figure 2.2. It is a significant issue because reliability of tonnage estimates directly depends on that of estimation domains. Therefore, quantitative analysis of contacts through geologic interpretational and conditional simulation techniques is substantially important.

![Figure 2.2 An illustration of higher uncertainty near contact (Rossi & Deutsch, 2014)](image)

2.3. Exploratory Data Analysis

Sound understanding of the data and mineral deposit is an essential foundation for resource modelling. Tradition statistical techniques serve as effective data analysis tools that help enhance understanding of the data and ensure data quality. The data analysis is also substantial for selecting the most appropriate estimation method.
Equal sample support is the primary requirement of the data analysis i.e., samples should represent equal volume. Therefore, a special treatment known as compositing is performed to regularize the sample support. There are various compositing methods. However, bench compositing and downhole compositing are the most commonly applied ones. A key consideration about compositing is selection of the compositing length. Abzalov (2016) suggests the chosen composite size to be larger than average sample length and approximately equal to half of the block size.

Frequency table and histogram are the most common presentations of univariate data i.e., data of a single variable (Figure 2.3). Probability plots are other univariate data analysis tools and are utilized to identify the distribution and assess presence of multiple populations (Figure 2.3). Summary statistics is useful as a descriptive tool that is capable to capture key features of the data presented by histograms.

Correlations and dependencies between variables sometimes help improve understanding of the data. The methods that are utilized in the analysis of relationship between two variables are in the scope of bivariate statistics. Scatter plots are used in comparison of different variables, facilitate detection of clusters and identification of outliers. The relationship between variables are quantified by correlation coefficient ($\rho(h)$). Q-Q plots and P-P plots are practical tools to compare
distributions of two variables. Together with scatterplots, these are also effective instruments for error checking.

An important aspect of analysis of earth science data is clustering. Considering the resources available for exploration, there is a natural tendency towards preferentially sample higher-grade zones. It is an effective and legitimate strategy to allocate limited exploration resource to delineate high potential areas faster. However, clustering introduces bias to both statistical analysis and variography. Declustering is the method by which influence of data clustering is overcome by assigned weights which are representative of data clustering.

Cell declustering technique divides the sample space into regularly sized cells (Figure 2.4). The weights are assigned to data based on the number of data within the cell $n$, and number of occupied cells $L$ as follows:

$$w = \frac{1}{n \times L} \tag{2.1}$$

The weight calculated in this way are greater than zero and sum to one.

Figure 2.4 Cell declustering technique (left), plot of declustered mean vs. cell size (right) (Rossi & Deutsch, 2014)

The estimate of weights obtained by cell declustering method is not unique and depends on the cell size chosen. Plot of declustered mean vs cell size is an effective tool in selecting the optimum cell size (Figure 2.4).
As it is the most common case in mineral exploration, high grade areas are preferentially sampled which result in overrepresentation of those areas. Our purpose is to prevent potential overestimation by declustering. Therefore, the optimum cell size is selected to be the one for which minimum declustered mean is obtained as shown in Figure 2.4. The opposite applies in a case where low-grade area is preferentially sampled for a particular purpose.

Cell declustering perform well with the sample locations following a pseudo regular grid. When it is not the case, polygonal declustering can be considered (Figure 2.5). It is a technique by which declustering weights are assigned proportional to the area of polygons.

![Polygonal declustering technique and declustering weights](image)

Figure 2.5 Polygonal declustering technique and declustering weights (Abzalov, 2016)

Another declustering technique is nearest-neighbor. It is applied to a regular grid of nodes or blocks. With this technique closest datum is assigned to each grid block or grid node.

Analysis of local spatial behavior of the data is also concerned in exploratory data analysis. Moving window is a useful tool to understand local mean and local variability across sampling space. When the local mean and variance are found to be correlated, it is called as proportional effect. Presence of proportional effect may indicate skewed data, lack of spatial homogeneity or presence of spatial trends (Rossi & Deutsch, 2014). When it is not treated appropriately, it may lead to distortions in variograms making their interpretation more difficult.
2.4. Variography

Spatial continuity or variability is an essential concept for geostatistical studies. Mineral deposits are generated through successive geological processes. Most of the time, physical and chemical factors that are controlling ore genesis result in distinctive patterns of spatial correlation. Quantitative description of spatial continuity is fundamental in geostatistics.

The most obvious way to compare two values $Z(u)$ and $Z(u+h)$ whose locations are separated by $h$ (certain distance in a particular direction) is to take the difference, $[Z(u) - Z(u+h)]$. Then, plots can be generated by pairing all possible data values that are separated by a lag distance “$h$” along a particular direction. These diagrams are known as h-scatterplots (Figure 2.6).

![Figure 2.6 Data pairing and h-scatterplots for three separation distances (Abzalov, 2016)](image)

In essence, samples located closer to each other are more likely to have similar values than those located further apart. Therefore, the shape of cloud of points gets more diffuse as the similarity decreases with increasing separation distance as it is observed in Figure 2.6. Correlation coefficient ($\rho(h)$) makes quantification of information presented on a h-scatterplot. The relation between correlation coefficient and distance along a particular direction can be analyzed with plots that are known as correlation function or correlogram (Figure 2.7). Correlogram is a measure of spatial continuity, and calculated as:
\[
\rho(h) = \frac{E[(Z(u) - m) + (Z(u+h) - m)]}{\text{Var}(Z)}
\]

(2.2)

\[
m = E[Z(u+h)] = E[Z(u)]
\]

(2.3)

A similar measure of spatial continuity is the covariance function. The plots representing
the relationship between covariance and distance is known as covariance function (Figure 2.8).
Covariance is calculated as:

\[
C(h) = E[(Z(u) - m) \times (Z(u + h) - m)]
\]

(2.4)

Figure 2.7 Correlogram (left) versus covariance function (right) (Caers, 2011)

Moment of inertia is another index to quantify the spread of point cloud around y=x line.
The plot representing the relationship between moment of inertia and separation distance is
traditionally called as semivariogram or simply variogram. Variogram is a measure of dissimilarity
of data values expressed as a function of increasing separation distance. It is calculated as:

\[
\gamma(h) = \frac{1}{2} E[(Z(u) - Z(u + h))^2]
\]

(2.5)

For a stationary case, following relationships exists between variogram (\(\gamma(h)\)), covariance
(C(h)):

\[
\gamma(h) = C(0) - C(h) \quad \text{or} \quad C(h) = C(0) - \gamma(h)
\]

(2.6)

Constant and location independent mean and variance is the model decision forming the
basis of this relation (Rossi & Deutsch, 2014).
Nugget effect, sill and range are the principal features of the variogram (Figure 2.9).

At the origin where the separation distance \( (h) \) is zero the value of the semivariogram is also zero. However, sampling errors or small-scale variability in the data values may result in a discontinuity in the origin which is known as nugget effect. The semivariogram value is continuously increasing with increasing distance. Then it reaches a plateau and flattens. The value of the plateau is called as sill. The distance at which variogram flatten out and beyond which samples are spatially uncorrelated is known as range.

Unfavorable field conditions make it difficult to find data pairs that are located separated exactly by the same distance. Therefore, reasonable tolerances need to be specified for both distance and direction. It is also common practice to introduce a limit for the bandwidth (Figure 2.10).
Any sample falling within an area defined by lag distance, azimuth and associated tolerances would be paired with the sample at the origin.

For any particular separation distance, all the pairs are considered for all possible directions in an omnidirectional variogram for which angular tolerance is 90°. Due to large number of data pairs, omnidirectional variograms are generally well-behaved and easily interpretable giving early warning for erratic directional variograms (Isaaks & Srivastava, 1989).

As the name implies, downhole variograms are constructed along down the hole direction hence adjacent samples are considered. Therefore, it provides a good estimate of nugget effect as well as short scale continuity (Rossi & Deutsch, 2014).

2.5. Anisotropy

In many mineral deposits, the data values represent more continuity along certain direction than others. This concept known as anisotropy. Geometric anisotropy is primarily concerned type of anisotropy for which range of variograms are different for different directions. On the other hand, zonal anisotropy represents the case where sill of the variogram changes with direction.

Directional variograms are utilized to identify anisotropy potentially existing in the data. Conventional approach in finding major anisotropy axis rely on construction of directional variograms in several directions and tracing one of the contours. These types of plots are known
as rose diagrams and represent elliptical shapes in the case of anisotropy. The diagrams representing several contours of variogram values are known as variogram contour maps. An alternative tool to quantify spatial anisotropy is the variogram map which is a 2D diagram representing variogram values for different distances (Figure 2.11).

![Variogram map and contour map](image)

Figure 2.11 Variogram map (left) and contour map(right) showing anisotropy directions (Abzalov, 2016)

Longest continuity direction on either rose diagram, variogram contour map or variogram map is the direction along which largest range value is observed. Similarly, minimum continuity direction is the one along which range gets the smallest value.

2.6. Model Fitting

Spatial continuity is effectively described by experimental directional variograms. However, solution of the kriging system might necessitate knowledge of variogram values for some distance or direction for which we do not have a sample variogram value (Isaaks & Srivastava, 1989). Therefore, special models that can be utilized to derive variogram values for any possible vector is needed. Positive definiteness is the condition for a function to be a valid variogram model and it guarantees the solution to exist and be unique.

Nugget effect, spherical, gaussian, exponential and linear are the basic models that are characterized by different behaviors and functions (Figure 2.12).
It is not necessary to model the sample variogram using just one of the basic models. Owing to the fact that any linear combination of positive definite models, called as nested structures, also satisfies the condition of positive definiteness, two or more models can be linearly combined to improve representativeness of sample variogram by the model. However, it is often recommended to keep the model as simple as possible while capturing necessary detail in the sample variogram.

2.7. Estimation Criteria

Assessment of the performance of different estimation methods relies on comparison of estimates ($\hat{v}$) with true grade values ($v$). Such a comparison is a straightforward process when the performance is assessed for estimation at a single point. On the other hand, some estimation criterion is needed for comparing estimates at several locations. A perfect estimation method is the one that yields estimates matching the true values. However, all methods involve some error no matter how sophisticated it is. Therefore, a method is adequate as long as it produces estimates that are very close to the true values. Error can simply be defined as the difference between estimate and true value at a given location. It is also often referred as residual. Univariate and bivariate statistical tools can be utilized to assess the performance of estimation methods. Ideally, estimation should result in residuals whose distribution centered at zero. This represents absence of clear estimation error hence referred as unbiasedness condition.
Figure 2.13 Hypothetical error distributions; underestimation (left), overestimation (middle) and no bias (right) (Isaaks & Srivastava, 1989)

Figure 2.13 represents three hypothetical error distributions. Mean of the residuals for the histogram in the left is negative which is referred as underestimation. The histogram in the middle illustrates the opposite case, thus it is overestimation. Mean of the residuals are centered at zero for the histogram on the right so no bias is evident.

It is also preferable that the error distribution is symmetric and has a small spread. Median and variance of error distribution are good checks on symmetry and spread, respectively.

Figure 2.14 Three different hypothetical error distributions; skewed distribution (left), symmetric distribution with small spread (middle), symmetric distribution with large spread (Isaaks & Srivastava, 1989)

Mean absolute error and mean squared error are two summary statistics incorporating both bias and spread of error distribution. They are defined as:

\[
Mean\ Absolute\ Error = MAE = \frac{1}{n} \sum_{i=1}^{n} |error| \tag{2.7}
\]

\[
Mean\ Squared\ Error = MSE = \frac{1}{n} \sum_{i=1}^{n} error^2 \tag{2.8}
\]

It is also significant to assess the performance of an estimator for full spectrum of estimates because global unbiasedness does not guarantee unbiasedness at different scales. It is known as
conditional unbiasedness and can be diagnosed from scatterplots of estimates versus the true values (Figure 2.15).

![Conditional Bias](image)

Figure 2.15 Conditional bias. Globally unbiased but conditionally biased estimates (left), both globally and conditionally unbiased estimates (Isaaks & Srivastava, 1989)

2.8. Search Neighborhood

Kriging strategy involves decisions about size and shape of the search neighborhood as well as restrictions to prevent redundancy and ensure relevance of nearby samples to be used in estimation. Shape of the search neighborhood is a decision that is guided by variogram analysis. It is usually an ellipse whose major axes align with the anisotropy pattern. On the other hand, size of the search neighborhood is a function of both variogram range and data spacing along with the relative nugget i.e., the ratio of nugget variance to total variance. Quadrant search is a customary practice that is utilized to deal with possible redundancy of samples. It typically involves definition of maximum and minimum number of samples for any particular quadrant.

Kriging is often described as best, linear, unbiased estimator minimizing the error variance. Vann et al. (2003) emphasized that kriging is the minimum variance estimator only when kriging search neighborhood is properly defined. Determination of search strategy is a critical process having substantial impacts on the quality of outcomes. It is not an arbitrary decision rather calling for quantitative criteria to optimize search neighborhood.

Overly-restricted search neighborhoods result in conditional bias (Krige 1994, 1996, Vann et al., 2003). Therefore, kriging neighborhood analysis involves quantitative measures to minimize conditional bias through optimizing search neighborhood. Following are some of the most
commonly utilized evaluation criteria in quantitative kriging neighborhood analysis outlined by Vann et al. (2003):

- Kriging variance
- Slope of regression for true values and associated estimates
- Proportion of negative kriging weights
- Weight of the mean value for simple kriging

Kriging variance is also referred to as estimation error and was proposed as a criterion to optimize neighborhood. It depends on data configuration and variogram model but independent of individual data values. It is an effective tool giving an idea about relative quality of estimation in which search neighborhood resulting in lower kriging variance is more favorable.

Perfect estimation is the one for which the estimates exactly matching corresponding true values. Therefore, it makes slope of regression to be equal to 1. Departure from unity for slope of regression is a good check for degree of bias. Slope of regression \( \left( \rho(Z_v | Z_v^*) \right) \) is defined in term of covariance \( \text{Cov}[Z_v, Z_v^*] \) and variance \( \text{Var}[Z_v^*] \) for true \( Z_v \) and estimated values \( Z_v^* \):

\[
( \rho(Z_v | Z_v^*) ) = \frac{\text{Cov}[Z_v, Z_v^*]}{\text{Var}[Z_v^*]} 
\]

(2.9)

It can also be expressed in terms of correlation coefficient (r) and standard deviations (StD) as:

\[
( \rho(Z_v | Z_v^*) ) = r \times \frac{\text{StD}(Z_v)}{\text{StD}(Z_v^*)} 
\]

(2.10)

Proportion of negative kriging weights is another quantitative criterion proposed to optimize search neighborhood. Negative weights in kriging arise as a result of screening effect. Vann et al. (2003) suggests that it is not problematic as long as negative weights represent a small proportion (<5%). One of the objectives of quantitative kriging neighborhood is therefore to find most optimum search neighborhood that minimizes percentage of negative weights.

Weight of the mean value in simple kriging is yet another measure of kriging quality. It is a measure of weakness of screening effect and suggested to be close to zero for better quality estimation.
2.9. Grade Estimation

Traditional or classical estimation methods are a family of non-geostatistical methods including polygonal method, nearest-neighbor, triangulation, cross-sectional method, and inverse distance weighting. They are useful tools for preliminary assessment of the resources providing order-of-magnitude estimates.

Polygonal method is a 2-D estimation technique applicable for tabular deposits. Construction of polygonal area of influence around drillholes and grade and thickness of the drillhole is extrapolated to the surrounding polygon. Nearest-neighbor is a variant of polygonal method. In this technique, the grade of the nearest data is allocated directly to blocks in the block model. Both methods provide unsmoothed estimates. Consequently, artificial discontinuities are produced. An alternative estimation method is triangulation that overcomes this limitation. Triangulation is based on joining adjacent drillholes to form triangles. Then, the drillholes located in the vertices are used to estimate resources of associated triangular area. In this method, results of the estimation depend on the triangulation method.

Polygonal method and triangulation becomes ineffective when dealing with deposit with complex shapes. In such cases, cross-sectional methods can be considered as an alternative technique. Cross-sections are generated along traverses and either extrapolated half distance between drillholes or linked to form wireframes (Figure 2.16).

![Figure 2.16 Cross-sectional estimation method (Abzalov, 2016)](image)

Inverse distance weighted is a weighted estimation method where weights are inversely proportional to a power of distance between sample and target location, \( d_i \). The weights, \( \lambda_i \), are calculated as follows:
\[
\lambda^i = \frac{1/d_i^q}{\sum_1^N 1/d_i^q}
\]  

(2.11)

Although choice of power is arbitrary, inverse distance square i.e., power of two, is most commonly used one.

Kriging is a linear geostatistical interpolation technique where the weights are derived from variogram model (Krig 1951; Matheron 1963, 1968). It is considered as “best linear unbiased estimator” since estimates obtained by the solution of kriging system are weighted linear combinations of samples within a specified neighborhood. It is unbiased because mean of the residuals is tried to be equal to zero and kriging weights adding to one. The distinguishing feature making it “best” among other methods is minimization of the error variance.

Some of the variable definitions used in geostatistics are as follows:

\[Z(u_i)\] – the data value of each sample

\[Z^*(u)\] – the estimate at target location

\[\lambda_i\] – kriging weights of each sample

\[\mu\] – the Lagrange parameter

\[C\] – the covariance matrix between sample points

\[W\] – the weight matrix

\[D\] – the covariance matrix between sample locations and the target point

The kriging system can be written in matrix notation as:

\[
\begin{bmatrix}
C_{11} & \cdots & C_{1n} & 1 \\
\vdots & \ddots & \vdots & \vdots \\
\vdots & \ddots & \vdots & \vdots \\
C_{n1} & \cdots & C_{nn} & 1 \\
1 & \cdots & 1 & 0
\end{bmatrix}
\begin{bmatrix}
\lambda_1 \\
\vdots \\
\vdots \\
\lambda_n \\
\mu
\end{bmatrix}
= 
\begin{bmatrix}
\lambda_1 \\
\vdots \\
\vdots \\
\lambda_n \\
\mu
\end{bmatrix}
\begin{bmatrix}
C_{10} \\
\vdots \\
\vdots \\
C_{n0} \\
1
\end{bmatrix}
\]  

(2.12)
Then, the solution of the kriging system gives the kriging weights as follows:

\[ W = C^{-1} \ast D \quad \text{(2.14)} \]

Kriging is a geostatistical method based on theory of regionalized variables and stationarity is the central concept. Three main classes of kriging are linear univariate, multivariate and non-linear kriging. Ordinary and simple kriging are the two linear univariate kriging techniques that are readily applicable for data characterized by a non-skewed distribution. Co-kriging and its variants are the multivariate kriging techniques that make integration of data into a single coherent model possible (Journel and Huijbregts 1978; David 1988; Goovaerts 1997). Disjunctive kriging, Uniform Conditioning and various varieties of indicator kriging are the non-linear kriging techniques all of which rely on non-linear transformation of data. Multiple indicator kriging is a particularly effective variant of indicator kriging techniques for estimating resources of a deposit characterized by multiple populations with different spatial trends (Journel & Huijbregts, 1978).

Risk and uncertainty are becoming increasingly concerned in mining industry. Traditional geostatistical tools those including several types of kriging lack the ability to address these issues. Additionally, unavoidable smoothing effect associated with kriging estimates results in misrepresentation of original variability. Conditional simulation, on the other hand, is a more sophisticated stochastic simulation technique that provides several equally probable realizations of the model through utilization of kriging and Monte Carlo sampling approach (Figure 2.17). Therefore, it provides ability to quantify uncertainty. Realizations of conditional simulation honor conditioning hard data in term of both statistical (i.e., reproduce the histogram) and geostatistical characteristics (i.e., reproduces the variogram).

Figure 2.17 Comparison of interpolation and simulation estimates (Rossi & Deutsch, 2014)
Conditional simulation is applicable for both continuous variables (e.g. grade, thickness and deleterious components) and categorical variables (e.g. geological structures and lithofacies). Although there are variety of conditional simulation techniques available, Sequential Gaussian Simulation (SGS) and Sequential Indicator Simulation (SIS) are the two most commonly utilized methods. Sequential Gaussian Simulation is a Gaussian-based technique that requires transformation of the data into standard Gaussian space. The main limitation of this technique is about its applicability on highly skewed data. Sequential Indicator Simulation, on the other hand, overcomes this limitation and it depends on transformation of data into indicators considering prespecified cut-off values.

Similar to kriging, exploratory data analysis is the first and essential step in conditional simulation. It is followed by definition of random path along which grid nodes will be simulated. Based on which technique employed, data is transformed into either gaussian or indicator variable. Later, an estimated is generated by kriging and conditional cumulative distribution function is constructed at chosen location. Then a simulation value is randomly drawn from conditional cumulative distribution function and assigned to the simulated node. Once estimation is completed for all the nodes in the simulation grid, the values are back-transformed from gaussian to original space. Lastly, reproduction of histograms and variograms are verified for validation purposes.

2.10. Recoverable Resources

Accurate estimation of tonnage and grade in a resource model necessitates consideration of several types of dilution. Geologic contact dilution, operational mining dilution and internal dilution are the main sources of dilution.

Geologic contact dilution is also referred to as external dilution. It is the type of dilution that arises when waste outside of the orebody extracted with the mining block. The degree of external dilution is governed by the orebody geometry, blasting practices and mining selectivity. Sub-cell method and direct calculation of proportions of each unit within each block are the two alternative methods by which external dilution can be incorporated into the model (Rossi & Deutsch, 2014).
Operational mining dilution is often a planned dilution source that occurs at the time of production and can simply be estimated through geometric calculations.

Internal dilution is the type of dilution resulting from resource estimation at a support (volume) which is different than that of original data. Block size is a crucial decision in resource estimation. It primarily depends on data spacing. Journel and Huijbregts (1978) suggest 1/3 to 1/2 of data spacing to be an appropriate size to utilize available resolution and prevent artificial smoothing. Height of the blocks is typically a function of operational parameters and mining method. However, estimation of recoverable resources often necessitates consideration of a smaller support representing mining selectivity. It is known as smallest mining unit (SMU) and depends on many factors including mining method, available data and equipment size.

It is a well-known fact that variability at larger support is less than that in of smaller support (Figure 2.18). This is a concept commonly known as volume-variance relationship. Change of support methods are utilized to achieve representative distribution for a specific mining selectivity. Following equation is known as Krige’s additivity relationship which forms the basis of change of support techniques.

\[ D^2(v, G) = D^2(v, V) + D^2(V, G) \]  

(2.15)

where \( D^2(v,G) \), \( D^2(v,V) \), and \( D^2(V,G) \) represent dispersion variance for different scenarios and \( v \), \( V \), \( G \) stands for increasingly larger support.

Figure 2.18 Volume-variance relationship (Rossi & Deutsch, 2014)
Depending on the nature of correction, they are classified as global or local change of support methods. Global change of support methods is those allowing to infer grade-tonnage relationship at a target support from sample data. On the other hand, local change of support methods allows estimation of recoverable resources within each mining panel (Abzalov 2006, 2016).

Affine correction, indirect lognormal and discrete gaussian change of support are the global change of support techniques. They achieve volume-variance correction through utilizing the link between support effect and spatial continuity. Therefore, variogram is an effective tool in assessment of change of support.

Affine correction is a global change of support technique that is limited to non-skewed data. Permanence of distribution shape is the primary assumption of this methods. It allows calculation of quantile for target distribution \( q' \) in terms of quantile of the input distribution \( q \), mean of both distributions \( m \) and variance correction factor \( f \) as follows:

\[
q' = \sqrt{f} \ast (q - m) + m
\]

(2.16)

Variance correction factor in this equation is also referred to as variance adjustment factor, and it represents the ratio of variance at target support to total variance.

Indirect lognormal correction is an alternative global change of support technique that overcomes limitation of affine correction. Transformation of the quantiles for a positively skewed distribution is in the form of an exponential equation as follows:

\[
q' = a q^b
\]

(2.17)

where the coefficients \( a \) and \( b \) are defined as:

\[
a = \frac{m}{\sqrt{f + CV^2 + 1}} \left[ \frac{\sqrt{CV^2 + 1}}{m} \right]^b
\]

(2.18)

\[
b = \frac{\ln(f + CV^2 + 1)}{\ln(CV^2 + 1)}
\]

(2.19)

One of the primary features of change of support methods is to leave mean of the distribution unchanged. Therefore, indirect lognormal correction technique necessitates rescaling of the transformed values so that the mean of distributions match. This final adjustment is defined mathematically as:
\[ q^* = \frac{m}{m'} q' \]  
(2.20)

where \( m' \) represents the mean of transformed values while \( m \) is the mean of original distribution.

Discrete gaussian is the most sophisticated global change of support technique for which Hermite polynomial expansion is used to express the distribution of SMU grades. It is also applicable to skewed data and involves correction through transformation of distributions for different supports to Gaussian units.

Uniform conditioning and localized uniform conditioning are the local change of support methods that involve estimation of recoverable resources for each mining panel (Abzalov, 2016). Uniform conditioning is a non-linear geostatistical technique by which tonnage and grade for SMU size blocks constituting larger panels are calculated. However, actual locations of these small blocks are not specified with this method. On the other hand, localized uniform conditioning (LUC) was proposed by Abzalov (2006) in order to overcome this limitation of uniform conditioning technique. LUC is a robust method allowing accurate production of grade-tonnage functions. It involves partitioning of the panels into SMU size blocks and then ranking them in increasing order of grade (Abzalov, 2006).

2.11. Model Validation

Validation of resource model is needed to ensure internal consistency as well as global and conditional unbiasedness. It can be conducted using various statistical and graphical tools. Comparison of histogram and summary statistics for estimates and input data of each domain allows to verify global unbiasedness. Similarly, histogram of residual errors and scatterplot of estimate versus true value are useful to check for validity of global estimates. On the other hand, conditional unbiasedness condition is assessed through validation of local estimates for which density of the data distribution is a major factor. Spider diagram is a useful tool to validate the local mean. It enables comparison of average grades of both estimate and input data along different directions. It is also particularly effective to check presence of systematic bias which will be represented as consistent over or underestimation in the spider diagrams. Contour map of residuals can also be utilized for similar purposes.

Graphical validation techniques rely on visual comparison of estimates with input data on graphical plots of sections and plans. Comparison of kriged blocks with drillhole intersections is a
simple but powerful tool to assess the degree of smoothing. Excessive smoothing is a serious issue which can also be diagnosed from grade-tonnage curves.

Cross validation is an alternative technique used in resource model validation as well as comparison of different variogram models and search strategies. It depends on comparison of the estimates obtained at successively removed sample locations with true values. Therefore, it allows assessment of estimation errors only where information is available. Through utilization of aforementioned statistical and graphical tools, cross-validation can be used as a both qualitative and quantitative validation instrument. In most practical applications, misclassification might result in much more profound consequences than inaccurate estimation. In those cases, cross validation techniques can be utilized in examination of goals of the study as a goal-oriented tool.

![Figure 2.19 Misclassification due to information effect (Vann et al., 2003)](image)

There is always a risk of misclassification because ore/waste classification is done based on estimates rather than true values. Therefore, minimization of misclassification might be a much more relevant criterion to judge the goodness of estimates that various other statistical criteria (Isaaks & Srivastava, 1989). The points in quadrant I and III in Figure 2.19 are misclassified. On
the other hand, those in the other two quadrants are correctly classified despite the estimates are not the same as the true values.

Validation of grade estimates is the primary target with the previous validation procedures. On the other hand, there are some other procedures which deals with accuracy of tonnage estimates. Validity of geological interpretations is the main factor in accuracy of tonnage estimates. Therefore, auditing and confirmation of validity of interpretations as well as subsequent extrapolation procedures are essential.

2.12. Resource Classification

Resource models are one of the primary assets of mining companies. In most mining jurisdictions, publicly listed mining companies are required to comply with certain principles in their public disclosures. Transparency, materiality and competence are the fundamental principles that are common almost for all reporting codes that are related with disclosure of mineral resources. Specific need of different mining jurisdictions resulted in development of a variety of reporting systems (Rossi & Deutsch, 2014). Among those, JORC Code (Australia), NI 43-101 (Canada), SAMREC (South Africa) and SEC Industry Guide 7 (United States) are the most widely used ones.

In all of the jurisdictions mentioned above, resources are classified as inferred, indicated and measured in order of increasing level of geological knowledge and confidence (Figure 2.20).

![Figure 2.20 Relationship between exploration results, mineral resources and ore reserves (JORC Code, 2012)](image-url)
Reporting codes provide the definition of mineral resource and distinct resource categories. They also attach non-prescriptive guidelines. Inferred category represents the lowest level of confidence among three and is not allowed to be converted to mineral reserves. On the other hand, indicated and measured resources have higher level of confidence sufficient to be converted into reserves through application of “the Modifying Factors”. Modifying factors include a set of technical, economic, legal and social factors to be considered for conversion of resources to reserves.

There exists a variety of resource classification techniques that are based on different criteria. Traditional geometric methods of resource classification use distances to drill holes, number of samples used for estimation, multi-pass kriging estimation and reasonable combinations of these (Rossi & Deutsch, 2014). An alternative resource classification technique is use of methods based on kriging variance. However, limitations of all these methods motivated development and application of conditional simulation in resource classification.

The technique which uses distance to drill holes has two varieties. The resource classification is based on either distance from nearest sample or average distance of all samples used in interpolation. It is also a common practice to consider the number of samples within defined search neighborhood as a criterion. Multi-pass kriging technique relies estimation of resources at several kriging iterations with different levels of restrictions generally defined in terms of different search neighborhood and minimum number of samples (Rossi & Deutsch, 2014). Use of kriging variance is a different approach to construct confidence intervals. In this method, error arising from estimation is the criteria used in classification. However, its application is limited with normally distributed data. Additionally, misleading results may result in the presence of proportional effect.

Conditional simulation is becoming increasingly popular as a resource classification tool. It quantifies the grade confidence considering data configuration and continuity (Glacken & Snowden, 2001). Therefore, conditional simulation allows systematic and quantitative definition of principle aspects considered in resource classification; volume, measure of uncertainty and confidence represented as the probability to be within limits defined by uncertainty (Figure 2.21).
Volume is the first aspect considered in resource classification and it represents a certain production amount corresponding to a time increment such as annual or quarterly production rate. Measure of “+/−”uncertainty and confidence interval, on the other hand, are used to express variability of grade and probability to be within particular interval.

Following is a summary of the quantitative guidelines widely accepted in industry for resource classification (Parker & Dohm, 2014):

**Inferred:** mineral resource category characterized by presence on insufficient geological information to establish confidence levels

**Indicated:** mineral resource that is predicted to be ± 15% of the predicted grade 90% of the time over an annual production increment

**Measured:** mineral resource that is predicted to be ± 15% of the predicted grade 90% of the time over monthly or quarterly production increment
CHAPTER 3
GEOLOGY OF THE DEPOSIT

The volcanogenic massive sulfide type polymetallic mineralization of the case study is located in western Turkey. A Turkish mining company and an international mining company have 50/50 ownership of the property through their joint venture company. The deposit has been discovered as a result of geochemical stream sampling program that has been completed in 2011. In June 2011, the licenses have been transferred to the JV company which is the current operator for the project. This chapter mostly relies on information provided in geology section of the prefeasibility report published in 2016.

3.1. Regional Geology

Amalgamation of several continental fragments which were once separated by narrow oceanic seaways of Tethys ocean resulted in a single landmass, Anatolia. Pontides, Anatolides-Taurides and Arabian Platform are the three main tectonic units representing either Laurassian or Gondwana affinities that comprise the geology of Turkey (Ketin, 1966).

The Pontides exhibit Laurassian affinity, and are located north of Izmir-Ankara-Erzincan suture zone that formed as a result of complete closure of northern branch of Neo-Tethys ocean. The Anatolides-Taurides show Gondwana affinities, and were detached from Gondwana by southern branch of Neo-Tethys. The Arabian platform is the other major tectonic unit, and is in contact with the Anatolides-Taurides along the Assyrian suture.

The study area is located within Afyon Zone. It is ascribed as a belt by Okay (1985) that is located between Menderes Massif and the Tavşanlı Zone (Figure 3.1). On the other hand, Goncuoglu (2007) describes the Afyon Zone as a part of Kutahya-Bolkardag Belt which represents the north-facing passive margin of the Tauride-Anotolide Platform.

Relatively northern units that are located immediately south of the Neo-Tethys ocean constitutes a distinct high-pressure/low-temperature metamorphic belt called as Tavşanlı Zone. On the other hand, Afyon Zone comprises southerly located low-grade medium to high pressure metamorphic units of Kutahya-Bolkardag Belt.
3.2. Local Geology

Local geology of the study area comprises a variety of rock types that formed as a result of a series of major tectonic events closely related with the evolution of the Tethys ocean. Figure 3.2 presents the geological map of the study area and its near vicinity together with the license boundary indicated close to the center of the map.

Paleozoic metamorphics consisting of gneiss, schist, mica schist, amphibolite, marble, phyllite and quartzite are tectono-stratigraphically the lower most unit in the study area (Figure 3.3). This unit is tectonically overlain by Triassic carbonates and Upper Cretaceous ophiolitic mélange which is characterized by presence of olistostromal blocks and ophiolite sections.

Oligocene-Lower Miocene granitic intrusions are comprised of units that are products of extensional tectonism and associated magmatic activities. It consists of granite porphyries and aplitic dikes, and represents cross-cutting relationship with the units belonging to Paleozoic metamorphics, Triassic carbonates and Upper Cretaceous ophiolitic mélange.
Such a magmatic activity resulted in abundant skarn and hornfels formation along the contact of Paleozoic metamorphic rocks and carbonaceous units belonging to Upper Cretaceous ophiolitic mélange, respectively.

All these units are stratigraphically overlain by Lower Miocene felsic to intermediate volcanics represented by andesite and dacite complex intrusions, dykes, domes, lava flows and
volcanogenic sedimentary rocks. Among those pyroclastics are the most abundant volcanic rocks particularly represented by ignimbrites. Pliocene terrestrial sediments and Quaternary alluvial deposits sourced from the older lithologies unconformably overly all the units mentioned earlier.

3.3. Deposit Geology

The deposit is a polymetallic volcanogenic massive sulfide deposit (VMS) hosted by Paleozoic metamorphic units. Among those quartz schist, chlorite-sericite schist and quartz-feldspar schist are the most distinct lithologies outcropping around the region (Figure 3.4). Lower-Middle Miocene volcanics are the second most abundant unit and particularly observable towards southwest of the deposit.

![Figure 3.4 SE-NW geological cross section](image)

Quartz schist is beige-grey to beige-pale green colored unit which is characterized by abundance of quartz porphyroblasts. This unit represents stratigraphically the lower most unit in the study area.

Chlorite-sericite schist is the primary host lithology for ore and is consisting of minerals including quartz, calcite, chlorite, muscovite and sericite. It is green to dark green colored and presents a well-developed schistosity. Pyrite-chlorite-sericite schist is used by the company to describe the parts of chlorite-sericite schist with a pyrite abundance greater than 15-20% by volume.
Quartz-feldspar schist is stratigraphically the uppermost unit. It is the unmineralized, beige-pale green colored hangingwall lithology that is characterized by the presence of feldspar and quartz porphyroblasts.

3.4. Mineralization

The polymetallic massive sulfide mineralization is hosted by metamorphic units exhibiting evidence for greenschist facies metamorphic conditions. Among those units, chlorite-sericite schist is the primary host lithology.

Exposed and near surface parts of the deposit is weathered and oxidized as a result of interaction with meteoric water. In this oxide zone, meteoric water leached copper and zinc. The intensely oxidized leached out parts of the sulfide body are named as gossan zone, associated with elevated gold and silver grades especially along the sulfide-oxide contact.

The sulfide zone represents other the major zone of the deposit which is characterized by two primary ore types namely massive pyrite and massive pyrite magnetite. These two names are used to describe those parts of the deposit where mineralization completely overprints the host lithology. Primary ore minerals observed in the sulfide zone includes sphalerite and chalcopyrite while pyrite, tetrahedrite, tenantite, galena and magnetite constitute the gangue minerals.

Enriched zone and transition zone are the two further subdivisions of sulfide zone. Enriched zone is the thin chalcocite enriched parts of the deposit which is particularly associated with elevated copper grades. On the other hand, transition sulfide is a term used to describe parts of the deposit indicating a transition from unmineralized country rock to high-grade primary sulfide mineralization body.

The deposit is massive sulfide type polymetallic deposit exhibiting Cu + Au + Zn + Ag mineralization. As suggested by the deposit type and field evidences, the deposit formed as a result of volcanic-associated hydrothermal events. The attitude of the deposit is roughly NNE-SSW with a dip of 20-35° NW. Subsequent deformational events are evident from abrupt breaks in the mineralization especially along the strike direction. It is also inferred from the changes observed in the attitude of the deposit. However, potential post mineralization features could not be well studied and documented due to extensive cover.
CHAPTER 4

STATISTICAL CHARACTERIZATION & ESTIMATION DOMAIN DEFINITION

The data to be used in this study are sourced from an international mining company. They include collar, lithology, assay and survey files provided in .xlsx format, a digitized surface geological map, specific gravity readings, digitized topographical contours with 1 m contour intervals, license boundaries, detailed documentation and results of geotechnical, metallurgical, processing tests and geophysical surveys conducted for better understanding of the features of the mineralization.

The drillhole database of the case study comprised 517 holes (333 diamond core and 184 reverse circulation) completed in four phases between 2013 and 2017, with depths ranging between 20 and 376 m (average: 113.7 m). As presented in Figure 4.1, the holes were drilled in a regular grid with an approximate grid resolution of 25 m. Considering the attitude of the deposit, the drill grid is adjusted to NE-SW trend based on the attitude of the deposit.

Figure 4.1 Drillhole Locations
The JV company utilized various exploration tools for better understanding and characterization of the deposit in the last 7 years. Some of those are listed below:

- **Geochemical studies:**
  - Stream sediment sampling (20 samples)
  - Soil sampling @100m regular grid (786 samples)
  - Rock chip sampling (353 samples)

- **Geophysical studies:**
  - Ground based magnetic survey (32 N-S sections with a total 112.2km line length)
  - Induced polarization survey (22 NW-SE sections with a total 41.6 km line length)

- **Drilling:**
  - Phase 1 (11 core holes with a total length of 1,528.5m)
  - Phase 2 (143 core holes + 81 RC holes with a total length of 17,114.8m and 6,790.0m, respectively)
  - Phase 3 (149 core holes + 103 RC holes with a total length of 26,061.1m and 6,042.0m, respectively)
  - Phase 4 (30 core holes with a total length of 1241.1m)

Two outlying drillholes located in the far north-east of the map do not geographically belong to the estimation domain. Therefore, those peripheral drillholes are not considered in the subsequent stages of this research. The vertical and sub-vertical drillholes (dip: -60 to -90 degrees) comprising the drillhole database are located between 636,600-638,000E and 4,357,500-4,359,000N.

4.1. Quality Assurance and Quality Control

Quality control and quality assurance (QA/QC) is an integral part of the exploration program. Such information is regularly collected and analyzed to ensure the compliance of all the stages of data collection, handling, analysis and documentation with industry standards. A comprehensive chapter documenting the analysis of the QA/QC practices utilized by the operator for the project that is included in the prefeasibility study is provided together with the database. Therefore, this chapter is intended as a summary of that section.
Standards, duplicates and blanks are the principal components of the quality assurance and quality control system followed by the company.

There are three standards (certified reference material) used in the project with an intention to assess the accuracy of assaying. G907-4 and G910-8 are the two standards for gold that are sourced from Geostats Pty Ltd which provides confirmation at 3.84 g/t and 0.63 g/t, respectively. On the other hand, GBM398-1 is the third standard with provided certified values of 0.183 g/t Au, 1.482% Cu, 2.03% Zn, 2.667% Pb, and 5.1 g/t Ag. This standard is also sourced from the same company to be used for base metal intervals. There is a total of 1,571 gold standards and 244 base metal standards inserted for 31,495 assays in the database covering the first three phases of drilling which equated to 1 out of every 20 samples for gold and 1 out of every 130 samples for base metals. Qualified person reported that only about 2% of the 1,572 standards samples differ more that 10% from the original value which is an issue particularly associated with gold value of the standard used for base metals. Therefore, qualified person has not suggested a potential for material impact on the mineral resource estimates.

Insertion of blanks samples as the last sample to the end of every single drillhole is another common QA/QC procedure. It done with an intention to control contamination. QP reported that there is a total of 1,134 blank samples inserted into the whole sample stream which makes an average blank insertion rate of roughly 1 out of 28 samples. Assay results of blank samples are compared against pre-determined cut-off representing trace level and ore value. Out of 1,134 blanks inserted just one sample reported to be over economic gold grade and small percentage of blanks are out of the tolerance (trace level).

Duplicates are the third form of QA/QC instruments, and are utilized to assess the precision of the assay procedure. Split core and reverse circulation coarse rejects represent the two primary form of duplicates used for this project. Based on the QA/QC report, there identified a total of 1,219 duplicates within the database with a duplicate inserted as every 25th sample in the sample stream. Comparison of duplicate samples with the original samples on scatterplots confirmed the precision of the procedure.

Round robin test is another form of check included as a part of QA/QC system for the project. It involved analysis of 269 check samples for gold by a third party laboratory using the
same method of analysis. This practice is conducted as an interlaboratory test in order to assess
the reproducibility of the process.

Yet another analysis included in the QA/QC chapter of the prefeasibility study is the
comparison of diamond drilling and reverse circulation drill results. Nearest neighbor based
comparison of results indicated that the data gathered from RC samples is generally comparable
with that of diamond drilling to ensure statistical reliability despite being slightly conservative for
the oxide zone.

All in all, QA/QC analysis conducted by the QP indicated that the database for the project
is in acceptable quality in terms of data gathering, handling, analysis and documentation. Thus, it
is decided to be reliably used in the modelling and subsequent analysis.

4.2. Database Validation

Acknowledging the significance of quality of the data on reliability of the estimates, a
number of actions are taken to ensure validity and integrity of the database. Project drillhole
database is first checked for interval errors (missing and overlapping intervals). It is followed by
checks and corrections for negative and non-numeric grade values. There aren’t any negative grade
values detected during validation. Non-numeric grade values, on the other hand, are commonly of
two types: (i) typo errors resulted during data entry, and (ii) grade values reported to be outside of
the range defined by lower detection limit (LDL) and upper detection limit (UDL). There aren’t
any non-numeric value errors detected in the form of typo errors and grade values larger than UDL.
There are grade values reported to be lower than LDL, which necessitated a degree of data
manipulation. For those intervals, grade value is assigned as the half of the lower detection limit
which is a common industry practice.

Comparison of collar positions with respect to topography was also an essential component
of the database validation to ensure collars honor the surface topography. Validation of the collar
positions included both visual inspection of the drillhole collars with respect to topography as well
as quantitatively. The latter approach involved projection of drillhole collar onto surface
topography in order to generate a new variable that will store projected collar coordinates. Then,
that variable is used in the calculation of difference in the elevation of drillhole collars from the
topography as presented in Figure 4.2.
Both visual inspection and the graph above indicated some of the collar positions does not honor the topographic surface. There are nine drillholes labeled above whose collar positions are off by more than 2.5m from the topography. DRD-295 is the drillhole whose collar position presented the most severe discrepancy which is - 9.5m. The database was then checked one more time for a potential data entry and transfer error. The collars still did not honor the topographic surface; thus, they are excluded from the estimation procedure.

4.3. Statistical Data Analysis

Preparation and statistical characterization of the data is the following step. Data preparation involves regularization of raw data through compositing. The drill cores and RC chips recovered from the deposit are sampled with an average length of 1.58 m and vast majority of sampling conducted at 1 m, 1.5 m and 2 m intervals. Based on 25 m drill grid resolution, 10 m is thought to be an appropriate horizontal block dimension to fully utilize the available resolution and prevent artificial smoothing.

The deposit is a near surface polymetallic mineralization for which open pit mining method at a bench height of 5 m is proposed and incorporated into the preliminary feasibility study. Considering average sample length and proposed bench height, 5m decided to be a reasonable composite size. Vertical and sub-vertical dip of the drillholes in the database makes fixed-length downhole compositing preferable over optimum length compositing approach. The composite data
is compared with raw data in terms of summary statistics to assure the compositing approach does not introduce bias (Table 4.1).

Table 4.1 Summary statistics for all the raw and composite data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Count</th>
<th>Min/Max</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Coefficient of Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Raw</td>
<td>Composite</td>
<td>Raw</td>
<td>Composite</td>
<td>Raw</td>
</tr>
<tr>
<td>Au</td>
<td>32,561</td>
<td>10,305</td>
<td>0/150</td>
<td>0/61.44</td>
<td>0.245</td>
</tr>
<tr>
<td>Ag</td>
<td>32,723</td>
<td>10,459</td>
<td>0/5621</td>
<td>0/1039</td>
<td>9.09</td>
</tr>
<tr>
<td>Cu</td>
<td>0/16.4</td>
<td>0/12.25</td>
<td>0.201</td>
<td>0.138</td>
<td>0.613</td>
</tr>
<tr>
<td>Zn</td>
<td>0/32.2</td>
<td>0/15.88</td>
<td>0.343</td>
<td>0.238</td>
<td>1.203</td>
</tr>
</tbody>
</table>

As presented in above table mean of the composite data is not identical to raw data. However, this does not necessarily mean compositing introduced a bias. It is rather an outcome of unweighted calculation of average grade which particularly has a pronounced impact on the results for the raw data due to non-regular sample lengths ranging from 0.4 m to 9.0 m.

Table 4.2 Summary statistics for raw and composite data in length-weighted scenario

<table>
<thead>
<tr>
<th>Variable</th>
<th>Count</th>
<th>Min/Max</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Coefficient of Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Raw</td>
<td>Composite</td>
<td>Raw</td>
<td>Composite</td>
<td>Raw</td>
</tr>
<tr>
<td>Au, g/t</td>
<td>32,561</td>
<td>10,305</td>
<td>0/150</td>
<td>0/61.44</td>
<td>0.17</td>
</tr>
<tr>
<td>Ag, g/t</td>
<td>32,723</td>
<td>10,459</td>
<td>0/5621</td>
<td>0/1039</td>
<td>6.5</td>
</tr>
<tr>
<td>Cu, %</td>
<td>0/16.4</td>
<td>0/12.25</td>
<td>0.14</td>
<td>0.14</td>
<td>0.51</td>
</tr>
<tr>
<td>Zn, %</td>
<td>0/32.2</td>
<td>0/15.88</td>
<td>0.24</td>
<td>0.24</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Comparison of length weighted mean grades of raw and composited data for all the variables resulted identical or almost identical values as shown in Table 4.2. Furthermore, standard deviation and coefficient of variation values are reduced for all variables significantly which is a natural outcome of reduced spread of the data.

Another objective of data analysis is assessment of data distribution. Based on the histograms presented in Figure 4.3, grade values span couple orders of magnitude and strongly positively skewed exhibited by a pronounced asymmetry.
Cumulative probability plots are also utilized in the assessment of the data distribution. Similarly, non-linear shape of such plots indicates that the composite data for gold, silver, copper and zinc grades represent neither normal nor log-normal distribution. On the other hand, multi-modal shape of the histograms for log-transformed data together with presence of inflection points on cumulative probability plots suggest presence of multiple data populations which we are already aware based on geological information provided in chapter 3.

Summary statistics of the primary protolith rock types and generic names for the ore times identified earlier are presented in Table 4.3. It clearly shows that ClyGos and Gos are the two units that are characterized by elevated gold and silver grades. It is primarily a natural outcome of the leaching and oxidation process took place in the near surface portions of the deposit resulting in relative enrichment of comparatively immobile components (gold and silver) and depletion and downward migration of mobile components (copper and zinc) within the gossan zone.

Massive pyrite (MPy) and Massive pyrite magnetite (MPM) are the two units which are associated with the largest mean base metal grades in the deposit. As mentioned earlier in chapter 3, these are the units indicating the ore type encountered with the chlorite-sericite schist (ClSerSch) where the host rock is completely overprinted by the mineralization. When the intercept belonging to these two units examined in 3D, they look like the continuation of gossan zone below oxide-sulfide boundary along the plane defining the attitude of the mineralization.
Table 4.3 Summary statistics for primary protolith and ore types

<table>
<thead>
<tr>
<th></th>
<th>Count</th>
<th>Au</th>
<th>Ag</th>
<th>Cu</th>
<th>Zn</th>
<th>Mn</th>
<th>Fe</th>
<th>Mg</th>
<th>Ca</th>
<th>Na</th>
<th>K</th>
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<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Max</td>
<td>61.44</td>
<td>24.61</td>
<td>4.06</td>
<td>22.02</td>
<td>7.74</td>
<td>3.27</td>
<td>1.44</td>
<td>3.07</td>
<td>2.37</td>
<td>1.11</td>
<td>0.93</td>
<td>5.74</td>
</tr>
<tr>
<td>Mean</td>
<td>0.07</td>
<td>1.75</td>
<td>1.12</td>
<td>1.42</td>
<td>0.84</td>
<td>0.52</td>
<td>0.10</td>
<td>0.06</td>
<td>0.02</td>
<td>0.01</td>
<td>0.03</td>
<td>0.29</td>
</tr>
<tr>
<td>CV</td>
<td>16.61</td>
<td>2.03</td>
<td>0.71</td>
<td>1.85</td>
<td>0.93</td>
<td>1.25</td>
<td>3.17</td>
<td>3.11</td>
<td>5.75</td>
<td>3.01</td>
<td>3.15</td>
<td>2.03</td>
</tr>
</tbody>
</table>

Enriched zone is a subdivision of sulfide zone which is described as the thin chalcocite enriched parts of the deposit. As presented above, it is the unit with the highest average grades for all the variables included in the summary statistics table.

It is clear based on all these observations and analysis that the database is composed of a number of data populations which are needed to be identified to proceed with subsequent phases of the study.

4.4. Delineation of Estimation Domains

Estimation domains represent geostatistical stationary zones characterized by statistically homogeneous populations. Traditional method of estimation domain delineation is an iterative process involving definition of based on simple statistics and geological knowledge. On the other hand, alternative approach involves utilization of multivariate statistical techniques. In this study, a two-step approach is followed in delineation of estimation domains for the Cu-Au-Zn-Ag deposit.

Traditional method is the first step in the domaining practice. It mainly involved utilization of available knowledge about the genesis of the deposit. Initially there are around a dozen geologic attributes (protolith rock types and ore types) involved in the raw data base some of which are filtered out as a result of 5m downhole compositing or found to be only present in the two drillholes...
located far north-east (DRD-186 and DRD-188) that are decided to be excluded from the study. Then, the genetically related attributes such as ClyGos-Gos and MPy-MPM are grouped in order to identify primary estimation domains in oxide and sulfide zones, respectively. As an assessment of the domaining practice, contact plots and statistical comparisons are conducted. Contact plots were particularly helpful to characterize the behavior of grade across the boundary between two units. In a case where two units are going to be combined into a single population, we expect not to have a sharp change. On the other hand, comparison of coefficient of variation for each single unit considered to be combined into a population and that of the population was the major statistical consideration. Assessment of the performance of the domaining practice was based on a check whether there is any improvement in the coefficient of variation value. The domaining approach based on these three criteria (genetical association, boundary analysis and statistical comparison) indicated that ClyGos-Gos and MPy-MPM can each be combined into a population which are later decided to be representing the dominant components of the two domains within oxide and sulfide zones, respectively.

Second step of estimation domain delineation involved utilization of geostatistical hierarchical clustering algorithm that is a machine learning based process used to group samples into statistically homogenous domains according to their spatial dependency and degree of similarly in terms of grade and geological features like lithology, mineralization or alteration (Fouedjio, 2016). With this method two statistically distinct sub units are identified for each of the chlorite-sericite schist, pyrite-chlorite schist and transition sulfide units. These units later grouped into previously identified major domains for oxide and sulfide zones. As a result of this two-step domaining approach following six estimation domains (Figure 4.4) are identified for the deposit:

- Domain 1 is named as gossan zone (GOS). Gossan zone is composed of clay gossan (ClyGos) and gossan (Gos) units that are exhibiting elevated gold and silver grades. It is also the unit where mobile elements are leached out and transported towards the sulphide zone. Therefore, gossan zone is associated with low copper and zinc grades.
- Domain 2 is named as non-gossan oxide (NGO. Non-gossan oxide consists of the intercepts that are between the oxide-sulfide boundary and the topographic surface but not considered within the gossan zone.
Domain 3 is named as barren wall rock (BW). Barren wall rock represents the poorly mineralized or non-mineralized parts of the deposit in the sulfide zone. It is mainly made up of chlorite-sericite schist 1, quart-feldspar schist (hangingwall rock) and quartz-schist (footwall rock).

Domain 4 is named as high-grade sulfide (HGS). High-grade sulfide represents the primary sulfide mineralization of the deposit, and it is composed of massive-pyrite, massive-pyrite magnetite, pyrite-chlorite-sericite schist 2 and transition sulfide 2.

Domain 5 is named as low-grade sulfide (LGS). Chlorite-sericite schist 2, pyrite-chlorite-sericite schist 1 and transition sulfide 1 comprise the low-grade sulfide which forms a low-grade mineralization envelope around high-grade sulfide zone.

Domain 6 is named as enriched zone (ENR). Enriched zone is characterized by presence of elevated grades for all gold, copper, zinc and silver which is initially considered as a part of high-grade sulfide. However, this zone is later modelled as a separate domain due to distinct response of the material during metallurgical tests. Enriched zone is the domain that consists only of material represented by chalcocite enriched thin intercepts which are described as enriched zone during geological logging.

Figure 4.4 Estimation domains in a SE-NW cross-section
Box-plot diagrams presented in Figure 4.5 clearly indicates statistical dissimilarities between estimation domains. In addition to relative composition of different elements, it also useful to make comparisons in terms of relative variability and distribution of the grades.

As stated earlier, the gossan zone (GOS) and the enriched zone (ENR) are the two estimation domains that are associated with the largest mean precious metal concentrations. However, these two units are distinct from each other with respect to the variability of the grades in that the box representing the range between 25th and 75th percentiles of the data considered within the gossan zone is longer, thus the gossan zone is more variable compared to enriched zone. One another observation is regarding data distribution. Median and mean grades (indicated by blue and red lines, respectively) are close to each other for the enriched zone. On the other hand, mean grade is much larger that the median value for gossan zone which suggests a skewed distribution. It is also evident from the figure that high-grade sulfide is also an important domain in terms of these components.

Similar comparisons can also be done for copper and zinc grades from the lower two diagrams of Figure 4.5. In terms of these two variables enriched zone and high-grade sulfide are the two most significant estimation domains. Low-grade sulfide is exhibiting a strongly asymmetric distribution and has the third largest mean copper and zinc grade.

The box-plot diagrams which are utilized here to make comparisons between geostatistical estimation domains in terms of statistical properties are provided in log-transformed format with an intention to enhance the presentation and facilitate relative comparison. Therefore, statistical summary table (Table 4.4) would be more convenient for absolute numeric comparisons.

Statistical analysis of estimation domains delineated for the deposit indicated that the two-step domaining approach yielded satisfactory results suggested by significantly improved coefficient of variation values particularly for gossan zone, high-grade sulfide, enriched zone and low-grade sulfide. Besides, there is still some room for improvement through introducing high-grade cut-offs to deal with outlier values suspected both from box-plots and statistical summary table.
Figure 4.5 Box-plot diagrams for geostatistical estimation domains
Table 4.4 Summary statistics for geostatistical estimation domains

<table>
<thead>
<tr>
<th></th>
<th>Cu</th>
<th>Zn</th>
<th>Au</th>
<th>Ag</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Count</td>
<td>360</td>
<td>360</td>
<td>360</td>
</tr>
<tr>
<td></td>
<td>Min</td>
<td>0</td>
<td>0</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>1.82</td>
<td>5.04</td>
<td>22.02</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>0.1</td>
<td>0.1</td>
<td>1.29</td>
</tr>
<tr>
<td></td>
<td>St Dev</td>
<td>0.17</td>
<td>0.15</td>
<td>2.69</td>
</tr>
<tr>
<td></td>
<td>CV</td>
<td>1.74</td>
<td>1.67</td>
<td>2.09</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>CoS</th>
<th>NCO</th>
<th>BW</th>
<th>NGS</th>
<th>LGS</th>
<th>ERI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cu</td>
<td>6151</td>
<td>6151</td>
<td>660</td>
<td>2341</td>
<td>52</td>
<td></td>
</tr>
<tr>
<td>Zn</td>
<td>12.5</td>
<td>12.25</td>
<td>7.22</td>
<td>7.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Au</td>
<td>15.88</td>
<td>2.33</td>
<td>0.3</td>
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<td></td>
</tr>
<tr>
<td>Ag</td>
<td>3.07</td>
<td>0.79</td>
<td>0.79</td>
<td>0.79</td>
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<td></td>
</tr>
</tbody>
</table>

High-grade cut-off is also known as top-cut is essential in order to prevent risk of smearing of
the high-grades which might result in overestimation. Following are some of the widely utilized
alternative approaches in determination of high-grade cut-off values:

- Sum of the data mean and twice the standard deviation
- Four times the data mean value
- The point where the ragged tail starts on the histogram

Among these three alternatives, last approach found to be the most appropriate option for this
particular case that will eliminate the long tail of high-grade value representing the outlier as
illustrated below (Figure 4.6).
High-grade cut-off values identified in this manner for all variables in each domain are presented in Table 4.5. It also includes a column where the number of samples cut for each scenario is indicated. Based on that the capped assay values only represent a small percentage (0.64%) of all composites.

Table 4.5 High-grade cut-off values

<table>
<thead>
<tr>
<th>Domain</th>
<th>Variable</th>
<th>Mean (µ)</th>
<th>Standard Deviation (σ)</th>
<th>µ+2σ</th>
<th>4µ From histogram</th>
<th>Top-cut</th>
<th># Samples Cut</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cu</td>
<td>0.1</td>
<td>0.17</td>
<td>0.44</td>
<td>0.40</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>Zn</td>
<td>0.09</td>
<td>0.15</td>
<td>0.39</td>
<td>0.36</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>Au</td>
<td>1.29</td>
<td>2.69</td>
<td>6.67</td>
<td>5.16</td>
<td>11.6</td>
<td>11.6</td>
</tr>
<tr>
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<td>Ag</td>
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<td>102.7</td>
<td>250.20</td>
<td>179.20</td>
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<td>350</td>
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<td>0.45</td>
<td>0.28</td>
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<td>1.6</td>
</tr>
<tr>
<td></td>
<td>Zn</td>
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<td>0.40</td>
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<td>2.65</td>
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<td>236</td>
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<tr>
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<td>0.27</td>
<td>0.12</td>
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<tr>
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<td>0.39</td>
<td>0.86</td>
<td>0.32</td>
<td>6.3</td>
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<td>0.24</td>
<td>0.52</td>
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<tr>
<td></td>
<td>Ag</td>
<td>1.5</td>
<td>12.9</td>
<td>27.30</td>
<td>6.00</td>
<td>135</td>
<td>135</td>
</tr>
<tr>
<td>4</td>
<td>Cu</td>
<td>0.88</td>
<td>0.83</td>
<td>2.54</td>
<td>3.52</td>
<td>6.5</td>
<td>6.5</td>
</tr>
<tr>
<td></td>
<td>Zn</td>
<td>1.65</td>
<td>2.03</td>
<td>5.71</td>
<td>6.60</td>
<td>11.75</td>
<td>11.75</td>
</tr>
<tr>
<td></td>
<td>Au</td>
<td>0.67</td>
<td>0.69</td>
<td>2.05</td>
<td>2.68</td>
<td>3.7</td>
<td>3.7</td>
</tr>
<tr>
<td></td>
<td>Ag</td>
<td>26</td>
<td>37</td>
<td>100.00</td>
<td>104.00</td>
<td>181</td>
<td>181</td>
</tr>
<tr>
<td>5</td>
<td>Cu</td>
<td>0.18</td>
<td>0.39</td>
<td>0.96</td>
<td>0.72</td>
<td>4.6</td>
<td>4.6</td>
</tr>
<tr>
<td></td>
<td>Zn</td>
<td>0.3</td>
<td>0.7</td>
<td>1.70</td>
<td>1.20</td>
<td>4.3</td>
<td>4.3</td>
</tr>
<tr>
<td></td>
<td>Au</td>
<td>0.14</td>
<td>1.31</td>
<td>2.76</td>
<td>0.56</td>
<td>9.15</td>
<td>9.15</td>
</tr>
<tr>
<td></td>
<td>Ag</td>
<td>4.4</td>
<td>12.3</td>
<td>29.00</td>
<td>17.60</td>
<td>110</td>
<td>110</td>
</tr>
<tr>
<td>6</td>
<td>Cu</td>
<td>3.26</td>
<td>2.17</td>
<td>7.60</td>
<td>13.04</td>
<td>7.65</td>
<td>7.65</td>
</tr>
<tr>
<td></td>
<td>Zn</td>
<td>2.33</td>
<td>1.84</td>
<td>6.01</td>
<td>9.32</td>
<td>6.05</td>
<td>6.05</td>
</tr>
<tr>
<td></td>
<td>Au</td>
<td>1.02</td>
<td>0.83</td>
<td>2.68</td>
<td>4.08</td>
<td>3.35</td>
<td>3.35</td>
</tr>
<tr>
<td></td>
<td>Ag</td>
<td>50.4</td>
<td>94.9</td>
<td>240.20</td>
<td>201.60</td>
<td>150</td>
<td>150</td>
</tr>
</tbody>
</table>
Contact characterization or boundary analysis is another consideration which is aimed to describe the grade trends and behavior near domain boundaries. Contact plots were particularly effective in this analysis. The boundary between oxide and sulfide zones is one of the major contacts that is examined within this part of the study. Figure 4.7 below shows the behavior of the grades for gold, silver, copper and zinc near the oxide-sulfide boundary.

![Figure 4.7 Contact plots for oxide-sulfide boundary](image)

There are a number of inferences made from these plots: (i) grades for both precious and base metals represent distinct behavior in oxide and sulfide zones, (ii) the change of the grades across the boundary is sharp, (iii) near the boundary precious metal grades are noticeably higher in the oxide zone which is already explained by relative enrichment of gossan zone as a result of leaching and oxidation process, (iv) opposite case is valid for the base metal grades i.e., copper and zinc grades are considerably higher in the sulfide zone especially near the oxide-sulfide boundary, and (v) gold and silver grades are typically increasing within the oxide zone towards
the contact. As a result of all these observations, the oxide-sulfide boundary is will be treated as a hard boundary during grade estimation process.

The boundaries between all other populations were analyzed in this manner will be treated as hard boundaries in order to prevent smearing of grades across estimation domains (Appendix A).
CHAPTER 5

ESTIMATION DOMAIN MODELLING

Domain modeling is a fundamental component of contemporary mineral resource estimation. A geological model is a simplified three-dimensional representation of the physical features. For a mineral deposit those features might consist of lithology, alteration, mineralization, oxidation state and structural elements. Geological models are constructed with an intention to delineate the primary controls on the mineralization. On the other hand, a domain model is a more comprehensive construction which calls for both geological and statistical input. Furthermore, domain models use the knowledge about the mineralization controls, and are utilized as a key guiding tool during estimation of a property.

Stationarity is the key characteristic of robust estimation domains. In the simplest terms, it represents statistically homogenous data populations. Delineation of stationary estimation domains is an iterative process that involves consideration of many aspects. There are six estimation domains identified for the deposit through a two-step domaining approach whose details are presented earlier in chapter 4. Following stage of the study involves construction of 3D estimation domain model.

The tools and approaches employed for mineral resource estimation have been evolved noticeably in the last couple decades. There exist a variety of 3-D domain modelling alternatives exhibiting differences in terms of complexity, time and effort requirement. Considering its implications for downstream mining practices, quality of the model is crucial. In this perspective choice of the modelling approach is a significant consideration.

This part of the study involves construction of alternative domain models through execution of four alternative modelling approach which are (i) explicit modelling approach, (ii) implicit modelling approach, (iii) indicator kriging approach, and (iv) conditional simulation approach. It compasses the details for the assumptions involved, the main steps followed as well as results obtained for all these alternatives.
5.1. Explicit Modelling Approach

Explicit modelling is the modelling approach utilized in construction of solid models representing statistically homogeneous estimation domains. This method represents the traditional technique for construction of 3D models which involves manual digitization of interpreted geologic features on cross-sections. Despite being a time-consuming approach, explicit modelling provides complete user control and facilitate better understanding of the mineralization controls as well as major features of the deposit.

There are 517 drillholes constituting the drillhole database that are drilled at a pseudo-regular pattern which is oriented along NE-SW where grid resolution is roughly 25 meters. Analysis of mineralized intercepts also revealed that this trend is consistent with the strike of the mineralization. Therefore, orientation of cross-sections is chosen as NW-SE, roughly parallel to the dip direction. Figure 5.1 illustrates digitized contacts for high-grade sulfide (HGS) zone for one of the cross-sections along the chosen orientation.

![Figure 5.1 An illustration of digitized contacts for HGS zone along a SE-NW cross-section](image)

Digitized contacts along NW-SE cross-sections belonging to the estimation domains largely defined the geometry. A further improvement for the explicit model has been achieved through considering the orthogonal direction as the orientation for the long-sections (NE-SW). The mineralization geometry is delineated from 53 cross-sections and 26 long-sections as shown in Figure 5.2A.
In the next step of estimation domain modelling, manually digitized cross-sections are linked to form three-dimensional triangulations, also known as wireframes, with the help of tie lines. Figure 5.2B is an illustration of the solid model belonging to high-grade sulfide zone constructed with this way.

Figure 5.2 Digitized contacts along orthogonal directions (left) and solid model of HGS zone generated by explicit modelling approach (right)

One of the major assumptions made during generation of 3D models by explicit modelling approach is extrapolation distance. Common practice within the industry is to use nearly half of the distance between adjacent drillholes. For this particular study, the same strategy has been followed. Another substantial consideration is the final adjustment of the wireframes based on cross-cutting relationships defining the chronology. In this respect, construction of the resource domain model for the deposit through explicit modelling approach necessitated exhaustive review of all available geological information and facilitated better comprehension of the deposit in terms of attitude and continuity of the mineralization.

5.2. Implicit Modelling Approach

Implicit modelling technique is a more recent approach compared to explicit modelling. It relies software driven algorithms (e.g. radial basis function) for generation of surfaces
corresponding to boundaries between different data populations. In this study, Leapfrog Geo is used to generate the implicit model of the estimation domains comprising the deposit.

The estimation domain codes assigned as a new attribute for the drillholes considered for this research is one of main inputs. Resolution of the model is a critical aspect which determines the minimum length of input data that will be considered within implicit modelling practice. Therefore, it is a crucial decision calling for understanding end use of the product. The deposit is planned to be exploited with open pit mining using 5m benches. Considering the bench height and average sample length of the raw data, the compositing length is decided to be 5 m. Thus, resolution of the model is set as 5 m. Other key information required for generation of preliminary model with the implicit modelling approach is age relationships because it directly controls 3D extends of each individual unit. The oxide-sulfide boundary modelled using points representing oxide bottom in each drillhole is used as the limit of two primary zones (i.e. oxide zone and sulfide zone) of the deposit. The topographic surface and oxide-surface boundary defines the limits of oxide zone where gossan zone is modelled as the younger unit. On the other hand, sulfide zone occupies the space between oxide-sulfide boundary and 1,015 m elevation which stands for bottom limit of the model in vertical direction. Enriched zone, high-grade sulfide, low-grade sulfide and barren wall rock are the four units comprising sulfide zone for which units are given in younger to older. It is clear that the relationship defined for some of these units does not necessarily indicative of the timing of formation. For instance, high-grade sulfide and low-grade sulfide are the two units that are probably formed concurrently, thus, suggested relationship is used merely for geometric purposes.

The results obtained for the preliminary model uses the defaults of the implicit modelling where use of isotropic search strategy generated solids that does not reflect the spatial characteristics of the deposit. In this respect, the knowledge gathered regarding attitude of the mineralization in terms of dip, dip azimuth and pitch was a valuable contribution guiding implicit modelling. Final editing of the solids following introduction of trend is the last and an important step to ensure the model is clean of unrealistic isolated bodies or other artifacts.
The solid model generated for high-grade sulfide zone in this manner is presented in Figure 5.3B while the product of explicit modelling approach is shown in Figure 5.3A. Visual comparison of outcomes suggests that both methods resulted in globally consistent solid models exhibiting differences in terms of details.

5.3. Indicator Kriging Approach

Application of indicator kriging provides an alternative approach for modelling categorical variables. The codes assigned as a new variable for each estimation domain are used in generation of a new set of codes indicating whether or not an intercept belongs to a particular estimation domain. Therefore, the codes generated in this way are in binary format and are called as indicator values or variables. They are essential components of indicator kriging technique where these binary values are used in quantification of spatial continuity using indicator variograms. Following is the indicator variogram constructed to assess the spatial continuity of high-grade sulfide, low-grade sulfide, gossan and enriched zones (Figure 5.4).

The results of the variography study for the indicator variables belonging to these zones are also presented along with the indicator variograms in the form of model parameters. It is...
noteworthy that this approach was effective to capture the major attitude of the mineralization. Therefore, indicator variogram results are considered as satisfactory for subsequent analysis.

Figure 5.4 Indicator variogram constructed for HGS+LGS+ENR+GOS zones

Next step involved in this approach for modelling estimation domains delineated for the deposit is execution of indicator kriging routine using information derived from indicator variograms as a guide for estimation. As a result of this process, 10m x 10m x 5m blocks of the block model are assigned to represent an element of an estimation domain. Finally, shells corresponding to each estimation domain are generated as separate 3D wireframes.

Figure 5.5 Solid Models for HGS zone generated with explicit modelling, implicit modelling and indicator kriging approaches

Figure 5.5 illustrates the products of explicit modelling, implicit modelling and indicator kriging approaches to generate solid models of high-grade sulfide zone. Side by side comparison
of the outcomes is an easy way to reveal discrepancies between solid models. It is clear that indicator kriging approach was also successful to capture the major features of high-grade sulfide zone as suggested by previous two models but there exist significant dissimilarities particularly in terms of spatial continuity of the domain.

5.4. Conditional Simulation Approach

Conditional simulation technique constitutes the fourth approach employed in estimation domain modelling for the deposit. Sequential indicator simulation is the specific conditional simulation technique which enables generation of mathematically equiprobable outcomes, commonly referred as realization, for categorical variables. Therefore, this technique is utilized in generation of a set of realizations for the deposit in which the indicator variogram model obtained for modelling with indicator kriging approach is used. There are ten realizations with this approach. Figure 5.7 presents the solid models of oxide zone modelled through four alternative approaches. It provides the outcomes only for gossan and non-gossan oxide in plan view in order to facilitate visualization and comparison.

Similar to other modelling approach, sequential indicator simulation method was also effective to capture the main trend of the mineralization. Furthermore, it resulted in comparable volumes for estimation domains with that of indicator kriging approach which are considerably larger than volumes generated by both explicit and implicit modelling approaches. Figure 5.6 below presents the volumes for HGS domain for alternative modelling approaches.

![Figure 5.6 Bar chart of the volumes for HGS solids generated with alternative approaches](image-url)
Figure 5.7 Map view of solid models for oxide zone generated by four alternative approaches
The mineral resource estimates for the deposit is developed from a 3D block model generated using a commercial mine planning package (MineSight3D). The estimates are based on part of the database which is found to be reliable to be used in this study. As stated earlier, primary objective of this research is to execute a comparative analysis of 3D domain modeling alternatives. It further aims to document implications of each modelling routine on mineral resource estimates. Therefore, this part of the study involves estimation of resources based on identical estimation parameters, method and assumptions. This is why, this chapter is dedicated to present the primary aspects regarding grade estimation, model validation and resource classification applied for estimation domains generated through explicit modelling approach.

6.1. Grade Estimation

The polymetallic massive sulfide deposit is associated with anomalous concentrations of copper, gold, zinc and silver which are considered in the estimation of resources. On the other hand, metallurgical test work results do not indicate presence of any deleterious components that may materially affect the concentrate quality. Moreover, economic contribution of lead grades is negligible (mean grade of non-composited data:0.08%), thus excluded in the subsequent analysis. That being the case, grade estimation is focused on procurement of estimates for aforementioned precious and base metals concentrations.

6.1.1. Block Model Setup

The block model setup is a term used to describe the extends and orientation of the model as well as block size and model fields. Considering the strike of the deposit and orientation of the drillholes, the block model is rotated 45° clockwise as shown in Figure 6.1 where model limits are indicated as callouts at four corner points and coordinates are provided for Universal Transverse Mercator projection system European Zone 35.
Block size is a crucial decision in resource estimation which is a function of data spacing. Journel and Huijbregts (1978) suggest 1/3 to 1/2 of data spacing to be an appropriate size for optimum utilization of the available resolution. Considering 25m average drillhole grid spacing, 10m is decided as the horizontal block dimensions. Moreover, vertical block dimension is chosen based on proposed 5m bench height. Therefore, the block model comprised of 10m x 10m x 5m sized regular blocks.

Model fields are the last component of the model setup. They represent the variables used to store information for each individual block within the model. Table 6.1 is the complete list of model fields and their descriptions.

Table 6.1 Block model fields

<table>
<thead>
<tr>
<th>Model Field</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>East, North, Elevation</td>
<td>Block center coordinates</td>
</tr>
<tr>
<td>DOM</td>
<td>Estimation domain</td>
</tr>
<tr>
<td>Au, Ag, Cu, Zn</td>
<td>Block grade estimates</td>
</tr>
<tr>
<td>NSR</td>
<td>Net smelter return (£/t)</td>
</tr>
<tr>
<td>TP</td>
<td>Percent of the block below topographic surface</td>
</tr>
<tr>
<td>SG</td>
<td>Specific gravity</td>
</tr>
<tr>
<td>FLAG</td>
<td>Variable used for resource classification purposes</td>
</tr>
</tbody>
</table>

East, north and elevation are three default variables used for block center coordinates. DOM variable for each block indicates which of the six domains they are a part of. In cases where
a block is a part of more than one domain, then the DOM code is set as the domain comprising the majority of the block. Au, Ag, Cu and Zn are variables used for kriging or inverse distance weighted block estimates. NSR stands for net smelter return which is a variable generated for ultimate pit limit analysis. Similarly, TP is generated for ultimate pit limit analysis and it indicates the percentage of individual blocks below topographic surface. Flag is used to store codes that will be employed later for resource classification purposes.

Finally, SG is used for specific gravity. It is one of the most crucial parameters in resource estimation considering its direct control on tonnage, metal content, and stripping ratio. Therefore, quality of resource estimates and subsequent technical and financial studies clearly reliant on accuracy and representativeness of specific gravity measurements as well. Specific gravity values assigned to blocks belonging to one of the six estimation domains determined as a result of statistical analysis carried out using over 5000 specific gravity measurements. SG measurements are performed as a part of sample preparation program. Water immersion technique utilized in determination of specific gravity requires measurement of mass of sample for air-dried (A), wax-coated (B) and water submerged (C) cases. Then, the specific gravity is calculated as follows:

\[
Specific \ Gravity = \frac{A}{B - C - \frac{B - A}{0.86}}
\]

SG values for each estimation domain determined in this manner are shown in Table 6.2.

<table>
<thead>
<tr>
<th>Estimation Domain</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gossan</td>
<td>1.62</td>
<td>4.61</td>
<td>2.56</td>
<td>0.42</td>
</tr>
<tr>
<td>Non-gossan oxide</td>
<td>1.84</td>
<td>4.71</td>
<td>2.73</td>
<td>0.56</td>
</tr>
<tr>
<td>Barren wallrock</td>
<td>1.83</td>
<td>4.88</td>
<td>2.80</td>
<td>0.40</td>
</tr>
<tr>
<td>High-grade sulfide</td>
<td>2.47</td>
<td>4.89</td>
<td>4.30</td>
<td>0.47</td>
</tr>
<tr>
<td>Low-grade sulfide</td>
<td>1.94</td>
<td>5.91</td>
<td>3.28</td>
<td>0.63</td>
</tr>
<tr>
<td>Enriched Zone</td>
<td>2.14</td>
<td>4.80</td>
<td>3.47</td>
<td>0.85</td>
</tr>
</tbody>
</table>

Table 6.2 clearly indicates the distinctions between estimation domains in terms of specific gravity. Barren and poorly mineralized parts of the country rock (BW) and domains comprising oxide zone (GOS and NGO) are associated with lower specific gravities. On the other hand, three
units that are associated with sulfide mineralization (HGS, LGS and ENR) are the ones with relatively larger specific gravity values. Following determination of summary statistics presented above, average specific gravity value is assigned to individual blocks based on which estimation domain they belong to.

6.1.2. Geostatistical Data Analysis

Quantification of spatial continuity of the data through variography is one of the most fundamental aspects of geostatistical resource estimation. Therefore, variography was a crucial tool in geostatistical analysis of estimation domains. Initially, variography has been carried out for each single domain which resulted in erratic experimental variograms. Therefore, it has been realized that it is quite difficult to characterize the spatial continuity with this approach. Later, variography study is decided to be performed for one variogram in each of the oxide and sulfide zone. Composite data belonging to gossan zone is considered for the oxide zone while the data for enriched zone, high-grade sulfide and low-grade sulfide are used together for variography.

As explained earlier in chapter 2, variography study aims to quantify spatial continuity or variability of the data which is expressed in terms of principal features of the variogram namely nugget effect, sill and range. Nugget effect represents the discontinuity at the origin which means the semivariogram value for data pairs that are separated very small distance apart. Therefore, most practical tool to quantify the nugget effect is downhole variogram. On the other hand, omnidirectional variograms (where angular tolerance is 90°) are utilized in quantification of the total sill. Then, directional experimental variograms are constructed at a lag spacing roughly capturing the drillhole grid resolution for log-transformed composite data. Logarithmic transformation of the data considerably improved the experimental variograms and facilitated subsequent analysis. Later, resultant experimental variograms are modelled with spherical variogram structures and
previously determined nugget and total sill values. Model fitted variograms for GOS and HGS+LGS+ENR are presented in Figure 6.2.

Figure 6.2 Modelled Variograms for GOS (left) and HGS+LGS+ENR (right)

Final step in the geostatistical analysis of the data is back-transformation of the outcomes. Principal features of the variogram identified in this manner are compiled in Table 6.3. The anisotropy suggested by nonidentical ranges along the major, semi-major and minor axis orientations is consistent with the main attitude of the deposit.

<table>
<thead>
<tr>
<th>Domain</th>
<th>Model</th>
<th>Orientation</th>
<th>Range, m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gossan zone</td>
<td>Spherical</td>
<td>-</td>
<td>Major</td>
</tr>
<tr>
<td></td>
<td>1.00</td>
<td>31</td>
<td>Semi Major</td>
</tr>
<tr>
<td></td>
<td>3.70</td>
<td>152</td>
<td>Minor</td>
</tr>
<tr>
<td></td>
<td>-8</td>
<td>110</td>
<td>Major</td>
</tr>
<tr>
<td></td>
<td></td>
<td>71</td>
<td>Semi Major</td>
</tr>
<tr>
<td></td>
<td></td>
<td>62</td>
<td>Minor</td>
</tr>
<tr>
<td>Non-gossan oxide</td>
<td>-</td>
<td>-</td>
<td>Major</td>
</tr>
<tr>
<td>Barren wallrock</td>
<td>-</td>
<td>-</td>
<td>Semi Major</td>
</tr>
<tr>
<td>High-grade sulfide</td>
<td>-</td>
<td>-</td>
<td>Minor</td>
</tr>
<tr>
<td>Low-grade sulfide</td>
<td>Spherical</td>
<td>152</td>
<td>Major</td>
</tr>
<tr>
<td></td>
<td>0.8</td>
<td>31</td>
<td>Semi Major</td>
</tr>
<tr>
<td></td>
<td>-8</td>
<td>139</td>
<td>Minor</td>
</tr>
</tbody>
</table>

6.1.3. Estimation Strategy

Estimation strategy here is used to describe considerations regarding grade estimation mainly including estimation method, search and high-grade restriction strategies employed.

Ordinary kriging is used in estimation of precious and base metal components for 10m x 10m x 5m block of the resource model. There exist many reasons behind the choice of this estimation method. First of all, it is the most widely used linear univariate geostatistical estimation technique because of relative ease of use. More importantly, deposit geology and statistical characteristics of the data population after domaining does not necessitate use of more sophisticated techniques in grade estimation.
Grade estimation is made using ordinary kriging on whole block basis and sub-blocking and block partials are not considered.

Search strategy is the other key component of grade estimation. It involves considerations for (i) minimum and maximum number of samples, (ii) size and geometry of the search neighborhood, and (iii) measures to deal with data redundancy.

Minimum and maximum number of samples are two important estimation parameters determining the estimation accuracy. Ideally, quantitative kriging neighborhood analysis might be considered for optimum number of samples. However, the numbers used in this study are as follows:

- Minimum number of samples: 1
- Maximum number of samples: 10
- Maximum number of samples per hole: 3

Size and geometry of the search neighborhood is another aspect of search strategy. Similarly, quantitative kriging neighborhood analysis is an effective approach to obtain optimum parameters for search neighborhood. On the other hand, size and geometry of the search neighborhood is guided by the variography study. In estimation of grades for block which are a part of gossan zone, high-grade sulfide, low-grade sulfide and enriched zone, the kriging neighborhood is defined as ellipses to reflect the anisotropy of spatial continuity captured by directional variograms. On the other hand, grade estimation for non-gossan oxide and barren wall rock blocks are guided by isotropic search neighborhoods. Parameters defining the size and geometry of search neighborhood for each estimation domain are presented in Table 6.4.

<table>
<thead>
<tr>
<th></th>
<th>Range, m</th>
<th>Orientation, degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Major</td>
<td>Semi Major</td>
</tr>
<tr>
<td>Gossan zone</td>
<td>110</td>
<td>71</td>
</tr>
<tr>
<td>Non-gossan oxide</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Barren wall rock</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High-grade sulfide</td>
<td>139</td>
<td>64</td>
</tr>
<tr>
<td>Low-grade sulfide</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Enriched Zone</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Yet another aspect of search strategy involves measures against data clustering. It is a common practice to deal with data clustering through a quadrant or octant search when there exists a risk related with preferential sampling hence data clustering. However, a regular pattern has been
followed for drilling, thus no actions were taken to deal with data clustering through dividing the ellipsoid into sectors.

High-grade restriction is the final consideration regarding search strategy. It describes actions to prevent smearing of extremely high-grade value hence over-estimation. Extremely high-grade values are also named as outliers. They are identified and reported for each estimation domain earlier in chapter 4. Grade capping and high-grade restraining are two of the commonly utilized treatment methods. Former involves truncation of the histogram before the outlier value in order the eliminate influence of extreme value. On the other hand, latter necessitates use of restricted search neighborhood. For estimation of Au, Ag, Cu and Zn grades of the block model, high-grade restraining method is utilized where the size of the search neighborhood is set as 10% of the base case whose parameters are provided in Table 6.4. With this technique, the outliers within the restricted kriging neighborhood is considered for grade estimation. Beyond this region extremely high-grade value is capped to the top-cut value. Such an approach allows both representation of high-grade value by the blocks in the very near vicinity and elimination of the risk of excessive smearing.

6.1.4. Resource Classification

There exists a number of reporting guidelines that are widely accepted around the world. Those codes ask for reporting of confidence of estimation as a part of the disclosure. Resource classification is a way to meet that requirement. It involves delineation of resource classes as measured, indicated and inferred with decreasing level of geological knowledge and confidence. Therefore, resource classification is a way to express confidence of the estimates.

Multiple-pass estimation approach is utilized in classification of resources at this study. The classification approach involves progressively decreasing the size of the search neighborhood. FLAG is the model variable generated to store codes for resource classification purposes. Primary steps involved in identification of resource classes are as follows:

- initially FLAG variable for all the blocks are set as 0
- first pass of estimation is carried out for a search neighborhood whose sizes are 1.5 times of the base case summarized in Table 6.4, then FLAG variable for the blocks estimated during this pass are modified to 3
second pass of estimation is done for a search neighborhood with the sizes shown in the base case, then FLAG variable for the block estimated during this pass are modified to 2

Third pass of estimation involves a search neighborhood whose sizes are 0.5 times of the base case, and the FLAG variable of the blocks estimated during this pass are modified to 1

As a result of this procedure, FLAG variable for each block are assigned as one of the four integer values. Figure 6.3 is an illustration for the outcomes of mentioned resource classification procedure in a cross-section.

![Figure 6.3 An illustration of resource classification](image)

As presented in the cross-section, such a procedure resulted in resources classified as measured (FLAG =1) where the highest density of data exists. With decreasing data density, resources are classified as indicated (FLAG =2) and inferred (FLAG =3), respectively.

6.2. Model Validation

Validation of the resource model involves a number of checks to ensure internal consistency, global and conditional unbiasedness of the product. Validation of the case study resource model involves comparison of the model against input data as well as alternative estimation techniques.

First part of the procedure involves assessment of the performance of the estimation technique against two alternative estimation methods namely nearest neighbor and inverse distance weighted. In order to assess relative performance of the estimation method, two alternative models are generated for identical composite data and guided by same search strategy. Histograms are the
first tool used for comparison of the outcome. The histogram presented as Figure 6.4 below clearly indicates consistent results achieved by original resource model and two alternative models.

![Histogram of Cu grade estimates for original model vs. alternative models](image)

Figure 6.4 Histogram of Cu grade estimates for original model vs. alternative models

Grade-tonnage curve is another graphical validation technique employed to assess relative performance of the estimation method with respect to alternatives.

![Grade-tonnage curves for original model vs. alternative models](image)

Figure 6.5 Grade-tonnage curves for original model vs. alternative models

Grade-tonnage curves presented above suggests comparable performance for these three techniques in estimating the copper grades using the same input data (Figure 6.5).

One another tool used in this part of the comparison is swath plot which allows spatial comparison of the estimates. The swath plot in Figure 6.6 is a graphical display of average copper grade for a series of 10m slices along NW-SE direction which also suggest consistency between results of three estimation techniques.
Second part of model validation involves assessment of the quality of estimates by visual inspection of cross-sections. It further incorporates some of the graphical validation tools presented earlier to make comparisons of resource model estimates with composite data.

Visual validation may be the most important validation approach utilized for this study. It relies on inspection of block grade estimates against composite data as shown in Figure 6.7. The figure suggests that block grade estimates largely capture the grades and the spatial relationships in the input data.

Comparison of the histograms of block grades with composite grades on domain basis forms the other step in model validation. The histograms presented in Figure 6.8 indicates the
global unbiasedness of copper grade estimates. Furthermore, relatively smaller variance of the block model grades compared to composite grades is a natural outcome of smoothing effect of kriging particularly evident in the histogram for high-grade sulfide.

Figure 6.8 Histograms of block model grade vs. composite grade for six estimation domains

Comparison of grade-tonnage curves for block model and composites represents the last step of model validation. Grade-tonnage curves for block model and composites are provided in Figure 6.9 on domain basis. The curves generated for estimation domains which are associated with relatively enriched base metal mineralization (HGS, LGS and ENR) suggests satisfactory results. On the other hand, other three domains reported under-estimation of the copper grades over all cut-off grades. Analysis of grade-tonnage curves for precious metal components especially in two estimation domains (GOS and NGO) forming the oxide zone do not represent the same problem. Besides, base metal grades within the oxide zone do not have economic significance because there isn’t any process proposed to extract copper and zinc from the oxide zone. Therefore, the estimates are decided to be reliable enough to be used in subsequent analysis.
6.3. Ultimate Pit Limit Analysis

CIM best practices allow classification of part of the mineral endowment as resource that demonstrates “reasonable prospect for eventual economic extraction” (Abzalov, 2016). The deposit is a near surface polymetallic deposit which is planned to be extracted with open-pit mining. Therefore, determination of component of reasonable prospects for economic extraction achieved by ultimate pit limit analysis using Lerchs-Grossman algorithm in MineSight3D.

Estimated precious and base metal grades, metal prices, pit slope angle, smelter terms, process cost and recoveries are the main input parameters of this analysis.

CIM best practices are not prescriptive about the metal prices. They rather leave the responsibility to the qualified person to decide appropriate prices which should be reasonable over the project life. On the other hand, Securities Exchange Commission (SEC) requires 3-year trailing average metal prices in estimation of reserves. The metal prices used for resource estimation are: $1200/oz Au, $18.00/oz Ag, $3.00/lb Cu and $1.20/lb Zn. Lately, those prices are slightly adjusted...
for mentioned mineral resource estimation study. Therefore, recent values are also considered in this research.

Precious metal components are initially planned to be extracted by heap leaching of oxide ore at an average 3,000tpd rate roughly over three years. While sulfide material is planned to be processed at a flotation circuit to produce copper and zinc concentrates at a 6,500tpd rate. Subsequent metallurgical testing indicated that tank leaching would be a better alternative to extract high-grade gold and silver from the oxide zone with significantly higher recoveries. Furthermore, material classified as enriched zone, thin chalcocite enriched parts of the deposit associated precious and base metal grades, is found to be refractory in nature, thus currently it is not planned to be extracted. Table 6.5 presents updated recoveries used for resource estimation purposes.

<table>
<thead>
<tr>
<th>Table 6.5 Updated process recoveries</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Oxide Zone</strong></td>
</tr>
<tr>
<td><strong>Sulfide Zone</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Smelter terms comprised of payable percent of the metal content, treatment charge, refining charges are presented in Table 6.6 below. It is a CIF based agreement, thus smelter terms also include associated insurance, transportation and port charges.

<table>
<thead>
<tr>
<th>Table 6.6 Smelter Terms</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Oxide Zone</strong></td>
</tr>
<tr>
<td>Au transportation: $5.133/oz</td>
</tr>
<tr>
<td><strong>Sulfide Zone</strong></td>
</tr>
<tr>
<td>Payable Metal</td>
</tr>
<tr>
<td>Cu: pay lesser of 96.5% or Cu content less 1%</td>
</tr>
<tr>
<td>Au: pay lesser of 90.0% or Au content less 1g/t</td>
</tr>
<tr>
<td>Ag: pay lesser of 90% or Ag content less 30g/t</td>
</tr>
<tr>
<td>Treatment Charge : $90.0/ dry t</td>
</tr>
<tr>
<td>Refining Charges</td>
</tr>
<tr>
<td>Copper : $0.09/lb</td>
</tr>
<tr>
<td>Gold : $5.00/oz</td>
</tr>
<tr>
<td>Silver : $0.50/oz</td>
</tr>
<tr>
<td>Moisture (assumption) : 12%</td>
</tr>
<tr>
<td>Ocean Freight : $30.00/wet t</td>
</tr>
<tr>
<td>Port Charge : $15.35/wet t</td>
</tr>
<tr>
<td>Land Freight : $12.07/wet t</td>
</tr>
<tr>
<td>Insurance : 0.15% of CIF</td>
</tr>
</tbody>
</table>
As mentioned earlier in this chapter, a separate block model variable (NSR) is generated to store economic block values. Net smelter return value is then calculated for each individual block using grade estimates and provided smelter terms.

In ultimate pit limit analysis, pit slope angles suggested as a result of the slope stability analysis performed by Fugro-Sial is used. Mentioned study reports the maximum safe slope angles for weathered and intact rock as 42° and 48°, respectively. Weathered unit is reported to be present near surface parts of southeast side of the deposit. For the sake of simplicity, 48° is used as the pit slope angle in the analysis.

Mining and processing costs are the other parameters needed for ultimate pit limit analysis. Prefeasibility study provided the cost items for mining, heap leaching and flotation. However, the heap leaching is later planned to be replaced with tank leaching. Therefore, the processing cost used for tank leaching reflects the assumption of the author of this research. Briefly, mining, flotation and tank leaching costs used for determination of ultimate pit are $1.5/t, $18.5/t and $14.5/t, respectively. (processing costs includes general and administrative costs).

An illustration of the ultimate pit determined based on all these technical and economic parameters using the Lerchs-Grossmann algorithm is presented in Figure 6.10.

Figure 6.10 An illustration of the ultimate pit limits on a SE-NW cross-section
Ultimate pit limits define the limits of optimum economic extraction. Therefore, all the waste block within the ultimate pit are needed to be removed to expose ore blocks. That’s exactly why, mining cost is considered as a sunk cost for the blocks within the pit limits. Moreover, ore/waste classification of those blocks are based on whether net smelter return value is large enough to justify extraction of economic components by either flotation or leaching. Therefore, NSR value of a block need to be larger than $18.5/t and $14.5/t to be classified as an ore block in oxide and sulfide zones, respectively.

The resources reported as inferred, indicated and measured categories for oxide and sulfide zones in terms of tonnage and average grade based on explicit modelling approach.

The resources represent the part of the deposit that demonstrated reasonable prospects for eventual economic extraction i.e. within the ultimate pit and above given NSR cutoff for oxide ($18.5/t) and sulfide ($14.5/t) material. As a result, measured and indicated (M&I) resources are calculated as 4.33 and 30.49 million tons for oxide and sulfide zones, respectively (Table 6.7).

<table>
<thead>
<tr>
<th>Resource Class</th>
<th>Tonnage, Mt</th>
<th>Au, g/t</th>
<th>Ag, g/t</th>
<th>Cu, %</th>
<th>Zn, %</th>
<th>Tonnage, Mt</th>
<th>Au, g/t</th>
<th>Ag, g/t</th>
<th>Cu, %</th>
<th>Zn, %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inferred</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.34</td>
<td>0.58</td>
<td>24.4</td>
<td>0.53</td>
<td>1.57</td>
</tr>
<tr>
<td>Indicated</td>
<td>0.03</td>
<td>0.93</td>
<td>50.3</td>
<td>0.07</td>
<td>0.07</td>
<td>1.90</td>
<td>0.62</td>
<td>18.3</td>
<td>0.48</td>
<td>0.94</td>
</tr>
<tr>
<td>Measured</td>
<td>4.30</td>
<td>1.78</td>
<td>52.3</td>
<td>0.14</td>
<td>0.18</td>
<td>28.59</td>
<td>0.55</td>
<td>20.0</td>
<td>0.60</td>
<td>1.20</td>
</tr>
<tr>
<td>Measured &amp; Indicated</td>
<td>4.33</td>
<td>1.77</td>
<td>52.3</td>
<td>0.14</td>
<td>0.18</td>
<td>30.49</td>
<td>0.56</td>
<td>19.9</td>
<td>0.59</td>
<td>1.18</td>
</tr>
</tbody>
</table>

Table 6.7 Mineral resources of the deposit
CHAPTER 7

DISCUSSION & COMPARISON OF OUTCOMES

The comparative analysis of 3D domain modeling alternatives constitutes the primary objective of this research. It is aimed to assess the impact of the choice of domain modelling approach, thus the study involves execution of resource estimation routine using identical estimation parameters, method and assumptions. Earlier sections of this document are particularly focused on presentation of main steps and aspects such as estimation method and assumptions. This chapter, on the other hand, is dedicated for global and local comparison of outcomes as well as discussion of sources and implications of major discrepancies documented among different scenarios.

Classification and reporting resources in a format which is compliant with one of the widely recognized reporting systems constitutes an essential task of resource geologists. Resource classification is a way to communicate relative confidence of the estimates in that measured, indicated and inferred resources are distinct with respect to the confidence hence risks associated with estimates. Furthermore, best practices allow conversion of economically mineable part of measured and indicated resources into ore reserves as a result of a study involving consideration of a number of modifying factors. That being the case, it is a common practice to report measured and indicated resources separately from resources belonging to inferred category. In this respect, comparison of tonnage and average grade for measured and indicated resources is substantial for global comparison of outcomes.

<table>
<thead>
<tr>
<th>Model</th>
<th>Tonnage, Mt</th>
<th>Au, g/t</th>
<th>Ag, g/t</th>
<th>Cu, %</th>
<th>Zn, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explicit Model</td>
<td>4.33</td>
<td>1.77</td>
<td>52.3</td>
<td>0.14</td>
<td>0.18</td>
</tr>
<tr>
<td>Implicit Model</td>
<td>4.20</td>
<td>1.81</td>
<td>53.3</td>
<td>0.16</td>
<td>0.22</td>
</tr>
<tr>
<td>Indicator Kriging</td>
<td>6.10</td>
<td>1.82</td>
<td>55.0</td>
<td>0.15</td>
<td>0.19</td>
</tr>
<tr>
<td>Simulation - 1</td>
<td>6.11</td>
<td>1.77</td>
<td>54.4</td>
<td>0.15</td>
<td>0.17</td>
</tr>
<tr>
<td>Simulation - 2</td>
<td>6.04</td>
<td>1.85</td>
<td>55.9</td>
<td>0.15</td>
<td>0.19</td>
</tr>
<tr>
<td>Simulation - 3</td>
<td>6.03</td>
<td>1.83</td>
<td>55.1</td>
<td>0.15</td>
<td>0.19</td>
</tr>
<tr>
<td>Simulation - 4</td>
<td>6.05</td>
<td>1.80</td>
<td>54.7</td>
<td>0.15</td>
<td>0.19</td>
</tr>
<tr>
<td>Simulation - 5</td>
<td>6.04</td>
<td>1.85</td>
<td>54.1</td>
<td>0.15</td>
<td>0.20</td>
</tr>
<tr>
<td>Simulation - 6</td>
<td>6.15</td>
<td>1.83</td>
<td>55.6</td>
<td>0.15</td>
<td>0.19</td>
</tr>
<tr>
<td>Simulation - 7</td>
<td>6.01</td>
<td>1.82</td>
<td>55.9</td>
<td>0.15</td>
<td>0.18</td>
</tr>
<tr>
<td>Simulation - 8</td>
<td>6.14</td>
<td>1.82</td>
<td>54.1</td>
<td>0.15</td>
<td>0.20</td>
</tr>
<tr>
<td>Simulation - 9</td>
<td>6.11</td>
<td>1.84</td>
<td>55.0</td>
<td>0.15</td>
<td>0.19</td>
</tr>
<tr>
<td>Simulation - 10</td>
<td>6.10</td>
<td>1.82</td>
<td>54.1</td>
<td>0.15</td>
<td>0.19</td>
</tr>
</tbody>
</table>

Table 7.1 Measured and indicated resources for alternative scenarios

<table>
<thead>
<tr>
<th>Model</th>
<th>Tonnage, Mt</th>
<th>Au, g/t</th>
<th>Ag, g/t</th>
<th>Cu, %</th>
<th>Zn, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oxide</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sulfide</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Tonnage, Mt</th>
<th>Au, g/t</th>
<th>Ag, g/t</th>
<th>Cu, %</th>
<th>Zn, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explicit Model</td>
<td>30.49</td>
<td>0.56</td>
<td>19.9</td>
<td>0.59</td>
<td>1.18</td>
</tr>
<tr>
<td>Implicit Model</td>
<td>32.47</td>
<td>0.55</td>
<td>20.0</td>
<td>0.61</td>
<td>1.20</td>
</tr>
<tr>
<td>Indicator Kriging</td>
<td>37.56</td>
<td>0.56</td>
<td>21.3</td>
<td>0.60</td>
<td>1.27</td>
</tr>
<tr>
<td>Simulation - 1</td>
<td>38.12</td>
<td>0.58</td>
<td>21.2</td>
<td>0.61</td>
<td>1.27</td>
</tr>
<tr>
<td>Simulation - 2</td>
<td>37.45</td>
<td>0.57</td>
<td>21.2</td>
<td>0.59</td>
<td>1.29</td>
</tr>
<tr>
<td>Simulation - 3</td>
<td>37.83</td>
<td>0.57</td>
<td>21.3</td>
<td>0.60</td>
<td>1.28</td>
</tr>
<tr>
<td>Simulation - 4</td>
<td>38.44</td>
<td>0.58</td>
<td>21.3</td>
<td>0.60</td>
<td>1.29</td>
</tr>
<tr>
<td>Simulation - 5</td>
<td>37.44</td>
<td>0.57</td>
<td>21.1</td>
<td>0.60</td>
<td>1.27</td>
</tr>
<tr>
<td>Simulation - 6</td>
<td>36.31</td>
<td>0.57</td>
<td>21.1</td>
<td>0.60</td>
<td>1.28</td>
</tr>
<tr>
<td>Simulation - 7</td>
<td>36.52</td>
<td>0.56</td>
<td>21.0</td>
<td>0.61</td>
<td>1.27</td>
</tr>
<tr>
<td>Simulation - 8</td>
<td>35.27</td>
<td>0.58</td>
<td>21.4</td>
<td>0.61</td>
<td>1.29</td>
</tr>
<tr>
<td>Simulation - 9</td>
<td>38.46</td>
<td>0.57</td>
<td>21.2</td>
<td>0.61</td>
<td>1.29</td>
</tr>
<tr>
<td>Simulation - 10</td>
<td>37.35</td>
<td>0.59</td>
<td>21.5</td>
<td>0.60</td>
<td>1.30</td>
</tr>
</tbody>
</table>
Table 7.1 above presents the measured and indicated resources for oxide and sulfide zones of alternative scenarios in terms of tonnage and average grade of precious and base metals within associated pit limits at NSR cutoff of $18.5/t and $14.5/t for oxide and sulfide material, respectively. It is clear that there exists significant discrepancies between outcomes especially with respect to tonnage of estimates. Moreover, there are differences for average grade of zinc and silver. It is also evident that the estimates for sequential indicator simulation approach is consistent internally and with that of indicator kriging approach all of which are significantly larger than the resource estimates of explicit and implicit modelling approach. Despite being global in scale, such a comparison suggests either (i) mineralized estimation domains guiding resource estimation are too conservation for explicit and implicit modelling approaches or (ii) indicator kriging and sequential indicator simulation results are too optimistic.

Another component of the global comparison of outcomes is visual comparison of 3D estimation domains particularly the ones associated with elevated precious and base metal grades. A preliminary observation made during visual inspection is that highly mineralized domains are notably larger for indicator kriging and simulation compared the ones for explicit and implicit modelling approaches. Moreover, major discrepancies are observed especially beyond the outmost drillholes where the extend of estimation domain in other words degree of extrapolation is controlled by modelling assumptions i.e., range of indicator variogram defines the extend of an estimation domain beyond the outmost drillhole for indicator kriging and simulation approach while it is limited to the half of the distance between adjacent drillholes in explicit modelling approach. Those parts of the deposit are associated with lower confidence resource estimates. Thus, it is a fair expectation to observe notable differences especially for inferred and indicated resources. Table 7.2 presents inferred, indicated and measured resources for alternative scenarios.

It is clear that there exists pronounced differences between inferred and indicated resource estimates for alternative scenarios. However, this does not account for major part of the discrepancy between the outcomes.
Table 7.2 Measured, indicated and inferred resources

<table>
<thead>
<tr>
<th></th>
<th>Oxide, ktons</th>
<th>Sulfide, ktons</th>
<th>Oxide &amp; Sulfide, ktons</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Inferred</td>
<td>Indicated</td>
<td>Measured</td>
</tr>
<tr>
<td>Exp</td>
<td>-</td>
<td>24.9</td>
<td>4,304.5</td>
</tr>
<tr>
<td>Imp</td>
<td>-</td>
<td>2.2</td>
<td>4,201.6</td>
</tr>
<tr>
<td>Ik</td>
<td>0.8</td>
<td>91.9</td>
<td>6,004.6</td>
</tr>
<tr>
<td>Sim1</td>
<td>8.1</td>
<td>97.5</td>
<td>6,010.3</td>
</tr>
<tr>
<td>Sim2</td>
<td>7.3</td>
<td>128.3</td>
<td>5,911.3</td>
</tr>
<tr>
<td>Sim3</td>
<td>8.7</td>
<td>104.9</td>
<td>5,925.1</td>
</tr>
<tr>
<td>Sim4</td>
<td>-</td>
<td>114.5</td>
<td>5,932.2</td>
</tr>
<tr>
<td>Sim5</td>
<td>-</td>
<td>67.4</td>
<td>5,972.5</td>
</tr>
<tr>
<td>Sim6</td>
<td>3.1</td>
<td>144.7</td>
<td>6,002.0</td>
</tr>
<tr>
<td>Sim7</td>
<td>0.8</td>
<td>77.9</td>
<td>5,935.0</td>
</tr>
<tr>
<td>Sim8</td>
<td>0.3</td>
<td>87.4</td>
<td>6,050.4</td>
</tr>
<tr>
<td>Sim9</td>
<td>-</td>
<td>83.0</td>
<td>6,028.1</td>
</tr>
<tr>
<td>Sim10</td>
<td>-</td>
<td>80.3</td>
<td>6,017.4</td>
</tr>
</tbody>
</table>

Global comparison of outcomes by visual comparisons and utilizing resource tables suggested some preliminary sources for discrepancies. However, a further analysis is needed to both to illustrate the implications and to identify the causes of the discrepancies. Thus, local comparisons of outcomes are made to address those issues.

Visual inspection and comparison of estimation domains along cross-sections comprises the first and most important part of the local comparison.

Figure 7.1 Comparison of HGS domain generated with alternative modelling approaches

Figure 7.1 presents SE-NW cross-sections for high-grade sulfide estimation domain generated with four alternative domain modelling approaches. Products of explicit and implicit modelling approach are three-dimensional volumes while those for indicator kriging and
simulation are coded blocks. Therefore, the comparison is made on the basis of domain coded blocks for the sake of consistency.

Based on the cross-sections provided, all the modelling approaches are effective to capture attitude of the estimation domain. However, there exists significant distinctions in terms of continuity and extends of the domain modelled. As stated earlier, extend of the estimation domain is directly controlled by estimation parameters and assumptions. Figure 7.1 indicates that indicator kriging and simulation results are relatively less continuous compared to those for explicit and implicit modelling. This is an outcome of the fact that indicator kriging and simulation results are purely mathematical solutions for the modelling practice. While explicit and implicit modelling approaches involve considerably more user interference, thus they allow generation of geologically more meaningful volumes.

Swath plots generated roughly along the dip direction of the deposit are the other tools utilized for local comparison purposes (Figure 7.2). The plots presented below facilitates local comparison of average mean grade estimates for precious and base metals for alternative modelling approaches followed.

They suggest the discrepancy between the average grades of 10 m NW-SE slices is more distinct for gold and silver than those for copper and zinc. Furthermore, the results for indicator kriging and simulation are largely consistent. Gold and silver have the largest grade disparities comparing explicit/implicit to indicator kriging/conditional simulation models. The swath plot
delineates maximum divergence along the middle of the SE-NW traverse which is potentially a result arising from local domain modelling differences in higher grade Au-Ag in gossan.

Global and local comparisons of the outcomes explicitly revealed the discrepancies for alternative resource estimates in terms of tonnage and average grade which are two important technical considerations. However, other technical and economic aspects are also needed for a more comprehensive assessment and illustration of implications of the choice of estimation domain modelling approach.

Misclassification of estimation domain is one of the most significant problem. Considering distinctions between physical properties (e.g. density) and technical factors such as recovery and treatment charges among different material types, misclassification has pronounced economic implications.

![Figure 7.3 Misclassification of the central block](image)

Figure 7.3 presents a hypothetical case to illustrate the significance of the problem. Cherry brown and orange blocks indicates high-grade sulfide and low-grade sulfide domains, respectively. While white colored NE-SW polyline represents the boundary between two estimation domains. In the case presented above, central block is classified into different material types due to a slight difference between the boundary polylines. As a result, pronounced differences observed in terms of net smelter return (NSR) and net economic block values of the same 10mx10mx5m centrally located block. NSR of the block for the given precious and base metal grades is calculated as $61.65/t and $68.49/t when it is classified as HGS and LGS, respectively. On the other hand, net economic block values are calculated as $98,142.7 (HGS) and $86,081.3 (LGS). The results can even be more serious when an ore grade block is misclassified as a waste block, and hence excluded from the resources.
Ultimate pit limit represents the extend of economic extraction. Therefore, the size of the ultimate pit is an indication of the scale of potential future operation as well as size of part of the deposit meeting reasonable prospects for eventual economic extraction criteria. That being the case, it is used to illustrate the implications of the modelling approach.

Figure 7.4 shows the ultimate pit limits for alternative modelling approach in a SE-NW cross-section. Similar to the previous observations, indicator kriging and simulation results are significantly distinct from those for explicit and implicit modelling approaches. Additionally, the degree of dissimilarity between the outcomes is clearly a function of the data density.

Figure 7.4 Ultimate pit limits for alternative modelling approaches in section view

Figure 7.5 presents the extends of the ultimate pits belonging to alternative scenarios in map view. Such a comparison is thought to be particularly an important aspect for surface infrastructure placement. The figure below suggests that none of the ultimate pits are consistently larger or smaller than the others.
The comparative analysis whose details has been presented so far indicates that estimation domain modelling decision also has implications in terms of ore, waste tonnages and stripping ratio.

Figure 7.6 Bar charts for ore tonnage, waste tonnage and stripping ratio
Histograms of the ore tonnage, waste tonnage and stripping ratio belonging to alternative scenarios are presented in Figure 7.6. Based on the histograms, explicit and implicit modelling approaches resulted in smaller ore and waste tonnages compared to the ones obtained by indicator kriging and simulation. The histogram of the stripping ratios, on the other hand, indicates that explicit modelling approach yields the largest value among alternative results.

Similarly, histogram of total value of the pits for alternative scenarios is utilized to illustrate the implications of the modelling choice in term of economic considerations.

![Figure 7.7 Bar chart of pit values for alternative scenarios](image)

Figure 7.7 above clearly shows the significant discrepancies between the pit values of different scenarios. Once again, it has been aimed to illustrate implications of estimation domain modelling alternatives on resource estimates not to decide on the optimum approach. Therefore, one of the most valuable findings of the study is the range of outcomes defined by the extremes of the histogram. It is crucial to emphasize that the range of outcomes for technical and economic considerations are directly related with underlying method and assumptions.

Finally, comparison of outcomes revealed that explicit-implicit pair and indicator kriging-conditional simulation pair are significantly different while the models yield similar results within the pairs. Mentioned similarity of indicator kriging and simulation results is due to identical estimation criteria considered. On the other hand, explicit and implicit modelling results are comparable because implicit model is guided by the geological knowledge obtained during explicit modelling.
Accurate estimation of resources is a significant task in mineral project evaluation. Therefore, the study presented in this document focused on an essential component of such a substantial process. It constitutes estimation of resources for alternative scenarios for which 3D estimation domains are generated with four different modelling approaches namely explicit modelling, implicit modelling, indicator kriging and sequential indicator simulation. In order to demonstrate the discrepancies resulted only from the choice of the domain modelling approach and underlying assumptions, identical grade estimation method and parameters are considered. Comparison of the outcomes indicated the significance of domain modelling decision on resource estimates of a polymetallic massive sulfide deposit located in western Turkey. As a result of the study following conclusions are made:

- The study demonstrated economic implications of four different modelling decision that are distinct from each other with respect to method complexity, time and effort. Although it involves time consuming manual digitization of interpreted geological features, explicit modelling is the suggested modelling technique because of complete user control. It has been seen that implicit modelling results when guided by geological knowledge particularly regarding attitude of the mineralization can be preferable when modelling need to be completed in relatively shorter time. Application of indicator kriging provides an alternative method to model categorical variables. Even though it can still be consulted for procurement of order of magnitude estimates, indicator kriging is not found particularly preferable for domain modelling purposes. Finally, conditional simulation technique can be effectively utilized for quantification of uncertainties as long as modelling parameters are guided by sound geological knowledge.

- It is a challenging task to model volcanogenic massive sulfide type deposits due to complex deposit geometries and post mineralization deformations. However, this particular deposit was an ideal case study considering fairly simple deposit geometry and huge amount of data availability.
There exist distinct domain discontinuities along the strike direction suggesting presence of potential NE-SW structures. However, structural features are poorly documented due to extensive cover.

Fairly tabular mineralization geometry suggests that metamorphism didn’t result in significant deformation of the original deposit geometry.

The deposit is associated with economic concentrations of gold, copper, zinc and silver. On the other hand, lead (non-composited mean grade: 0.08%) and trace elements are in negligible concentrations. Therefore, grade estimation is focused on procurement of block grade estimates for gold, copper, zinc and silver.

Polymetallic nature of studied volcanogenic massive sulfide deposit necessitated calculation of net smelter return value for each individual block in the model based on estimated metal grades, price, cost and concentrate recoveries, etc.

Measured plus indicated resources for the case where the domain models are generated with explicit modelling are estimated to be 4.33 million tons (average grade of Au:1.77 g/t, Ag:52.3 g/t, Cu:0.14 % and Zn:0.18 %) and 30.49 million tons (average grade of Au:0.56 g/t, Ag:19.9 g/t, Cu:0.59 % and Zn:1.18 %), respectively.

Measured plus indicated resource estimates for oxide zone range from 4.20 million tons to 6.15 million tons. While those for sulfide zone range from 30.49 million tons to 38.46 million tons.

The cases involving modeling estimation domains using indicator kriging and sequential indicator simulations resulted in resource estimates and pit values whose variability is less than 5%. It is primarily due to identical variogram model parameters and indicator codes used in both methods.

Analysis showed that the explicit modelling (37.0 million tons) and implicit modelling (38.0 million tons) resulted in comparable ore tonnages which are significantly smaller that the values obtained for indicator kriging (45.6 million tons) and conditional simulation (min: 43.1 million tons and max: 46.7 million tons).

Explicit modelling (211.2 million tons) and implicit modelling (201.2 million tons) results are also somehow comparable in term of waste tonnages. Furthermore, waste tonnages for indicator kriging (248.3 million tons) and conditional simulation (min: 225.5 million tons and max: 251.2) are similarly larger than the results for other two techniques.
Explicit modelling (5.71) and implicit modeling (5.30) results are distinct with respect to stripping ratio. The results obtained by the case where domain modeling is performed by explicit modeling technique represents the most unfavorable case with the largest stripping ratio.

Different ultimate pit limit extents identified by this analysis might be considered as a guide for decisions regarding surface infrastructure placement.

The range of outcomes defined by the minimum ($1.04 billion for explicit modelling) and maximum ($1.45 billion for simulation #9) pit values is proposed as a way to express downside risks and upside potential of the project for given modelling assumptions.

The analysis of both cross-sections and 3D models of estimation domains generated using four different methods indicated that major discrepancies observed beyond the limit defined by the outermost drillholes. Therefore, underlying assumption of modeling techniques regarding extrapolation distance is the main source of mentioned dissimilarities.

Aforementioned differences in domain models especially for domains that are associated with elevated metal grades (i.e. gossan zone and high-grade sulfide) may represent potential drill targets.

The discrepancies identified between the outcomes of the alternative scenarios explicitly demonstrated the substantial role of the geological understanding in mining project evaluation. Considering its potential influences as well as economic implications on downstream mining practices which are discussed earlier, quality of the estimation domain model, which is utilized as a key guiding tool during estimation of a property, is clearly important. Therefore, decision of the modelling approach should involve consideration of not only complexity, time and effort requirement but also its potential influences on subsequent applications.

All in all, the estimation of resources requires detailed consideration of various aspects involving contribution of experts from various disciplines. Like a chain, they are linked in that the quality of the overall resource estimate will be equal to the quality of the weakest link.
REFERENCES


APPENDIX A

CONTACT PLOTS

Figure A.1 ClyGos-Gos contact plots

Figure A.2 Mpy-MpyMag contact plots
Figure A.3 HGS-LGS contact plots

Figure A.4 GOS-NGO contact plots
Figure A.5 HGS-BW contact plots

Figure A.6 LGS-BW contact plots
APPENDIX B

MODELLING METHODS

This section of the report is prepared to provide further details regarding major steps and assumptions made during generation of three-dimensional estimation domain models using four modelling techniques: (i) explicit modelling, (ii) implicit modelling, (iii) indicator kriging, and (iv) conditional simulation. A digital appendix is also included in the form of a flash drive which can be referred for review purposes. Original dataset containing whole drillhole database as well as other complementary data are included in the folder names as Original Data. On the other hand, part of the database that has been used in this study can be found under folder named as Model Data.

Explicit Modeling

It represents traditional technique for construction of three-dimensional models. Explicit modelling heavily relies on manual digitization of interpreted geological features on cross-sections.

**Main steps of explicit modelling:**

- **Step 1** - Delineation of stationary estimation domains
- **Step 2** - Interpretation of continuity of estimation domains and construction of cross-sections and long-sections
- **Step 3** - Digitization of interpretations on cross-sections
  - Contacts digitized along cross-sections and long-sections are provided under X-Sections folder (MineSight3D) in the digital appendix
- **Step 4** - Building wireframes (also known as triangulations) through linking digitized boundaries representing the contacts between adjacent estimation domains
  - Domain wireframes are provided under Explicit approach subfolder of Estimation domains folder in the digital appendix
- **Step 5** - Final adjustment of wireframes based on cross-cutting relationships
- **Step 6** - Validation of the model with input data, sections and maps
**Assumption(s):**

Major assumption made during generation of 3D models by explicit modelling technique is **extrapolation distance**. Similar to the common industry practice, nearly **half of the distance between adjacent drillholes** is considered for extrapolation purposes.

**Additional remarks:**

The best practices suggest interpretation of geology on all three orthogonal planes including cross-sections, long-sections and plan views. This study involves definition of the mineralization geometry along NE-SW and NW-SE sections.

**Implicit Modelling**

It is a more recent technique compared to explicit modelling. Implicit modelling relies on software driven algorithms (i.e. radial basis function) for generation of surfaces corresponding to boundaries between data populations.

<table>
<thead>
<tr>
<th>Main steps of implicit modelling:</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Step 1</strong> - Delineation of stationary estimation domains</td>
</tr>
<tr>
<td><strong>Step 2</strong> - Modelling surfaces representing boundaries between adjacent estimation domains using RBF</td>
</tr>
<tr>
<td>➡️ Contact surfaces are modelled in Leapfrog Geo. However, they are not provided with the digital appendix</td>
</tr>
</tbody>
</table>

| **Step 3** - Definition of contact surface chronology and identification of the background lithology |
| ➡️ Contact surface chronology is defined from younger to older as gossan zone (GOS) and non-gossan oxide (NGO) for the oxide zone, enriched zone (ENR), high-grade sulfide (HGS), low-grade sulfide (LGS) and barren wall rock (BW) in the sulfide zone |
Main steps of implicit modelling (cont.)

- **Step 4**- Generation of 3D solid models based on modelled contacts and defined surface chronology
  
  Domain wireframes are generated in a commercial modelling software, Leapfrog Geo. They have later been imported into MineSight3D. Domain wireframes are provided under Implicit approach subfolder of Estimation domains folder in the digital appendix

- **Step 5**- Validation of implicit model by comparing with input data, cross-sections and surface geological maps

**Assumption(s):**

Main assumption made in generating 3D domain models using implicit modelling technique is model resolution which determines the minimum length of input data that will be considered for modelling purposes. Considering composite length (5m), **resolution of the model** is set as 5m.

**Additional remarks:**

- Preliminary implicit model which is generated based on isotropic search strategy was not successful to capture the spatial characteristics of estimation domains. Thus, the model is improved by introducing a trend reflecting the attitude of the deposit (strike: N15E and dip: 25°) which has been identified during explicit modelling

- A further improvement is achieved through use of 3D polylines both to limit extents of each volume and to get rid of modelling artifacts observed in the form of isolated bodies
Indicator Kriging

Application of indicator kriging, a non-linear kriging technique, provides an alternative approach for three-dimensional modelling of categorical variables.

**Main steps of indicator kriging:**

- **Step 1-** Delineation of stationary estimation domains
- **Step 2-** Non-linear transformation of data into six set of binary indicator codes (0: interval **not belonging** to the estimation domain, 1: interval **belonging** to the estimation domain)

**Step 3-** Construction of directional indicator variograms

- Directional indicator variograms are provided under Variograms subfolder of MSDA folder in the digital appendix. V1 and V456 prefixes are used for the indicator variograms for oxide and sulfide zones, respectively

- **Step 4-** Characterization of spatial continuity of individual estimation domains by fitting variogram models for experimental directional variograms

- Fitted variogram model parameters file is provided as a text file within Variogram subfolder of MSDA folder in the digital directory

- **Step 5-** Execution of indicator kriging with generated indicator codes and variogram model parameters to generate 3D solid models of estimation domains

- Estimation domain codes used to store domain information for the block model named as BM-IK provided under Block models folder of the digital directory are as follows: GOS: 1, NGO: 2, BW: 3, HGS: 4, LGS: 5 and ENR:6

- **Step 6-** Validation of solid models by comparing with input data, cross-sections and surface geological maps
Conditional Simulation

Conditional simulation is the fourth technique by which 3D solid models can be generated. The method is utilized to generate mathematically equiprobable realizations in other words outcomes.

**Assumptions:**

- Ellipsoidal search whose dimensions are the same as the ranges of indicator variogram along major continuity directions
- For variography intercepts belonging to gossan zone are considered for oxide zone while those for high-grade sulfide, low-grade sulfide and enriched zone employed for sulfide zone
- Indicator threshold = 0.5 (i.e. if the indicator kriging estimate for a block is greater than 0.5, then the block belongs to associated estimation domain)

**Additional Remarks:**

Even though, 3D domain modeling is performed on 10m x 10m x 5m sized regular block basis, it has been thought that contacts between adjacent estimation domains might be better defined for smaller sized blocks.

**Main steps of conditional simulation:**

- **Step 1**- Delineation of stationary estimation domains
- **Step 2**- Non-linear transformation of data into six set of binary indicator codes (0: interval not belonging to the estimation domain, 1: interval belonging to the estimation domain)
- **Step 3**- Construction of directional indicator variograms

Directions indicator variograms are provided under Variograms subfolder of MSDA folder in the digital appendix. V1 and V456 prefixes are used for the indicator variograms for oxide and sulfide zones, respectively.
Main steps of conditional simulation (cont.)

- **Step 4**- Characterization of spatial continuity of individual estimation domains by fitting variogram models for experimental directional variograms
  
  ➔ Fitted variogram model parameters file is provided as a text file within Variogram subfolder of MSDA folder in the digital directory

- **Step 5**- Execution of sequential indicator simulation with generated indicator codes and variogram model parameters to generate 10 realizations for 3D solid models of estimation domains
  
  ➔ Estimation domain codes used to store domain information for the block models named as BM-SIM1 to BM-SIM10 provided under Block models folder of the digital directory are as follows: GOS: 1, NGO: 2, BW: 3, HGS: 4, LGS: 5 and ENR:6

- **Step 6**- Validation of solid models by comparing with input data, sections and maps

---

**Assumptions:**

- Ellipsoidal search whose dimensions are the same as the ranges of indicator variogram along major continuity directions
- In variography, intercepts belonging to gossan zone are considered for oxide zone while those for high-grade sulfide, low-grade sulfide and enriched zone employed for sulfide zone
- Indicator threshold = 0.5 (i.e. if the estimate for a block is greater than 0.5, then the block belongs to associated estimation domain)

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**Additional remarks:**

Similar to indicator kriging, consideration of smaller blocks could be effective to better define the contacts between adjacent estimation domains.
APPENDIX C

3D DOMAIN MODELS

Figure C.1 3D models of gossan zone (GOS)
Figure C.2 3D models of non-gossan oxide (NGO)
Figure C.3 3D models of barren wall rock (BW)
Figure C.4 3D models of high-grade sulfide (HGS)
Figure C.5 3D models of low-grade sulfide (LGS)
Figure C.6 3D models of enriched zone (ENR)
Table C.1 Volumes for estimation domain solid models

<table>
<thead>
<tr>
<th></th>
<th>Solid Model Volumes, million m3</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>GOS</td>
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<tr>
<td>Explicit Modelling</td>
<td>2.12</td>
</tr>
<tr>
<td>Implicit Modelling</td>
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</tr>
<tr>
<td>Indicator Kriging</td>
<td>3.14</td>
</tr>
<tr>
<td>Simulation 1</td>
<td>3.06</td>
</tr>
<tr>
<td>Simulation 2</td>
<td>3.09</td>
</tr>
<tr>
<td>Simulation 3</td>
<td>3.24</td>
</tr>
<tr>
<td>Simulation 4</td>
<td>2.98</td>
</tr>
<tr>
<td>Simulation 5</td>
<td>3.00</td>
</tr>
<tr>
<td>Simulation 6</td>
<td>3.02</td>
</tr>
<tr>
<td>Simulation 7</td>
<td>3.35</td>
</tr>
<tr>
<td>Simulation 8</td>
<td>3.06</td>
</tr>
<tr>
<td>Simulation 9</td>
<td>3.11</td>
</tr>
<tr>
<td>Simulation 10</td>
<td>3.05</td>
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</tbody>
</table>
APPENDIX D

MEASURED, INDICATED AND INFERRED RESOURCES OF INDIVIDUAL ESTIMATION DOMAINS

Table D.1 Measured, indicated and inferred resources for oxide zone

<table>
<thead>
<tr>
<th></th>
<th>Barren wallrock, ktons</th>
<th>High-grade Sulfide, ktons</th>
<th>Low-grade Sulfide, ktons</th>
<th>Sulfide Zone, ktons</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>Inferred</td>
<td>Indicated</td>
<td>Measured</td>
<td>Inferred</td>
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<tr>
<td>Exp</td>
<td>6.9</td>
<td>524.9</td>
<td>3,802.1</td>
<td>6.0</td>
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<tr>
<td>Imp</td>
<td>6.9</td>
<td>493.4</td>
<td>4,163.6</td>
<td>6.9</td>
</tr>
<tr>
<td>lk</td>
<td>254.7</td>
<td>1,330.7</td>
<td>3,734.2</td>
<td>66.7</td>
</tr>
<tr>
<td>Sim1</td>
<td>285.4</td>
<td>1,243.7</td>
<td>3,749.4</td>
<td>81.2</td>
</tr>
<tr>
<td>Sim2</td>
<td>290.3</td>
<td>1,366.4</td>
<td>3,641.2</td>
<td>77.9</td>
</tr>
<tr>
<td>Sim3</td>
<td>254.7</td>
<td>1,303.8</td>
<td>3,832.3</td>
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<tr>
<td>Sim4</td>
<td>291.9</td>
<td>1,357.3</td>
<td>3,609.1</td>
<td>67.7</td>
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<tr>
<td>Sim5</td>
<td>289.6</td>
<td>1,276.6</td>
<td>3,454.7</td>
<td>71.0</td>
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<tr>
<td>Sim6</td>
<td>289.5</td>
<td>1,268.0</td>
<td>3,444.5</td>
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<tr>
<td>Sim7</td>
<td>5.6</td>
<td>547.9</td>
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<td>5.6</td>
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<td>Sim9</td>
<td>254.7</td>
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<tr>
<td>Sim10</td>
<td>291.9</td>
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<td>3,572.6</td>
<td>94.6</td>
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</table>

Table D.2 Measured, indicated and inferred resources for sulfide zone
APPENDIX E

COMPARISON OF ESTIMATION DOMAINS

Figure E.1 Comparison of LGS domain generated with alternative modelling approaches

Figure E.2 Comparison of Gossan zone generated with alternative modelling approaches