UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

COMPARATIVE ANALYSIS OF LINEAR AND NON-LINEAR ESTIMATION TECHNIQUES FOR THE DETERMINATION OF RECOVERABLE RESOURCES IN A SEDIMENTARY HOSTED Cu-Co TYPE DEPOSIT

Research Stream: Mineral Resource Estimation

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DECLARATION

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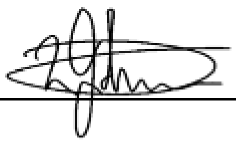

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ABSTRACT

Mineral Resource estimation heavily impacts the technical and financial merits of mining feasibility studies, carried out prior to any material extraction. Since exploration requires significant investment, the feasibility of a project needs to be understood as soon as possible in the development of a mining lifecycle. To help define the feasibility of a mining project, resource geologists estimate the Mineral Resource and in-situ recoverable resources available for mining. Techno economic studies are then carried out to assess the economic viability of mining and metallurgical extraction of the recoverable resource. This is achieved by geostatistically estimating the tonnage and grade of mineralisation above a given cut-off grade and at a chosen mining unit or size, (Isaaks and Srivastava, 1989).

The research presented is a comparative case study aimed at assessing the suitability of linear and non-linear estimation techniques in the determination of recoverable resources from exploration drilling data in a sedimentary hosted copper-cobalt type deposit. In an operating mine, recoverable resources are typically determined after a grade control drilling programme, drilled on a tight grid to identify subtle variations in grade within a deposit. By comparison, exploration data is inherently broadly spaced and occurs at a much earlier stage in the mining project life-cycle. The geostatistical techniques considered for the estimation of recoverable resources are ordinary kriging, uniform conditioning, and localised uniform conditioning. The localised estimate is contrasted against a grade control estimate, produced from ordinary kriging, to verify the success in determining the recoverable resources from exploration drilling data.

The research study found that the dense drilling pattern of the grade control data provides an increased understanding of the distribution of average copper grades at Tshifufia than localised uniform conditioning from exploration data. The success of uniform conditioning on exploration data and the subsequent localisation is dependent on the size of the selective mining unit and grades that have been ranked and spatially referenced according to the average ordinary kriging block estimates. This direct proportionality means that where ordinary kriging estimates are high or low,

the localised uniform conditioning estimate will be proportionally high and low as well.

Despite the aim of determining the recoverable resources at selective mining unit-scale, localised uniform conditioning grades performed on exploration data provide no more resolution than the ordinary kriging mineral resource estimate, since the underlying data inherently determines the uniform conditioning and localised uniform conditioning. Any additional resolution on the distribution of average grades at selective mining unit level and determination of recoverable resources is subject to the amount and spatial representation of available information during estimation. Therefore, no suitable substitute was determined for grade control drilling and the resulting ordinary kriging grade control mineral resource estimate.

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LIST OF SYMBOLS

Average co-variance between panel of support V	$\bar{C}(V,V)$
Average co-variance between SMU, of support v	$\bar{C}(v,v)$
Average variance within a panel, of support V	$\bar{\gamma}(V,V)$
Average variance within an SMU, of support v	$\bar{\gamma}(v,v)$
Estimated grade at point location i	$\mathrm{T}^*(\mathrm{g}_i)$
Panel estimate "V"	$Z(V)$
SMU estimate "v"	$Z(v)$
Hermite coefficient ("phi")	ϕ
Hermite polynomial	H
Lagrange multiplier	μ
Large block support (panel)	V
Sample variance ("sigma squared")	σ^2
Small block support (SMU)	v
Sample weight	w_i
Gaussian variable	$Y(v)$
Hermite polynomial	H_k
Coefficient of a Hermite polynomial	k
Point to SMU change of support coefficient	r
Point to Panel change of support coefficient	s
Tonnage at the cut off (z_c)	$T_v\ (z_C)$
Quantity of contained metal at the cut off (z_c)	$Q_v\ (z_C)$
Mean grade at the cut off (z_c)	$M_v\ (z_C)$
Gaussian anamorphosis	ϕ_v

LIST OF ABBREVIATIONS

Block variance	BV
Coefficient of variation	CoV
Democratic Republic of Congo	DRC
Diamond drillhole	DD
Discrete Gaussian Model	DGM
Exploration Data Analysis	EDA
Grade control	GC
Grade tonnage	GT
Grammes per tonne	g/t
Localised Uniform Conditioning	LUC
Minerals and Metals Group	MMG
Mineral Resource	MR
Ordinary Kriging	OK
Quantitate Kriging Neighbourhood Analysis	QKNA
Reverse circulation	RC
Selective Mining Unit	SMU
Uniform Conditioning	UC

1 Introduction

The mining project lifecycle is made up of several stages which span from generation and grassroots exploration to closure and rehabilitation (Figure 1). Each stage is associated with a level of risk and uncertainty commonly associated with geological, economic, metallurgical, political, environmental and legal factors. As confidence in each stage increases through the generation of multiple datasets, the associated risks lower over time as there are fewer unknown variables to be considered.

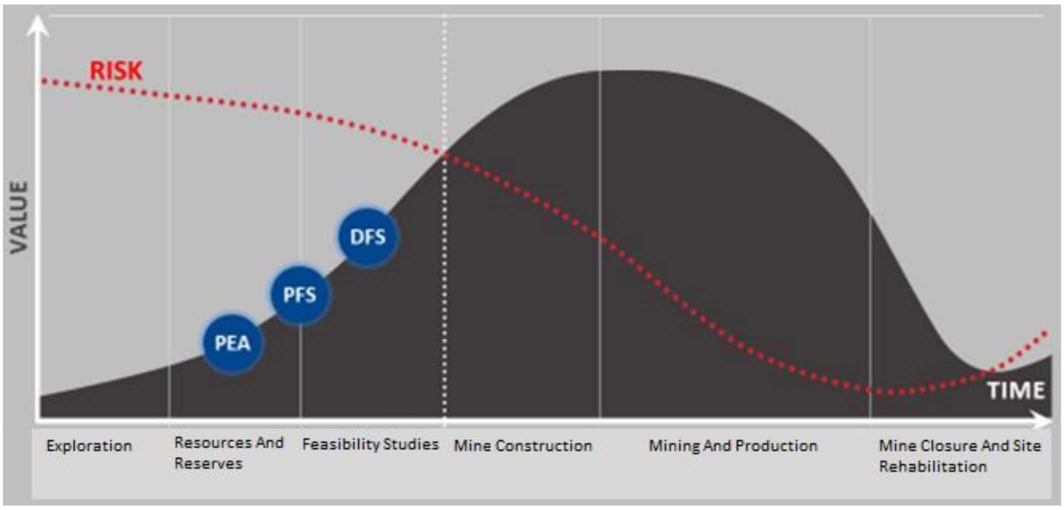

Figure 1:Value versus Risk in the Mining Project Lifecycle (*modified after Njowa and Musingwini, (2011))*.

As can be seen in Figure 1, exploration represents the first stage in the mining project lifecycle. Exploration activities are generally associated with preliminary investigative techniques used to locate anomalous mineralisation in the Earth's crust. However, exploration drilling and recovery of physical core from an area of interest remains the best method for basing Mineral Resource (MR) estimates on.

In its conversion to a Mineral Reserve, MR estimation heavily impacts the feasibility of mining projects based on the technical and financial merits before material is extracted. Since exploration requires significant upfront capital expenditure with minimal return on investment, the feasibility of a project needs to be understood as soon as possible in the mining lifecycle. To help define the feasibility of a mining project, resource geologists estimate MR's and *in-situ* recoverable resources available for mining that can be economically extracted. This is achieved by geostatistically estimating the tonnage and grade of mineralisation above a given cut-off grade and at a chosen mining unit or size, (Isaaks and Srivastrava, 1989).

There are a variety of estimation techniques available today, all of which are by nature of being estimates incapable of exactly quantifying a MR. Some techniques provide better estimates than others depending on, but not limited to, deposit type, structural controls, and style of mineralisation. These defining factors strongly influence or determine the estimation technique to be used, (Armstrong and Matheron, 1986).

1.1 Purpose of the Study

This research study is a proof-of-concept assessment to determine the most appropriate estimation technique for the determination of recoverable resources. The research study compares and distinguishes between ordinary kriging (OK) and localised uniform conditioning (LUC), as well as estimates the *in situ* recoverable resources using LUC. The results will be contrasted against the grade control (GC) drilling data for the Tshifufia deposit.

This case study investigates and assesses the suitability of linear and non-linear estimation techniques on a historically (2014) mined area within Minerals and Metals Group's (MMG) Kinsevere Mine.

1.2 Research Background

Exploration and mining are capital intensive undertakings for any mining company, (McCuaig *et al.*, 2014). Successful early-stage investment and progression through the mining lifecycle is largely dependent on MR estimation results. The ability to accurately estimate the MR's and from that the recoverable resources can significantly de-risk mine planning and have a positive financial impact on the buy-in from stakeholders. This creates a responsibility for mining companies to try to improve the interpretation of their estimates wherever possible and indicate the estimated recoverable resources far sooner than the current practices do.

Various linear estimation methods exist; however, OK is one of the most favoured estimation techniques in resource estimation. OK uses a direct spatially weighted averaging of sample data to calculate the grade at an unknown point or block, (Krige, D. G., 1978). This estimation methodology provides the best linear unbiased estimate. The OK MR estimate is based on the spatial configuration of samples and blocks to be estimated (the kriging neighbourhood) as well as the variogram model, assumed to capture the spatial variability or spatial correlation of grades within a unique geologic environment. The OK MR estimate is the linear sum of weighted sample values, where the optimal set of weights are determined by minimising the estimation variance. The resulting minimum estimation variance is the kriging variance which depends only on the kriging neighbourhood and not the sample grades. Meaning that OK is limited by drillhole spacing and should be carried out on a large block size that is no smaller than half the drilling grid, (Clark, 1979). This results in a single grade value being applied to each block. However, kriging inherently smooths the estimates causing conditional bias. Practically, this is unrealistic for the estimation of highly variable recoverable resources, which require selective mining at smaller block sizes than OK can produce, (Neufeld and Deutsch, 2005). Additionally, the presence of outliers within a deposit can further deteriorate the quality of an estimate and incorrectly represent the spatial distribution of grade between blocks.

This natural variability, influence of outliers and conditional bias make OK a limited estimator of recoverable resources and highlights the need for more densely drilled mineral deposits (e.g. GC drilling). GC drilling assists in removing some of these limiting factors from the estimation of recoverable resources. However, if the GC data is of poor quality due to bad sampling practices in the field or contamination at analytical facilities, it introduces other factors of uncertainty.

Alternative non-linear estimation techniques are available for resource geologists to use exploration data to model and estimate the recoverable resources from a deposit. UC was first described by (Matheron, 1974) and it outlined the ability of UC to calculate the grade distribution within large blocks or panels which allows for the use of a change of support model to be applied.

However, UC cannot determine the spatial localities of grade at SMU scale within the panel or block. The UC MR estimate needs to be localised in a process known as localised uniform conditioning (LUC). LUC incorporates a change of support model to condition an estimated panel into a known distribution of smaller grade blocks or SMU's, representative of the recoverable resources within the panel, (Abzalov, 2006).

1.3 Research Motivation

The estimation methodology in place for the case study considered might be enhanced through non-linear estimation techniques such as UC and LUC. The aim of this research study is to investigate and identify whether, in addition to OK, the recoverable resource estimation methodologies can be applied to produce positive impact on mine planning and consequently mine valuation. Furthermore, the findings of this study could potentially be applied to other deposits with similar geological characteristics.

It is expected that by comparing the estimates of the different estimation techniques described above, one should be able to assess the most appropriate estimation technique to determine the recoverable resources above a given cut-off. Identifying the most appropriate method for the estimation of recoverable resources for the Kinsevere Mine could improve the technical merits of the project and improve the future financial valuations.

1.4 Research Methodology

The methodology for this research study follows a quantitative analysis of secondary drillhole data for the determination of recoverable resources by comparing linear (OK) and non-linear (UC and LUC) resource estimation techniques.

An extensive literature review was conducted to fully understand the requirements and steps necessary for OK, UC and LUC estimation. MMG supplied a comprehensive historical exploration dataset for the Kinsevere Project which included multiple phases of exploration drilling and a single phase of grade control drilling. OK, UC and LUC MR estimates was determined by using a combination of Datamine Studio RM and GSLib software framework.

The methods and steps used in this research study were as follows:

- Exploratory Data Analysis (EDA) of the exploration and grade control drillhole data was performed to prepare the data for block modelling and estimation. The EDA process included the validation, statistical and geostatistical analysis, spatial data validation, compositing of drillhole data, declustering and a goodness of fit test to assess stationarity.
- A block model and grade estimate for the exploration drillhole data was performed using OK. The exploration drillhole data requires domaining, which was defined according to geological and statistical factors, normal score transformation, variography, variogram modelling and quantitative kriging neighbourhood analysis. The results from these processes help generate a robust grade estimate and block model that was visually validated.
- The exploration drillhole data was then prepared for UC and LUC estimation. This required the use of the change of support model using the discrete Gaussian model equation to determine the change of support coefficient for the SMU or panel based on block variance and block size.

- The UC MR estimate was generated using the stepwise Datamine UC Wizard that declustered exploration drillhole data and utilises the OK MR estimate and variograms determined earlier. The UC MR estimate resulted in the estimation of volume or tonnage and grade of a deposit above a specified cut-off grade.
- The UC MR estimate was then localised resulting in determination of the distribution of SMU's within the panels.
- An OK grade control estimate was done last to assess the success of the LUC MR estimate in determining the recoverable resources from exploration data.
- The performance of the LUC MR estimate was compared to the kriged estimates for exploration and grade control drilling data to determine the recoverable resources for the Tshifufia deposit.

1.5 Research Report Layout

Chapter 1 is an introductory chapter stating the purpose and objective of the research study. It gives context to the study by discussing the background to the research leading to the motivation thereof. The research methodology is presented followed by a summary of the report layout and assumptions made.

Chapter 2 consists of an extensive literature review applicable and related to linear and non-linear resource estimation techniques to be used in the research study presented.

Chapter 3 contextualises the geological environment investigated in this research study and highlights key factors that characterise the Tshifufia deposit.

Chapter 4 is dedicated to the EDA which includes data validation, statistical and geostatistical analyses of exploration and grade control data. Providing insight into the underlying statistical distribution and spatial variability characteristics of the dataset.

Chapter 5 addresses the block model and grade estimation based on exploration data by following the natural steps in developing a resource estimate: from consideration of domain boundaries to variography, kriging neighbourhood analysis to the OK grade estimation and validation, culminating in a grade tonnage estimate based on exploration data.

Chapter 6 covers the UC process and the application of the change of support model to produce UC recoverable resource estimates i.e. the proportion of tonnes above and average grade above cut-off in terms of the SMU. Followed by the implementation of the localisation of the SMU estimates to produce local estimates (LUC) of the SMUs within estimated blocks. Validation of the localised estimation SMUs is visually presented and further supported by a SMU grade tonnage resource estimate.

Chapter 7 addresses the block model and grade estimation based on grade control data and the subsequent OK grade estimation and validation. Culminating in a grade tonnage estimate based on grade control data at SMU scale that will be compared to the LUC MR estimate from exploration data.

Chapter 8 discusses the various estimation techniques and compares the estimation results against each. Chapter 8 is divided into two parts where the estimates related to exploration data and grade control are discussed by comparing various grade tonnage curves, P-P plots, and Q-Q plots.

Chapter 9 summarise the findings of the research study with a conclusion on the appropriateness of LUC estimation for the determination of recoverable resources from exploration data within the Case Study area.

1.6 Assumptions

Strict quality control and quality assurance (QAQC) standards are applied to all data to ensure that mineral resources are based on accurate and precise data. It is assumed that the data available at the time of this project has passed QAQC tests.

The Minerals and Mining Group (MMG) has released several mineral resource estimates in the past, all of which are in accordance with Joint Ore Reserves Committee (JORC) (JORC, 2012) guidelines. QAQC issues raised by external auditors have been rectified prior to this project.

Consent to use the Kinsevere Mine data and has been given with all data available up to and including 2014.

1.7 Chapter Summary

By comparing linear and non-linear resource estimation techniques, this research study will identify the most appropriate estimation method for the accurate estimation of the Kinsevere deposit. Furthermore, the technical and financial merits for mine planning will be assessed by performing a localised uniform conditioning (LUC) estimate. These questions will be answered through reviewing literature and comparative analysis between OK, UC and LUC.

2 Literature Review

MR estimation typically begins with a maiden MR estimate based on exploration drilling. If the deposit is deemed suitable for mining, additional infill drilling and GC drilling campaigns are performed prior to mining extraction to provide resolution on the recoverable reserves by drilling at a much higher density than the exploration campaign that led to the maiden MR estimate. MR estimation of mineral deposits is modelled using linear and non-linear resource estimation techniques. Linear estimation techniques are commonly used in the estimation of the maiden MR and the determination of recoverable resources from exploration and GC drilling, respectively. However, non-linear estimation techniques are capable of providing estimates of recoverable resources at the exploration stage well in advance of GC drilling being implemented.

The estimation of recoverable resources requires the modelling of the grade-tonnage relationship at a chosen mining selectivity, (Rivoirard, 1990). This allows us to predict an economically viable portion or block of modelled mineralisation (above a given cut-off grade) without knowing the spatial location of the recoverable resource.

Two contrasting techniques used for the estimation of recoverable resources are to be considered in this research study. These are:

- Ordinary Kriging (OK) - Linear Estimation Techniques; and
- Uniform conditioning and localisation (UC and LUC) - Non-linear Estimation Techniques.

2.1 Linear Estimation Techniques

Linear estimation techniques produce smooth estimates of MR’s resulting in small blocks inadequately supported by widely spaced drillholes, typical of exploration drilling, (Abzalov, 2006). Linear estimation does not produce any estimates which represent values matching or exceeding the highest and lowest values of the deposit, but rather interpolates grades to somewhere in between, (Hansmann, 2015). The result is an estimate for large blocks or panels with associated global tonnage and grade estimates above cut-off.

2.1.1 Ordinary Kriging

The familiar linear estimation technique OK MR estimates a direct weighted average of surrounding data to calculate the grade at an unknown point or block. In the case of OK, the weights are optimised to minimise the estimation error and variance, (Clark, 1979). OK is preferentially chosen as an estimator as it minimises estimation variance and optimises the weighting of samples whilst remaining independent of grades of those samples, (Vann and Guibal, 1998). OK is based on the spatial covariances between known sample locations. OK estimation achieves this by weighting each sample's contribution to the unknown sample location, based on the spatial arrangement and distance to known sample. The spatial variability across the deposit is then modelled using an experimental variogram, (Isaaks and Srivastava, 1989 and Clark, 1979).

The experimental variogram measures the spatial variability between samples values at specific distances between sample locations. This spatial variance can be empirically calculated using the following equation:

$$\gamma * (h) = \frac{\Sigma\big(Z(x_i) - Z(\,x_i + h)\big)^2}{2N_h} = \frac{\Sigma\big(g_i - g_j\big)^2}{2N_h}$$

Where:

$\gamma * (h)$	The average experimental semivariance of all samples that are at a specific distance "h" apart in a specific direction
h	The distance between the two samples
$N(h)$	The number of pairs found at a distance h apart in a specific direction
$z(x_i)= g_i$	The grade $g_i$of a sample at location x_i
$z(x_i + h)= g_j$	The value g_j of a sample at location x_{i+h}

The experimental variogram captures the spatial variability of the grade within a domain and the variogram model estimates the spatial variability within it. Modelling the spatial variability between samples across a deposit is a critical step in OK estimation (Clark, 1979). The variogram is a good indicator of stationarity. The following notation is described by Isaaks and Srivastava, 1989 and Clark, 1979.

The OK Estimate T* is a linear estimator:

$$\mathrm{T}^{*} = \sum_{i=1}^{n} w_i . g_i$$

Where w_i is the weight of sample *i*.

The estimation error is $\varepsilon = T - T^{*}$ the difference between the true value T and the estimated value T^{*}at any location.

It is assumed that the domain is stationary i.e., there is no trend in the data and the underlying grade distribution is the same throughout the domain of interest. Then the

1. Mean error: $\mu_\varepsilon = 0$ on average the errors are equal to zero
2. Variance of the errors, expressed in terms of the variogram model is:

$$\sigma^2{}_{\varepsilon} = 2 \sum w_i \gamma\,(T, g_i) - \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \gamma\big(g_i g_j\big) - \gamma(T, T)$$

To ensure the “best linear unbiased estimate” is derived the estimation variance $\sigma^2{}_{\varepsilon}$ is minimised with respect to the weights subject to the constraint that

$$\sum_{i=1}^{n} w_i = 1$$

Which is achieved by the introduction of a LaGrange Multiplier λ and then minimising $\sigma_\varepsilon^2 - \lambda(\sum w_i - 1)$ with respect to the weights and λ. The minimum estimation variance at any location is the kriging variance:

$$\sigma_K^2 = \sum_{i=1}^{n} w_i (T, g_i) + \lambda - \gamma(T, T)$$

Where:

T^*	estimated grade at a specific location
n	number of samples used for the estimation at the specific location
w_i	individual weight of each sample i contributing to the estimate
g_i	known grade of sample i
${\sigma^2}_\varepsilon$	estimation variance
$\gamma(h)$	the variogram model as a function of the distance h

The application of OK in MR estimation is widely accepted as it is a robust MR estimation technique, commonly described as the “best linear unbiased estimation” otherwise known as BLUE, (Isaaks and Srivastrava, 1989). The unbiased weighting of the grade to an interpolated point produces the best possible average estimate for a block, regardless of its spatial arrangement, ensuring minimum estimation variance, (Vann and Guibal, 1998).

Due to the practical limitations of exploration drilling campaigns and their inherently broad spaced drilling pattern, early-stage projects where OK is used to estimate a maiden MR tend to be used for undesirably large block sizes. The lack of resolution at the SMU-scale unrealistically deals with the influence of outliers and conditional biases during estimation.

The influence of outliers on the estimates for unknown locations is dependent on the contributing samples within the kriging neighbourhood. Conceptually, if we were to consider an area of low copper grade samples with one very high-grade sample immediately adjacent, the OK estimation at a location near that high value would be unrealistically “high” relative to the low values in the kriging neighbourhood. Outliers deviate from the expected value or trend influencing the nugget effects and sill of the modelled variogram.

Additionally, OK inherently causes a conditional bias, (Fourie, *et al*., 2019). This is due to OK smoothing the estimates between samples, potentially over and underestimating grades for unknown locations. The effects of the conditional bias are present in the grade-tonnage relationship and can impact the calculation of a MR at a given cut-off grade. Conditional biases occur when the kriging neighbourhood is poorly defined for a particular deposit and will require optimization of the slope of regression, (Vann, *et al*., 2003).

Linear estimation techniques such as OK produce robust grade tonnage and representative domain averages, but the consequence of smoothing observed in linear estimation is undesirable and unsuitable for selective mining and thus, a more appropriate technique is required.

2.2 Consequences of linear block estimation

The resource model derived from conventional linear estimation techniques provides an accurate representation of the mean grade and the grade tonnage curve that can be expected for a particular deposit. However, it does not adequately represent the areas within the panel at the SMU scale which can be mined selectively, refer to Figure 2. The distribution of grade within a panel is poorly represented by linear methods, (Rivoirard, 1990). The central block indicates the natural variability that exists within the panel, that is masked or smoothed in the blocks or panels calculated during linear estimation. Figure 2 illustrates the need for internal subdivision (SMU) of the panel or block to model the grade distribution more accurately for selective mining, (Vann and Guibal, 1998).

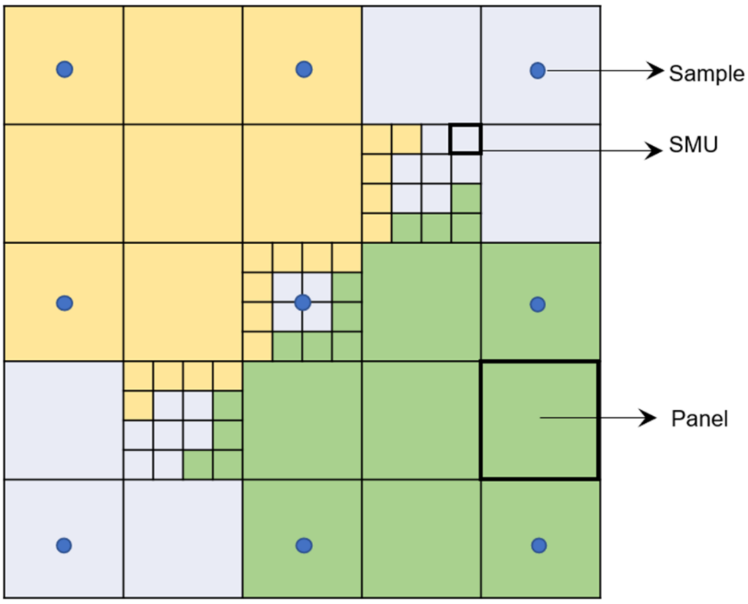

Figure 2:Hypothetical estimation scenario and the need for a SMU.

2.3 Non-linear Estimation Techniques

Non-linear estimation techniques more effectively deal with:

1. The lack of sample data and broad drillhole spacing,
2. Estimating into large panel or parent cells, and
3. Reporting grade-tonnages which may not be appropriate at mining scale.

Multiple non-linear estimation techniques were developed to individually address the issues raised above. Some of these techniques include, log-normal kriging, indicator kriging and UC, (Vann and Guibal, 1998). Log-normal kriging produces estimates for highly skewed grade distributions and indicator kriging better resolves the presence of outliers, (Vann and Guibal, 1998). However, this project has been designed to contrast OK with UC and a localised UC MR estimate. UC incorporates a change of support model to condition an estimate from a panel, where a stable and robust estimate can be transformed into a known distribution of smaller grade blocks.

2.3.1 Uniform Conditioning

Uniform conditioning (UC) is a non-linear estimation technique that was first introduced by Armstrong and Matheron (1986) when highlighting limitations of disjunctive kriging and identifying the need for other types of estimation methods detailed by Rivoirard (1990). Disjunctive kriging and UC use the Gaussian change of support model, which produces realistic grade-tonnage estimation at high- or low-grade cut-offs (Neufeld and Deutsch, 2005). Vann and Guibal (2001) as well as Vann, *et al*. (2000) motivated that the use of UC is suitable to non-stationary environments and that it performs better than disjunctive kriging. However, Vann, *et al.*, (1998) opined on the application of UC and established that although UC is a robust technique, applicable to environments where stationarity is poor it is greatly dependent on the quality of kriged panel estimation and a sound change of support model.

2.3.2 Discrete Gaussian Model – Change of Support

All estimation techniques must deal with the problem of scale. The data collected from drilling is small scale where the samples represent point data. During estimation, the samples are scaled up into practical SMU's, blocks and panels, respectively. These various volumes are termed "support". Support refers to the volume, either a sample point or a panel, at which average values are measured, (De-Vitry, Vann and Arvidson, 2007). Small supports are dispersed indicating that there is a high variance between sample points. The opposite is true for larger supports where less dispersion is observed between points, refer to Figure 3. This change of support effect results in locally inaccurate predictions of SMU's and therefore grades above a chosen cut-off grade, (De-Vitry, Vann and Arvidson, 2007). The influence of support on variability is known as the "support effect" or "volume-variance", (Journel and Huijbregts, 1978).

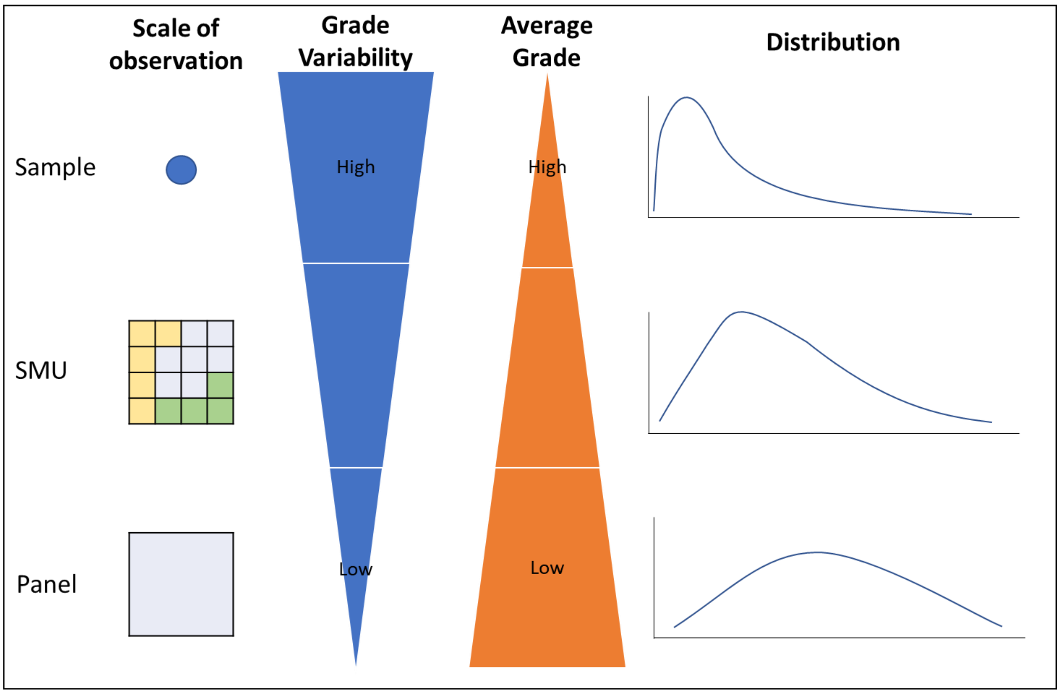

Figure 3: Impact of the change of support on variance, *(modified after (Hansmann, 2015)*.

Figure 3 shows that the grade of samples is generally higher, (or much lower) when compared to the grade of an SMU or panel. However, smaller supports are more disperse, which corresponds to a higher variance between samples.

For selective mining of deposits, a panel estimate is still sufficient to model the grade, however SMU's provide far higher resolution of the grade distribution at deposit scale. The panel estimate is usually the result of a linear estimation technique such as OK. This is where the change of support model is used as it describes the distribution of SMU grades for a panel grade. As such, an average panel grade is conditioned to a series of cut-off grades and produces estimates of tonnes and grades above these cut-offs.

This is done using the discrete Gaussian model (DGM) of change of support. The DGM will standardise the mean values for the SMU and the sample support, (Hansmann, 2015).

For the change of support model the data must be converted from its original state into Gaussian "space" via the normal score transformation (Figure 4), (Deutsch, 2002 and Barnett et al., 2014). This is achieved by transforming the cumulative grade distribution function $(F(z))$ into a Gaussian probability cumulative distribution function $(G(y))$.

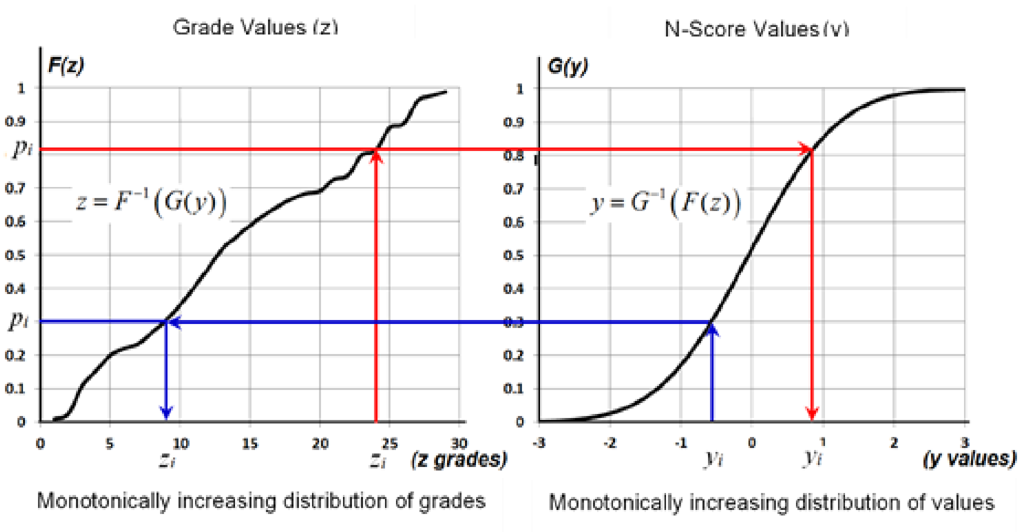

Figure 4: Schematic normal score transformation rationale, *(modified after Deutsch, 2002)*.

UC considers the panel and SMU block sizes, but practically requires the panel grade estimates calculated during OK since we do not know the panel grades $(Z(V))$. The panel grade estimates $Z(V)^*$ calculated during OK act as a suitable substitute for the determination of recoverable resources.

Estimation of a nonlinear function $\Psi(Z(v))$ is achieved by using the sample variable $Z(v)$ and discrete. The methodology described by (Abzalov, 2014; Rivoirard, 1990; and Chilès and Delfiner, 1999) for the calculation the tonnage (Tv) and mean grade (Mv) within a large panel (V) is described by two discrete Gaussian anamorphosis models, namely; point-to-SMU and point-to-panel.

Point-to-SMU (v) (Hermite polynomial expansion)

$$Z(v) = \phi_v\, Y(v) = \sum_{k=1}^{\infty} \frac{\varphi_k}{k!} r^k\, H_k\big(Y(v)\big)$$

And, for the point-to-panel (V)

$$Z(V) = \phi_v\, Y(V) = \sum_{k=1}^{\infty} \frac{\varphi_k}{k!} s^k\, H_k\big(Y^*(V)\big)$$

Where:

k is the coefficient of a Hermite polynomial expansion,

$Y(v)$ is the Gaussian point anamorphosis (μ = 0 and $\sigma 2$ = 1),

$Y(V)$ is the Gaussian Panel anamorphosis (μ = 0 and $\sigma 2$ = 1),

r is the point to SMU change of support coefficient, and

s is the point to Panel change of support coefficient.

Both models are calculated using the discrete Gaussian correction approach. The underlying assumption of the above models is that they are bi-Gaussian linearly correlated, (Abzalov, 2014). The point-SMU and point-Panel coefficients are to be calculated in the following way.

The r coefficient is calculated from a modelled empirical point variogram $\gamma(h)$ which is generated from sample data. The variogram indicates the geostatistical variance relationship between the point and block anamorphosis functions:

$$Var\big(Z(v)\big) = Var\big(\phi_v Y(v)\big) = \sum_{k=1}^{\infty} \frac{{\varphi_k}^2}{k!} r^{2k}$$

Variance of $Z(V)$ is equal to a block covariance $\overline{C}\ (V,V)$, calculated from the variogram model, (Abzalov, 2014):

$$Var(v) = \overline{C}(V,V) = \gamma(\infty) - \overline{\gamma}(v,v)$$

Using the above equation, we can calculate the point-to-block correction coefficient r can be expressed as follows:

$$\gamma(\infty) - \overline{\gamma}(v,v) = \sum_{k=1}^{\infty} \frac{{\varphi_k}^2}{k!} r^{2k}$$

This allows for the calculation of the recoverable resources, more specifically, the calculation of the tonnage (T) and contained metal (Q) as shown in the following calculation:

$$T_v(z_c) = E\big(I_{Z(v) \geq Z_C} \big| Z^*(V)\big) =$$

$$E\big(I_{Z(v) \geq Z_C} \big| {Y^*}_V\big) = 1\text{-}G\left\{\frac{y_C - \frac{s}{r}{Y^*}_v}{\sqrt{1-\left(\frac{s}{r}\right)^2}}\right\}$$

$$Q_v(z_c) = E\big(Z(v) I_{Z(v) \geq Z_C} \big| Z^*(V)\big) =$$

$$\sum_{k=1}^{N} \left(\frac{S}{r}\right)^k H_k\,({Y^*}_V) \sum_{j=1}^{N} \varphi_j\, r^j \int_{y_C}^{+\infty} H_k(y) H_j(y)\, g(y) dy$$

Where ${Y^*}_V = {\phi^{-1}}_V(Z^*(V))$ and $y_C = {\phi^{-1}}_V(Z_C)$

Allowing, the mean grade $M_v(z_c)$ of the SMU grades above a given cut-off z_C to be estimated by

$$M_v(z_c) = \frac{Q_v(z_c)}{T_v(z_c)}$$

The change of support model is not applicable for mines where selective mining is not being used. Rather the necessity for a change of support is applicable for the estimation of recoverable resources in mines where selective mining is being done (Vann and Guibal, 1998).

2.3.3 Localised Uniform Conditioning

LUC is a procedure carried out on the UC model. The process analyses the grade tonnage distribution for each panel to define individual SMU grades for the panel. Importantly, the ranking of the SMU is obtained by directly kriging SMU blocks into the panels using OK. The SMUs are then ranked from low to high based on their kriged estimate. The ranked SMU blocks are then assigned grades based on the uniform conditioned grade and tonnage distribution unique to each panel.

Ranking of the SMU determines the accuracy of the LUC MR estimate. In the presence of a large nugget effect, the accuracy of the location of the ranked SMU grades decreases. Ranking and its effect on spatial distribution can be improved using geological data, enhancing the LUC technique, (Abzalov, 2006).

2.3.4 Uniform Conditioning and Localised Uniform Conditioning analysis

Practical implementation of the UC and LUC techniques described above are used to determine the distribution of grades above specified cut-offs inside a panel, or in terms of SMU size, as well as to produce a block model representing variability of grades at a defined SMU.
This analysis can be carried out to give grade-tonnage curves at different SMU sizes to assess the recoverable resources at different scales. Figure 5 illustrates the change of support model and the distribution of grades at the SMU volume. From Figure 5, the detailed distribution of grades at SMU scale is more informative than the OK block estimate and its respective grade distribution.

For geologically complex and variable deposits the use of UC and LUC is more favourable in reconciling the recoverable resources for a deposit in comparison to OK (Graham, 2012). Furthermore, the identification of low-grade SMU's from high grade SMU's statistically (and visually) informs the resource geologist of the grade variations that can be expected within each panel or block.

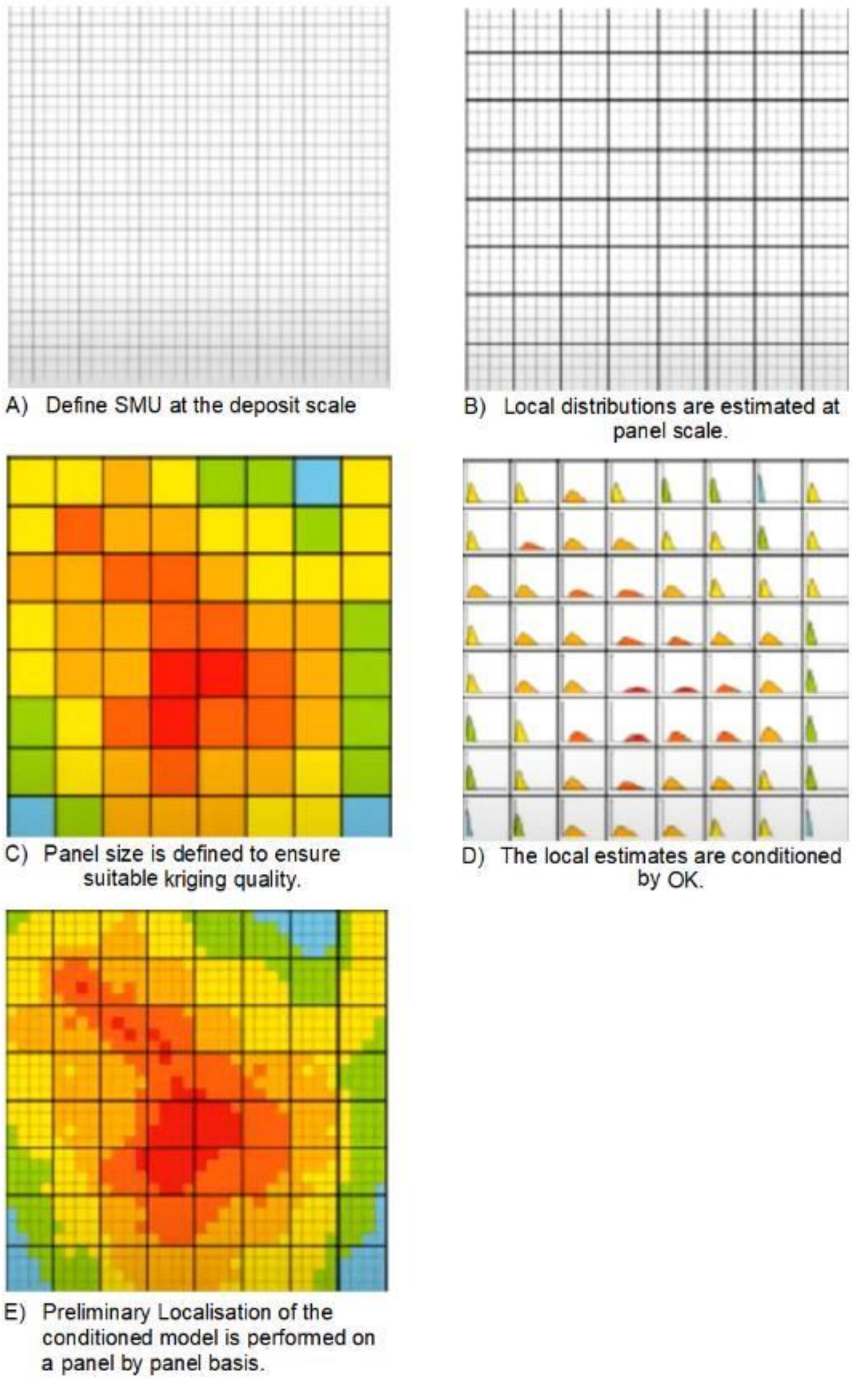

Figure 5: Stepwise illustration of uniform conditioning analysis and localisation of hypothetical data, *(modified after Graham, 2012)*.

2.4 Chapter summary

OK is preferentially chosen as an estimator for the determination of MR as it minimises estimation variance and optimises the weighting of samples whilst remaining independent of grades of those samples, (Vann and Guibal, 1998). In the case of OK, the weights are optimised to minimise the estimation error and variance, (Clark, 1979).

In summary, linear estimation techniques such as OK provide estimates that are robust and represent the least variance between blocks. OK MR estimates based on widely spaced drilling data tend to be over-smoothed since the block sizes produced are required to be at least half of the drillhole spacing. OK is a powerful estimation technique commonly used in industry today, however OK poorly estimates the recoverable resources of deposits with short-range variability. In practical terms, OK provides poor estimates of deposits that require selective mining.

By contrast, non-linear estimation techniques such as UC are potentially more appropriate tools to estimate and model deposits that are to be selectively mined. In the UC process, the effect of smoothing of OK is addressed through the application of a change of support model. More specifically, the DGM that transforms data into "Gaussian" space, is used to predict the proportion of grade above a cut off and the average grade above cut off if selectively mined.

Additionally, LUC estimation is a useful alternative estimation technique for the determination of recoverable resources in terms of SMU's compared to OK, since OK estimation is limited by drillhole spacing and should not be carried out on a block size that is smaller than half the drilling grid, (Clark, 1979). The smoothed OK blocks do not represent the recoverable resources fairly and can lead to under valuation of a deposit.

A practical application of the techniques and theory discussed above will be investigated by comparing OK and LUC resource estimates for the Tshifufia deposit of the Kinsevere Mine.

3 Geological Setting

The Kinsevere Mine is a copper-cobalt mine located in the Katanga Province of the DRC and located approximately 30 kilometres north of Lubumbashi (Figure 6).

Figure 6: Location of Kinsevere Mine within DRC, (MMG, 2014)

The mineralisation style of the Central African Copperbelt is classically defined as sedimentary stratabound with varieties of copper, cobalt, lead, zinc and uranium mineralisation present within the Katangan Supergroup, (Kampunzu and Cailteux, 1999). The Katangan region has been mined for copper and cobalt for over 100 years.

The copper-cobalt systems in the Lufilian Arc, situated in Zambia and DRC, are recognised as the largest sedimentary hosted copper deposits in the world, collectively known as the Central African Copperbelt. Apart from copper mineralisation, approximately half of the world's cobalt reserves are found within the Lufilian Arc along with significant concentrations of lead-zinc sulphides and uranium oxides, (Jackson *et al.*, 2003).

3.1 Katangan Supergroup

The Katangan Supergroup is composed of metacarbonates, metapelites and sandstones stratigraphically divided into the Roan, Nguba and Kundelungu Groups, (Jackson *et al.*, 2003; Cailteux *et al.*, 2005) as shown in Table 1. The Groups are separated by two extensive glacial diamictites (Grand and Petit Conglomerates) which occurred 765 Ma and 600 Ma respectively, (Wendorff and Key, 2009).

Table 1: Stratigraphy of the Katangan Supergroup (modified after Cailteux *et al*, 2005).

Period	Supergroup	Group	Subgroup	Lithologies
Proterozoic	+/-550 Ma	Kundelungu	Plateaux	Shales and Arkoses
			Kiubo	Dolomitic Shales, sandy shales and sandstones
			Kalule	Dolomitic shales or shandy shales, pink limestones
				Petit Conglomerate - Diamictite
	Katanga Supergroup	Nguba	Monwezi	Dolomitic shales or siltstones
			Likasi	Dolomitic or sandy shales, dolostones or limestones
				Grand Conglomerate - Diamictite
		Roan	Mwashya	Dolomitic shales, dolostone, jaspers, and pyroclastics
			Dipeta	Interbedded dolostones, argillaceous and dolmitic siltstones
			Mines	Dolostones, dolomitic shales and siltstones
	+/-880 Ma		RAT	Argillaceaous dolomitic siltstones, sandstones and pelites
Kibaran Basement				

Both the Grand and Petit Conglomerates are overlain by cap carbonate complexes termed lithological coupling. The formation of these cap carbonates is important as it provides the “seal” necessary for the prolonged hydrothermal fluid circulation and subsequent mineralisation observed in the various basins within the Lufilian Arc (Kennedy *et al.*, 1998).

3.2 Lufilian Arc

The Lufilian Arc is a major Pan-African structure, straddling the DRC - Zambian border, preserved as an arcuate belt that extends over 800 km in a roughly east-west direction with a NE-trending convex curvature, (Jackson *et al.*, 2003). The Lufilian Arc formed during the Pan-African collision between the Kalahari and Congo Cratons that took place 650-600 Ma, (Hanson *et al.*, 1993; Frimmel, *et al.*, 2011).

The Lufilian Arc is divided into four domains between Zambia and DRC, (Kampunzu and Cailteux, 1999 and El Desouky *et al.*, 2008) namely:

1. External fold-and-thrust belt.
2. Domes region.
3. Synclinorial Belt; and
4. Kundelungu Aulacogen

The geological map (Figure 7) below shows the anticlines and synclines of the Roan, Nguba and Kundelungu Groups that make up the External fold-and-thrust belt. The location of the Kinsevere Mine (project area) relative to the External fold-and-thrust belt is highlighted in red (Figure 7).

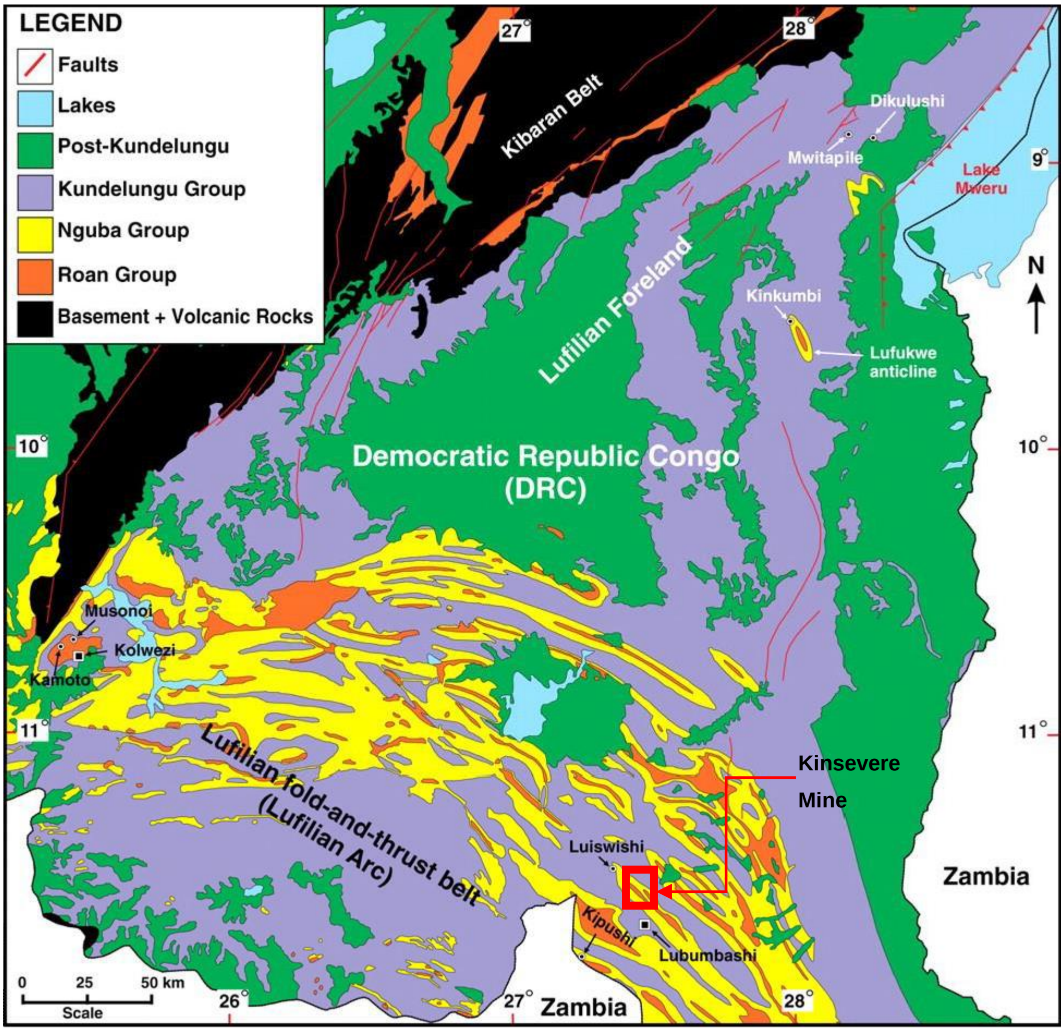

Figure 7: Geological map indicating the 800 km long arcuate Lufilian Arc in relation to Lubumbashi and the Kinsevere Mine (*modified after* El Desouky *et al.*, (2008)).

3.3 Kinsevere Mine Local Geology and Mineral Resources

This case study focuses on the Kinsevere Project owned by MMG who took ownership of the mine in 2012 from Anvil Mining. The Kinsevere Project is made up of four deposits, namely, Tshifufiamashi, Tshifufia Central (Tshifufia), Tshifufia North and Kinsevere Hill (Figure 8). Collectively the Tshifufiamashi and Tshifufia Central deposits make up the Kinsevere Mine.

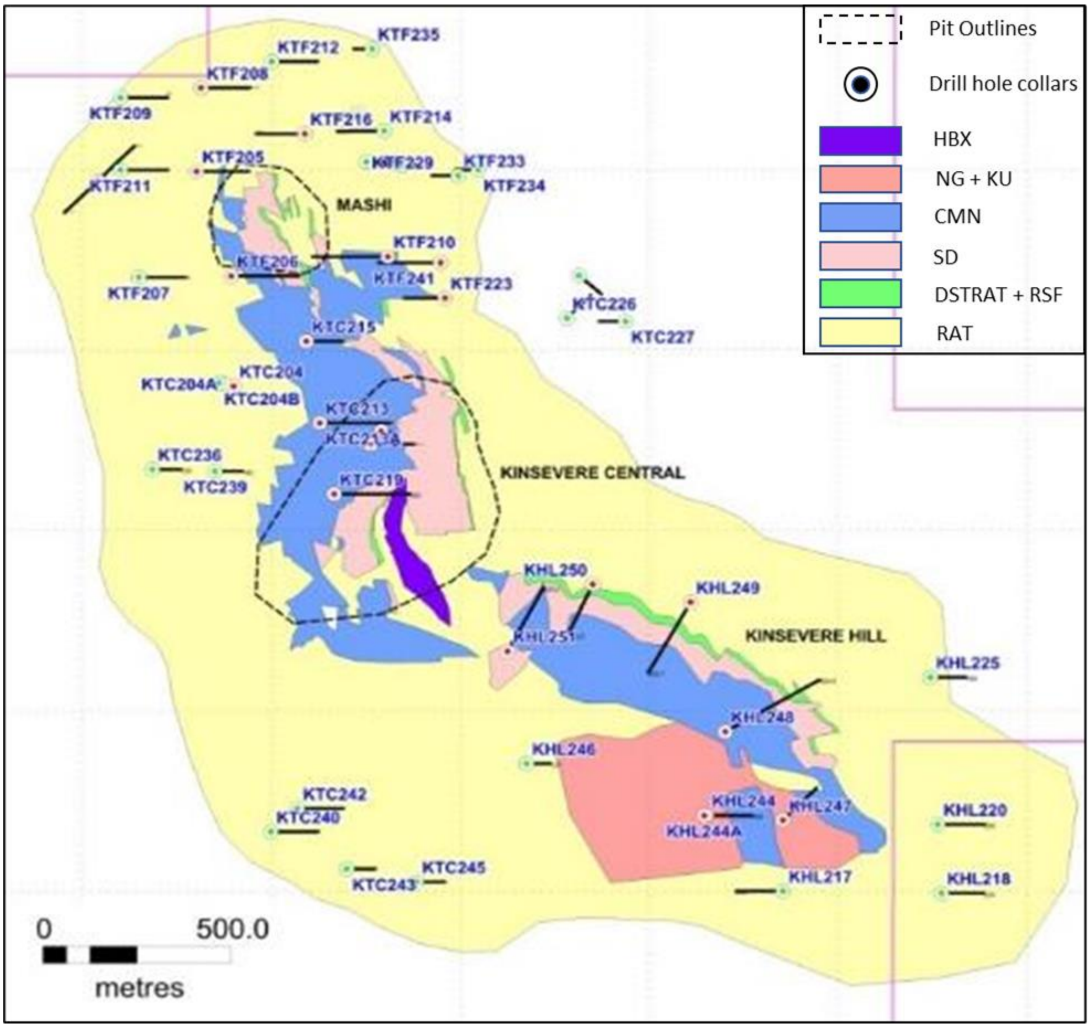

Figure 8: Plan view of the Kinsevere Deposit (MMG, 2014)

The deposits occur within a folded and faulted portion of R1 “lilas roches argilo-talcqueuse” (Red RAT) and Mines Series rocks. The main domain comprises the Tshifufiamashi and Tshifufia deposits and is 1.3 km in length, trending approximately north south.

The stratigraphy at Kinsevere is atypical of other neighbouring Mines Series deposits in that the Lower Orebody, is separated from the Upper Orebody, (MMG, 2014). The Lower Orebody is hosted by the “dolomites stratifies” (DStrat) and “roches siliceuses feuilletees” (RSF) units of the Kamoto Dolomite Formation. The Upper Orebody is in the “shales dolomitiques” (SD) unit. The 15 m to 20 m thick barren zone of roches siliceuses cellulaires (RSC) typically developed between the LOB and UOB is absent (Table 2). The Third Orebody is located in the lower part of the Kambove Dolomite Formation “calcaire á minèraux noirs” (CMN), (MMG, 2014). Significant mineralisation commonly extends uninterrupted from the “grise roches argilo-talcqueuse” (Grey RAT) at the base into the lower CMN at the top, refer to Table 2.

Table 2: Stratigraphy of the Kinsevere Project

Formation	Unit	Lithology	Kinsevere Orebody	Thickness
Kambove Dolomite	CMN	Pale coloured dolostone	Barren	80-120 m
		Cyclic dolomite and pale olive shale towards base	Third Orebody	
		Grey or black dolostone and shales		<50 m
Dolomitic Shales	SD	Graphitic shale and siltstone with minor dolomitic shale and evaporitic textures	Upper Orebody	60-90 m
Mines Series	RSC	Silicified dolomite	Absent at Kinsevere Mine	
	RSF	Finely banded laminated argillaceous dolostone	Lower Orebody	<2 m
	Dstrat	Planar bedded, shaley dolomite		3-4 m
	Grey Rat	Chloritic and dolomitic sandy argillite, siltstone		8-20 m
Breccia Footwall	Red Rat	Massive to poorly bedded and silty argillite	Superficial oxide mineralisation	>200 m

The deposit is best described as a sediment-hosted stratiform copper deposit. However, the mineralisation has been remobilised and tends to occur predominantly in veins and fractures with little primary sedimentary mineralisation remaining. The layering is folded but generally dips steeply to sub-vertically to the east or west, depending on the location within the deposit.

A thin layer of soil occurs on top of the deposit followed by oxide facies mineralisation down to approximately 100 m below surface. The base of the oxide facies is irregular, exhibiting troughs and valleys, roughly following the steep dip of the sediments. The dominant copper mineral is malachite and azurite in the oxide facies with chalcocite, bornite and chalcopyrite becoming more common at depth in the sulphide facies. Below the oxide zone is a mixed zone of oxides and sulphides (transitional) that generally becomes progressively more sulphide-rich with depth. As a result, the oxide-transitional-sulphide boundary is vague.

Mineral Resources

The MR at Kinsevere is confined to three deposits: Tshifufiamashi, Tshifufia and Kinsevere Hill. The Tshifufia deposit has produced most of the ore at Kinsevere, with mining activities targeting oxide facies mineralisation.

3.4 Chapter Summary

The Lufilian Arc is well known for hosting world-class base metal deposits as a result of the Pan African events that occurred approximately 560 Ma. Deposits vary in mineralisation style based on where they are located within the four domains that subdivide the Lufilian Arc. The Central African Copperbelt is situated within the external fold-and-thrust belt that straddles the DRC and Zambian border.

Mineral deposits within the external fold-and-thrust belt typically occur on the anticlines and synclines of the Roan-Nguba and Kundelungu Groups. The geological setting and NE-vergence of the Lufilian Arc has resulted in a regional structural control between deposits of the Central African Copperbelt making proximally spaced deposits somewhat comparable in terms of mineralisation style and structural controls.

The sub vertically dipping copper cobalt Tshifufia and Tshifufiamashi deposits are deeply weathered with well-developed oxide and sulphide facies. The deposits are hosted in altered dolomitic and argillaceous sediments of the Mines Series, Dolomitic and Kambove Formations. Mineralisation is known to be laterally continuous both along strike and down dip within the orebodies identified from exploration and GC drilling.

The Kinsevere Project is considered to be a suitable environment for the comparative analysis of linear and non-linear estimation techniques for the determination of recoverable resources in a sedimentary hosted copper-cobalt type deposit.

4 Exploration Data Analysis

Data should always be validated and cleaned prior to any statistical and geostatistical analysis. EDA is a first pass assessment, interrogation, and analysis of various types and sources of data. EDA describes the qualitative and quantitative summary statistics that characterise a given drillhole dataset. A significant benefit of EDA is that it provides the analyst with the ability to tailor the estimation approach based on observations of the original dataset and by making several assumptions.

The Kinsevere Project's various drilling datasets are predominantly stored in MS Excel or CSV format under the Collar, Assay, Survey and Geology file names. From inspection of the available files, there is no density data recorded for the samples and as such density data will not form part of the estimations. Instead, only proportion above cut-off and volumes are estimated. Therefore, for estimation purposes, density values were set to 1 for all samples.

4.1 Validation and Quality Control-Quality Assurance

Data validation was done on both the exploration and GC data. The original dataset used in this project contained various drilling campaigns and drilling programmes targeting either Tshifufiamashi, Tshifufia and Kinsevere Hill deposits. All three deposits are slightly different and would typically be modelled separately. This study focusses on the Tshifufia deposit.

The drillholes were filtered using the 0.3 Cu % grade shell "0pt3cmas" wireframe supplied by MMG using the "SELWF" Datamine process. The 0pt3cmas wireframe represents the 0.3 Cu $\%_{total}$ grade shell for the Tshifufia and Tshifufiamashi pits and constrains the area being assessed to a mineralised volume that is indicative of a maiden Cu MR from the Congolese Copperbelt.

The data was further constrained to only fall within the Tshifufia deposit by truncating the dataset against the subvertical northeast-southwest trending fault separating the Tshifufia and Tshifufiamashi pits. The characteristics of the Tshifufia exploration and GC drilling programmes that were used and or considered for estimation purposes. These characteristics are:

- Orientation or strike of the Tshifufia Deposit.
- The angle of intersection between the drillholes and the strike of the Tshifufia deposit is high.
- Diamond drillholes (DD) are orientated both east and west with a variable inclination between -60° to sub vertical.
- DD holes vary in depth between 22 m and 400 m.
- Reverse circulation (RC) GC holes are oriented both east and west with dip of- 60°. The CG drillholes are shorter than the exploration drillholes length ranging between 3 m and 30 m.
- Exploration drillhole spacing ranges between 30 m and 100 m.
- GC drillhole spacing grid is 5 m (X) x 15 m (Y).
- Mineralisation is recorded in three ore zones, namely, the oxide, transitional and sulphide facies.

The resulting data outputs to be used in the estimation process are tabulated in Table 3.

Table 3: Drillhole data for estimation

Data File Supplied	Filtered Exploration Data Count	Filtered Grade Control Data Count
Collar	278	3 736
Survey	5 398	7 340
Assay	11 498	39 760
Geology	12 471	23 957

Figure 9 and Figure 10 respectively show the collar coordinates of the 278 exploration and 3 736 GC drillholes. The google imagery over which the collar coordinates are overlain was taken in 2020 and not 2014 when drilling was done. As a result, the mine has changed shape and does not truly illustrate the drilling conditions experienced in 2014. However,

Figure 9 and Figure 10, help conceptualise the scenarios discussed in this research study.

Figure 9: Exploration drilling collar positions relative to the Tshifufia pit

Figure 10: GC drilling collar positions relative to the Tshifufia pit

4.2 Statistical Analysis

Statistical analyses of the validated and filtered Tshifufia data, including spatial statistics, were carried out using Datamine, GSLib and MS Excel software. Statistics for total copper related to the Tshifufia deposit was investigated according to the 0.3 Cu % grade shell supplied by MMG. Drillhole spacing per drilling campaign are illustrated in Figure 11 and Figure 12 and their corresponding sample summary statistics are tabulated in Table 4 and Table 5.

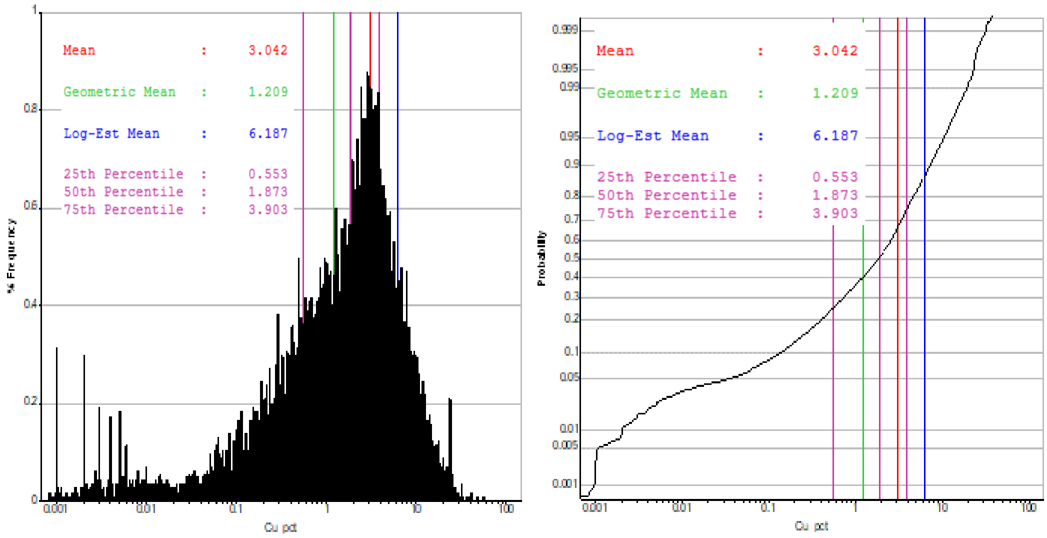

Figure 11: Log histogram and probability plot of the total copper % for the exploration drillholes at Tshifufia filtered on the 0.3Cu % grade shell.

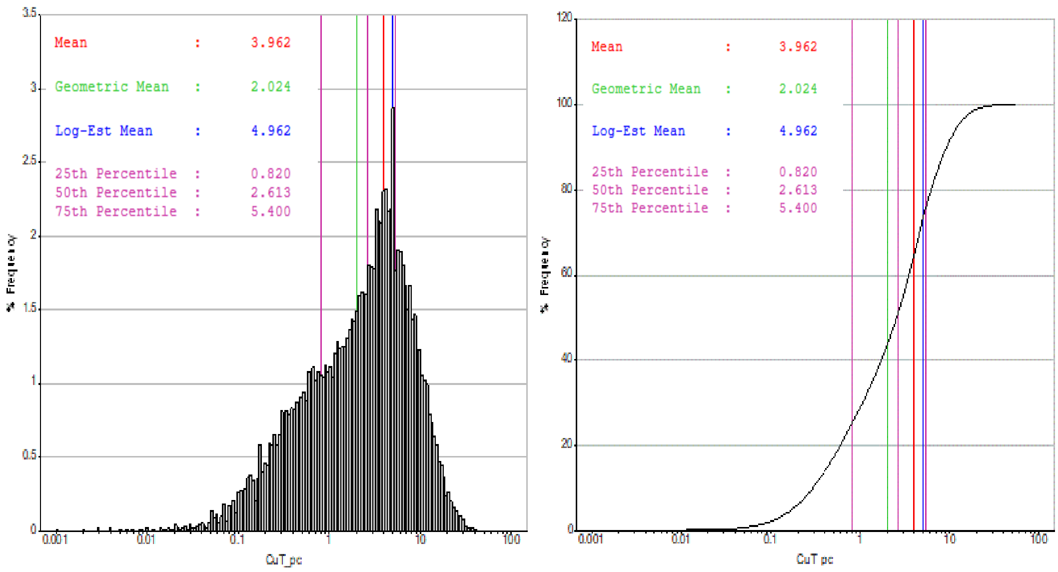

Figure 12: Log histogram and probability plot of total copper % for GC drilling at Tshifufia filtered on the 0.3 Cu % grade shell

Table 4: Cu % Summary statistics exploration drilling data

All Cu (%)	
Min	0.0004
Max	56.381
Range	56.381
N	11498
Mean	3.042
Median	1.8725
Mode	0.001
Variance	15.008
Std Dev	3.874
Cov	1.274
Skewness	3.123
Kurtosis	16.285

All ln (Cu %)	
Min	-7.8240
Max	4.0321
Range	11.8561
N	11498
Mean	0.1893
Median	0.6273
Mode	-6.9078
Variance	3.2667
Std Dev	1.8074
Cov	9.5478
Skewness	-1.4541
Kurtosis	2.6747

Table 5: Cu % Summary statistics GC drilling data

All Cu (%)	
Min	0.001
Max	53.000
Range	52.999
N	39728
Mean	3.965
Median	2.619
Mode	0.200
Variance	19.261
Std Dev	4.389
Cov	1.108
Skewness	2.282
Kurtosis	7.930

All ln (Cu %)	
Min	-6.908
Max	3.970
Range	10.878
N	39728
Mean	0.705
Median	0.963
Mode	-1.609
Variance	1.793
Std Dev	1.339
Cov	1.899
Skewness	-0.667
Kurtosis	0.237

As per the methodology outlined in Chapter 1, the exploration drilling dataset will be used to generate OK and UC MR estimates. The GC data will be used to generate an OK MR estimate to validate and assess the success of LUC in determining the SMU grades. The following spatial statistical analyses are focussed on the exploration drilling data, however, the assumptions and methodologies used are also applicable to the GC estimation. The GC OK MR estimate will be presented at the end as a comparative analysis with the LUC MR estimate.

4.3 Spatial data validation

Modelling of the datasets for the OK, UC and LUC MR estimates was completed using the mine grid coordinate system in the collar file. The surveyed collar easting and northing coordinates corresponds with the

WGS84 34 S datum, however, MMG used LIDAR collar elevations to determine the elevation coordinates. Additionally, MMG documented that all handheld determined collar elevations were adjusted to LIDAR elevations.

The drillhole database was converted to a 3D environment using the Datamine command “HOLES3D” (Figure 13). The process included the correction of overlapping data, adjustment of negative assay values to absent, duplicated samples were identified and corrected in the database and finally a single sample interval of 44 m at a copper grade of 23.9 % from hole TCDH008 was identified and corrected. This exceptionally large sample interval corresponded with a poor drill core recovery interval where only 1.05 m of core was recovered. This interval was set as absent in the data file since it would significantly skew the estimate.

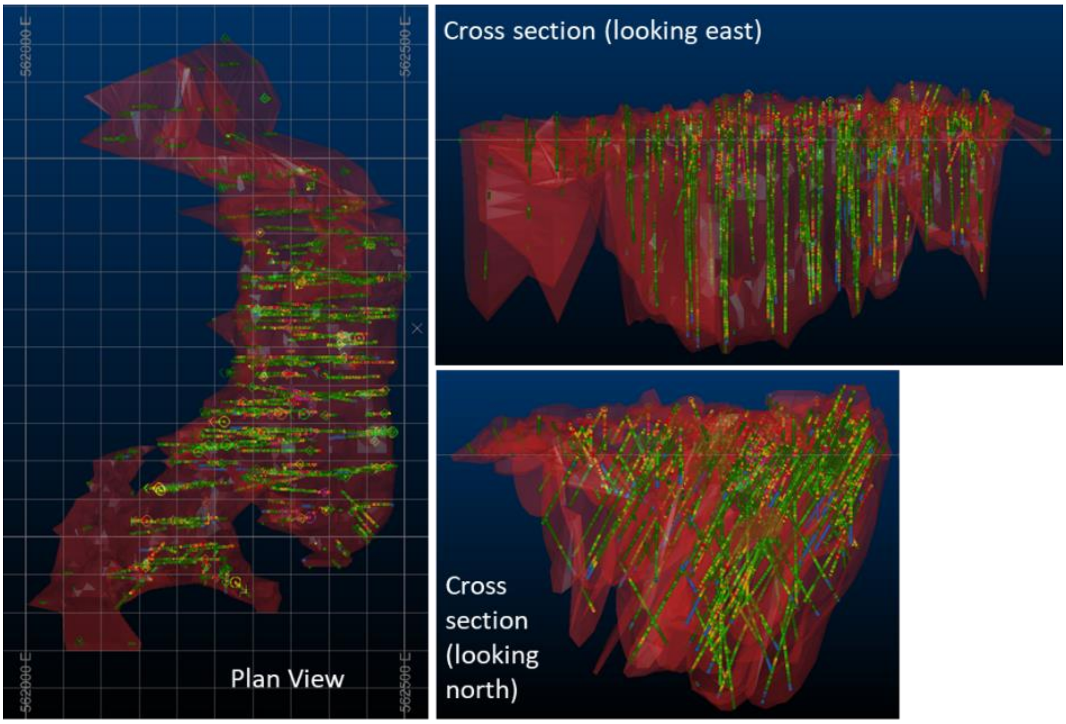

Figure 13: De-surveyed drillholes relative to the 0.3Cu % grade shell for exploration drilling data

4.4 Compositing Drillhole Data

The various drilling techniques and drilling campaign objectives involve different run lengths and as a result composite data needs to be used in preparation of geostatistical analysis and estimation (Figure 14).

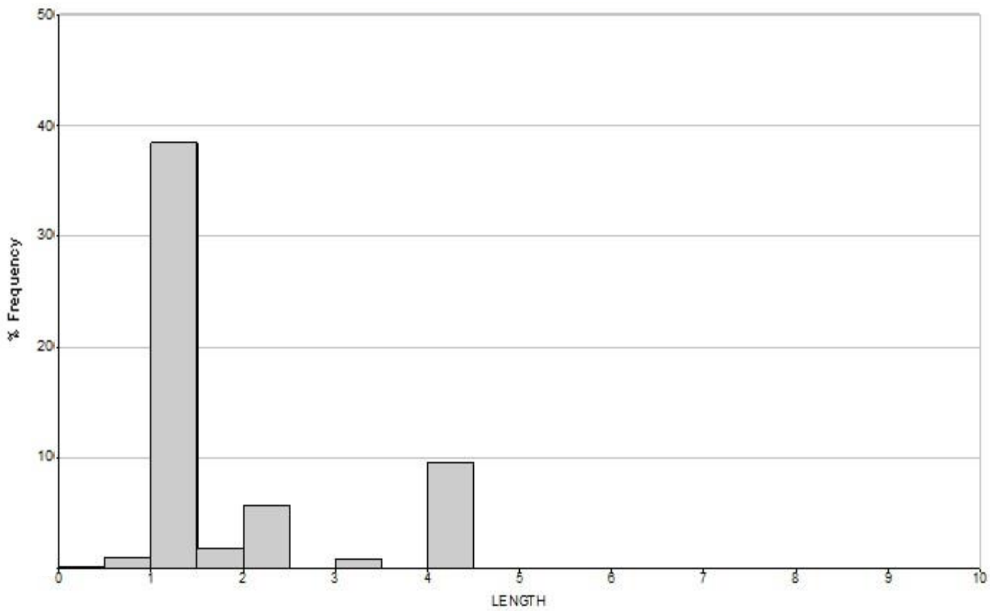

Figure 14: Various sample lengths for the exploration drilling database

To determine the most appropriate sample length the distributions of the raw data is graphically illustrated in a histogram (Figure 14). Figure 14 shows that approximately 65% of the sample lengths are between 1.00 m and 1.50 m, 17% is between 4.00 m and 4.50 m and 10% is 2.00 – 2.50 m. All data was composited to 2.00 m sample length intervals. The result of compositing sample lengths is that the 99% of the data is approximately 2.00 m with one sample only composited to between 1.00 and 1.50 m (Figure 15).

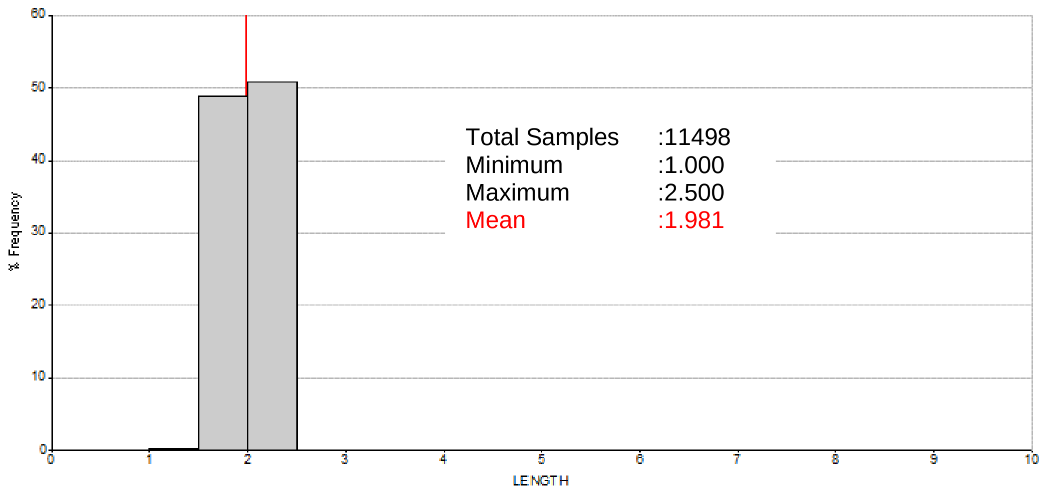

Figure 15: Composited sample lengths

Overall, this sample length should allow for good resolution of the copper grades for geostatistical and resource estimation purposes, as well as provide a comparable platform on which grades are interpolated between drillholes. In addition to compositing sample lengths, drillhole data often needs to be declustered in order to create an unbiased estimate.

4.5 Declustering

Due to the often highly clustered nature of exploration drilling and the fact that there exists a bias towards targeting mineralised areas over barren areas, the composited exploration drilling data needed to be declustered. Declustering assigns a weight to each data point proportional to the area or volume occupied by each sample. This is known as gridded declustering, where grids applied over an area of interest and the weights of all the samples that fall into each grid area are calculated.

It is important to note that UC is dependent on a Gaussian anamorphism, which itself requires a sufficiently declustered drillhole dataset for the determination of the sample weights.

Declustering uses the following formula to calculate the weighted mean for the cell ($Wi\ (c)$), (Isaaks and Srivastrava, 1989):

$$Wi(c) = \frac{1}{n_l . Lo}$$

Where,

n_l is the number of samples,

Lo is the number of blocks

Declustered weights are proportional to the area of influence. (A is the area)

$$Wi(p) = \frac{Ai}{\Sigma\, Aj}$$

Where

$Wi(p)$ is the gridded declustered weights.

A declustering process was run on the composited exploration drilling data using Datamine. To correctly decluster the drillhole data an optimisation grid size analysis was run to choose the appropriate declustering cell size (Figure 16).

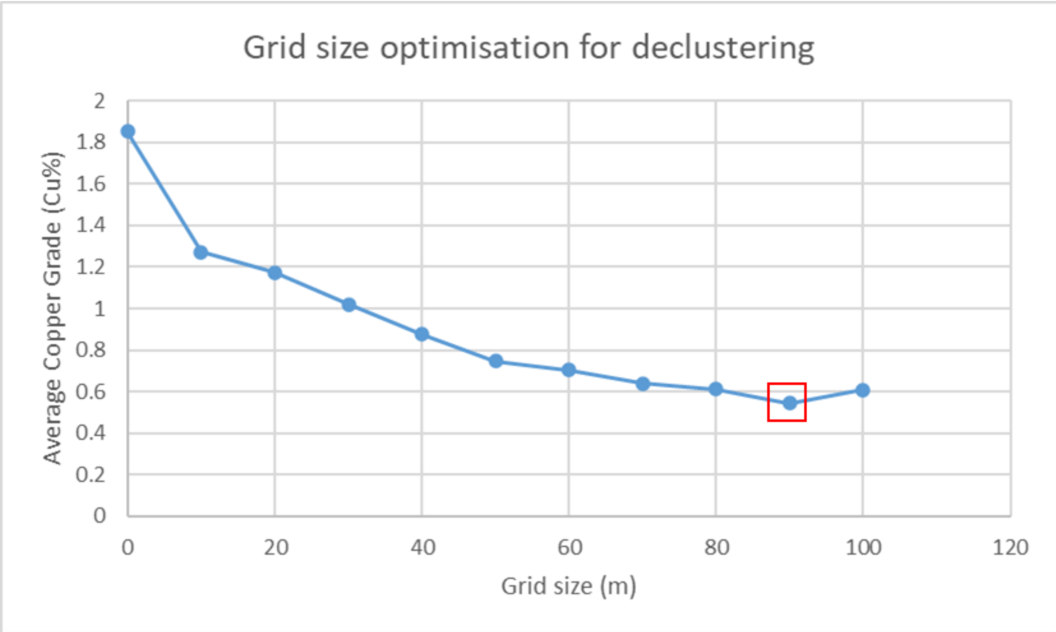

Figure 16: Grid size optimisation for declustering

The declustering process illustrates that the copper data is sensitive to declustering. To find the best declustering parameter, 10 m incremental grid sizes up to 100 m were run in 3D. This was done to see how the declustered mean copper grade changed with a change in the cell size, and what the stable cell size is. A grid size of 90 m (X) x 90 m (Y) was determined to be the optimal grid size for declustering the drillhole data Figure 16.

The declustering process assigns a weighted mean to each composited interval. The composite copper grades and weighted means are then used during the estimation process to calculate a realistic and representable distribution of the copper within the block model. The original and declustered histograms presented in Figure 17 illustrate the effect of declustering on the original and output declustered data. Table 6 shows the effect of declustering on the maximum data values, narrowing the representative range of the copper grades to be estimated.

Table 6: Effect of grid declustering on the minimum and maximum Cu %

	Original (Cu %)	Declustered (Cu %)
Minimum Value	0.0004	0.0004
Maximum Value	56.381	20.34495
Range	56.38	20.35

By comparing the two histograms, we see that the copper values above 25 Cu % in the original data have been successfully declustered. The declustering has removed spurious high-grade biases related to single, very high-grade values. Additionally, the range of the declustered data is narrowed to a representable grade range at a deposit scale.

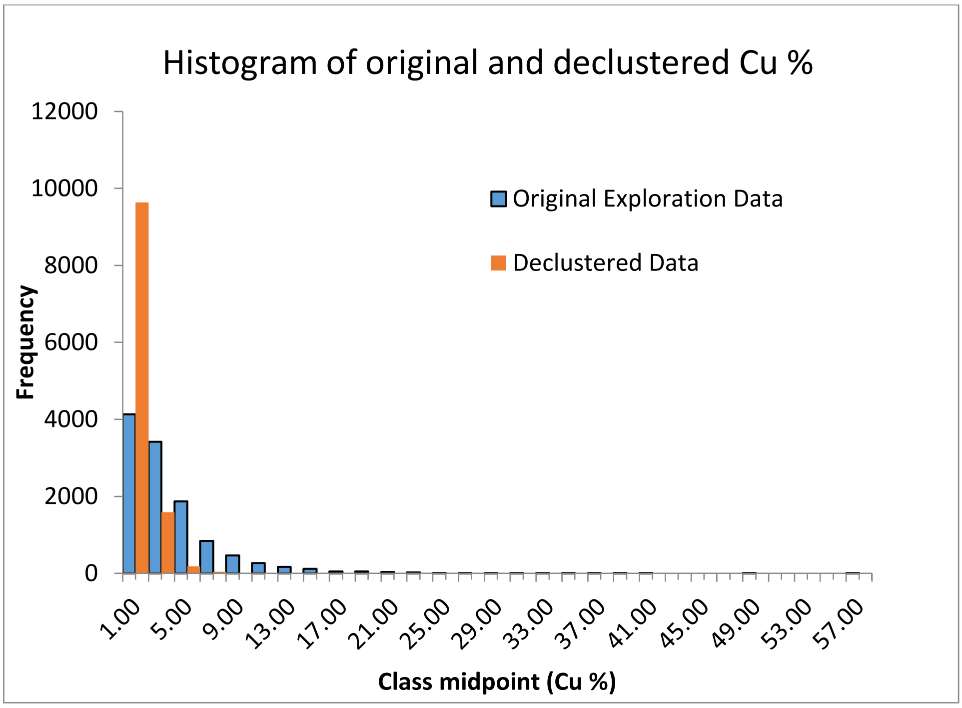

Figure 17: Original and declustered data comparison

Although composited and now declustered, the exploration drilling data remains highly positively skewed.

5 Block Model and Grade Estimation

The process of validating the drillhole dataset creates a reasonable and realistic foundation upon which geostatistical assumptions are based. Assumptions made for the block model estimates in this project are made during stationarity and assume that:

- the sample assays are precise and repeatable,
- the sample values are accurate and reflect the true sample value,
- the samples are a representative subset of the population, and
- the samples are taken randomly and independently.

5.1 Boundaries

The dimensions and parameters of the OK and LUC block models were based on the 0.3 Cu % grade shell and the average drill grid spacing. Parent cells controlled the block dimensions and sub-celling was used to make sure that the block model honoured the wireframe boundary (hard boundaries used).

5.2 Normal Score Transform

Normal score transformations were used for variogram modelling and back transformed to provide actual values (Figure 18 and Figure 19). Normal score transforms are rank preserving (high values remain high values) and are a quantile-quantile matching procedure calculated using, (Deutsch, 2002)

$$Y = G^{-1}\big(F(z)\big)$$

This can be back transformed to:

$$Z = F^{-1}\big(G(y)\big)$$

Figure 18: Normal score transform on validated exploration data.

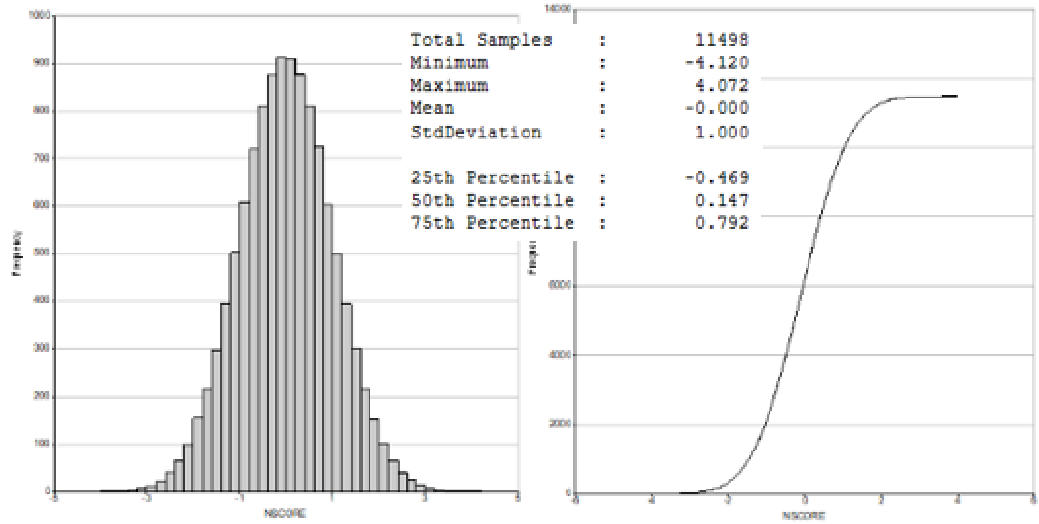

Figure 19: Post processing back-transformed data

5.3 Geological Considerations for Tshifufia

Sedimentary hosted copper deposits from the Katangan district are located on synclines of the fold and thrust belt, where the Mines Series fragments and strata are exposed. Common brittle and ductile deformation is observed in the local geology resulting in faults and large-scale folding. The orientation of the orebodies and the structural features identified from surface and within drillholes will be used to guide estimation. In order to produce a robust estimate, the spatial variability between samples needs to be modelled. For Tshifufia, variogram models will intuitively have their longest range of continuity parallel to the strike of the stratigraphy within the deposit, down dip along the bedding plane and finally laterally across the stratigraphy. This can conceptually be thought of as a pancake or cigar shaped search ellipses to be used in variography.

However, both sulphide and oxide facies mineralisation are present at Tshifufia. The pervasive oxide facies roughly extends to a depth of 100 m and is continuous parallel to the strike of the stratigraphy, down dip along the bedding plane and across the stratigraphy. Comparatively, the sulphide facies occurs at depth and predominantly within bedding planes and veins of Mines Series Formation. This might impact the lateral continuity of sample pairs perpendicular to the strike orientation, possibly creating a more rugby ball shaped variogram ellipse. The resultant estimation domain for Tshifufia will therefore be based on zones that are geologically and statistically homogeneous, supported by variography and statistical analysis.

5.4 Lag distance - Variography

Variogram maps assess the spatial continuity and degree of anisotropy in the data set. More specifically, variography is used to study how variable the spatial continuity is as well as the orientation of the spatial continuity relative to the dataset. Variography of the composited data was analysed using GSLib software.

Since the drillhole spacing for the exploration drilling programme is variable, between 30 m to 100 m, it is important to assess how variable the deposit is at different scales. This is a fundamental step in determining an appropriate lag distance for the experimental variogram and eventually the modelled variogram. Variography for Tshifufia was analysed at different blocks sizes to determine the axes of maximum and minimum continuity at different scales (Figure 20).

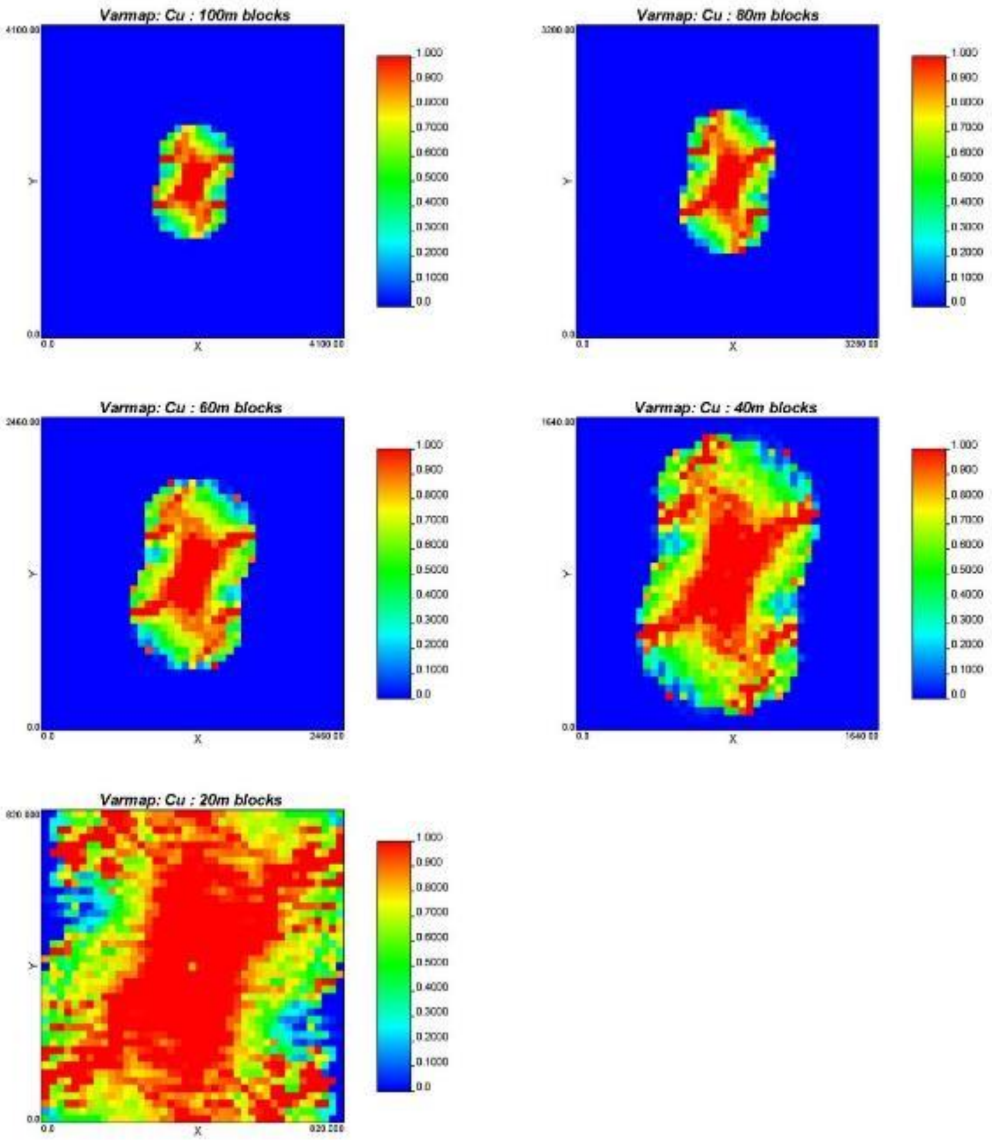

Figure 20: Standardised variogram maps of the Tshifufia deposit at different block sizes viewed in the XY plane.

Figure 20 illustrates that the highest variability is oriented northwest-southeast perpendicular to the bedding planes and directly across the Tshifufia deposit. Conversely, the most continuous direction is approximately 345 degrees (roughly north south). This is parallel with the strike of the bedding planes in the central and northern portions of the Tshifufia deposit. A second long range continuity axis is observed in the northeast- southwest direction, although it is narrower and slightly shorter than the primary axis described above.

Additionally, variability in the Tshifufia deposit is sensitive to block size. Long range continuity remains constant regardless of the block size used. However, short range continuity is sensitive to the block size with an increase in variability as the block size decreases. This can be attributed to the fact that as the block size increases, more samples become homogenised within the block and there is less difference between larger blocks than smaller blocks. A realistic approach used in this project is to look for a block size that honours the geology of the deposit. The optimal or stabilised cell size for variability is between 20 m and 40 m. This ideally suits the range of the drillhole spacing for DD. A lag distance of 20 m was chosen for the calculation of the experimental variograms.

5.5 Exploration Data - Variography

OK is reliant on an assumption of stationarity, i.e., there no trend in the random variable and the underlying probability distribution of this random variable of interest is the same throughout the domain, (Isaaks & Srivastava 1998). Understanding how sample grades relate to each other in space is a vital step in interpolating grades into the various blocks within a block model.

The Tshifufia deposit was domained according to the Mines Series Formation. Experimental variograms were calculated and analysed using composited data located within the mineralised domain. The following methodology was used for variogram modelling:

1. Axes of anisotropy were determined using variogram fans,
2. Down hole variograms were modelled to determine the nugget effect,
3. Normal scores variograms were modelled for each of the major axes of anisotropy using the nugget effect determined from the downhole variogram, and
4. back-transformation of the variograms to the original distribution for the determination of the search parameters for OK estimation.

The downhole semi-variogram was modelled first to determine the nugget effect. The nugget was determined to be 0.21 or 21%. Figure 21 and Figure 22 illustrate the variogram models for Tshifufia.

Variogram analysis was guided by the dip and strike angles of the Mines Series Formation stratigraphy. As observed on the variography map, the orientations of the principal axes of anisotropy are largely controlled by the strike of the mineralised bedding planes (Table 7 and Table 8). Based on these parameters the following experimental and modelled semi-variograms were produced.

Table 7: Axes of anisotropy for Tshifufia Variogram models.

VANGLE1	VANGLE2	VANGLE3	VAXIS1 (Z)	VAXIS2 (X)	VAXIS3 (Z)
90	130	-175	3	1	3

Table 8: Standardised variogram model for exploration data

	Spherical Structure 1				Spherical Structure 2			
Nugget	Sill 1	Range 1	Range 2	Range 3	Sill 2	Range 1	Range 2	Range 3
0.21	0.319	15.3	24.2	22	0.445	140	80	94

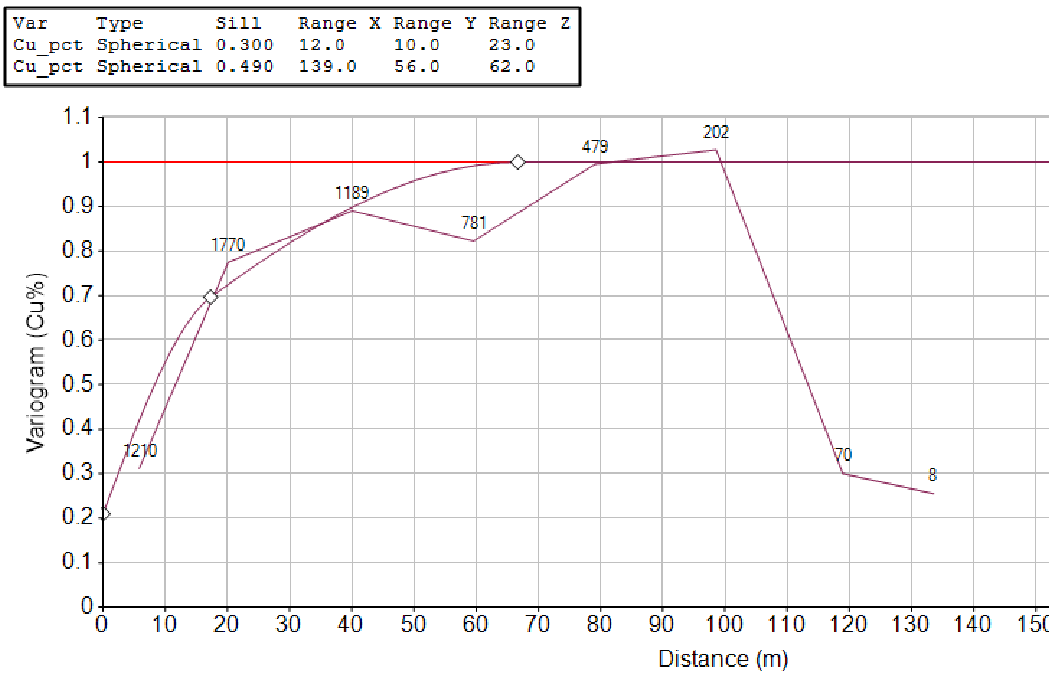

Figure 21: Downhole variogram to determine the nugget effect.

Type	Variance	90/0	0/30	180/60
Nugget	0.21	–	–	–
Spherical	0.319	15.3	24.2	22.0
Spherical	0.445	140	80	94

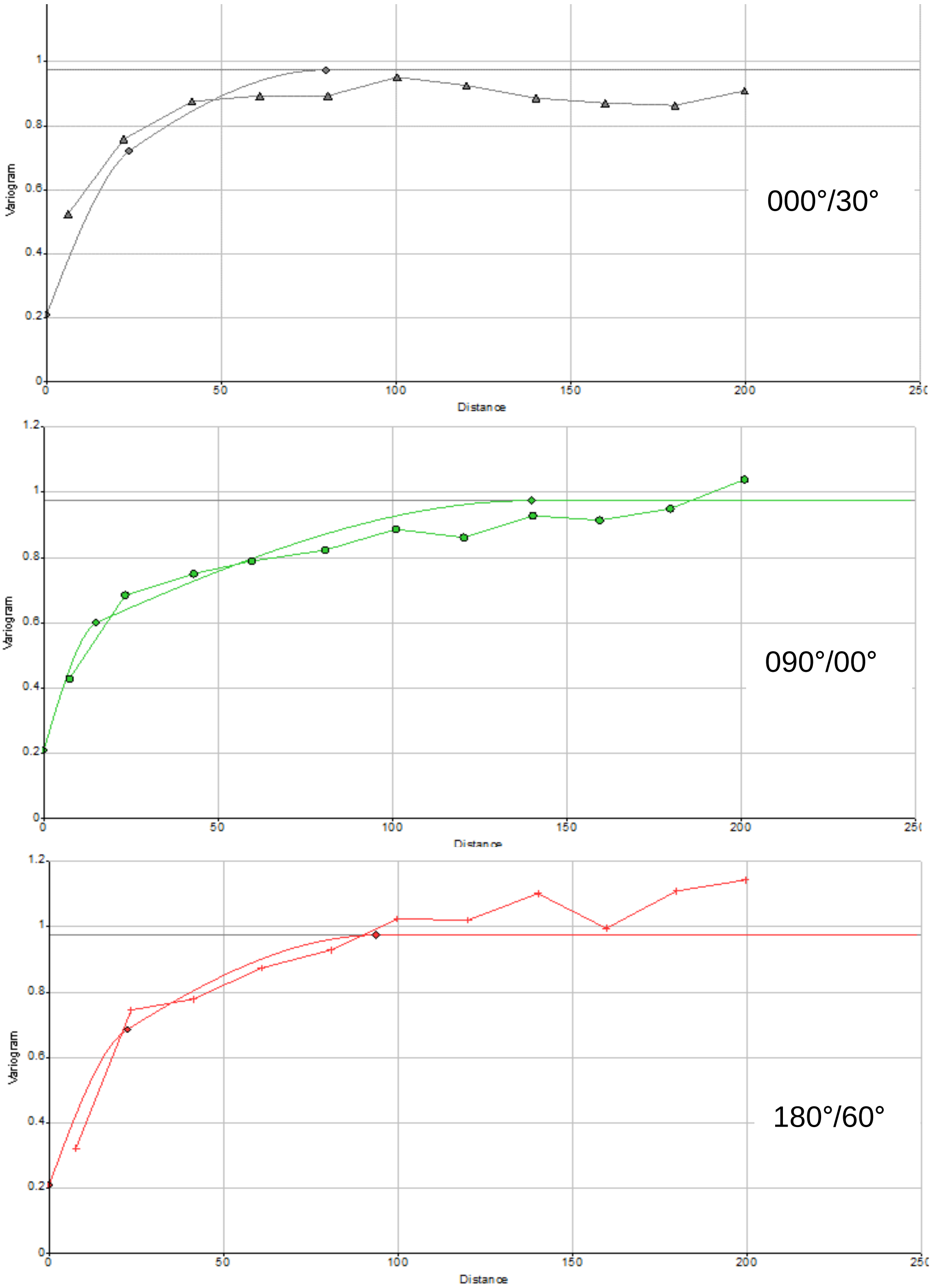

Figure 22: Experimental variograms and models for the principle, semi-major and minor axes of continuity at Tshifufia

5.6 Quantitative Kriging Neighbourhood Analysis

In order to produce the best possible estimates at optimum panel sizes, Quantitative Kriging Neighbourhood Analysis (QKNA) was run on the exploration data. QKNA for the exploration data and LUC determined individual parent block dimensions of 25 m E x 25 m N x 15 m RL with sub-blocks allowed (Figure 23, Figure 24 and Figure 25).

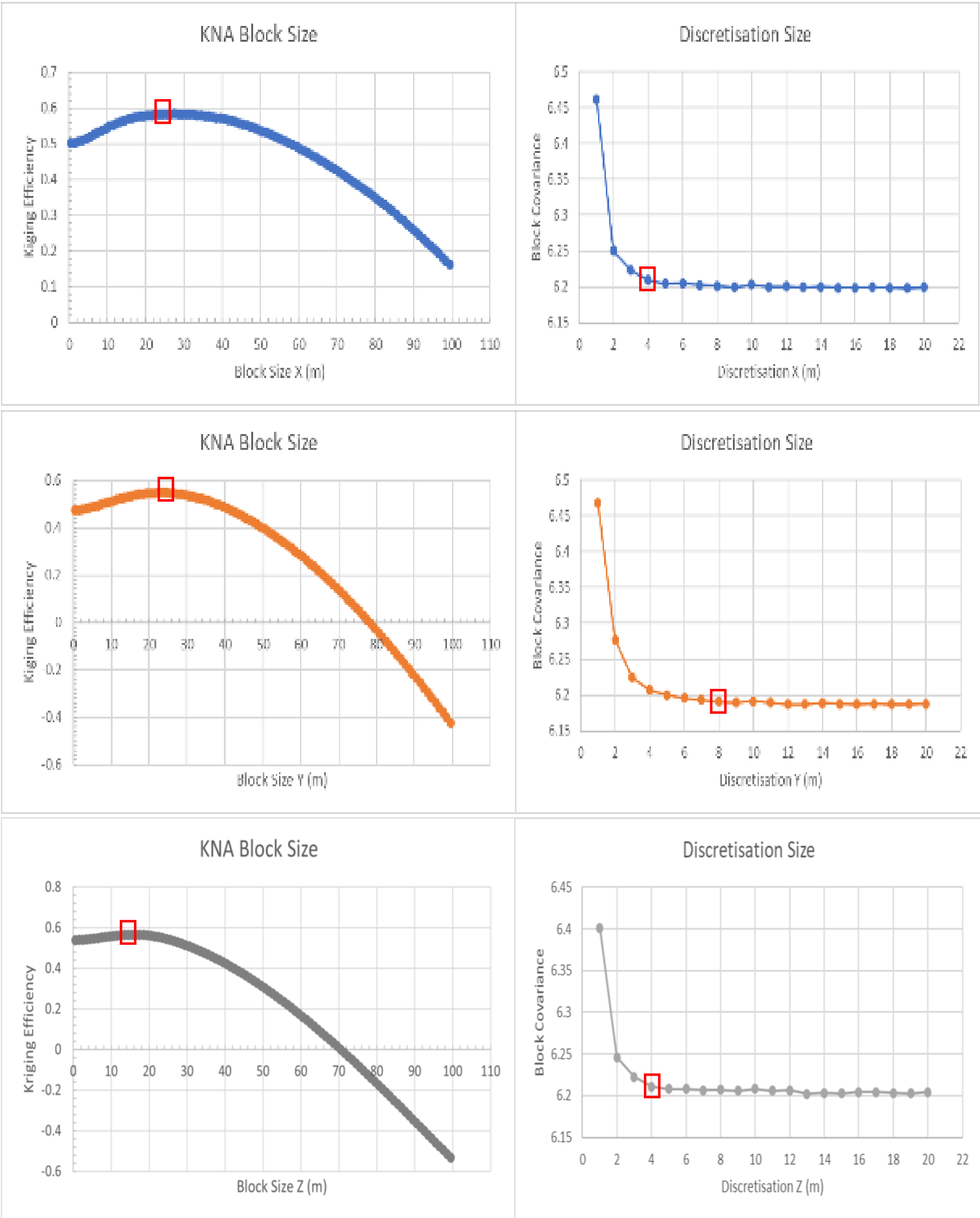

Figure 23: Block size and discretisation analysis for X, Y and Z parameters for exploration data

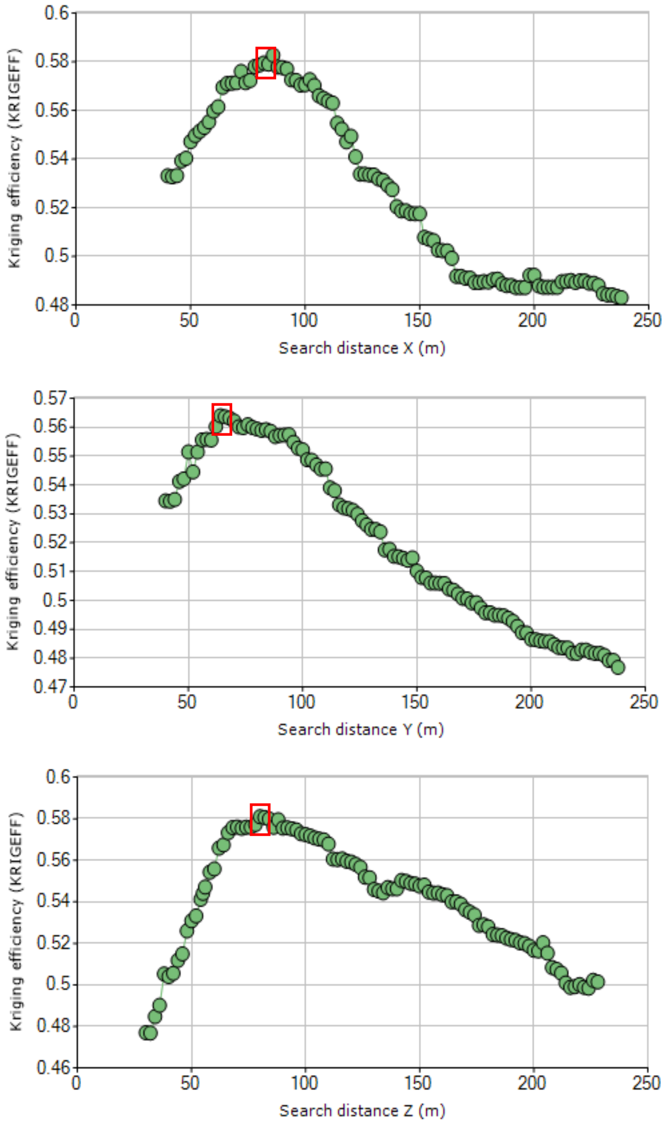

Figure 24: Search radius analysis of the Kriging efficiency of the estimates at different distances.

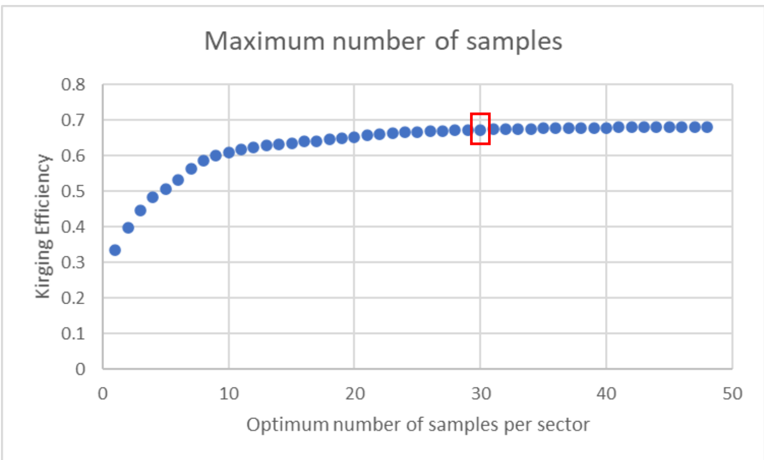

Figure 25: Optimum number of samples per sector for estimation

The results of the QKNA analysis indicates that estimation is optimized using the following parameters (Table 9):

Table 9: QKNA optimised discretisation, block and search volume parameters.

Description	X (m)	Y(m)	Z (m)
Discretisation cell size	4	8	4
Block Size	25	25	15
Search Volume	80	60	75

The optimum number of samples was determined to be 30 where the Kriging efficiency stabilizes. The block dimensions that resulted from the QKNA study outlined in this project are supported by a kriging efficiency study performed by MMG at various block or panel sizes.

With regards to the SMU size, an appropriate SMU size of 5 m E x 10 m N x 5 m Z had already been defined in the Anvil Mining NI 43-101 technical report, (Gray, *et al.*, 2012), where a reserve calculation showed that the smallest SMU size appropriate for mining the Tshifufia and Tshifufiamashi deposits was 5 m E x 10 m N x 5 m Z. The various block sizes and estimation parameters used for this project are tabulated in Table ***10***.

Table 10: Block Model Dimensions and Sizes

Description	X	Y	Z
Origin	561750	743800	700
Maximum Value	562575	744700	1300
Block Model Extent	825	900	600
OK Resource Block Model	25	25	15
LUC SMU Model	5	10	5
Grade Control	5	10	5
Search Radius	75	60	75

5.7 Grade Estimation

The estimation parameters for OK were based on spatial distribution of samples, geological continuity of the Tshifufia deposit and variography. Three search radius passes were used for estimation. The first search radius was set at half the variogram range. This was done to improve the block grade estimate for areas of densely spaced drilling. Additionally, this ensures that grade was not smeared laterally. The first search radius estimated most blocks. The second and third search radii were set at a factor of two and three, respectively. This was done to ensure that blocks limited drilling block model had an interpolated copper grade.

Estimation into parent blocks uses a discretisation of 4 m E x 8 m N x 4 m Z to better represent to block volumes, based on the parameters defined in the QKNA and illustrated in Figure 23.

The results of the OK estimation are tabulated in Table 11 and graphically represented in Figure 26 where the change of support effect is clearly illustrated by the variance reduction for the block model estimates (narrow range).

Table 11: Summary of the OK estimation results

Description	Quantity	Units
Number of blocks	8049	Blocks
Kriging Mean	2.795	Cu%
Standard Deviation	2.012	Cu%
Minimum Grade	0.28	Cu%
Maximum Grade	25.66	Cu%
Mean Absolute Deviation	1.64	Cu%
Tonnes	23.36	Mt

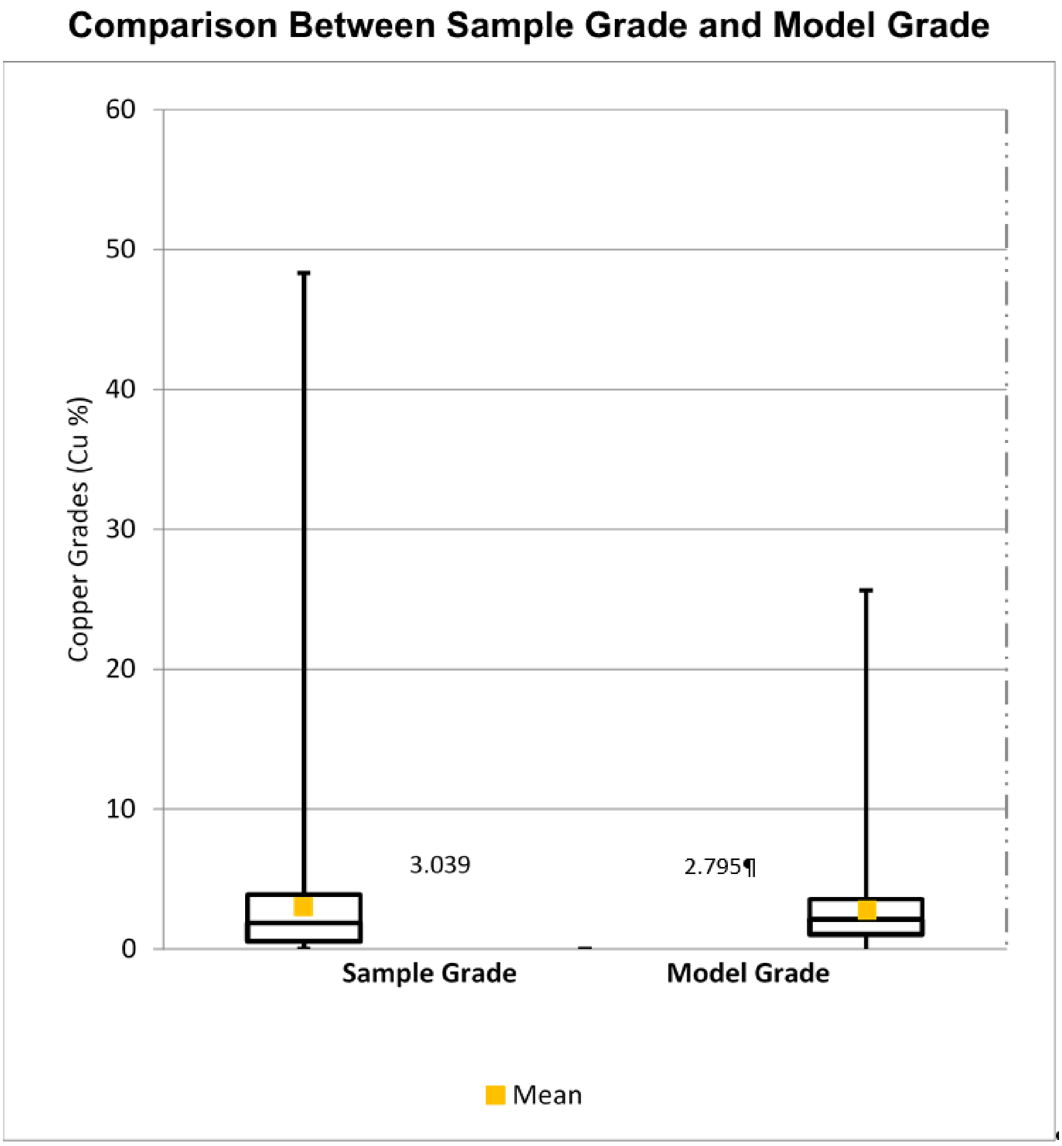

Figure 26: OK Model to sample grade comparison for exploration data

From Figure 26 it can be seen that the means are similar, but the variance of the block model is reduced due to smoothing. Although the block model has a similar average copper grade per block, the average grade for the entire block model is understandably slightly lower than the average copper grade for samples (Figure 26). OK model to sample grade comparison for exploration data is further illustrated in Figure 27. Figure 27 represents a cross section grade comparison between average copper grade for samples and the average copper grade of the corresponding block model.

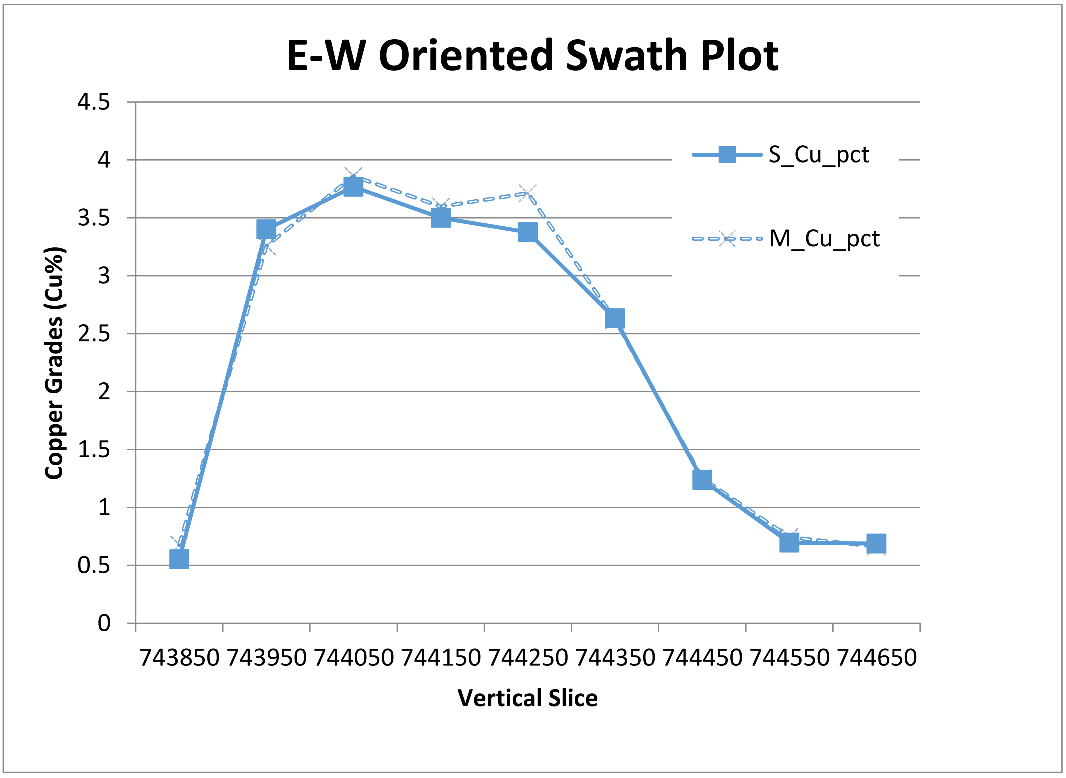

Figure 27: Grade variation cross-section of samples and the model estimates across the centre of the pit in an E-W direction

5.8 Model Validation

The output model was initially validated as follows:

- Negative estimate check. Negative estimates were set to a minimum grade of 0.0 Cu %.
- Proximity check on drillholes and blocks. This is to ensure that only blocks unsupported by drillholes remained without grade estimates.
- Visual comparison of block estimates to drillhole composited sample values.

Visual representation of the OK block model is defined by the grade range intervals observed in the raw data. The colour legend for the deposit was created by using the cumulative average grade for the samples (Figure 28) as described by Sinclair and Blackwell, (2002)

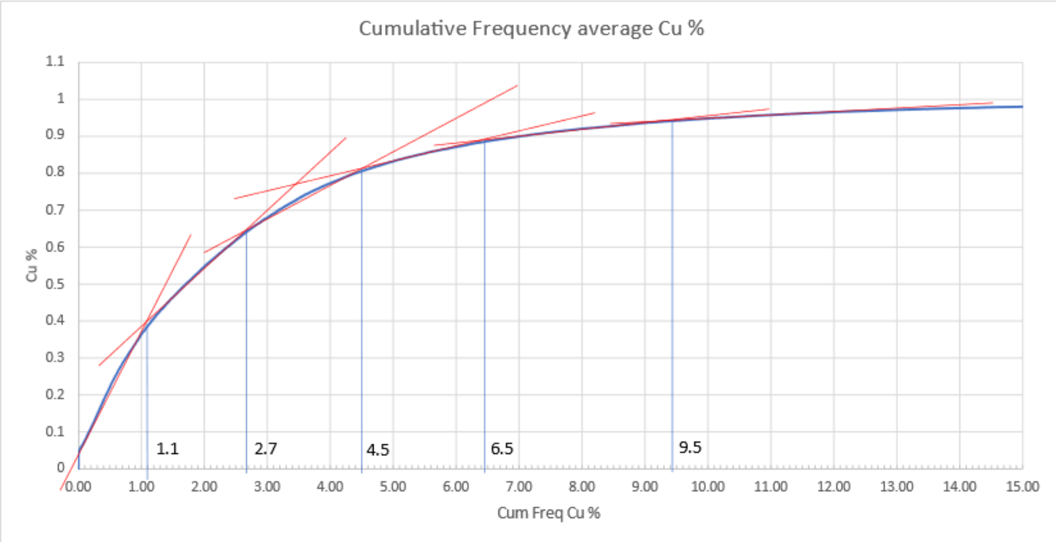

Figure 28: Cumulative frequency distribution of the raw exploration data for the determination of the colour intervals for the block model

Using the inflection points identified in Figure 30 the resultant legend for the estimated Cu % is shown in Figure 31.

Category 0: Absent
Category 1: 0.00 - 0.01 Cu %
Category 2: 0.01 – 1.10 Cu %
Category 3: 1.10 – 2.70Cu %
Category 4: 2.70 – 4.50 Cu %
Category 5: 4.50 – 6.50 Cu %
Category 6: 6.50– 9.50 Cu %
Category 7: 9.50 – 13.00 Cu %
Category 8: 13.00 – 46.00Cu %

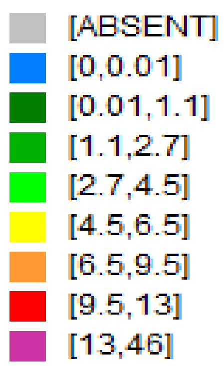

Figure 29: Copper grade ranges for block models

Attributes exported from the block model must be analysed to determine the confidence in the estimates created. To verify the quality of the OK MR estimate a histogram of the kriging variances has been generated. Figure 30 shows that the kriging variance is tightly clustered with a low average kriging variance being 0.20 Cu $\%^2$.

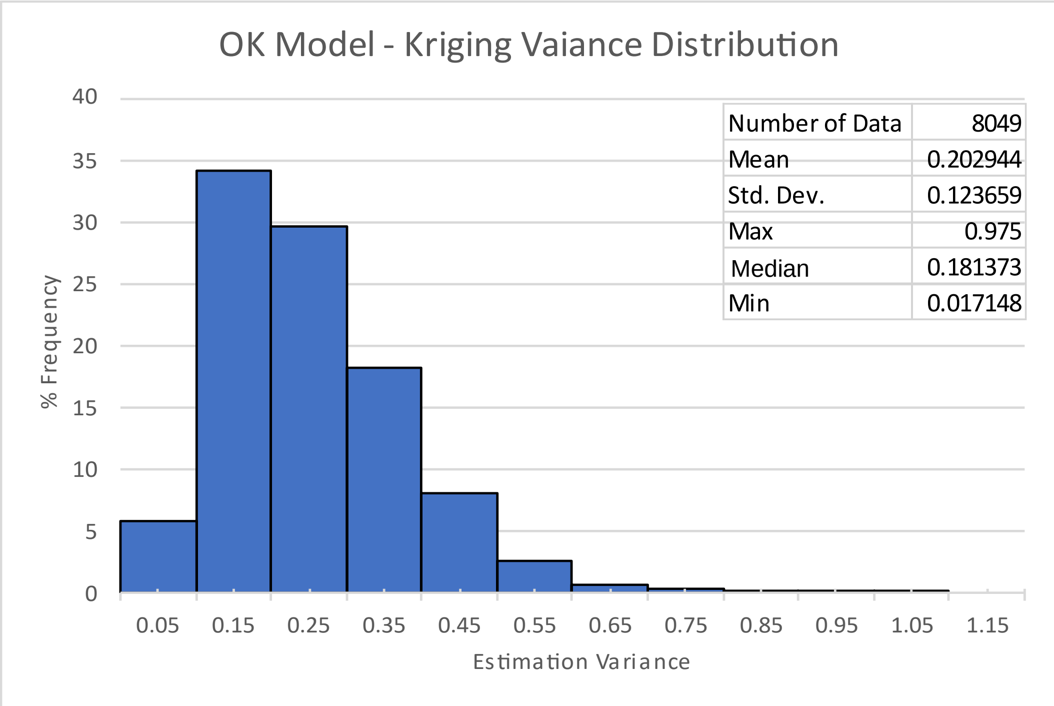

Figure 30: Kriging variance histogram

The kriging variance indicates the estimation error associated with the kriged estimates within a deposit and should ideally be low a low value for a good estimate. More specifically, a low kriging variance indicates where higher confidence in the block estimate is located. The highest confidence estimates with the least variability should be observed close to drillhole data.

The kriged variance is further illustrated as a legend in

Figure 31, categorised using the Sinclair and Blackwell, (2002) method as follows:

- Category 0: Absent
- Category 1: 0.036 - 0.045 Cu $\%^2$
- Category 2: 0.045 – 0.195 Cu $\%^2$
- Category 3: 0.195 – 0.270 Cu $\%^2$
- Category 4: 0.270 - 0.350 Cu $\%^2$
- Category 5: 0.350 - 0.420 Cu $\%^2$
- Category 6: 0.420 – 0.600 Cu $\%^2$
- Category 7: 0.600 - 1.000 Cu $\%^2$

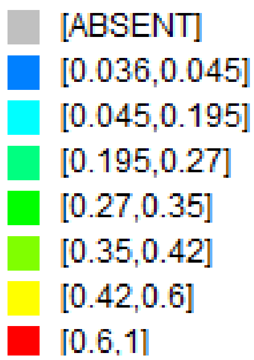

Figure 31: Kriging Variance ranges for block models

The continuous variance inside the OK block model represents low variability between the sample pairs. This is desirable as it shows that the kriged estimate has used all the data available and resulted in a low kriging variance between samples pairs. Higher variability is observed where the data becomes sparse, seen as the green and yellow colours along the edges. This output is a good check of the kriged estimate and shows that we have a reasonable number and distribution of drillhole data. Figure 32 to Figure 37 visually represent the OK block model in terms of estimated grade and variance.

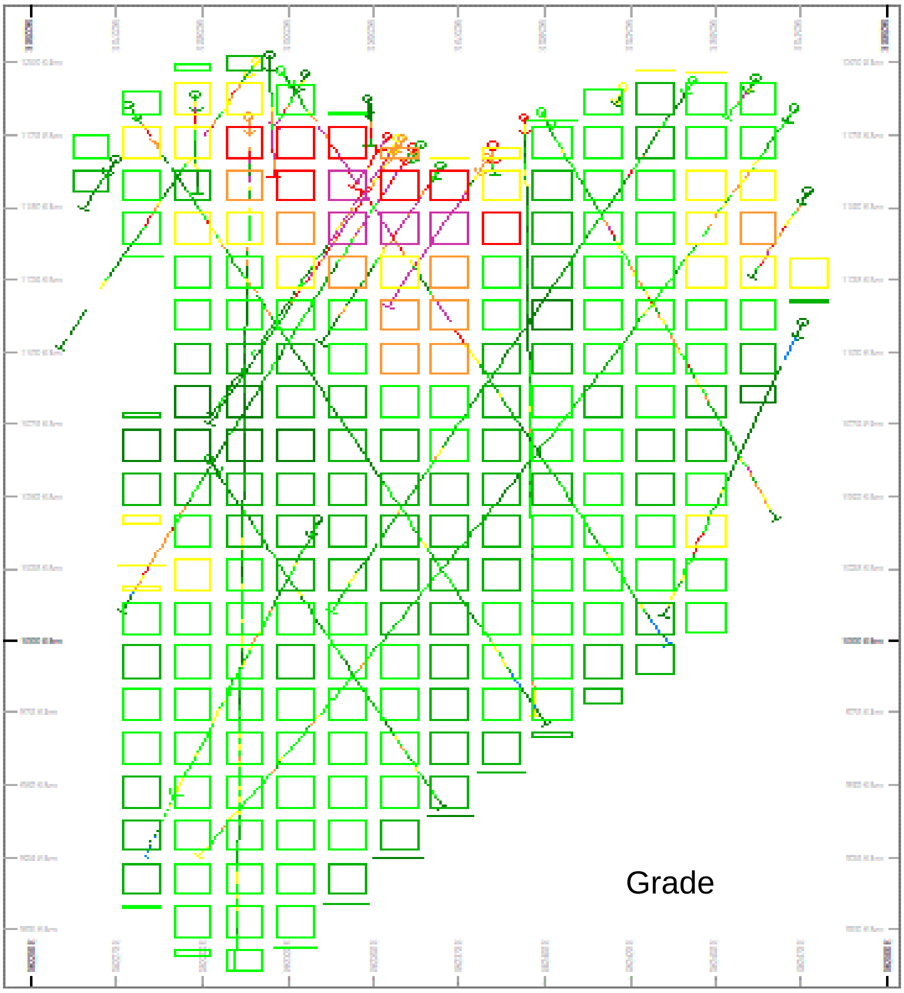

Figure 32: Visual validation of an E-W cross-section through the OK block model relative to the drillholes.

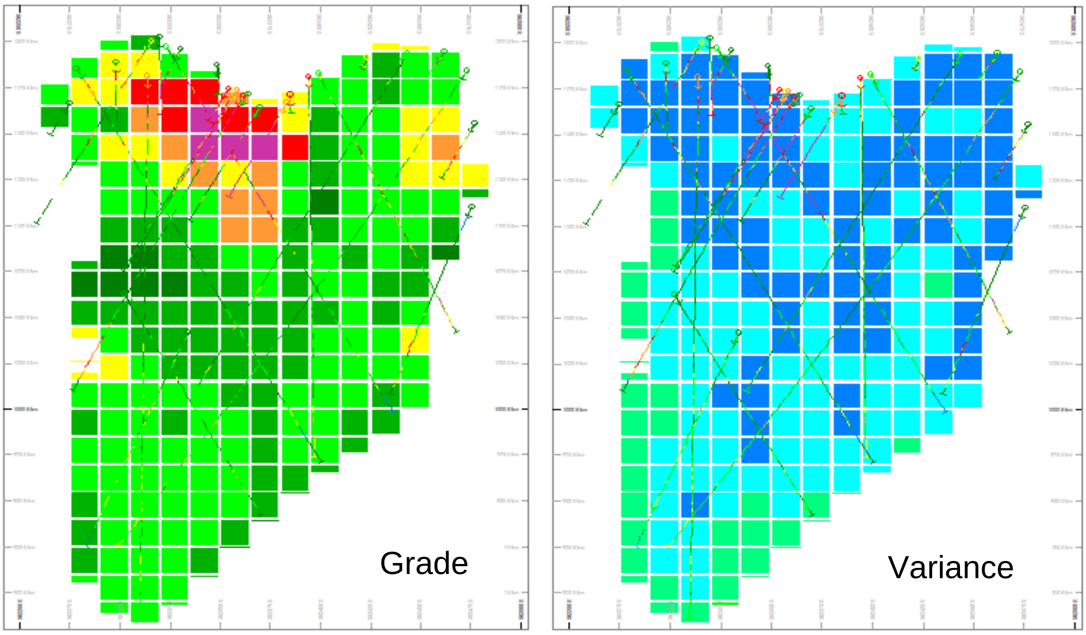

Figure 33: E-W Cross section of grade and variance in the OK block model.

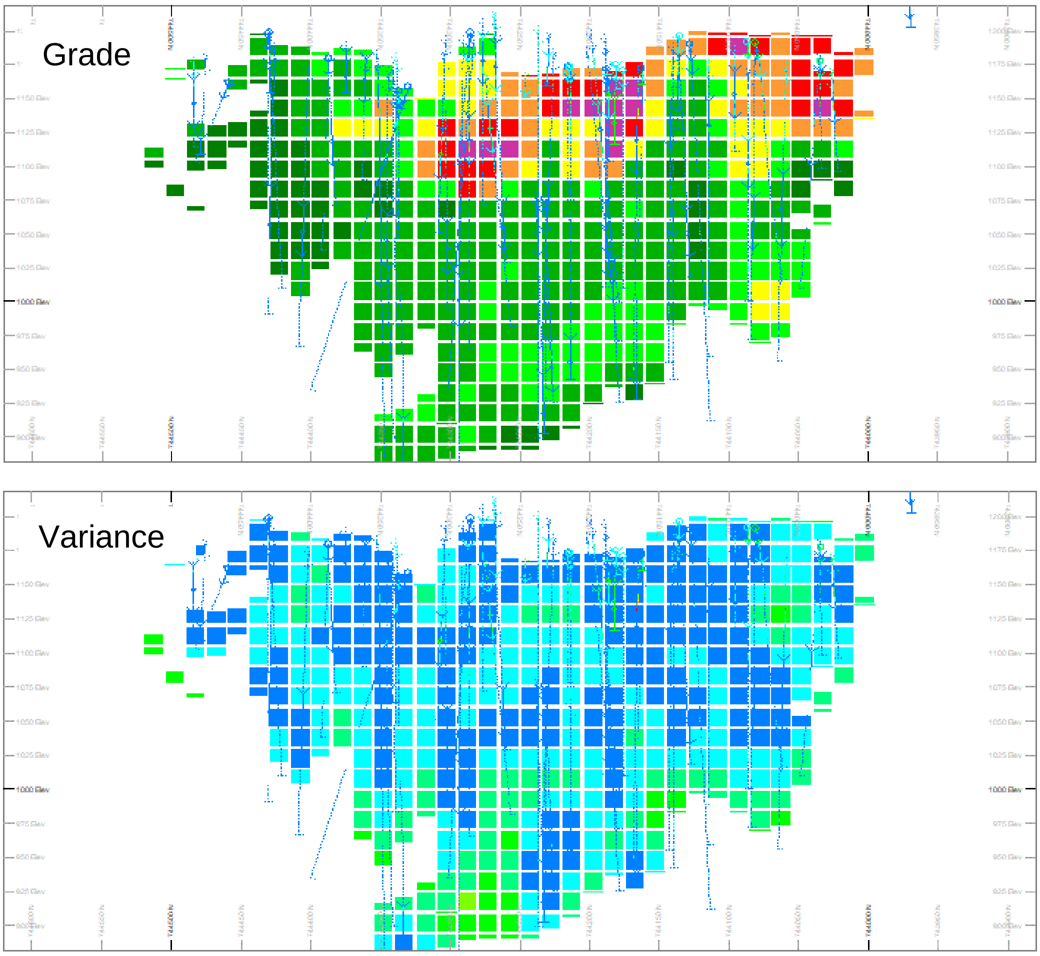

Figure 34: N-S Cross section of grade and variance in the OK block model.

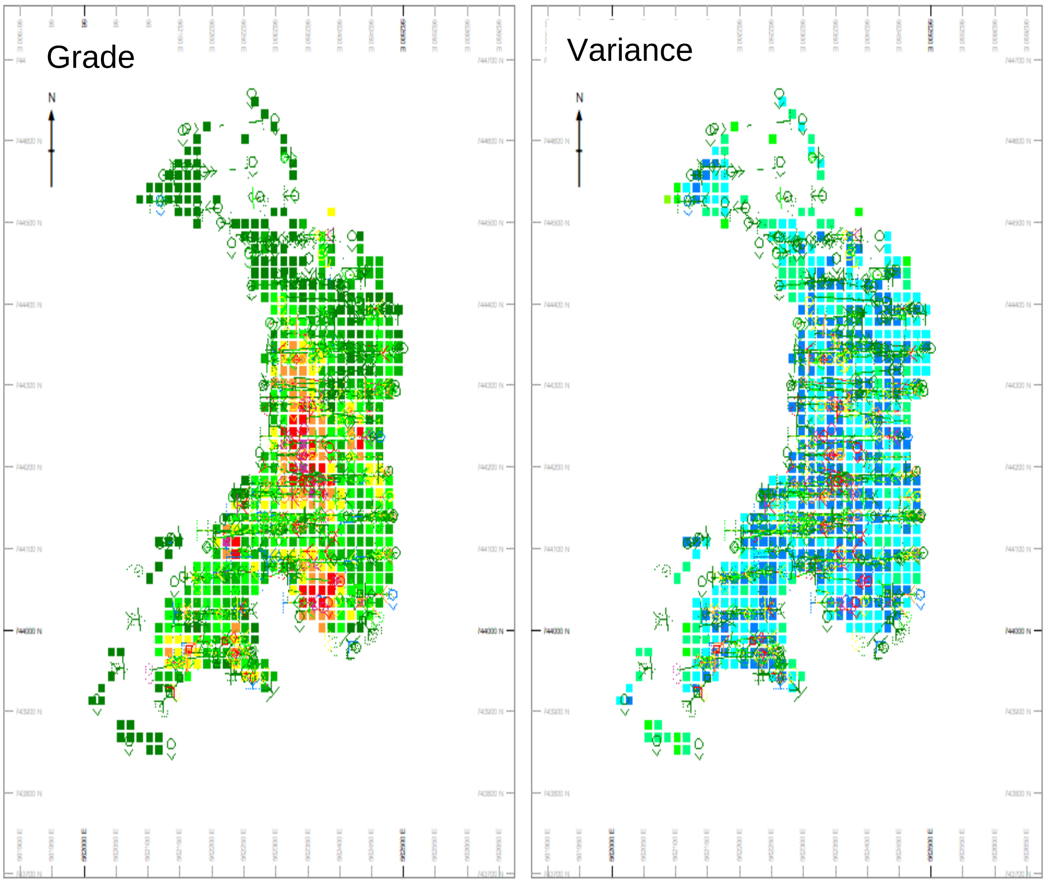

Figure 35: Plan section of grade and variance in the OK block model.

The summary statistics, statistical analysis and visual validations for the OK MR estimates are believed to fairly represent the distribution of mineralisation within the Tshifufia deposit.

Figure 33 and Figure 34 shows that there is very high-grade copper mineralisation near surface, comparable with oxide facies mineralisation. Figure 35 shows the general trend of the deposit and in a N-S direction.

5.9 Mineral Resource Estimate

The Tshifufia OK MR estimate is derived from the portion of the block model which occurs in the 0.3 Cu % grade shell. A 0.3 Cu % cut-off grade is estimated to be 98.5% of the total tonnes, which is equivalent to 23.36 million tonnes (Table 11) of sulphide and oxide copper ore. Figure 36 is the grade tonnage curve for the deposit and illustrates the average copper grade above cut-off grade against the proportion above cut-off.

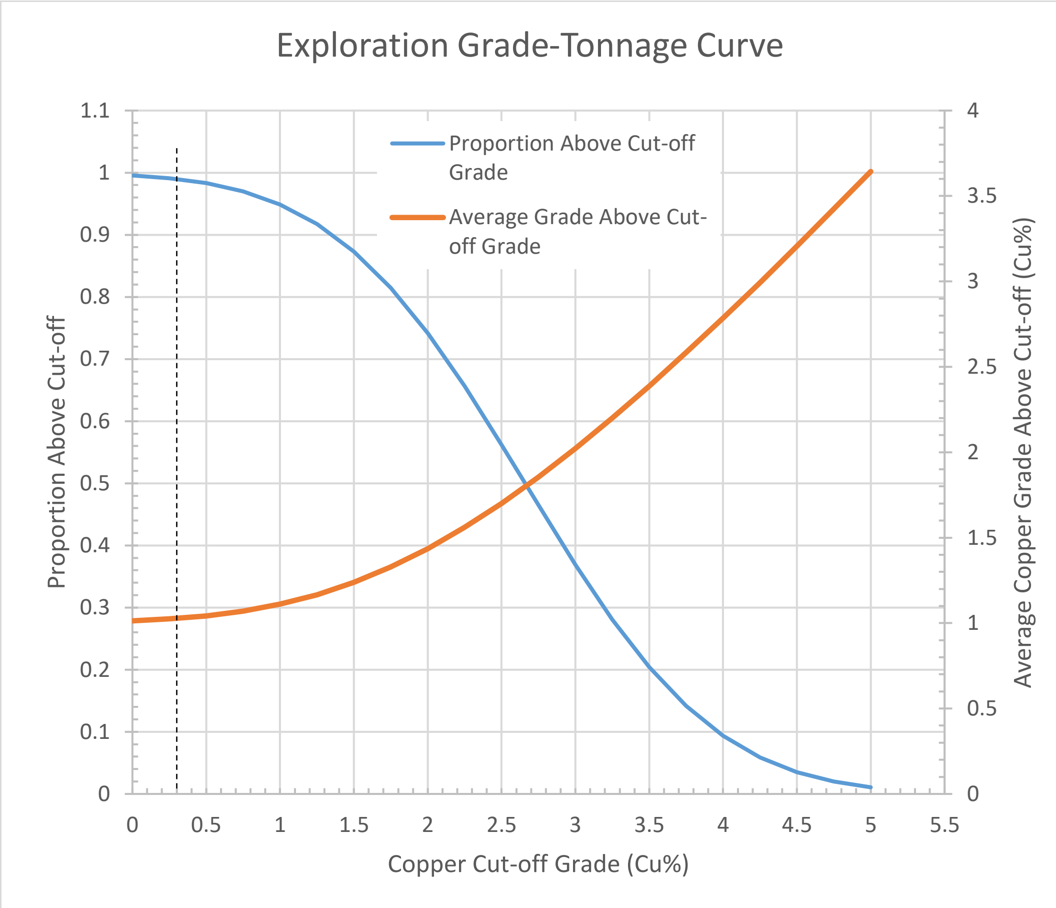

Figure 36: Grade-tonnage curve for Tshifufia determined from an OK MR estimate on exploration data.

5.10 Chapter summary

The process of estimation is based upon certain criteria to help produce as best an estimate as possible. Variography determined the orientations of continuity and variability for application during variogram modelling. By performing a QKNA analysis, blocks and search distances were optimised to suit the composited exploration drillhole data distribution and produce a fair representation of the Tshifufia deposit.

The assumptions and parameters made for the OK estimation of exploration data has resulted in a robust estimate, validated by assessing the kriging variance and visual grade distribution relative to the drillholes.

The OK MR estimate is to be used at the panel estimate for the UC and LUC estimation and will later be compared to the LUC MR estimate to assess the differences in estimated deposit volume and mean copper grade.

6 Uniform Conditioning and Localised Uniform Conditioning

The estimation of UC and LUC are based on the OK output data. As presented earlier, the transformation of the data for UC and LUC modelling is described by two discrete Gaussian anamorphosis models, namely; point-to-SMU and point-to-panel, (Abzalov, 2006).

Point-to-SMU (Hermite polynomial)

$$Z(v) = \phi_v \, Y(v) = \sum_{k=1}^{\infty} \frac{\varphi_k}{k!} r^k \, H_k\big(Y(v)\big)$$

Point-to-panel (V)

$$Z(V) = \phi_v \, Y(V) = \sum_{k=1}^{\infty} \frac{\varphi_k}{k!} s^k \, H_k\big(Y^*(V)\big)$$

Where:

- k is Gaussian anamorphosis coefficient,
- $Y(v)$ is the Gaussian point anamorphosis,
- $Y(V)$ is the Gaussian Panel anamorphosis,
- r is the point to SMU change of support coefficient, and
- s is the point to Panel change of support coefficient.

Both models are calculated using the discrete Gaussian correction approach. The underlying assumption of the above models is that they are bi-Gaussian linearly correlated, (Abzalov, 2014,). The point-SMU and point-Panel coefficients are to be calculated in the following way.

To ensure that a representable and robust UC MR estimate is produced the assumption of bi-Gaussianity of the transformed grade data should be validated. Schofield, (1988) describes various practical tests on sample data to check for bi-Gaussianity prior to estimation. (Hansmann, 2015) successfully showed that by using a madogram-variogram ratio test and diffusion model described by Schofield, (1988) the bi-Gaussianity of a dataset can be proven.

Test 1: Madogram-Variogram Ratio Test

The madogram-variogram ratio test assess the intrinsic correlation between the variability of samples pairs. Rivoirard, (1987) described intrinsic correlation as "auto and cross covariances are all the same apart from a multiplicative factor". This means that the ratio between the normal score madogram and variogram is constant, as describe by the following equation:

$$\frac{\gamma_1(h)}{\sqrt{\gamma_2(h)}} = \frac{1}{\sqrt{\pi}} = 0.56419$$

The madogram-variogram ratio test was performed on the primary axes of continuity as defined in by the normalised OK variogram (Figure 37).

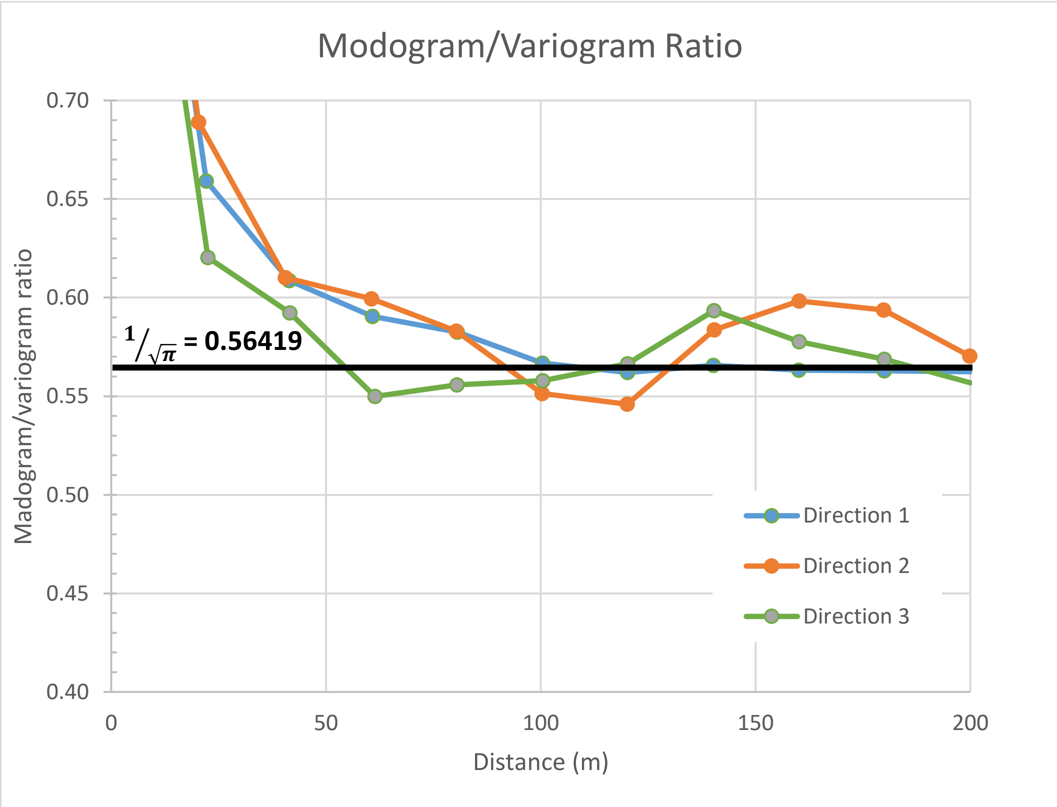

Figure 37: Normalised madogram-variogram ratio test

Figure 37 graphically illustrates that the transformed data are approximately bi-Gaussian within the range of the variogram, and by assumption beyond the range of the variogram.

Test 2 - Diffusion Model

The diffusion model is a model that separates the quality of evidence from decision criteria. The diffusion model is consistent with a Tshifufia type-deposit as Vann *et al.*, (2000) confirmed that mineral deposits exhibiting gradational grade transitions from high grade towards the outer rings of lower grade material (at various scales) is suitable for testing.

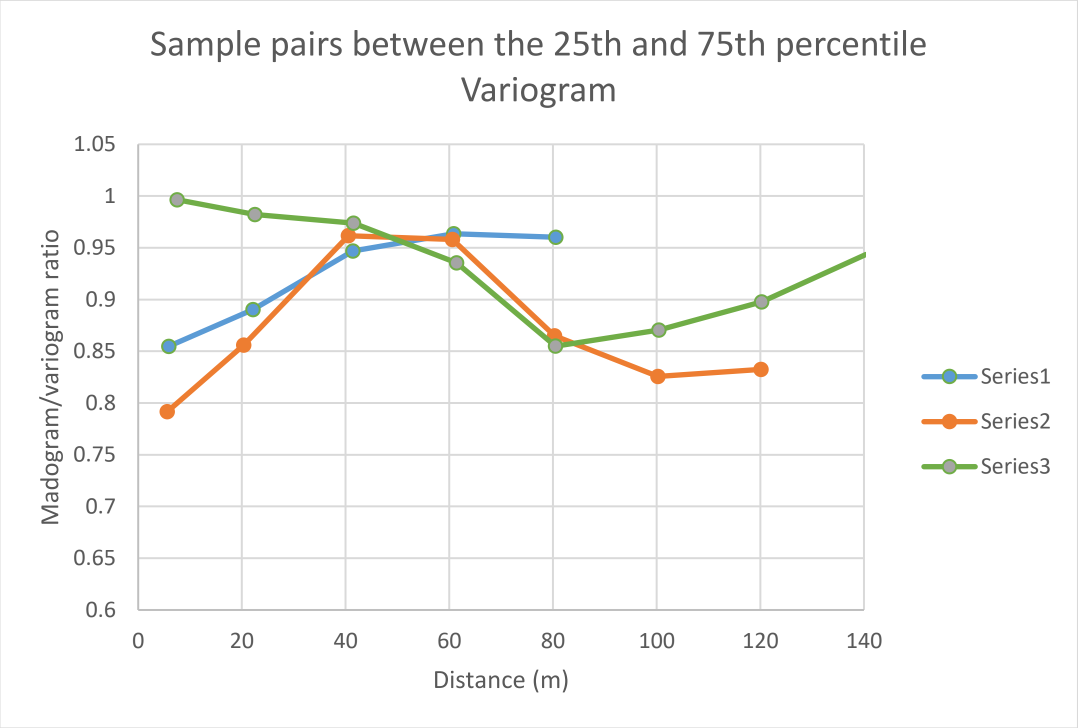

Figure 38: Diffusion model

Figure 38 illustrates poor correlation between variograms and therefore no intrinsic correlation between the 25th percentile and 75th percentile. As a result, no intrinsic correlation proves a diffusion model by deduction.

Bi-Gaussianity test results

The madogram-variogram ratio test and the diffusion model test both prove that the conditions of Gaussianity (bi- and multi) were proven. Based on these observations the exploration dataset upon which the UC MR estimate will be based, is bi-Gaussian.

6.1 Uniform Conditioning Process

UC is an alternative non-linear technique for estimating a MR of a deposit that is representative of a defined SMU and based on the variability of the deposit. UC models relies on the change of support to model the distribution of SMU grades within blocks.

6.1.1 Change of Support

Due to the inherent problem of “scale” in terms of sample → SMU → panel, the distribution of grades at larger scales and with less variability is difficult to model since there is insufficient data to accurately portray the distribution. The discrete Gaussian model uses the dispersion variance theory to enable the change of support to be made from the sample to block scale whilst controlling the shape and variability of the model based on the modelled variograms. For the change of support model, the data must be converted from its original state into Gaussian “space” via the normal score transformation (Figure 4). The point to sample coefficient is calculated from the theoretical block variance of the SMU and the Hermite coefficients.

6.1.2 Hermite Polynomial

Using Datamine, a set of 30 Hermite coefficients were calculated to fit the Hermite polynomials to the distributions (Table 12).

Table 12: Hermite Coefficients

Polynomial (Φ)	Hermite Coefficients
0	3.0387
1	-3.25108
2	1.965695
3	-0.72289
4	0.128432
5	0.071903
6	-0.11683
7	0.052935
8	0.027451
9	-0.02482
10	-0.01854
11	0.012208
12	0.024707
13	-0.01929
14	-0.01857
15	0.024025
16	0.005873
17	-0.01878
18	0.002618
19	0.007966
20	-0.00272
21	0.001485
22	-0.0035
23	-0.0055
24	0.011621
25	0.003657
26	-0.01783
27	0.002114
28	0.020167
29	-0.00921
30	-0.01844

Hansmann (2015), indicated that the Hermite polynomials should satisfy three conditions:

1. The first Hermite coefficient is equal to the mean of the sample data.
2. The sum of the squared coefficients equals the sample variance.
3. Hermite polynomial can be expanded to display the Gaussian anamorphosis model to check if it is consistent with the sample normal score transform.

Condition 1, 2 and 3 were satisfied for Hermite coefficients. Condition 3 is shown below in Figure 39. The Gaussian anamorphosis model is consistent with the sample normal score transform. The shape of model is a normal distribution. However, Figure 39 illustrates that there is a slight deviation from the expected lognormal distribution above an approximate grade of 23.5 Cu %. Below 23.5 Cu % there is a very good correlation or fit of the grade distribution to the normal distribution.

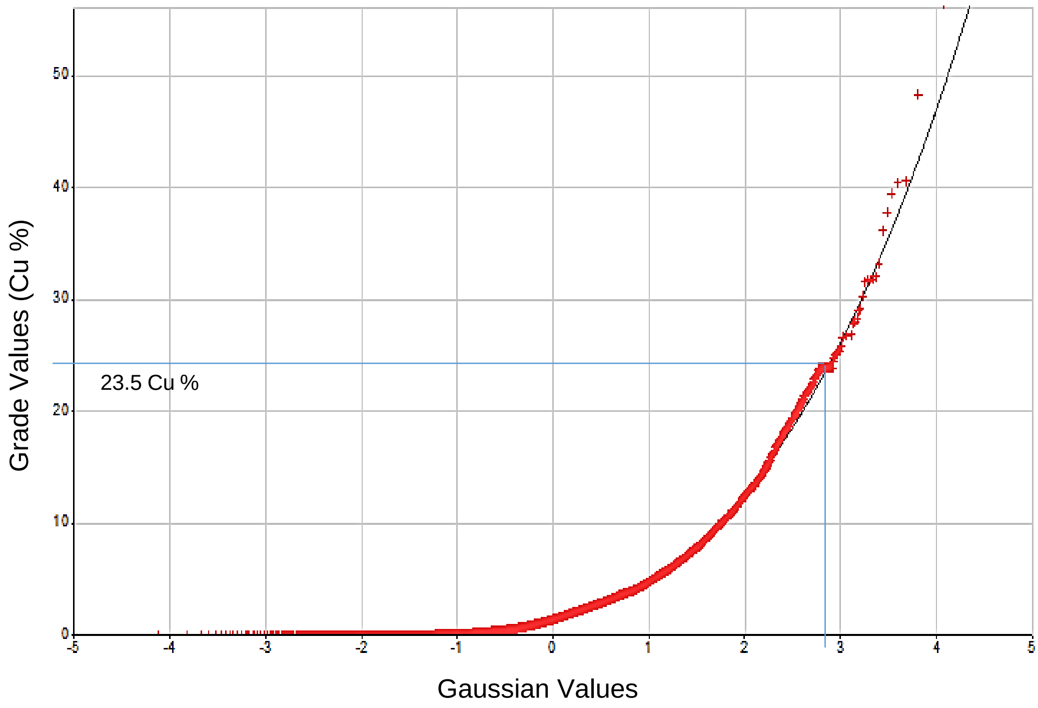

Figure 39: Normal Score transform and Gaussian anamorphosis graph.

Deviations from the expected log-normal distribution are likely the result of areas that have less “true” sample data. Good correlation is therefore representative of areas that are sufficiently supported by the sample data.

6.1.3 Calculating SMU distribution

To determine the UC and LUC MR estimates, the Datamine UC module was used. The UC stepwise process calculates the Gaussian anamorphosis, models the change of support and then carries out UC on the OK MRE model and finally produces an LUC to produce the SMU model.

Datamine uses the UC module process for UC and LUC. The UC module performs the following:

1. The composited sample data and OK MR model are uploaded into the UC module.
2. Declustered weights for the samples are calculated to ensure realistic sample distributions.
3. The true variance of the blocks are calculated from model variograms.
4. Global grade tonnage curves are generated.
5. UC block model estimated at a series of defined cut-off grades.
6. The discretisation points and information effect are calculated by stipulating a specific SMU size.
7. Average grade at SMU-scale above cut-off is determined.
8. LUC SMU block model is estimated.

The estimation of the UC block model uses the same prototype as the OK MR block model. Datamine estimates a series of grades and proportions above a range of cut-off grades as defined by the user. The proportion of grade defined the metal contained above a given cut-off in terms of the SMU's.

UC models were estimated in 2 g/t cut-off increments, from a cut-off grade of 0.3 g/t to 48.3 g/t. The range of the cut-off grades should reflect areas of interest in the block model. The distribution of the average grades per SMU can be displayed in a Q-T curve which compares the tonnage, or in this case volume, to average grade (Figure 40).

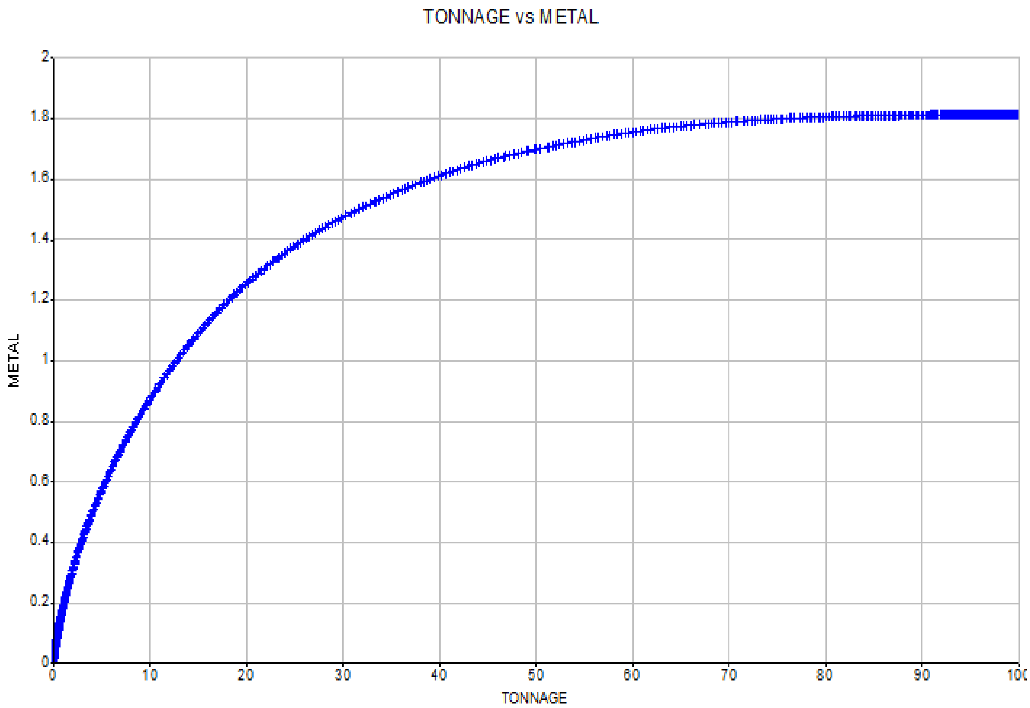

Figure 40: Q-T curve showing average grade calculations at various tonnages.

The parameters for the optimal SMU size are derived from the NI43-101 technical report which indicates that a suitable SMU size is 5 m (X) x 10 m (Y) x 5 m (Z).

6.2 Localisation

Step 6 of the Datamine UC module is the localisation of the sample UC data and placement of SMU's at plausible locations within a panel. It is important to note that the effect of localisation does not further estimate grades and thus does not provide a better estimate than UC. Localisation spatially indicates the position of the SMU within a panel that satisfies the sample data. The result is highly desirable when selective mining is being used or the recoverable resources are to be modelled. This is achieved using an ordinary kriging estimate and ranking the SMU's within the panel. The ranking of SMU grades is based on kriged estimate derived earlier for exploration data.

Within a panel there are 37.5 SMU's of dimension 5 m (X) x 10 m (Y) x 5 m (Z) resulting in 5 SMU's in the X-direction, 2.5 in the Y-direction and 3 in Z-direction. Each SMU is ranked from 1 and 38. The ranking is then applied to the set of SMU grades for a given panel. The localisation procedure calculates the mean SMU grades for a panel within the UC model. The grades are then ranked from lowest to highest and allocated mean SMU grades. Localisation then spatially correlates the ranked LUC SMU grades to the equivalent-ranked OK SMU grades. Figure 41 to Figure 44 visually represent the LUC block model in terms of estimated grade and variance.

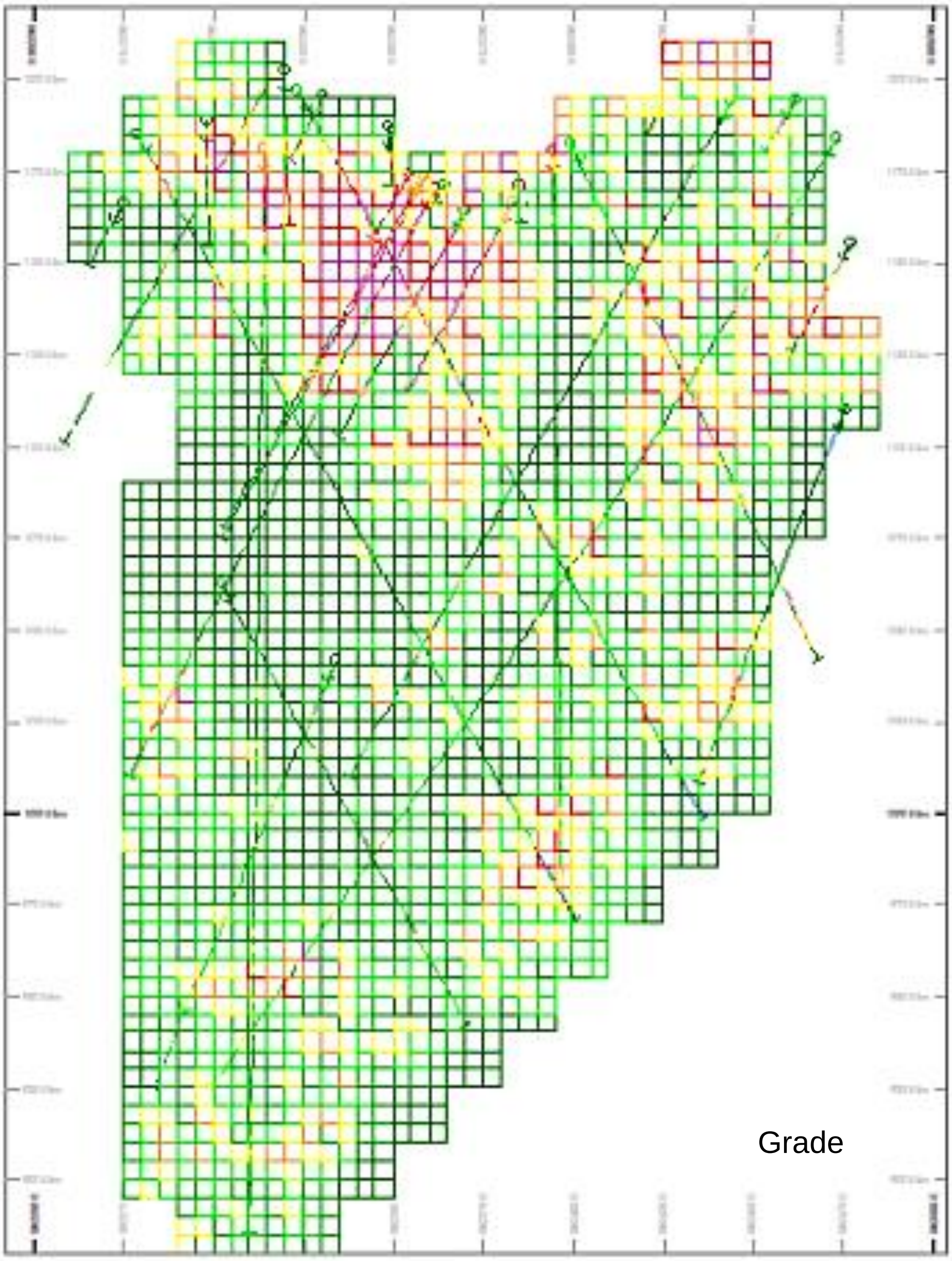

Figure 41:Visual validation of an E-W cross-section through the LUC block model relative to the drillholes.

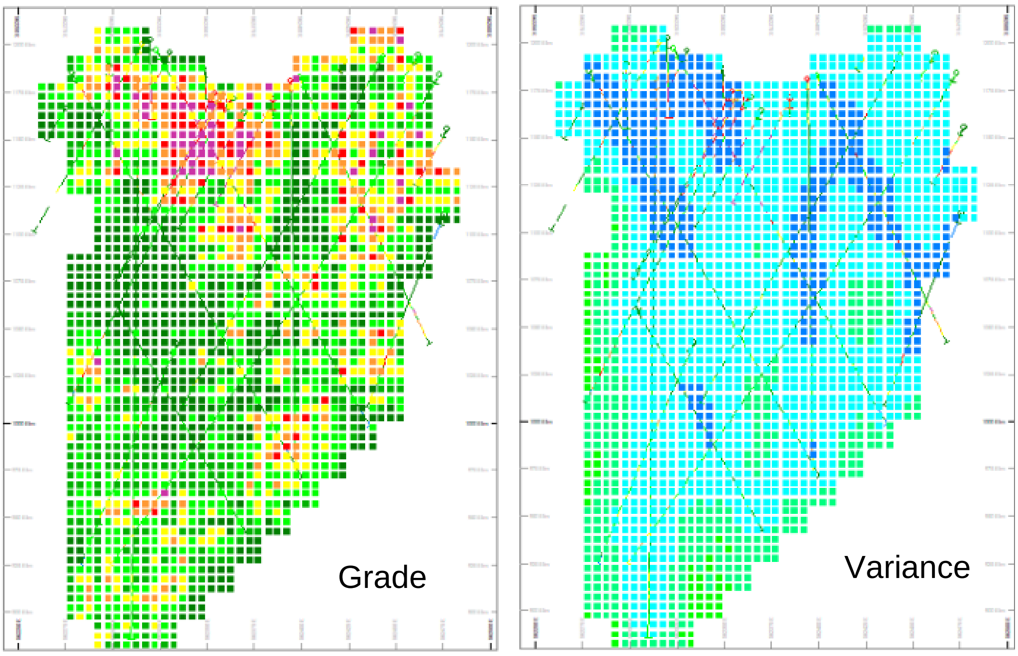

Figure 42: E-W Cross section of grade and variance in the LUC block model.

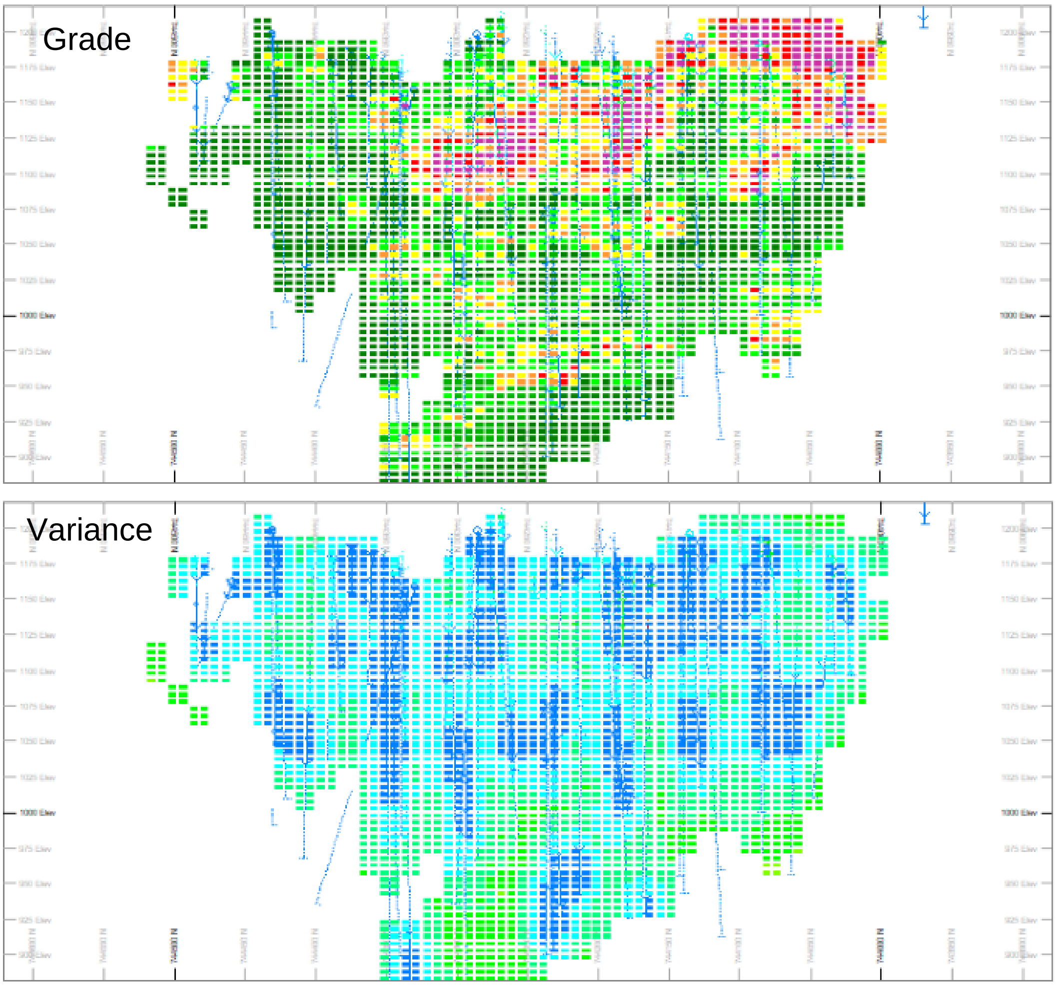

Figure 43: N-S Cross section of grade and variance in the LUC block model.

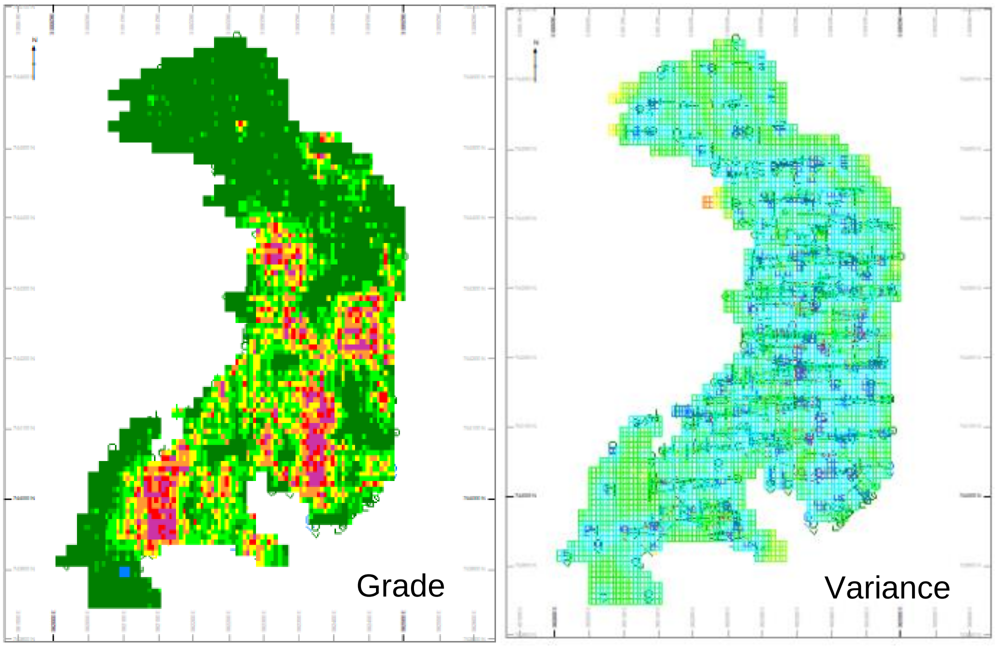

Figure 44: Plan section of grade and variance in the LUC block model.

6.2.1 Validity of the Uniform Conditioning and Localised Uniform Conditioning estimates.

The OK block model for exploration data is the basis upon which the UC and LUC MR estimates are based. During LUC, the panels are used to derive both the LUC and OK MR estimates at SMU scale by ranking the SMU blocks within each panel.

The LUC MR estimate honours the exploration drillhole data accurately. LUC has provided a higher resolution of the distribution of the copper grade within the Tshifufia deposit at SMU size. The LUC grade distribution in Figure 42 indicates that the highest grade mineralisation within the block model is near surface and is interpreted as the high-grade oxide facies mineralisation. Additionally, a somewhat linear grade distribution is seen at depth. This is comparable with the steeply dipping layers of the Mines Series Formation and believed to represent the transitional or sulphide facies mineralisation. The LUC grade distribution in Figure 44 clearly indicates the N-S strike of the Mines Series Formation in the Tshifufia deposit.

6.2.2 Localised Uniform Conditioning Mineral Resource Estimate

The Tshifufia LUC MR estimate is derived from the portion of the block model which occurs in the 0.3Cu % grade shell and totals 27.06 million tonnes of sulphide and oxide copper ore at an average grade of 2.695 Cu%. Figure 45 represents the grade-tonnage curve for Tshifufia determined from an LUC MR estimate on exploration data.

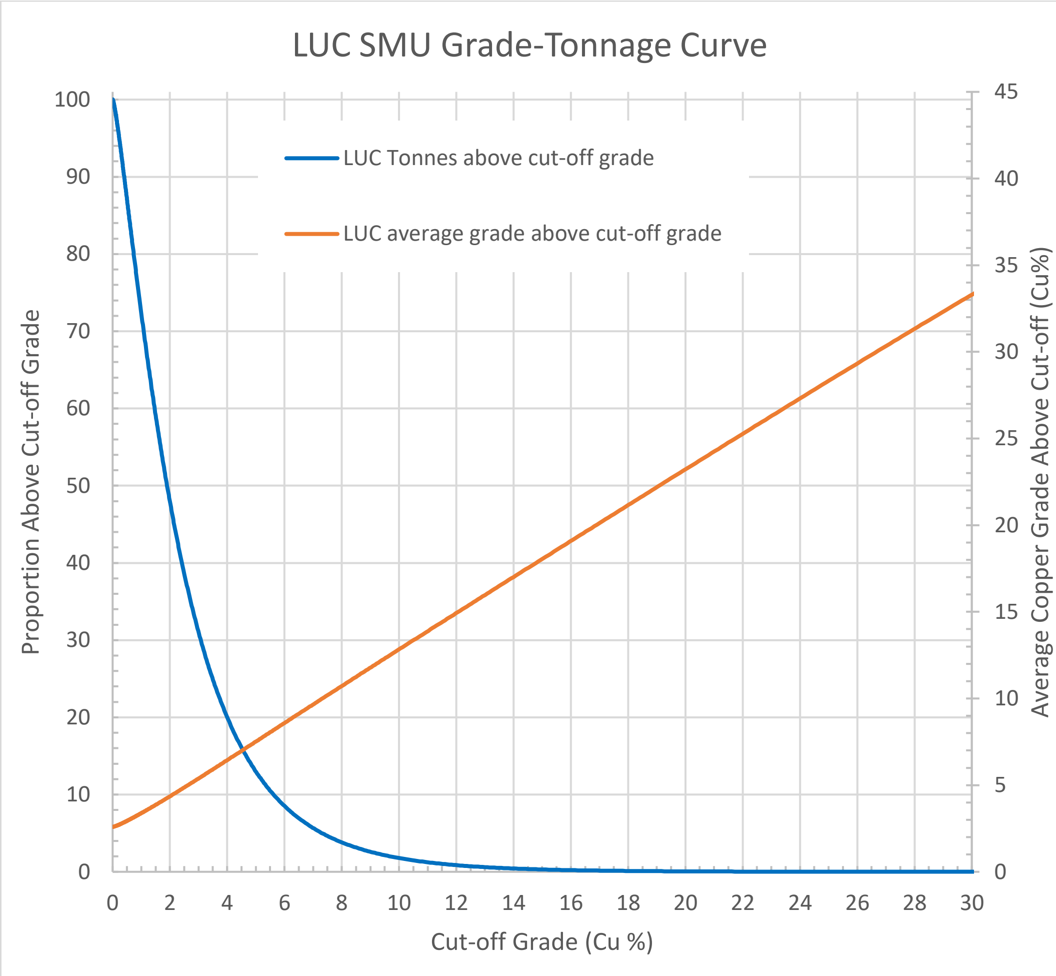

Figure 45: Grade-tonnage curve for Tshifufia determined from an LUC MR estimate on exploration data

The shape for the grade tonnage curve for LUC shows a rapid change between grades and tonnages above a given cut-off in comparison to the smoothed OK grade tonnage curve shown in Figure 36. This highlights that the LUC model introduces more realistic variability at SMU-scale than an OK block estimate could.

6.3 Chapter Summary

The UC and LUC MR estimates generated from composited exploration data produced adequate results for the modelling and grade distribution at SMU scale within the Tshifufia deposit. A clear constraint on both the UC and LUC estimates is their dependence on the OK estimate that is based on exploration data. UC cannot better predict the distribution of high and low grades in comparison to the OK MR estimate, (Hansmann, 2015). Rather corresponding high and low SMU grades are modelled within OK panel estimates that have high and low grade respectively.

7 Grade Control Estimation for Localised Uniform Conditioning Mineral Resource Assessment

To make a realistic assessment of the LUC MR estimate, GC data was estimated to draw a direct comparison of the LUC MR estimates. GC data was estimated using OK and the same SMU size used for the LUC model.

The OK technique used for exploration data was again used for the estimation of the GC data. GC drilling used the RC drilling technique and has the following characteristics:

- high angle of intersection, with dominant strike and dip of the Mines Series Formation. Maximum continuity is along the direction of strike. Maximum variability in copper grade is perpendicular to the strike direction.
- hole angles were set to 60°, east or west, according to layer strike and dip.
- depths up to 30 m (vertical).
- grid spacings was 10 m x 10 m and 5 m x 15 m grids, based on geology and block model.

RC GC samples were typically composited to a length of 2 m and as such the composite lengths were set to 2 m. This is comparable with the exploration sample composites used earlier.

GC data was similarly exposed to the same data validations and preliminary analysis as the exploration drillhole data, i.e., EDA. Mineralised intercepts between the exploration and GC drilling campaigns are, to a large degree, comparable with each other. However, it is important to note that the GC data is significantly closer spaced in comparison to exploration data which is widely spaced.

7.1 Variography- GC

The GC drilling is predominantly focused on the oxide facies. The oxide facies has pervasive mineralisation and is laterally continuous in all directions in the XY plane. For the purposes of this study the axes of anisotropy determined from the exploration data and are used during the LUC MR estimate. This was done to limit the impact of the search volume between the GC and LUC MR estimates albeit, at different ranges.

The variography and variogram modelling of the GC data followed the same steps, although the lag distance was set at 5 metres. The results of the GC variography analysis appear in Table 13 and Table 14.

Table 13: Axes of anisotropy for Tshifufia Variogram models.

VANGLE1	VANGLE2	VANGLE3	VAXIS1 (Z)	VAXIS2 (X)	VAXIS3 (Z)
90	130	-175	3	1	3

Table 14: Standardised variogram model for GC data

	Spherical Structure 1				Spherical Structure 2			
Nugget	Sill	Range	Range	Range	Sill	Range	Range	Range
0.23	0.395	6.6	10.9	3.8	0.328	99	79.9	95.3

Variography displayed reasonable continuity with moderate nugget values in domains with moderate to good sample support.

7.2 Grade Control Block Modelling

Ok estimation and block modelling of the GC data followed a similar process to that of the exploration data described earlier. GC drilling data was selected by using the 0.3 Cu % grade shell wireframe, GC samples were declustered and samples were composited to a length of 2 metres.

The original GC block dimensions were set to 5 m (X) x 10 m (Y) x 5 m (Z) size honouring the orientation of mineralisation, and the requirements for selective mining of the Mines Series Formation. Variography and sample selection criteria represent strongly anisotropic mineralisation. Key characteristics/differences between GC and Mineral Resource (MR) models are listed in Table 15.

Table 15: Table of Key Differences Between the GC and MR Modelling

	GC model	MR model
Input data	GC drilling	Exploration drilling
Geological data	In-pit mapping	Exploration mapping
Model limits	0.3 Cu % grade shell wireframe	0.3 Cu % grade shell wireframe
Block size	5 m (X) x 12.5 m (Y) x 5 m (Z)	25 m (X) x 25 m (Y) x 15 m (Z)
Variography	similar	similar
Search ellipse	similar	similar
Number of samples	8 min, 30 max	8 min, 30 max
Parent cell estimation	Used	Used

7.3 Grade Control Mineral Resource Estimate

The results of the OK GC estimation are tabulated in Table 16.

Table 16: Ordinary Kriging GC MR estimates

Description	Quantity	Units
Number of blocks	1 434 472	Blocks
Kriging Mean	3.64	Cu%
Standard Deviation	2.57	Cu%
Kriging CoV	70.43	
Kriging Variance	6.58	$Cu\%^2$
Minimum Grade	0.19	Cu%
Maximum Grade	18.50	Cu%
MAD	1.48	
Tonnes	11.18	Mt

7.4 Chapter Summary

The GC MR estimate generated provides much higher resolution on the distribution of grades within the block model and when modelled at SMU scale. Geological features and mineralisation controls are clearly observed at SMU, significantly increasing the confidence in determining the location of how the copper mineralisation is preserved at Tshifufia and provides valuable information on the determination of the recoverable resources available.

8 Discussion and Estimate Comparisons

The results presented in this report are considered to be robust and accurate estimations within the 0.3 Cu % grade shell of the Tshifufia deposit. Care has been taken to reduce the amount of error in the analyses and as such, direct comparisons between models can be assumed to be realistic. To understand the success of the estimations in reporting the recoverable resources at an SMU size of 5 m (X) x 10 m (Y) x 5 m (Z), the various estimates are discussed.

8.1 OK versus LUC for Exploration MR Estimates

The OK MRE is considered to be a good representation of the sample data for the Tshifufia deposit at a block (panel) size of 25 m (X) x 25 m (Y) x 10 m (Z). Comparably, the UC estimation and subsequent localisation were also found to be good estimates of the Tshifufia deposit at an SMU scale of 5 m (X) x 10 m (Y) x 5 m (Z). A comparison of the performance of each exploration data estimation is presented in Table 17.

Table 17: OK and LUC MR Estimate Comparison for exploration data

Estimation model	Tonnage (Mt)	Min Grade (Cu %)	Max Grade (Cu %)	Mean Model Grade (Cu %)
OK MRE	23.37	0.00	25.66	2.104
LUC MRE	27.07	0.00	37.85	2.695
Absolute Difference	3.7	0.0	12.19	0.591

Table 17 shows that the LUC MR estimate has approximately 3.7 Mt of ore, higher maximum grade, and higher mean model grade. This is interpreted to be the result of LUC being able to estimate higher average copper grades at SMU scale into the deposit, as well to include outliers smoothed during OK. The difference in the mean grades indicates that the grade of the deposit has changed with a change in block size. This is expected since the LUC model does not smooth the estimate as much as OK.

Histograms for the various estimation techniques further indicate the success of LUC in producing higher average grades per SMU estimate in comparison to the lower average grades observed for OK MR estimation (Figure 46).

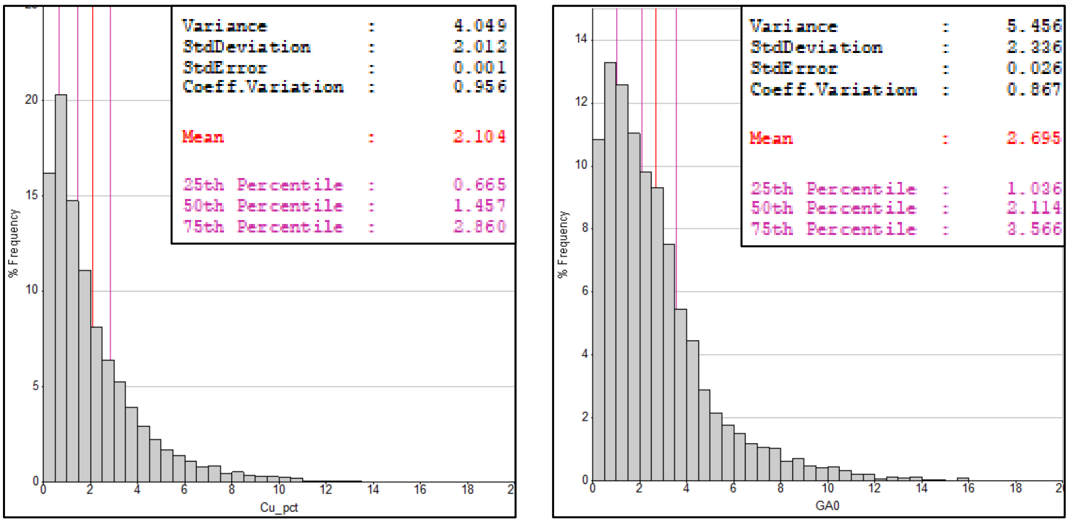

Figure 46: Comparison of the average grades for OK and LUC MR estimates

A good assessment for the success of the LUC estimation is to compare the OK SMU to the LUC SMU, (Hansmann, 2015). A scatter plot between the average OK SMU grades and the average LUC grades was created to illustrate how closely the estimated localised grades reproduce the panel grades at SMU scale (Figure 47). Panels representing well estimated blocks should have a high correlation coefficient between LUC and OK SMU’s, and cluster close to the 45-degree line representing a 1:1 correlation.

Figure 47 has a correlation coefficient of 0.897 between the OK and LUC SMU average grades. This indicates that the LUC MR estimated SMU’s within the panels well. The points close to the 45-degree line represent the best estimated SMUs within their respective panels and vice versa. Figure 47 further indicates that higher grades tend to be associated with the LUC MR estimates. This is possibly due to OK smoothing its average grades at SMU scale and LUC’s ability to estimate into a panel appropriate at mining scale.

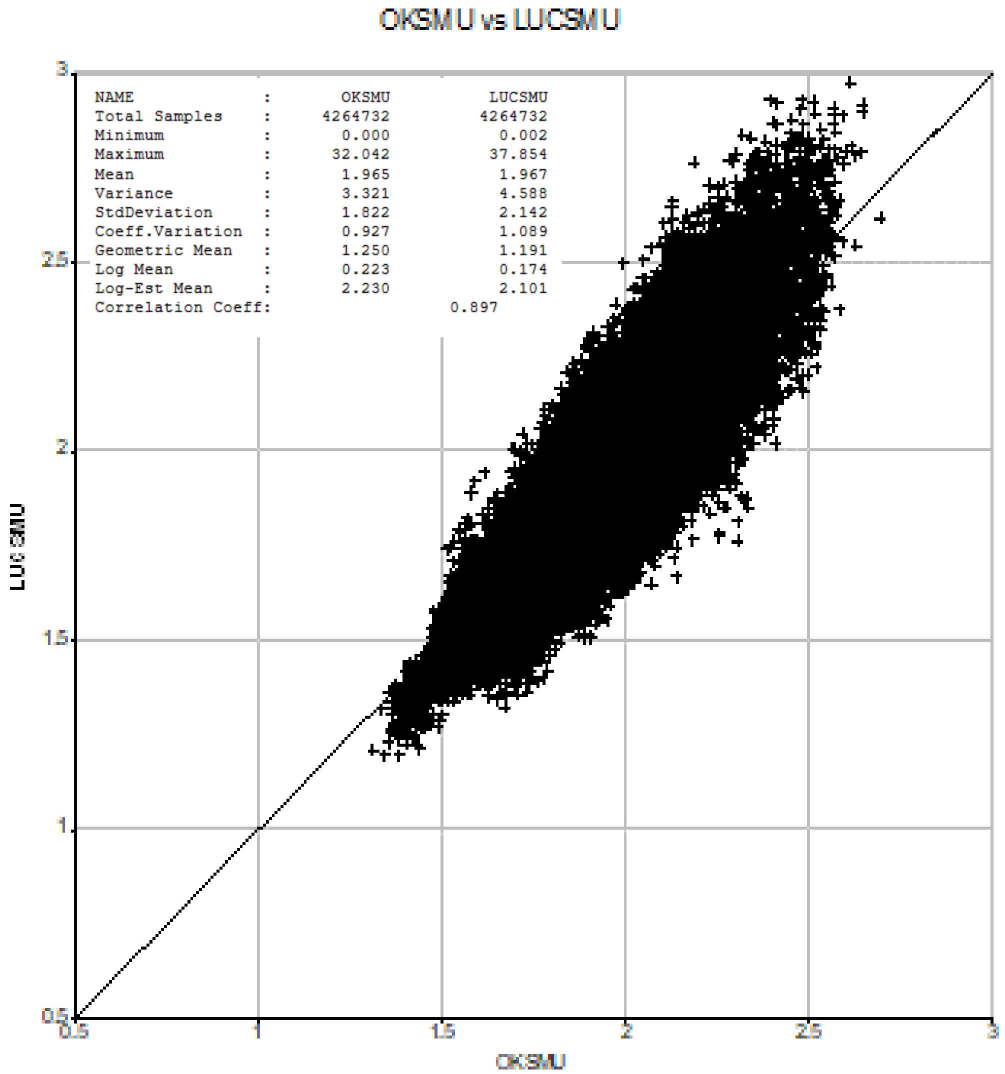

Figure 47: Correlation plot of OK and LUC SMU grades produced during LUC estimation.

The OK MR estimate has interpolated sample data into relatively large blocks or panels in comparison to the LUC MR estimate. By doing so, the average grade of each panel is lower than blocks of a smaller size since kriging smooths the data. A caveat of this is that large panels have less variance between panels. LUC estimation at SMU size resulted in higher average SMU grades and higher grade variability. This is desirable since the ability of LUC to highlight mining selectivity will identify more tonnes at higher grades and essentially create more value.

Practical comparisons for the performance of the OK and LUC MR estimates can be further described in a grade tonnage curves and mean grade above cut-off graphs in Figure 48 and Figure 49, respectively.

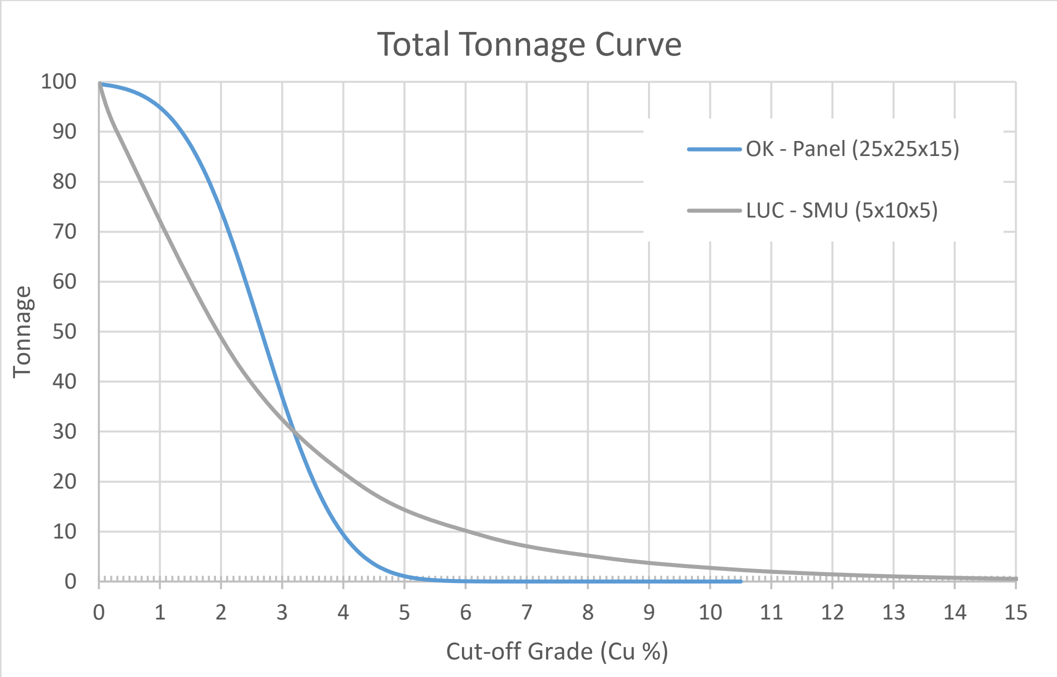

Figure 48:Tonnage estimate curve above cut-off

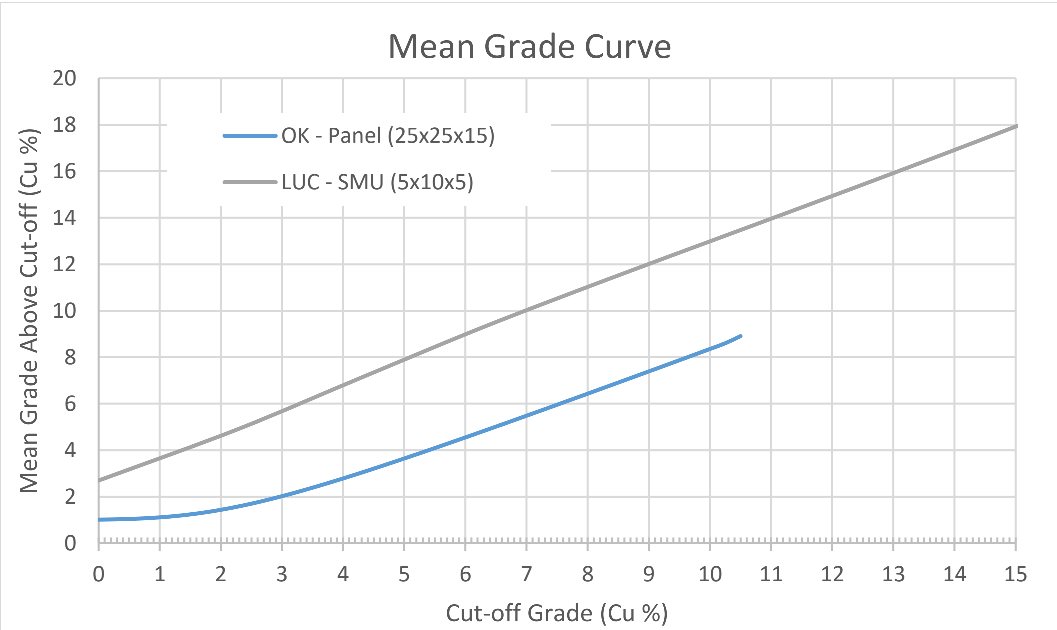

Figure 49: Mean grade above cut-off for LUC MR estimates

The use of OK and LUC estimation techniques to represent exploration data can be determined by comparing the samples to the two estimates (Figure 50, Figure 51 and Figure 52). Compared with the panel estimate, the LUC MR estimate has initial lower tonnes at higher grade indicative of selectivity.

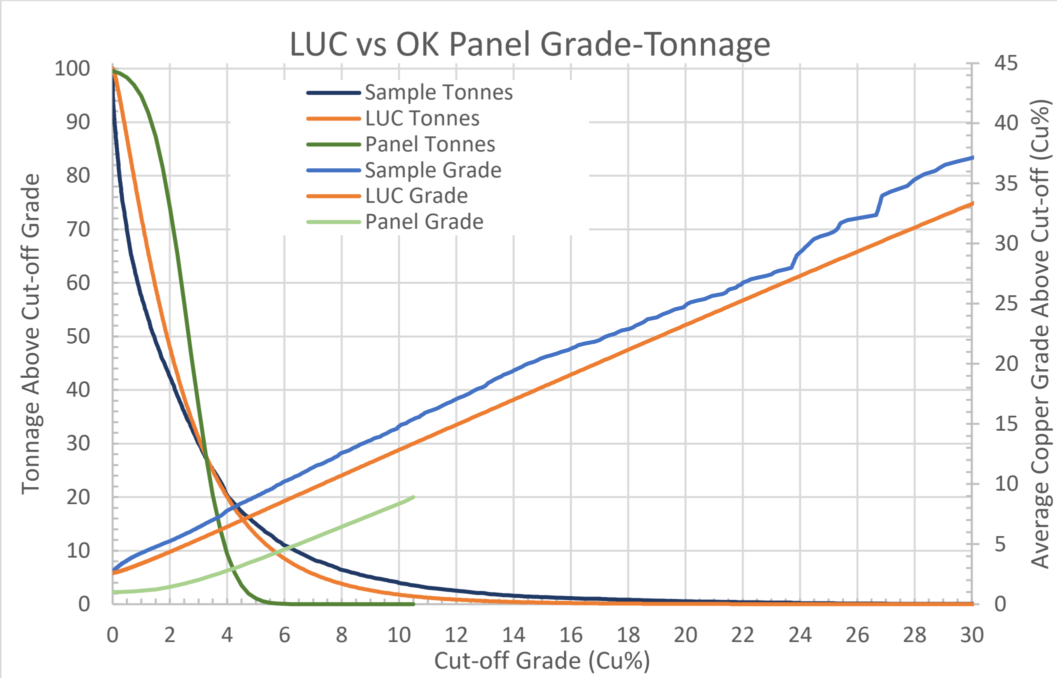

Figure 50: Global grade tonnage curve for lognormal distribution of samples, LUC MR estimate and the OK panel estimate for exploration data

Figure 50 displays the grade tonnage curves for the lognormal distribution of sample data, comparing the LUC and OK (estimated at an SMU block size) grade tonnage results. The samples rapidly decline in tonnage or volume as the cut-off grade increases because the selectivity of samples is very high; whereas OK generates a poor estimation of the grade and tonnage extractable for any cut-off grade interpreted to be the effect of smoothing and conditional bias. LUC is more comparable to the sample data than OK, highlighting the effect of the change of support. The resultant estimation of grades and tonnage closely tracks the estimation of grades and tonnage for the samples.

To see how well the estimates represent the composited sample data, a P- P plot was used to show the respective linear correlations (Figure 51). From the graph it can be concluded that both the estimates compare well with the sample data. However, the relationship between the samples and LUC MR estimate (SMU estimate) is closer than the relationship between samples and the OK block estimate due to smoothing. This corroborates the observations above where the LUC MR estimate better represented the volume tonnage relationship for samples.

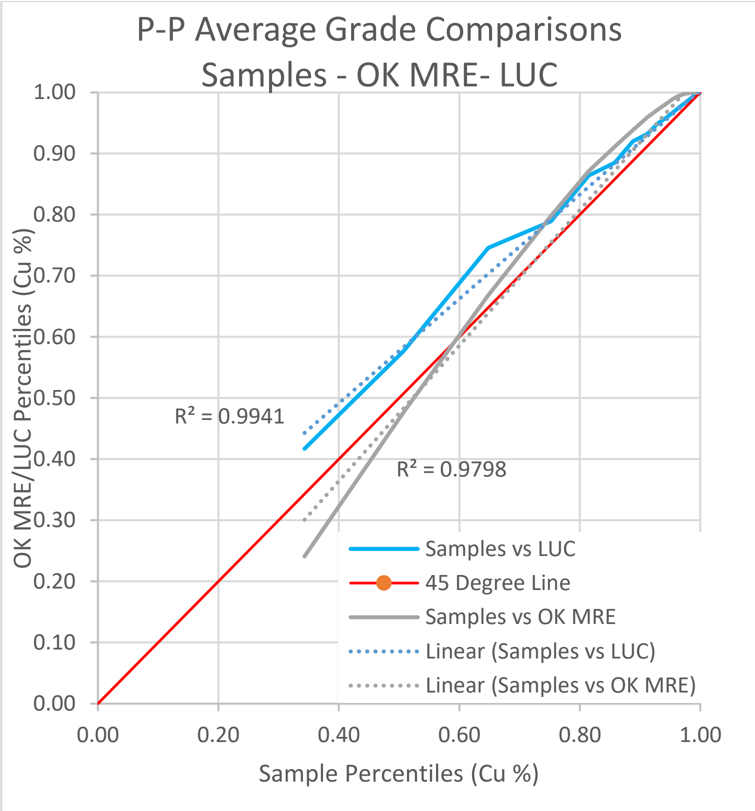

Figure 51: PP-plot of the relationship between samples-OK MRE and samples-LUC

A quantile plot of samples vs LUC and OK MR estimates was used to show the smoothing effect (Figure 52). As the average grade of copper increases the effect of smoothing becomes more apparent in the sample-OK MR estimate curve and the line deviates away from the expected path, equivalent to under estimation. Furthermore, over estimation is observed at very low grades, where the sample-OK MR estimate line rises slightly above the expected trajectory. The behaviour of the sample-OK MR estimate curve is an example of the smoothing effect. By contrast, the sample -LUC curve shows more erratic behaviour with an increase in average sample grade, however, it more consistently correlates to the 45-degree line.

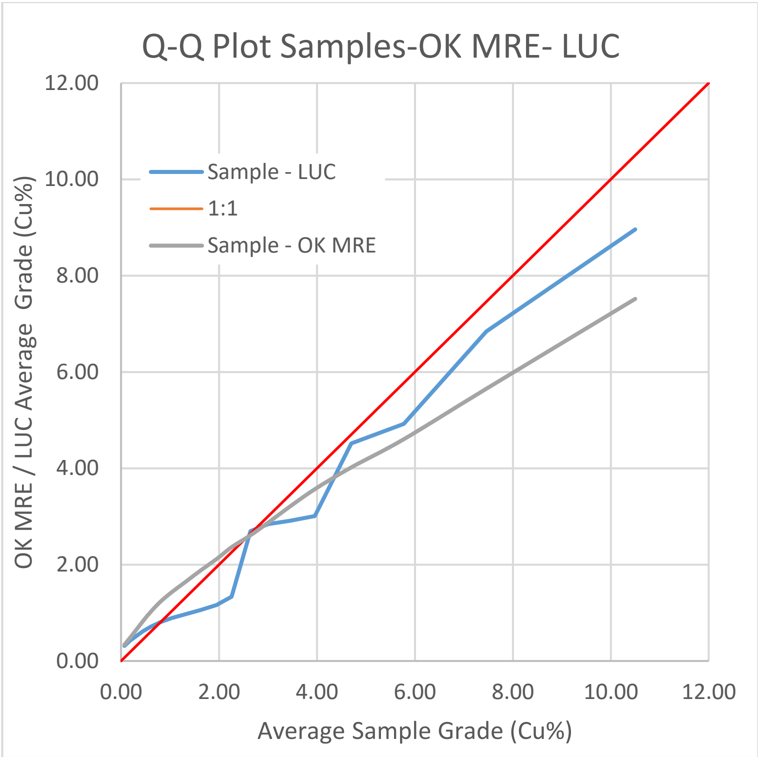

Figure 52: Q-Q plot of the average of OK and SMU grades from estimates and average sample grades

A visual comparison between the estimates further indicates the effect that LUC has had on the OK panel estimate Figure 53.

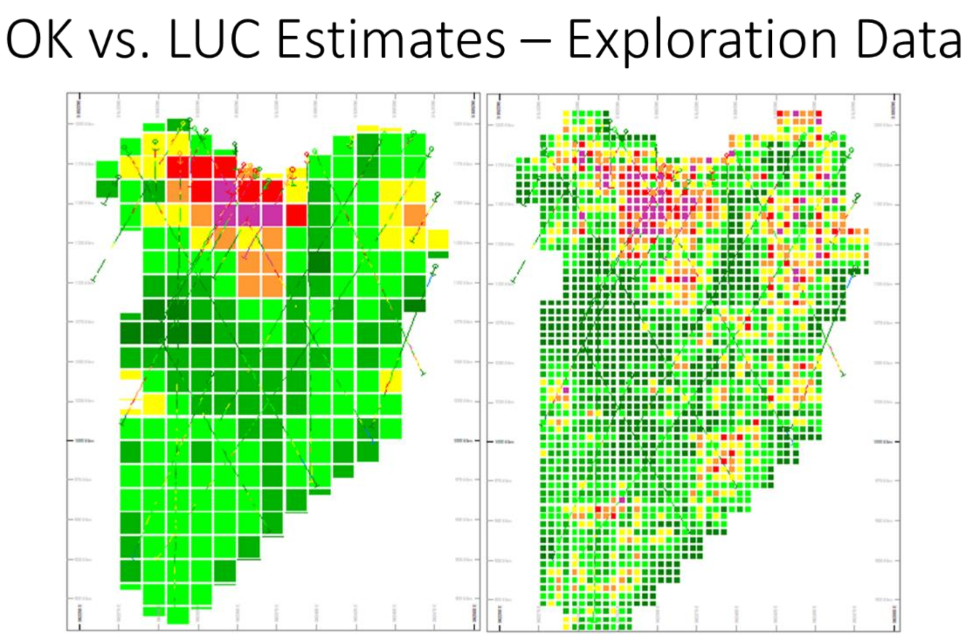

Figure 53: Visual comparison of the OK (left) and LUC (right) estimates for exploration data

Figure 53 visually demonstrates how the block size impacts the grade distribution within a deposit. The high grades observed in the near surface in the OK MR estimate are reproduced in the LUC MR estimate, but with more detail on where very high grades sit within each panel. The LUC MR estimate further identifies deeper extensions of semi-continuous mineralisation contiguous with the Mines Series formation. The OK MR estimate has smoothed the average grades of the corresponding panels and illustrated the lower grades at that position.

The LUC and OK MR estimates both appropriately model the exploration data. LUC has estimated higher average copper grades and more tonnes than the OK MR estimate because it is at SMU-scale. LUC estimation and its application in selective mining at SMU-scale increases variability within the model for mine planning. This relates directly to a more valuable assessment of the Tshifufia deposit at a relatively early stage in the mining life cycle. However, to determine the overall success of the LUC MR estimate and create a robust argument in favour of LUC, we need to compare it to the GC drilling estimate.

8.2 OK GC versus LUC MR Estimates

Localisation is dependent on the grade pattern predicted by the OK of the SMU, (Abzalov, 2006). The quality of the LUC MR estimate was assessed by comparing the OK GC MR estimate to the LUC exploration data estimate over the same volume (Table 18). This included visual comparisons as well as the grade-tonnage assessments for both estimation techniques.

Table 18: Grade Control and Localised Uniform Conditioning Mineral Resource Estimates Comparison

Estimation model	Tonnes (Mt)	Min Grade (Cu %)	Max Grade (Cu %)	Mean Model Grade (Cu %)
OK MRE	11.18	0.19	18.50	3.64
LUC MRE	13.41	0.00	39.73	3.38
Difference	2.23	0.19	21.23	0.34

Table 18 shows that the LUC MR estimate has approximately 2.23 Mt of ore, a higher maximum grade and slightly lower mean grade. Similar to the observations made for the differences between OK and LUC exploration estimates in Table 17, the LUC MR estimate has a higher tonnage and higher maximum copper grade. The difference in tonnages indicates that LUC MR estimate has estimated more recoverable resources at SMU-scale than the OK GC MR estimate. In terms of saleable product, this difference would directly over-quantify the volume of product to sell and create a false perception of the value of the recoverable resources. Additionally, the incorrect assessment of the grade of material being extracted can impact the performance of processing plants and its ability to recover available copper from the ore it processes.

To further understand the differences between the OK GC MR estimate and the LUC MR estimate, the average grade estimates for each technique were compared. Correlation between the OK GC and LUC MR estimates is poor (coefficient of 0.354) between them (Figure 54). LUC grades estimates have a lower average grade than OK GC estimates but have a wider grade range and higher grade intervals. This poor correlation and difference in average grades is expected and accounts for the higher average model grade for LUC MR estimate. The OK MR estimate is modelled at an identical SMU size, however, the OK GC MR estimate is again subject to smoothing during estimation which occurred in the OK MR estimate. The LUC MR estimate has given the analyst the ability to be more selective during mining.

Visual comparisons of the LUC and GC block models further indicate the inadequate modelling of SMUs from exploration data (Figure 55). The GC and LUC models compared poorly with each other. GC drilling has provided a significant amount of detail to the model, to the point that one can clearly see the impact of stratigraphy on the distribution of copper grades and the orientation of the orebody. By comparison, LUC has insufficient data from exploration drilling to provide this level of resolution and detail with regards to the copper grade distribution at SMU scale.

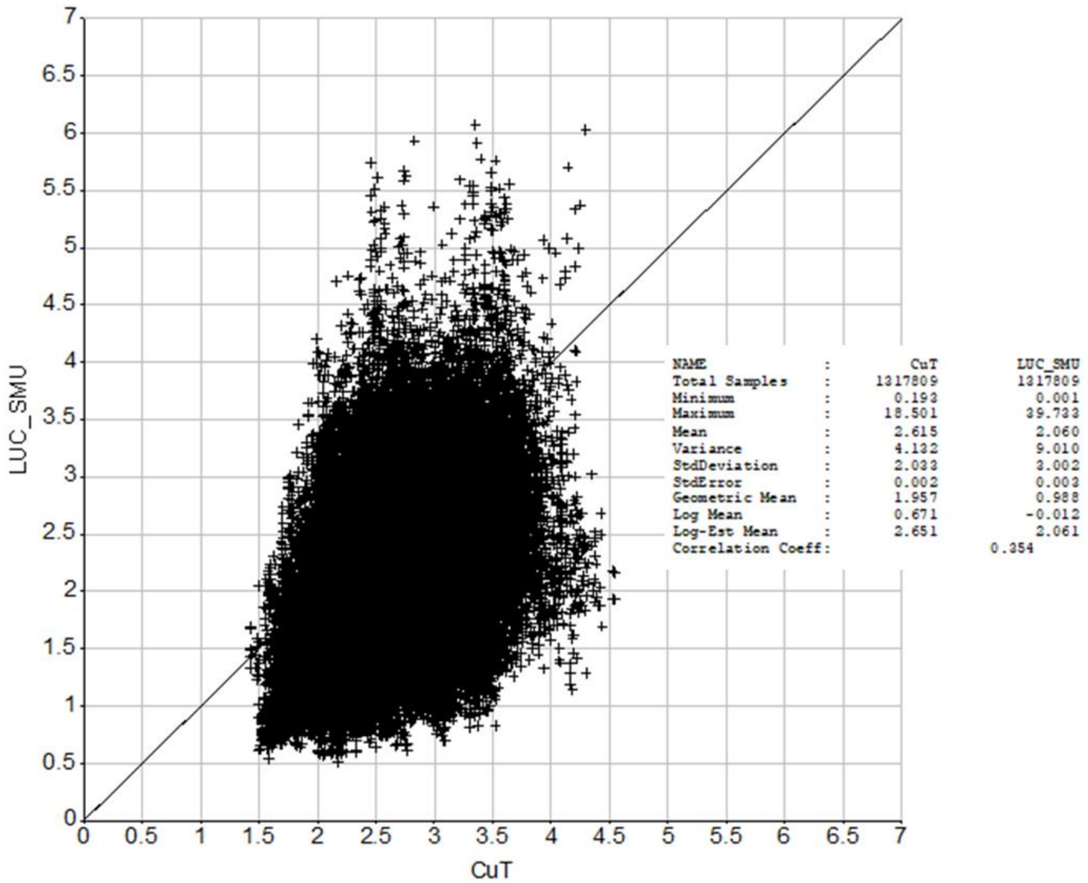

Figure 54: Scatter plot of the OK GC and LUC MR average grade estimates at SMU scale

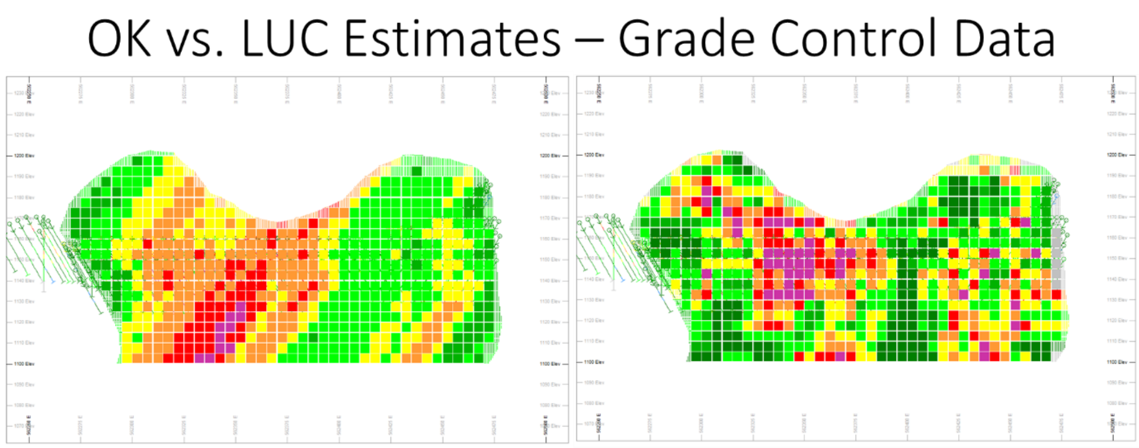

Figure 55: Visual comparison of the OK GC (left) and LUC (right) estimates

The results of the comparisons are best described in a probability plot (Figure 56). The discrepancy between the LUC and OK GC MR estimates is clearly apparent. The wide range of average grade estimates for LUC unrealistically represents the “real” recoverable resources for the Tshifufia deposit.

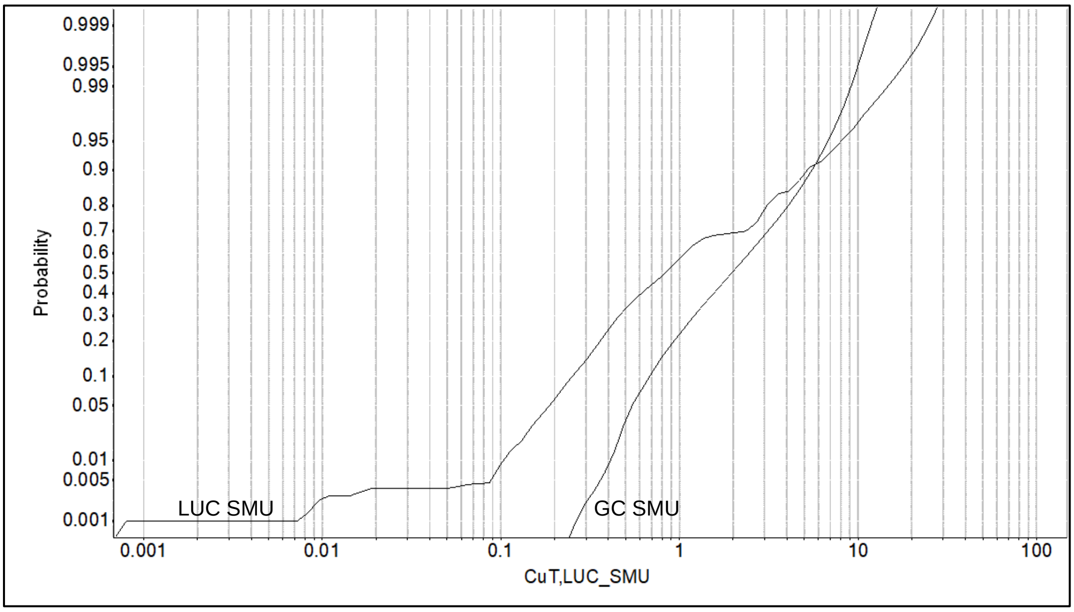

Figure 56: Probability plot of the GC SMU and LUC SMU

8.3 Chapter Summary

The various estimation techniques used in this research project fairly represented the exploration and GC data used. The performance of LUC to model exploration data at SMU scale was considered to be representative and adequate for the sample set used. However, an SMU comparison of the LUC MR estimate for exploration data and an OK GC MR estimate indicated that LUC did not have sufficient information to characterise the recoverable resources.

9 Conclusion

Mineralisation hosted within the Tshifufia deposit is controlled by the orientation of the Mines Series Formation and varying degrees of weathering and alteration. Copper is present in either the oxide, transitional or sulphide facies. Oxide facies mineralisation is characterised by supergene enrichment of copper metal predominantly hosted in malachite and azurite. Sulphide facies mineralisation generally occurs beyond depths of 100 metres below surface but is dependent on the variable degrees of weathering and alteration.

Both the exploration and grade control drilling data used were deemed suitable for the estimation of the Tshifufia deposit and all transformations compared with the original data. Therefore, any local over and under estimation may be attributed to the ordinary kriging and uniform conditioning estimation processes.

The block model averages for all estimates honoured the general trend of the input sample data and were validated visually by comparing the drillhole plots to cross sections through the model. The OK block model for exploration data was used as the panel estimate for the UC estimation and localisation. The OK MR estimate represents an unbiased estimation of the grade distributions based on the underlying sample data.

This study used the LUC technique to forward model the grade distribution at SMU level well in advance of GC drilling and mining. An SMU size, prescribed by the Kinsevere Mine, of 5 m (X) x 10 m (Y) x 5 m (Z) was used to model the grades of SMU from exploration data spaced between 30 and 100 metres apart.

The LUC MR estimate correctly predicted the distribution of SMUs, but its success is strongly dependent on the ranking of OK SMU estimates to produce the LUC MR estimates of the SMUs within the panels (Abzalov, 2014). It was concluded that, when during the SMU for ranking, drillhole spacing may have been too broad within the exploration drilling data to achieve adequate localisation. More specifically, the closer the drillholes, the more accurate the Gaussian anamorphosis was.

In the assessment the quality of the LUC MR estimate it was compared to the GC data. The GC data provides a direct measure of the suitability of the LUC MR estimate to portray the underlying sample distribution as there is no direct measure of correlation between ordinary kriging and LUC MR estimates during preliminary exploration drilling campaigns.

The GC model is predominantly focused on the oxide facies where copper oxides dominate the mineralisation style of the orebody. This portion has pervasive mineralisation that can account for the exceptionally high copper grades in part due to the minerals malachite and azurite which can contain up to 38% copper in their crystal structure. By comparison, copper sulphides such as chalcopyrite and bornite are only able to yield approximately 27% copper. Accounting for the higher grades observed in the GC MR estimate in comparison to the exploration MR estimate.

The LUC MR estimate poorly correlated with the OK GC MR estimate. The statistical and visual comparisons showed very little to no correlation between the two estimation techniques. Additionally, mining may have taken place between the drilling campaign and accounted for the significantly lower volume or tonnage estimated by the OK GC MR estimate above the 0.3 Cu % cut-off grade.

The success of UC and the subsequent localisation of the exploration data is dependent on the average SMU grades that have been ranked and spatially referenced according to the average OK block estimates. This direct proportionality means that where OK MR estimates are high or low, the LUC MR estimate will be proportionally high and low as well.

Despite the aim of determining the recoverable resources at SMU - scale, LUC grades provide no more resolution that the OK MR estimate provided since the underlying data inherently determines the UC and LUC. Therefore, any additional resolution on the distribution of average grades at SMU level and determination of recoverable resources is subject to amount of information present during estimation. Therefore, no suitable substitute was identified for grade control drilling and the resulting OK GC MR estimate.

The underlying question that results from this study is whether LUC is a suitable substitute for grade control drilling? More information is always better. LUC is only as good as the estimate and assumptions upon which it is based and the appropriateness of UC and LUC techniques for estimation may not be applicable for all deposit types.

An additional consideration worth noting is the number of samples used. By using such a high number of samples in the GC MR estimate the resulting OK estimate might be inherently smoothed, accounting for the lower grade and tonnage seen in the GC MR estimate relative to the OK MR and UC estimate. Conversely, lowering the maximum number of samples would increases the local variability and might increases the grades and tonnage of the Grade control estimate. This might be a contributing factor to why OK GC estimate had lower grades and tonnes.

Overall, it is considered that the use of the LUC technique applied to exploration drilling data may still be useful for mining companies that wish to represent the recoverable resources of similar deposit styles at an early stage in the mining life cycle. However, clarification of how the LUC MR estimate was derived and plans to update the LUC model continuously, with the additional drillhole data, would be required to justify any recoverable resource estimates released for investment purposes.

Therefore, this research study concludes that LUC should only be used iteratively and not as a substitute for the estimation of recoverable resources from GC drilling. This is to ensure that the LUC MR estimates are acceptable and that the spatial positioning predicted by the LUC MR estimates correlate to a specific period of mining.

REFERENCES

Abzalov, M. Z. (2006) ‘Localised Uniform Conditioning (LUC): A new approach for direct modelling of small blocks’, *Mathematical Geology*, 38(4), pp. 393–411. doi: 10.1007/s11004-005-9024-6.

Abzalov, M. Z. (2014) ‘Localized uniform conditioning (LUC): Method and application case studies’, *Journal of the Southern African Institute of Mining and Metallurgy*, 114(3), pp. 205–211.

Armstrong, M. and Matheron, G. (1986) ‘Disjunctive kriging revisited: Part I’, *Mathematical Geology*, 18(8), pp. 711–728. doi: 10.1007/BF00899739.

Barnett, R. M., Manchuk, J. G. and Deutsch, C. V. (2014) ‘Projection Pursuit Multivariate Transform’, *Mathematical Geosciences*, 46(3), pp. 337–359. doi: 10.1007/s11004-013-9497-7.

Cailteux, J. L. H. *et al.* (2005) ‘Genesis of sediment-hosted stratiform copper - Cobalt deposits, central African Copperbelt’, *Journal of African Earth Sciences*, 42(1-5 SPEC. ISS.), pp. 134–158. doi: 10.1016/j.jafrearsci.2005.08.001.

Chilès, J.-P. and Delfiner, P. (1999) *Geostatistcis: Modeling Spatial Uncertainty*. John Wiley and Sons Incorporated.

Clark, I. (1979) *Pratical Geostatistics*. Elsevier Applied Science. Available at: http://www.kriging.com/PG1979/PG1979.pdf.

De-Vitry, C., Vann, J. and Arvidson, H. (2007) ‘A guide to selecting the optimal method of resource estimation for multivariate iron ore deposits’, *Australasian Institute of Mining and Metallurgy Publication Series*, (August), pp. 67–77.

El Desouky, H. A. *et al.* (2008) ‘Postorogenic origin of the stratiform Cu mineralization at Lufukwe, Lufilian Foreland, democratic Republic of Congo’, *Economic Geology*, 103(3), pp. 555–582. doi: 10.2113/gsecongeo.103.3.555.

Deutsch, C. V. (2002) ‘Geostatistics’, *Academic Press Encyclopedia of Physical Science and Technology, Third Edition*, 6(3), pp. 697–707.

Fourie, A., Morgan, C. and Minnitt, R. C. A. (2019) ‘Limiting the influence of extreme grades in ordinary kriged estimates’, *Journal of the Southern African Institute of Mining and Metallurgy*, 119(4), pp. 391–401. doi: 10.17159/2411-9717/18/090/2019.

Frimmel, H. E., Basei, M. S. and Gaucher, C. (2011) *Neoproterozoic geodynamic evolution of SW-Gondwana: A southern African perspective*, *International Journal of Earth Sciences*. doi: 10.1007/s00531-010-0571-9.

Graham, J. (2012) *Uniform Conditioning Overview - Datamine*. Available at: https://www.youtube.com/watch?v=zZeBT7hll9Y.

Gray, D., Kalbskopf, S. and Lawlor, M. (2012) ‘Anvil Mining Limited Ni 43-101 Technical Report Kinsevere Copper Project Katanga Province’, (MAy), pp. 1–352.

Hansmann, K. M. (2015) ‘Application of Localised Uniform Conditioning on two hypothetical datasets’.

Hanson, R. E. *et al.* (1993) ‘UPb zircon ages from the Hook granite massif and Mwembeshi dislocation: constraints on Pan-African deformation, plutonism, and transcurrent shearing in Central Zambia’, *Precambrian Research*, 63(3–4), pp. 189–209. doi: 10.1016/0301-9268(93)90033-X.

Isaaks, E. H. and Srivastrava, M. R. (1989) *An introduction to applied geostatistics*. Oxford, New York: Oxford University Press.

Jackson, M. P. A. *et al.* (2003) ‘Neoproterozoic allochthonous salt tectonics during the Lufilian Orogeny in the Katangan Copperbelt, central Africa’, *Geological Society of America Bulletin*, 115(3), pp. 314–330.

JORC (2012) *JORC (2012). Australasian Code for Reporting of Exploration Results, Mineral Resources and Ore Reserves (The JORC Code). The Joint Ore Reserves Committee of the Australasian Institute of Mining and*

Metallurgy, Australian Institute of Geoscientists and Min.

Journel, A. G. and Huijbregts, C. J. (1978) *Mining Geostatistics*.Academic Press, New York.

Kampunzu, A. B. and Cailteux, J. (1999) 'Tectonic Evolution of the Lufilian Arc (Central Africa Copper Belt) during Neoproterozoic Pan African Orogenesis', *Gondwana Research*, 2(3), pp. 401–421. doi: 10.1016/S1342-937X(05)70279-3.

Kennedy, M. J. *et al.* (1998) 'Two or four Neoproterozoic glaciations?', *Geology*, 26(12), pp. 1059–1063. doi: 10.1130/0091-7613(1998)026<1059:TOFNG>2.3.CO;2.

Krige, D. G. (1978) *Geostatistics I: Lognormal-de Wijsian Geostatistics for Ore Evaluation*. Second Edi, *South African Institute of Mining and Metallurgy*. Second Edi. Edited by G. S. Baker and D. Phil. Johannesburg.

McCuaig, T. C., Vann, J. E. and Sykes, J. P. (2014) 'Mines versus Mineralisation – Deposit Quality , Mineral Exploration Strategy and the Role of " Boundary Spanners "', *Ninth International Mining Geology Conference*, (August), pp. 18–20. doi: 10.13140/RG.2.1.1937.8324.

Minnitt, R. C. A. (2019) 'Theoretical Simulation Techniques, Course Lecture Notes. Johannesburg, School of Mining Engineering, University of the Witwatersrand', in *MINN7054A*.

MMG (2014) *Mineral Resources and Ore Reserves Statement*. Available at: https://www.mmg.com/wp-content/uploads/2019/10/MMG-2014-June-Mineral-Resources-and-Ore-Reserves-Statement.pdf.

Neufeld, C. and Deutsch, C. V. (2005) 'Calculating recoverable reserves with uniform conditioning', *GIS and Spatial Analysis - 2005 Annual Conference of the International Association for Mathematical Geology, IAMG 2005*, pp. 1065–1070.

Njowa, G. and Musingwini, C. (2011) 'Overview of mineral asset valuation methods within a global institutional framework. University of Witwatersrand', *The Southern African Institute of Mining and Metallurgy*, (Mineral Project Valuation), pp. 1–18.

Rivoirard, J. (1987) 'Teachers Aide: Two Key Parameters When Choosing the Kriging Neighborhood', *Mathematical Geology*, 19(8), pp. 851–856.

Rivoirard, J. (1990) *Introduction to disjunctive kriging and nonlinear geostatistics*. France: Centre de Geostatistique, Ecole des Mines.

Schofield, N. (1988) 'Ore reserve estimation at the enterprise Gold mine, Pine Creek, Northern Territory, Australia. Part 1: structural and variogram analysis', *CIM Bulletin*, 81(909), pp. 56–66.

Sinclair, A. J. and Blackwell, G. H. (2002) *Mineral Inventory Estimation*. Edinburgh Building, Cambridge: Cambridge University Press.

Vann, J. and Guibal, D. (1998) 'Beyond Ordinary Kriging - An overview of non-linear estimation', *Beyong Ordinary Kriging, 30th October 1998, Perth Australia*, 23, pp. 6–23.

Vann, J., Guibal, D. and Harley, M (2000) 'Multiple indicator kriging: is it suited to my deposit?', in *4th International Mining Geology Conference, Australia*, pp. 9–17.

Vann, J., Jackson, S. and Bertoli, O. (2003) 'Quantitative kriging neighbourhood analysis for the mining geologist-a description of the method with worked case examples', *… Mining Geology …*, (November), pp. 17–19. Available at: http://gbhall2.squarespace.com/storage/Vann Jackson Bertoli QKNA as published.pdf.

Wendorff, M. and Key, R. M. (2009) 'The relevance of the sedimentary history of the Grand Conglomerat Formation (Central Africa) to the interpretation of the climate during a major Cryogenian glacial event', *Precambrian Research*, 172(1–2), pp. 127–142. doi: 10.1016/j.precamres.2009.03.013.