THE APPLICATION OF DYNAMIC ANISOTROPY IN THE KRIGING ESTIMATION PROCESS TO IMPROVE RESOURCE ESTIMATION ON A FOLDED AND UNDULATING STRATIFORM COPPER DEPOSIT

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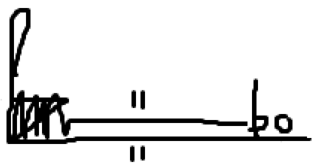
DECLARATION

I declare that this research report is my own unaided work. It is being submitted in partial fulfilment of requirements for the Degree of Master of Science to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination to any other University.



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ABSTRACT

This research study was motivated by the geological complexity of Konkola orebody. It is a well-known fact that the geological complexity of an orebody will add to the risk associated with the Mineral Resource estimation of the deposit. In this research report the applicability of Ordinary Kriging with a dynamic search ellipse is investigated on the Konkola copper orebody where traditionally Ordinary Kriging with a fixed global oriented search ellipsoid is applied in the resource estimation. The regional and local geology of the mine was studied including prominent structures that had potential to affect the final estimates. Exploratory Data Analyses were carried out and the orebody was domained into three zones based on grade variation and structural orientation. Variograms, capturing the spatial correlation of the Total Copper % (TCu%), were calculated and modelled for the individual zones, this was followed by a kriging neighbourhood optimisation process. Grade interpolation was done using both the interpolation techniques and the estimate results were compared to the input sample data. An analysis on the financial benefits of adopting Ordinary Kriging with dynamic search was also conducted. This research study concludes that it is beneficial to domain the orebody and to use Ordinary Kriging with a Dynamic Anisotropic search approach for resource estimation and therefore recommends that Konkola Mines adopt this methodology to improve its resource estimation and save costs.

DEDICATION

This research report is dedicated to my late father Trywell Z. Tembo. MHSRIP

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I would like to thank the Lord Jesus Christ, my parents and my siblings for strengthening and encouraging me during this period.

I also want to thank the following individuals for their specific contributions.

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LIST OF SYMBOLS

Covariance	$C\ (h)$
Correlation Coefficient	R
Degrees	^{o}
Distance vector	h
Greater than	$>$
Lagrange Multiplier	λ
Less than	$<$
Less than or equal to	$\leq$
Mean	μ
Nugget Effect	C_0
Number of samples	n_i
Percent	%
Pi	π
Target sample position	i
Sample Value	x_i
Semi-variogram	γ
Standard deviation	σ
Variogram	$2\gamma(h)$
Variogram Sill	C_1
Variance	σ^2
Weight	a_i

NOMENCLATURE

Assay Footwall	AFW
Assay Hangwall	AHW
Coefficient of Variation	CoV
Cobalt	Co
Copper	Cu
Cubic Metre	m^3
Dynamic Anisotropy	DA
Exploratory Data Analysis	EDA
Estimate	Est
Footwall	FW
Footwall Quartzite	FWQ
Gold	Au
Hanging Wall	HW
Inter Quartile Range	IQR
Konkola Copper Mines	KCM
Kilometre	km
Kriging Efficiency	KE
Kriging Variance	KV
Lead	Pb
Lower Porous Conglomerate	LPC
Lower Quartile	Q1
Metre	m
Minimum	Min
Maximum	Max
Ordinary Kriging	OK
Ore shale Unit	OSU
Pebble Conglomerate	PBC
Percent Total Copper	%TCu
Quality Control Quality Assurance	QAQC
Samples	SAMP

Selective Mining Unit	SMU
Slope of Regression	SLOR
Square Metre	m^2
Standard Deviation	Stddev
Three Dimension	3D
Total Copper	TCu
Traditional Ordinary Kriging	OK
Upper Quartile	Q3
Uranium	U
Quantitative Kriging Neighbourhood Analysis	QKNA

1 Introduction

Mineral Resource estimation projects mostly commence with a detailed study of the geology surrounding the deposit of interest. The geostatistical work that follows afterwards should always be confirmed with the known geological knowledge and interpretation before carrying on with the grade interpolation process (Dohm, 2018b). It is this geological knowledge and interpretation that dictates the estimation method to apply on a specific deposit since each deposit is unique and no fixed interpolation method applies to all.

Complexity in the orebody geometry is one of the major factors estimators use to make decisions on what types of estimation method to apply on any specific deposit. This complexity in geometry can only be fully captured if the geology surrounding the deposit is well understood. McArthur, (1988); de Sousa, (1990); Cardwell and Cartwright (2016) and Ronald (2018) have all highlighted on the importance of having a good understanding of the geology surrounding the deposit in Mineral Resources and Reserve estimation. This geological knowledge and understanding underpins every Mineral Resource estimation, since estimates are constrained by the geological complexity captured within the geological model (Chanderman *et al*,. 2017). It is concluded from the foregoing references that many of the problems encountered during a resource estimation process arise because of a lack of understanding of the geology of the orebody, its structural nature and grade continuity.

In this research a detailed study on the regional and local geology was done to obtain a good understanding of the geology surrounding the deposit. The complexity in geometry, that is huge variations in dip and dip directions including the folds and faults were analysed as well as their potential effect on the final estimation.

When faced with such complexity in the geology, it can be a daunting task for resource geologists when carrying out grade estimation. To circumvent this issue, the resource geologist may resort to dividing the deposit into domains, based on the structural orientation where a single stationary ellipsoid can be used as reasonable representation of the continuity of the enclosed grades. This method may however not always be satisfactory because the actual domains can also be deformed by folding, shearing and other structural processes (Machuca-Mory *et al*, 2015).

Traditional Ordinary Kriging (OK) has been the main interpolation method used on the Konkola deposit for resource estimations. During interpolation, a global oriented search ellipse, aligned to the major direction of the continuity of the mineralisation is used. The problem with this kind of grade interpolation is that it does not actually capture the local changes in the orebody geometry and may also not work well for deposits with dome-like shapes and undulating fold structures such as that of the Konkola deposit. According to (Zabrusky, 2013), using the OK methodology on orebodies with structural complexity may result in grade under-estimation because samples that are structurally continuous with the trend being estimated do not fall within the rigid search ellipse. The opposite was also found to be true where grades are over-estimated by unrelated samples being included in the search volume.

A more accurate and efficient way of handling orebodies with complex geology is to employ the Dynamic Anisotropy (DA) search method in the estimation. This methodology allows for the local rotation of angles of the variogram model and search ellipsoid with the aim to improve the grade interpolation by following the trend of mineralisation for each cell in a block model (CAE Datamine corporate Limited, 2014). Each single block within the block model is allocated a specific dip and dip direction according to its orientation which is used to align the anisotropic search ellipsoid to improve the ability of data capturing.

This research report is aimed at testing whether the DA grade interpolation methodology applied in Ordinary Kriging could significantly improve grade estimation on the folded and undulating orebody with a huge variance in dip and dip direction on the Konkola copper orebody. The objective of the research was achieved, in that the two estimation methodologies; the traditional method of fixed search ellipses applied to the two limbs of the orebody and the DA method applied to different zones, were carried out and the results compared. Validation of the results from both methodologies against the composite data using global statistics, swaths plots, scatter plots and the distribution of differences were carried out. Visual inspection was also employed to identify artificial breaks in grade continuity not representative of reality as observed from the sample grade distribution. The findings from this research formed the basis for recommending to Konkola Mine to adopt the DA estimation methodology for future Mineral Resource estimations, as it would improve the grade estimation accuracy of this folded and undulating copper deposit with its large variance in dip and dip direction.

It is important to make the reader aware that in this research OK estimation implies OK with a search ellipse of static or fixed orientation has been applied and when referring to the DA methodology it implicitly means that in the OK estimation process a dynamic search ellipse is used based on the local anisotropy.

1.1 Background Information

Grade estimation is the cornerstone of several mining activities such as short and long-range mine planning, underground and pit designs, mining cost, reserves calculations, metal recovery and reporting (Cardwell and Cartwright, 2016). All these activities depend upon a reliable grade block model. To create a reliable model, comprehensive statistical and geostatistical studies of the deposit need to be carried out as the major components in the Mineral Resource Estimation (MRE) process. The introduction of Geostatistics in mining has been one of the major steps to ensuring that there is improved accuracy in grade estimation.

De Sousa, (1990) describes Geostatistics as a mathematical technique used to perform statistical work on a Regionalized Variable selected from a geological zone or a certain population. The theory of Geostatistics was first formalised in the 1960's by George Matheron (Journel and Huijbregts, 1978, Clark, 1979) and is based on the theory of Regionalised Variables. Matheron considered the birth of Geostatistics the moment people in mining concerned themselves with foreseeing results of future mining operations, the moment they started collecting samples and computing mean grades for the mine blocks.

The birth of Geostatistics resulted in the development of several Geostatistical interpolation techniques. These techniques consider spatial correlation quantified by the variogram during grade interpolation e.g. Kriging and Simulation techniques. Previously, classical statistical methods were the main interpolation methods used to estimate resources and reserves. Several authors have highlighted the shortcomings of classical statistical methods in resource and reserve estimation because unlike geostatistical methods, the classical methods ignore the spatial distribution and spatial correlation between sample data, and consequently proved to be inaccurate (de Sousa, 1990; Armstrong, 1998; Dohm, 2018b). The use of geostatistical investigations has become an important tool to avoid financial failures when considering the possibility of investing in a new mining operation or deciding on expanding a current mining operation.

Kriging is one of the most used geostatistical interpolation methods to estimate resources and reserves. Sinclair and Blackwell (2002) defines it as a generic term applied to a range of methods of estimation that depend on minimising the estimation error by a least square procedure. The practical application of Kriging are widespread including simulations of deposits, grade estimation at a point or block, contouring, grade control and optimal location and spacing of drill holes (Bell and Reeves, 1979)

Kriging might have improved grade estimation but only to some extent. One of the areas that needed modification was the carrying out of estimations in folded and undulating deposits since kriging is most often based on a static oriented search ellipsoid, which cannot cope with the meandering nature of orebodies.

In reality, most orebodies in nature are either folded or undulating or both. Solving this problem required that a detailed geological model was done that captured all the necessary geological structures. The introduction of computerised resource and reserve software packages in the late 1970‘s (Glacken and Snowden., 2001) made the modelling of the 2D and 3D geological models possible and the inclusion of such models in computerised geostatistical methods to improve grade estimation. To date kriging interpolation techniques have been developed or adapted to cater for orebodies with complex geology.

1.2 Problem Statement

The most valuable asset of any mine is its Mineral Resource (MR); hence, it is very important that the risk associated with the estimation thereof, is as low as possible to avoid surprises during mining such as encountering low grades where high grades are expected and/or finding less tonnes than expected. There are three main factors that can increase risk in a MR; grade variability within the deposit, assumptions made during estimation process and particularly the estimation methodology applied (Dohm, 2018b). The estimation methodology employed is to some extent dictated by geology of the deposit; different orebodies may require different techniques depending on their geological complexity.

The Konkola copper deposit is one such orebody with complex geology (folded and undulating) with large variations in dip and dip directions. Traditionally Ordinary Kriging (OK) has been the main interpolation technique used at Konkola Mine. The paragraphs that follow explain the complexity of the orebody geometry and the difficulties faced when using this traditional interpolation technique.

The orebody is divided into two, fold-limbs along the fold axis trend in the NW-SE direction. The two limbs are the West Limb exploited through number 4 shaft and the North Limb accessed through number 3 shaft. The West Limb has a minimum dip of about 15° to a maximum of 65° with a dip direction ranging from 215° to 235°. The North Limb has a minimum dip of 12° to a maximum of 60° with a dip direction ranging from 348° to 24°.

Currently the orebody is domained along the fold axis and variograms are generated and modelled separately for each limb, and OK is separately performed on each Limb using the respective relevant variogram models, these results are combined to produce the resource estimates for the orebody. During interpolation average values for the dip and dip direction are used to orient the global search ellipse on each limb individually. An average dip of 50° and dip direction of 225° is used on the West Limb and an average dip of 45° and dip direction of 6° on the North Limb. Figure 1.1 shows a global search ellipse with an average dip and dip direction. This illustrates how a static fixed search ellipse fails to honour grade continuity.

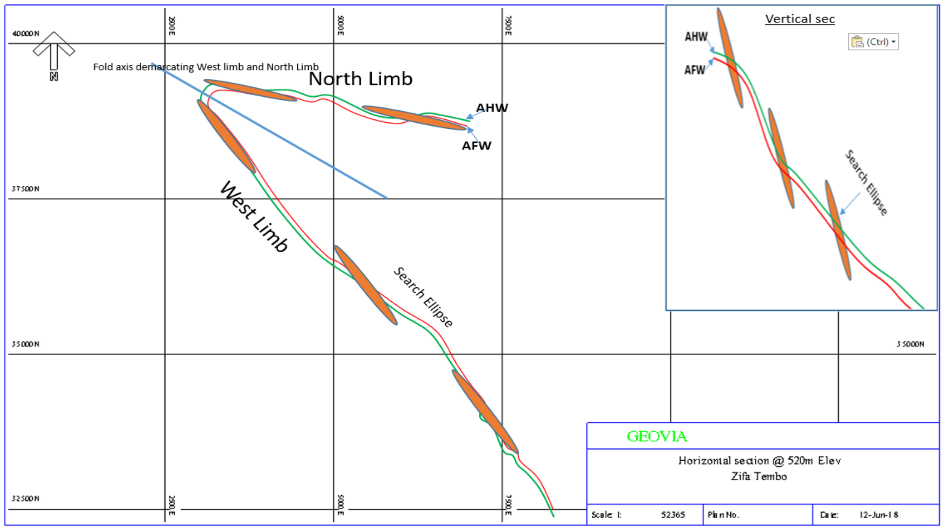


Figure 1. 1 Orientation of the global search ellipse in plan and inserted is a vertical section down dip. Sections are from the Konkola orebody wireframes used in this research.

Using a global search ellipse with an average dip and dip direction does not satisfactorily capture the copper grade continuity. Some of the samples may inadvertently be excluded during the interpolation process, not because they are beyond the range of influence of the variogram but simply because of how the search ellipse is oriented in a fixed direction. This will affect the Kriging efficiency (KE) and Slope of regression (SLOR) and also influence both the information effect and the regression effect purely because of having less samples, and consequently having an impact on the grade and tonnage estimates above cut-off. The Information Effect is a function of the lack of data at the time of estimation, which is often much less than the amount of data available during mining, when decisions are made about the destinations of mineralized rock, namely the plant, stockpile or dump (Dohm, 2018b).

When estimating a block on a fold crest, the search ellipse may easily capture the samples on another crest and ignore the ones nearer in the troughs. There is a concern that this may lead to underestimation or overestimation of the grade due to incorrect sample selection during grade interpolation. The current methodology also creates an artificial break in the grade continuity which is observed in the estimated grade values at the fold axis; this is where the two search ellipsoids overlap or meet.

1.3 Testing the Dynamic Anisotropy search methodology on the Konkola Orebody

The DA method allows the search ellipse to continuously change orientation i.e. its dip and dip direction in accordance with the sampling information, and thus it is possible for each estimation block to have a different alignment of the ellipse depending on the structural geometry surrounding it. To achieve this, the surfaces were created that honour the changes in dip and dip direction of the mineralisation as observed in the core logging. Additional attributes were added in the block model to store the dip and dip direction from the surfaces geometry. During estimation process, these attributes are selected and for each block, the ellipsoid is oriented exactly as per the values in the attributes for each block. It was envisaged that this method of interpolation would improve the perceived grade continuity and reduce the impact of the information effect that maybe as a result of not capturing enough samples. Figure 1.2 shows the orientation of the DA search ellipse and how it is following the Konkola copper orebody geometry dynamically thereby improving and honouring the grade continuity during the estimation.

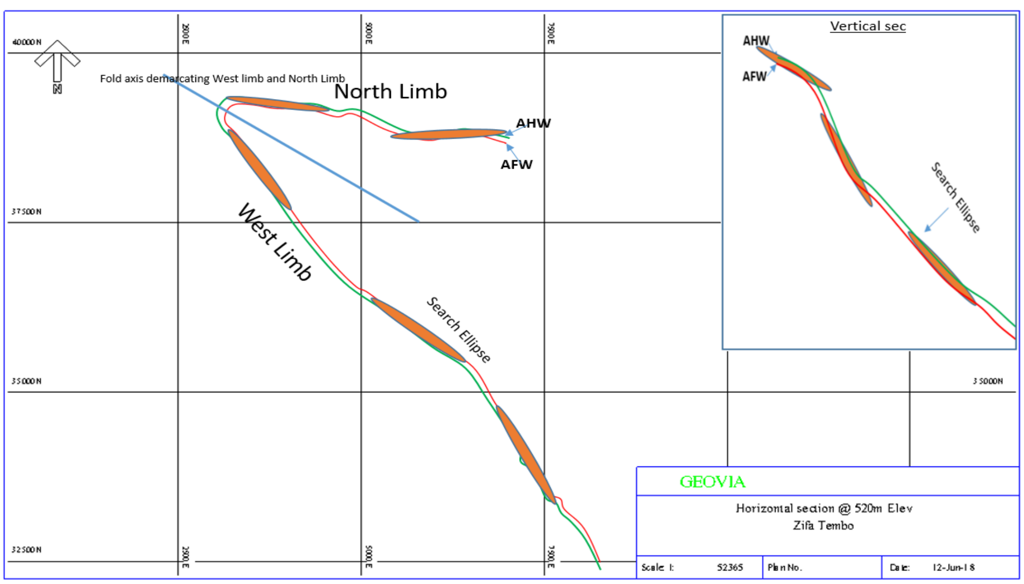


Figure 1. 2 Orientation of the DA search ellipse in plan and inserted is a vertical section down dip. Sections are from the Konkola orebody wireframes used in this research.

Using the DA method, the North and West limbs can be estimated together improving the efficiency of the estimation process by making it faster and also improve the estimate along the fold axis as there will not be any artificial break in grade continuity, as is currently the practice.

1.4 Literature Review

1.4.1 Kriging

Geostatistical interpolation (kriging) was developed in the 1960s by Georges Matheron, a French Mining Engineer and Mathematician. Matheron named this process of interpolation Kriging after Danie Krige, who had done significant work on weighted averages in an attempt to improve resource estimation on the South African gold mines in the early 1950's. Kriging is described as a 'Best Linear Unbiased Estimator' referred to as BLUE because it is a linear estimator based on weights that will give the minimum value of the estimation variance at the same time satisfying the condition that the sum of weights add up to 1. There are an infinite number of linear unbiased estimators and the best one is defined as having the smallest estimation variance. Kriging consists of optimizing the system of equations generally referred to as kriging system, under the constraint of minimising the estimation variance, and the estimator produced is the kriging estimator with an associated estimation variance called the kriging variance. The expression for the estimation variance depends on three things: The basic geometry of samples in the unknown area, the model of the semi variogram (spatial continuity), and the weighting allocated to each sample (Clark, 1979).

Matheron (1967) defines Kriging as a procedure for estimating the grade of a panel by computing the weighted average of available samples, some being located inside and others outside the panel. The grades of these samples being x_1, x_2, …., x_n, we attempt to evaluate the unknown grade Z of the panel with a linear estimator Z* of the form:

$$Z^* = \sum a_i x_i \qquad 1$$

Where a_i are the weights assigned to the samples

Matheron discusses the two conditions that need to be satisfied to determine the suitable weights assigned to each sample.

i. The first one requires that Z* (the estimate) and z (the sample grade) must have the same average value within the whole large field V, this is mathematically expressed by the requirement that:

   $\sum a_i = 1,$ where a_i are the weights assigned to the samples.

ii. The second condition requires that the weights a_i have values such that estimation variance of Z using Z*, should take the smallest possible value, known as the kriging variance.

1.4.2 Search Radius

The search radius is used to identify which samples are considered to be relevant for a particular block estimate, and on which the kriging system mentioned above is based. Khakestar *et al.* (2013) identifies the search radius as one of the most important parameters that needs to be defined in the kriging interpolation. It defines the parameters of the search volume and often is determined based on the range of influence of the variogram. Not every sample composite within a deposit can be used in estimating a block/point. The samples nearest to the block being estimated, are selected first up until a maximum search limit is reached or the maximum number of samples is reached. These authors pointed out that in OK, the search radius or ‘kriging neighbourhood’ is defined by the user and that the definition of this search radius can have a significant impact on the outcome of the Kriging estimate. In particular, a neighbourhood that is too restrictive can result in serious conditional bias. This is to say that arbitrary selecting a search radius can be a risk.

Besides deciding on the search volume parameters, there are several other steps that may need to be taken into consideration to guarantee a good estimation. The resource estimation process involves the definition of mineralisation constraints or geological domains, the statistical and/or geostatistical analysis of the sample data, and the application of a suitable grade interpolation technique (Glacken and Snowden, 2001).

Due to the importance of search parameters in estimating grades in an undulating orebody, the selection thereof is specifically addressed in this research report.

1.4.3 Dynamic Anisotropy

The use of DA is gaining ground especially when carrying out interpolation in undulating and highly folded orebodies. Machuca-Mory *et al.* (2015) explained that one of the major requirements before using DA, is a model of local anisotropies of the spatial continuity of grades. This model would include local angles of spatial continuity, and for some methods also the local anisotropy ranges of continuity and other parameters. Figure 1.3 below illustrates the difference in orientation between the Global Oriented search ellipse and the Dynamic search ellipse.

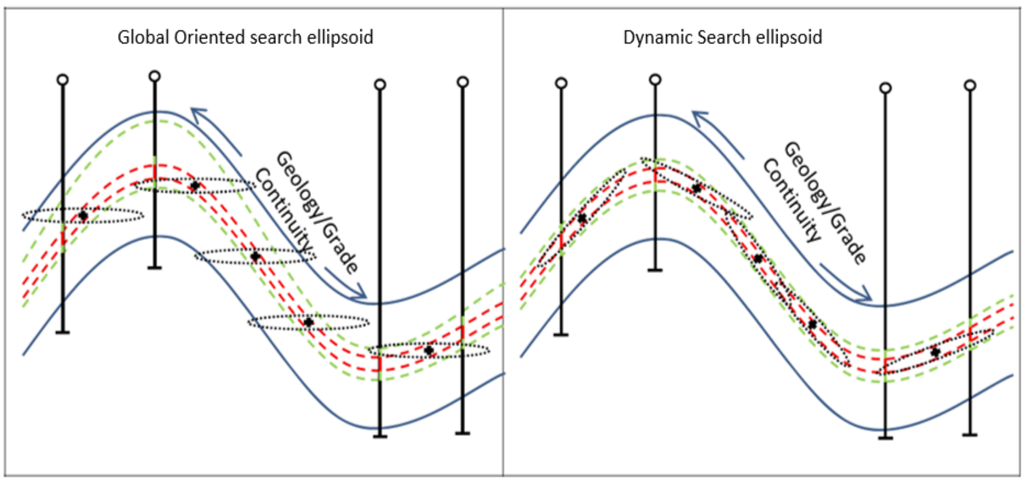


Figure 1. 3 Anisotropic ellipsoid in the presences of Global oriented search ellipse and Dynamic search using locally varying anisotropies. Adapted from Machuca-Mory et al. (2015).

The DA interpolation method has proved to reduce bias in the search parameter during estimation. With its ability to follow grade continuity in folded domains, much time is saved during estimation as sub-domaining due to geometry may not be needed. Gnamien, (2017) provides the four steps that are to be followed in order to perform an accurate DA search interpolation. These are summarised below:

1. *Create a trend surface*: This surface should honour the different variations in dip and dip direction (trend) of the mineralisation. The surfaces created should

be the upper hanging wall (HW) and lower (foot wall) (FW) surfaces that define the orebody.

2. *Smoothing of local angles***:** This involves removal of spurious angles caused by wrong triangle positioning. An important point is that Dynamic Anisotropy should mainly be based on the structural geology rather than an artefact of the domain wireframe.

3. *Add block model attributes*: In this step appropriate block model attributes for the dip and dip direction are added from the wireframe geometry and is stored for each block.

4. *Select attributes during block model estimation***:** For the estimation of each block, the ellipsoid will be set exactly as per the values in the orientation attributes for each block, as created in step three above.

1.4.4 Comparing Estimation results between Traditional method and DA method from previous case studies

At a Fennoscandian Exploration and Mining Conference of 2011 hosted in Perth Australia, Glacken and Gray, (2011) discussed several challenges faced when carrying out a resource estimation. Of those highlighted, one of the major challenges was carrying out resource estimation in flexure, undulating, faulted and folded deposits. They mentioned that initially the resource geologist only had three options when faced with such a deposit. First was to use a single search ellipse throughout the deposit, second was domaining the orebody and thirdly by performing a coordinate transformation or unfolding. They then proposed a fourth methodology using DA and presented a case study on Kylylahti Copper Gold-Cobalt Mine. The DA method of interpolation allowed the search and variogram ellipse to rotate according to the dip and dip direction of the wireframes. No comparisons were shown between the results from DA and the other methodologies in their presentation, but they concluded that the DA methodology offered a quick, simple and mostly effective solution compared to other options.

Zabrusky (2013) presented a study of an epithermal vein system with a significant change in dip and dip direction. Two models were created in this study; one using a traditional search method and the other based on the DA methodology in Datamine Studio 3 software. In the analysis, the author used visual illustrations to compare the difference from the two models. Without constraining the estimation to vein triangulations, the DA method was able to produce a model with grade distribution following the orebody geometry while the model created using the traditional method, resulted in an estimated grade distribution that could not be well defined nor followed the grade geometry. This explained why the DA methodology had more grade continuity in its interpolations compared to the traditional method. The author concluded that using a search ellipse with an average value for the two distinct dips caused the grade estimation to be less representative than desired and that this was due to the irregular geometries in the vein deposit that could not be captured by the traditional methodology.

At the onset of this research report it was thought that the Konkola Mine case study presented here would have similar outcomes to that of Zabrusky discussed above, and this was confirmed at the end of the investigation.

Machuca-Mory *et al*. (2015) carried out a case study using Ordinary Kriging with local anisotropy angles applied to a structurally controlled vein gold deposit in Ghana. They focused on various practical aspects of the construction of the model of local anisotropy angles from geological wireframes. In their final analysis they used cross-plots to compare the differences in the estimated gold grades between the model built using local anisotropy DA and the model using the Traditional Stationary Global Anisotropy. They observed that the differences in the estimated grade between the two methods could be as high as ±10 g/t gold which is roughly equivalent to 6.5 times the standard deviation of the estimated value. They concluded that the DA method gave a better estimate than the Traditional Stationary Global Anisotropy.

The introduction of the DA methodology caused a significant improvement in terms of interpolation as in the cases of Stroet and Snepvangers, (2005); Glacken and

Gray, (2011); Morrison and Grant, (2012); Zabrusky, (2013); Machuca-Mory *et al*., (2015) and Cardwell and Cartwright, (2016). This, however, was not the case for Mandava, (2016) who did a study on Driefontein Gold deposit to ascertain the significance of using the DA methodology to improve the resource estimation as compared to the convectional OK which was the estimation method used at the mine. The results showed that the DA had no significant improvement on the grade estimates compared to the estimates from OK methodology. The author concluded that Driefontein Gold mine should continue to use OK as the difference between the two methodologies was insignificant.

The literature reviews discussed above showed that the application of DA on several different deposits improved the resource estimation as compared to the traditional OK with fixed orientations for the search ellipsoids. However, most of the case studies reviewed were on folded and undulating vein type deposits, this research will however, focus on a folded and undulating stratiform copper deposit.

1.5 Plan and Layout of this Research Report

This research report study aims to investigate whether the application of a DA search approach in the ordinary kriging can improve resource estimation when dealing with a folded and undulating stratiform copper deposit. The study is supported by an industry case study from Konkola Mine located on the Zambian Copperbelt. In addition to this first introductory chapter, this research report contains a further four chapters.

Chapter 2 focusses entirely on providing a detailed description of the Konkola Mine case study area from which the data used in this research report is sourced. It describes the location and brief mining history of the mine since the discovery of the deposit to present day situation. Detailed regional geology of the Copperbelt province, local geology of the mine including prominent structures present in the deposit are all discussed in this chapter. This geological background is particularly relevant and significant to this research study as in this geological complexity lies the core motivation for the research on improving current estimation practices. The current practice and its associated geological modelling drawbacks are also outlined in this chapter.

Chapter 3 lays out the research methodology used to achieve the objectives of this research. A brief theoretical description of each stage of the estimation process is also included. Exploratory Data Analysis (EDA), Variography and Quantitative Kriging Neighbourhood Analysis (QKNA) are the main topics discussed in this chapter. The resource estimation using the traditional Ordinary Kriging (OK) method and one using OK with the DA search method concludes the chapter.

Results from the research methodology are presented and discussed in Chapter 4. Both estimation methodologies are compared using techniques such as: Global Statistics, Swath Plots, Scatter plots of block estimates vs the average block values from samples, Visual inspection and the distribution of differences in block estimates are all discussed in the chapter. The similarities and differences between the two estimation methodologies as observed from the results obtained are also discussed in this chapter including the significant improvement observed from the implementation of the DA search methodology.

Chapter 5 contains the conclusion and recommendations such as putting forward that the DA search methodology be adopted hence forth as the interpolation technique for resource estimation at Konkola Mine.

1.6 Study Objectives

The focus of this research is a comparative analysis of estimations results derived from the traditional Ordinary Kriging methodology (currently used at the mine) and DA methodology for Konkola Mine. The aim was to find out which of the two methodologies gave more accurate estimates when dealing with an orebody that has complex geology such as that of Konkola Mine. Stroet and Snepvangers (2005), Glacken and Gray (2011), Morrison and Grant (2012), Zabrusky-(2013), Machuca-Mory *et al* (2015) and Cardwell (2016) applied the DA interpolation technique to estimate Mineral Resources. They did a comparative analysis on their results and concluded that the application of DA to the estimation process produced better grade estimates.

In this research study an investigation was done to firstly determine whether the folding, undulation and changes in dip and dip direction at Konkola Mine had a significant effect on the estimation of the copper resources to warrant the use of the DA estimation methodology. This was achieved and gave the reason to proceed with the study. Estimate results from the two methodologies were tested by comparing with the input sample data both statistically and by visual inspection. Further investigations were done to determine the financial benefit of adopting the DA methodology as the future estimation technique for the Konkola orebody.

2 Research Case Study

2.1 Project Location

The data set used in this research project was sourced from Konkola Copper mines (KCM); a letter of consent to use this data was provided by the company. KCM is divided into four business units namely Konkola mine, Nchanga mine, Nkana Refinery and Nampundwe mine. The data set is specifically from Konkola mine which is an underground mine situated in Chililabombwe district on the Copperbelt province. From Lusaka, the capital city of Zambia, Chililabombwe is accessed by the Great North Road, via Ndola, Kitwe and Chingola. Chililabombwe is 25km to the north west of Chingola Town, the area is also about 15km from Democratic Republic of Congo boarder, see Figure 2.1.

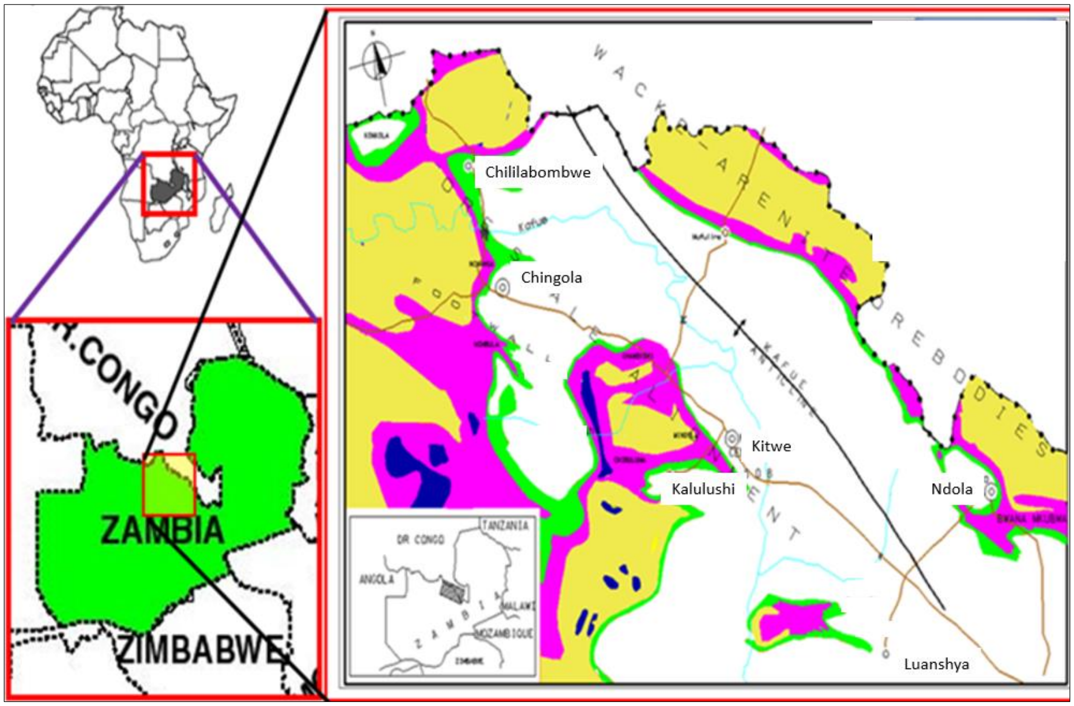


Figure 2. 1 Location of Konkola Mine in Zambia, Southern Africa. (Konkola Copper Mines, 2008)

Konkola Copper mines is a subsidiary of Vedanta Resources, a mining company which has its headquarters in London UK. Vedanta owns 79.4% Shares in KCM while the rest of the shares are owned by the Zambia Consolidated Copper Mines (ZCCM).

2.2 Mine history of Konkola Mine

James Williams and Babb in 1924 first discovered Malachite minerals along the Kirilabombwe stream in the town now known as Chililabombwe also referred to as Bancroft town in older literature. This prompted for further investigation in the area. By the late 1920's, a systematic prospecting campaign was initiated by Dr Austen Bancroft that followed up the mineralisation and correlated it with the geological sequence known from other parts of the Copperbelt. A diamond drilling program for surface exploration drillholes was carried out between 1949 and 1954. The drilling campaign proved to be very successful as the grade of the mineralisation was found to be good. The sinking of the first shaft (Shaft 1) commenced in 1953, thereafter ore production started in 1957 (Mwango, 2011) and since then mining activities have been going on to date .

Currently Konkola mine is operating from two Shafts No. 4 and No. 3 for exploiting the Orebody from the West and North limbs respectively. Konkola mine is the wettest mine on the Zambian Copperbelt, and possibly in the world, and is currently pumping approximately 350,000m^3 of water per day.

2.3 Geology of the Copperbelt

This encompasses the Regional Geologic Setting of the Zambian Copperbelt and the Stratigraphic Succession from the Basement Complex to the Katanga Supergroup. The Katanga Supergroup is the one that host the copper-cobalt mineralisation for both Zambia and Democratic Republic Congo (DRC). This section gives a detailed account of the understanding of the geology within Konkola mine and the surrounding areas. Geostatistical methods are used for quantifying geology and mineralisation by expressing them in numeric form so that financial decisions can be made on the viability of deposits (Dohm, 2018b). A good understanding of the geological setting, stratigraphy, depositional history and structures is fundamental to robust mineral resource estimation .This knowledge and understanding can assist in orebody domaining and provide insight into any anisotropy that might appear in the experimental variograms.

2.3.1 Regional Geologic Setting

The Central African Copperbelt is one of the richest and largest metallogenetic provinces in the world largely shared between Zambia and the Democratic Republic of Congo (DRC) (Cailteux *et al.*, 2005; Selley *et al.*, 2005; Torremans *et al.*, 2013). It is situated on the Lufilian Arc which is a northward-convex Pan-African orogenic belt comprising of the Neoproterozoic metasedimentary rocks of the Katanga Supergroup (Binda and Mulgrew, 1974; Unrug, 1983; Kampunzu *et al.*, 2009).

The Central African Copperbelt is divided into two major Zones, the Northern Zone which contains the DRC Copperbelt of tightly folded, thin skinned thrust sheets of weakly to non-metamorphosed Katanga strata, and the Southern Zone which contains the Zambian Copperbelt consisting of slightly metamorphosed Katanga strata (Hitzman, 2000).

Earlier Porada (1989), subdivided the Central African Copperbelt into four Zones: 1) the external arcuate fold-thrust belt; 2) the 'Domes region'; 3) the Synclinorial belt; and 4) the 'Katanga high'. The Majority of the mines on the Zambian Copperbelt are located in the Domes region and the Synclinorial belt. Figure 2.2 shows the location of the Copperbelt Regional tectonic setting in Africa and Zambia including the four different zones.

The Zambian Copperbelt is located in the North Western Part of Zambia situated along the 800km structural trend of the Lufilian arc fold belt. It extends from Angola on the west passing through Solwezi in Zambia and then through Katanga province in southern part of DRC then back again into Zambia at Konkola passing through the Copperbelt Province into the DRC pedicle. Most of the of the Zambian Copperbelt mines are concentrated in the last 200km of the fold belt (Bowen and Gunatilaka, 1976).

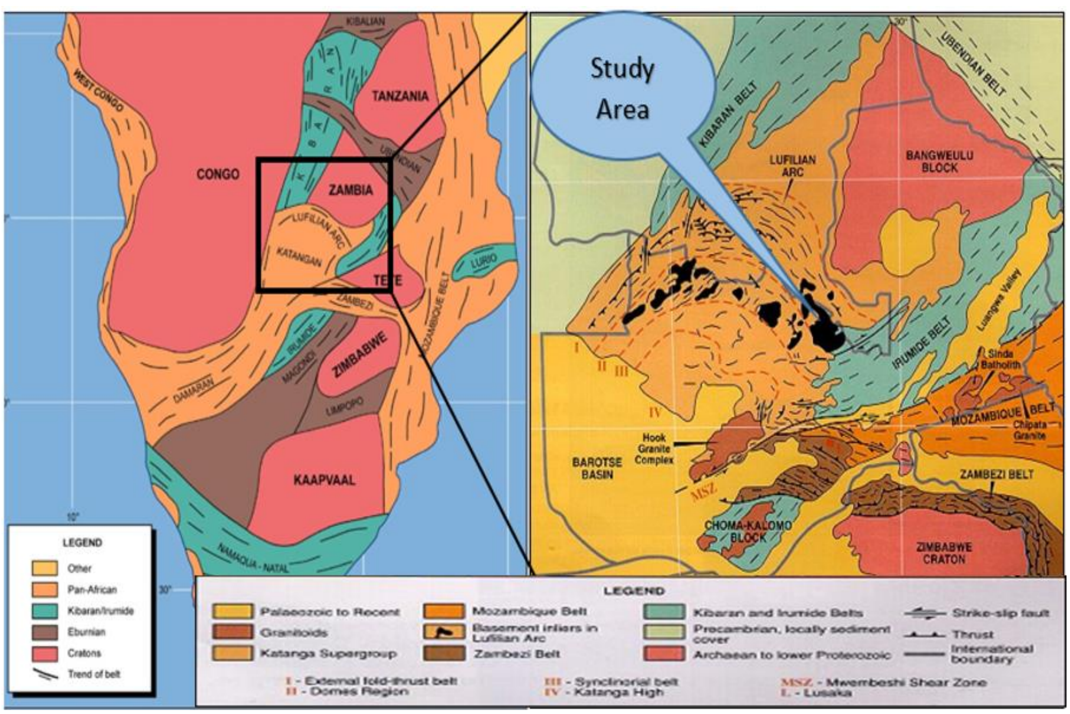


Figure 2. 2 Location of the Copperbelt tectonic setting in Africa and Zambia (Porada, 1989; McGowan *et al*., 2006)

The Central African Copperbelt has several prominent structural features formed because of the folding and thrusting from the Pan African orogenic event. This event resulted into formation of several synclines and anticlines around Region. One of the major dominant structural features on the Zambian Copperbelt is the Kafue anticline trending north-west to south-east and flanked on the east by the Mufulira syncline and on the west by a large Synclinorium type structure (Bowen and Gunatilaka, 1976). The other dominant features are the Konkola dome in the northwest and the Kirilabombwe dome in the southeast (Konkola Copper Mines, 2006). Draped around the Kirilabombwe dome is the Konkola orebody.

The Copperbelt stratigraphy can be subdivided into two major groups the Basement Complex overlain by the Katanga Supergroup (McGowan *et al*. 2006). The basement complex is subdivided into the Lufubu System, the overlaying Muva System and the granitic System (Mendelsohn, 1961;Fleischer *et al*., 1976; cited in McGowan *et al*., 2006)

The Katanga Supergroup a sedimentary succession ranges from 5km to 10km thick (Francois, 1974, 1995 cited in Cailteux *et al.*, 2005) unconformably overlays the Basement Complex . It comprises of metasedimentary rocks and is subdivided into the Roan, Lower Kundelungu also known as the Nguba and the Upper Kundelungu Supergroups (Master *et al.*, 2005). The sediments of the Katanga Supergroup were subjected to a low-level metamorphism characteristic of the green-schist facies. However, there is a gradual increase in metamorphic grade towards the south to south-westerly direction across the Copperbelt (Bowen and Gunatilaka, 1976).

2.3.2 Stratigraphic Succession of the Copperbelt

The stratigraphy of the Copperbelt can be subdivided into two major groups the Basement Complex and the Katanga Supergroup (McGowan *et al*., 2006).

Basement Complex

The basement complex of the Copperbelt consists of the pre- Katangan Lufubu system, Muva system and the old granites which forms the core of the Kafue anticline and the Domes around the region (Bowen and Gunatilaka, 1976). The

Lufubu system consists of schist, gneisses and the Intrusive Granitoids (Armstrong el al 2005) whereas the Muva system is composed of the quartzitic and metapelitic metasediments (Rainaud *et al.*, 2003; Armstrong *et al.*, 2005). The Nchanga Granite is the youngest intrusion in the pre-Katangan Basement Complex (Garlick and Brummer, 1951; Master *et al.*, 2005). It is a massive coarse-grained peraluminous biotitic alkali granite with A-type geochemical characteristics (Tembo *et al*., 2000 cited in Master *et al.*, 2005). It is non-conformably overlain by the Katanga Supergroup (Master *et al.*, 2005).

Several writers have regarded the basement complex as the most viable source for the metal ore deposit on the Copperbelt (Sweeney *et al.*, 1991; Sweeney and Binda, 1994; Van Wilderode *et al.*, 2014, Van Wilderode *et al.*,2015). This is still under debate as there are many theories on the possible sources of the Cu-Co mineralisation on the Copperbelt. Figure 2.3 depicts the geological map of the eastern part of the Zambian Copperbelt showing the basement rocks surrounded by the rocks of the Roan and Kundelungu supergroup.

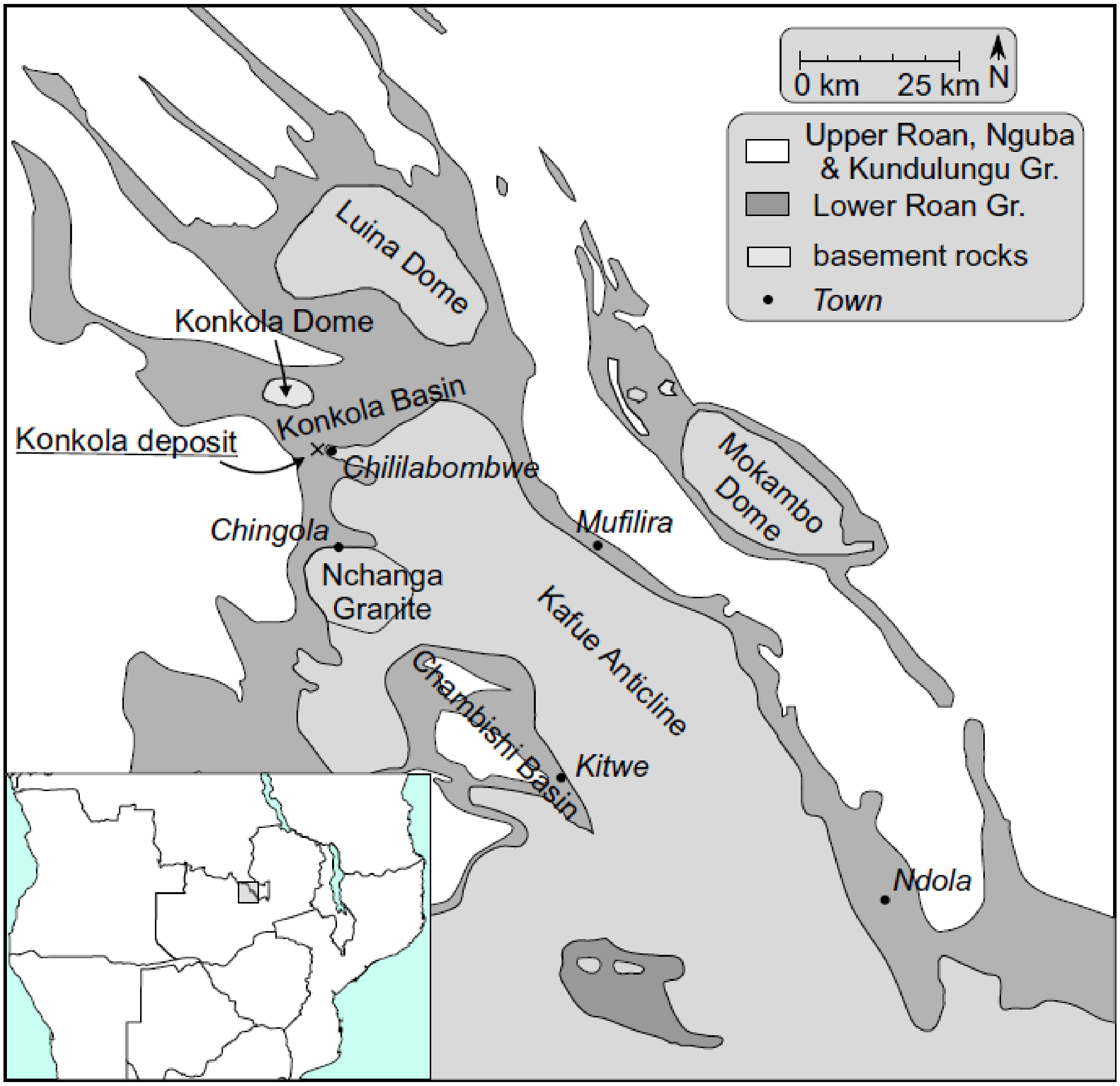


Figure 2. 3 Geological map of the eastern part of the Zambian Copperbelt. (Torremans *et al.*, 2013)

Katanga Supergroup

The Neoproterozoic Katanga Supergroup of the Central African Copperbelt in Zambia and the Democratic Republic of Congo (DRC) is the host of the major stratiform sediment-hosted Cu–Co deposits, as well as numerous other deposits of Cu, U, Zn, Pb, Au, Fe, etc. (Robert, 1956; Mendelsohn, 1961. cited in Armstrong *et al.*, 2005). According to Cailteux *et al.* (2005) it hosts more than half of the world's cobalt with major Cu-Co deposits having more than 10Mt copper. Initially defined in the Katanga province of DRC, The Katanga Supergroup is present in two

Pan African belts, The Lufilian Arc (DRC, Zambia) and the Zambezi Belt (Zambia, Zimbabwe and Mozambique) (Porada, 1989). It was exposed to deformation and low-level metamorphism in both belts.

Unrug, (1988) subdivided the Katanga Supergroup into three major groups, The Roan, Nguba (Ex Lower Kundelungu) and Kundelungu (Ex Upper Kundelungu) groups. This was consistent with other authors who later subdivided and named the groups in a similar manner (Cailteux *et al*., 1994; cited in Master *et al*., 2005) and (François, 1973, 1987, 1995; Cailteux, 2003; Batumike *et al*., 2007 cited in Kampunzu *et al*., 2009). Recently the Katanga has been revised taking into account major regional unconformities, lithological characteristics, provenance of sediments and genetic aspects (Wendorff, 2005). Based on those accounts, Wendorff subdivided the Katanga Supergroup into five units ranked as groups: “Roan and Nguba which originated in rift depositories, the Kundelungu, Fungurume and Plateau both deposited in synorogenic foreland basins”.

The Roan Group is the lowest unit of the Katanga Supergroup and it represents the initial phase of basin formation: uplift and rifting that resulted in the deposition of the coarse conglomerates at the base (Unrug, 1988). It forms a continuous succession of three lithostratigraphic unit unconformably overlaying the pre-Katanga Basement Complex (Binda, 1994 ; Wendorff, 2005): The basal siliciclastic unit (Mindolo subgroup), middle siliciclastic and carbonate unit (Kitwe subgroup) and an uppermost carbonate unit(Kirilabombwe subgroup) (Kampunzu *et al.*, 2009). Other literature only subdivide the Roan group into two subgroups the siliciclastic Lower Roan and the dolomitic Upper Roan subgroups(Bowen and Gunatilaka, 1976; Master *et al.*, 2005). Geologists on the Copperbelt use mostly the latter nomenclature than the former. The Roan group is largely composited of conglomerates, quartzites, arkoses, shales, siltstones, dolomitic shales and anhydrate bearing dolostones (Master *et al.*, 2005).

The Nguba group is the middle unit of the Katanga stratigraphic sequence and represents the second phase of basin formation (Cahen *et al*., 1984 cited in Unrug, 1988). It rests with an erosional unconformity on the Upper Roan group rocks and as well as on older Basement rocks in some areas (Wendorff, 2005). The Nguba is subdivided into three units: the Mwashya subgroup, formerly regarded as forming the top of the Roan Group (Key *et al.,* 2001) now regarded as forming the base of the Nguba Group: the mixed siliciclastic-carbonate Muombe subgroup and the predominately siliciclastic with minor carbonates Bunkeya subgroup (Kampunzu *et al.*, 2009).

Overlying the Nguba is the Kundelungu which begins with a tectonically induced Petit conglomerate of up to 50m and hosts most of the Kakonkwe Limestone fragments observed on the Copperbelt region (Porada, 1989). It is subdivided into three group: Gombela, Ngule and Biano observed from the DRC side (Batumike et al., 2007 cited in Kampunzu *et al*., 2009). The Gomela subgroup forms the base and it consists mainly of siltstones-shales-carbonate units and is marked by the basal glaciogenic petitc conglomerate (Kampunzu *et al.*, 2009). The author also discussed the composition of the Ngule subgroup as consisting of siltstones, pelites and sandstones whereas the Biano subgroup as being an arenaceous unit of conglomerate, arkose and sandstone.

The Kundelungu group is overlain by the Fungurume group which is a newly defined unit in the Katanga Supergroup regarded as a syntectonic foreland basin fill (Wendorff, 2003). It is characterized by synorogenic conglomerates that came from older strata uplifted to the south of the basin. The Katanga Plateau overlays the Fungurume group and it is the uppermost group in the stratigraphic sequence marked by the appearance of the feldspathic sandstone (Wendorff, 2005).

The Katanga rocks were deformed and metamorphosed to a lower greenschist facies (McGowan *et al.*, 2006). The regional metamorphism however, increases from the north to the south (Milesi *et al*., 2006) changing from a greenschist facies to epidote-amphibolite facies (Porada, 1989).

The nomenclature of the Katanga stratigraphic succession remains poor with different authors having different names for the same groups, subgroups or formations. This is because of the cultural and political divide that separates DRC and Zambian Copperbelt. The other major reason is that the majority of the ore deposits are restricted to the lower Roan group therefore little attention has been directed to other stratigraphic lithologies beyond these confines (Woodhead, 2013). Table 2.1 summaries the Copperbelt stratigraphic succession from the Basement Complex to the top of the Katanga Supergroup.

Table 2. 1 Copperbelt stratigraphic table Modified (Cailteux *et al*., 2005; Kampunzu *et al*., 2009)

ERA	SUPGROUP	GROUP	SUBGROUP	ROCK UNIT
NEO-PROTEROZOIC	KATANGA	KUNDELUNGU (U KUNDELUNGU)	BIANO	Argilaceous/ Arkose SSt Dolostone tilites(Petit Conglomerate)
			NGULA	
			GOMELA	
		NGUBA (L KUNDELUNGU)	BUNKEYA	Dolomitic Shales, Pelites, Kakonkwe Lst, Dolomite and Shales, Tilites(Grand Conglomerates)
			MUOMBE	
			MWASHYA	Carbonaceous shales, siltstones Dolomites, Gabbroic sills.
		ROAN	UPPER ROAN	Dolomites, Quartizte, Argillite, Shales , Dolomites and siltstones
			LOWER ROAN	Argillaceous, siltstones, Dolostones, Shales, Arkose, Argillaceous Siltstones, Qurtizites, Conglomerates at the base
	BASEMENT COMPLEX	MUVA SYSTEM		Quarzites, Conglomerates Schists
		LUFUBU SYSTEM		Micaceous Quartzite, Schists, Granite and Amphibolites

2.4 Geology of the Konkola Mine Area

The rocks of the Konkola mine area belong to the Basement Complex and the Katanga Supergroup. They experienced deformation at the same time resulting in the formation of anticlines and Synclines with the Basement rocks forming the core of the anticlines such as that of the Kafue anticline one of the major structural feature on the Copperbelt. The Katanga system comprises rocks of the Roan group also known as the Mine series and Kundelungu group separated from the Basement by a marked unconformity. The Roan group consists of the Lower Roan and the Upper Roan with the Copperbelt ore deposits being chiefly confined to the Lower Roan Group (Straskraba *et al*., 2012).

2.4.1 Stratigraphy

The known Stratigraphy of the Konkola mine starts with the basement complex at the base and ends with the Upper Roan group of the Katanga Supergroup. It is only the rocks of the Lower roan subgroup exposed in the mine working areas and this is why most of the studies have focused on increasing the knowledge of this group more than any other group.

Lower Roan

The Lower Roan lies uncomfortably on the Basement complex and comprises of three formations: Footwall formation, Shale Unit and Hangingwall formation. The footwall formation consists of rocks below the Shale unit namely the Basal Conglomerate, Footwall Quartzite, Argillaceous Sandstone and the Footwall aquifer. The Basal conglomerate is subdivided in three conglomerate groups; the Boulder conglomerate which is the bottom most rock unit exposed in the mine workings, the Pebble conglomerate (PBC) which is a coarse, well-cemented, quarzitic conglomerate and a slightly weathered Lower porous conglomerate (LPC). The LPC is generally leached, porous, poorly cemented and sorted with a micaceous clay matrix (Konkola Copper Mines, 2006).

The Basal Conglomerate is overlain by the Footwall quartzite (FWQ) which is a hard, massive, false bedded, grey quartzite with occasional boulder beds (Konkola Copper Mines, 2001). It is a competent rock were most of the primary developments are done. The Footwall quartzite is overlain by Argillaceous Sandstone a bedded sandstone with shale intercalations. On top of the Argillaceous sandstone is the Porous Conglomerate, the Footwall sandstone and the Footwall conglomerate, which together they make up the Footwall Aquifer, the second major aquifer at Konkola mine(Konkola Copper Mines, 2006). The footwall Aquifer is overlain by the Ore shale unit (OSU).

The OSU is a finely laminated, dark grey siltstone to fine sandstone with dolomitic bands and varies in thickness 4-20m (Konkola Copper Mines, 2010 cited in Torremans *et al*., 2013). At Konkola mine it is subdivided into five units A to E

(Konkola Copper Mines, 2001, 2006, 2007; Cailteux *et al.*, 2005; Torremans *et al.*, 2013) with each unit having a different characteristics in terms of the amount of dolomite, metal concentration and extent of weathering. It host most of the economic mineralisation in form of Bornite, Chalcocite and Chalcopyrite with some of it present in the immediate Hangingwall and footwall formation (Straskraba *et al.*, 2012; Torremans *et al.*, 2013).

The Hangingwall formation consist of the Hangingwall quartzite which overlays the OSU and the Hangingwall Aquifer. The Hangingwall quartzite is a strong massive quartzite with interbeds of arkose and occasional fine bands. It is weak in some areas as a result of kaonlinisation (Konkola Copper Mines, 2001). It is competent and acts as a barrier preventing water from the Hangingwall Aquifer flooding the production areas. Overlaying it is the Hangingwall aquifer which is the third major aquifer at Konkola mine and comprises of dolomites and interbedded siltstones(Konkola Copper Mines, 2006). It is overlain by the Shale with Grit formation which is the youngest formation in the Lower Roan Group and is a massive grey siltstone with arkosic grit bands (Konkola Copper Mines, 2001).

Upper Roan

The upper Roan subgroup is defined as a zone of abundant carbonate rich rocks. It's succession comprises of the lower Bancroft Dolomite Formation and an upper poorly-known interval of mixed carbonates breccia and fine-grained siliciclastics (Woodhead., 2013) with an intrusion of gabbro and amphibolite sills (Annels 1984; Simmonds 1998 cited in McGowan *et al*.,2006). This unit is considered to have very limited economic potential and is the least studied unit of the Roan group (Binda, 1994). This was earlier confirmed by Woodhead, (2013) when he described the upper unit of this subgroup as a poorly known interval. Figure 2.4 summarizes the stratigraphic succession of Konkola mine from the Basement Complex to the Upper Roan group.

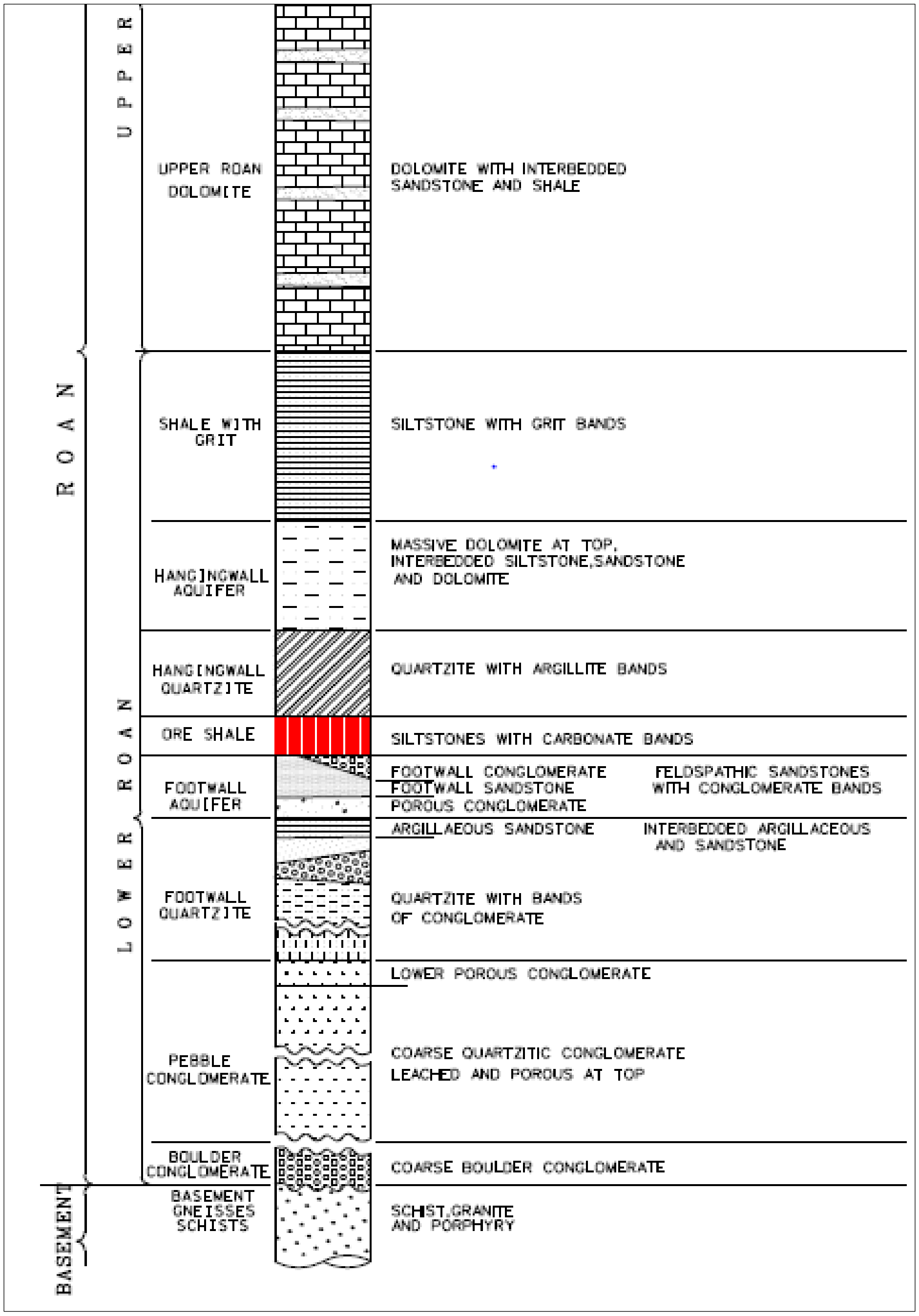


Figure 2. 4 The stratigraphy of Konkola mine (Mackay, 2000).

2.4.2 Structure of the Orebody

The Konkola orebody is part of the large Stratiform Cu–Co deposits of the Central African Copperbelt hosted in the Neoproterozoic metasediments of the Katanga Supergroup. Cailteux *et al*., 2005. Cited in (Torremans *et al.*, 2013) describes this region as one of the largest and richest metallogenetic provinces in the world which is largely shared by the Democratic Republic of the Congo (DRC) and Zambia.

The Konkola orebody is located in the eastern part of the Zambian Copperbelt, in a region commonly referred to as the Domes region. The region has two major Domes the Kirilabombwe Dome and 15km to the North West is the Konkola Dome and the two are separated by the Kawumbwe syncline. Draped around the Kirilabombwe dome is the Konkola Ore deposit from previous literature (Steel, 1957) referred to as Bancroft Orebody with the core of the Anticline comprising of basement rocks. The top of the anticline was eroded leaving two limbs jointed at the fold axis. The limb lying on the northern region trending from East to west is referred to as the North Limb and the other on the western side trending from North to south as the West Limb. Below Figure 2.5 shows major structures (faults and folds) as well as the position of the two major domes on the Zambian Copperbelt. Draped around the Kirilabombwe dome is the Konkola orebody.

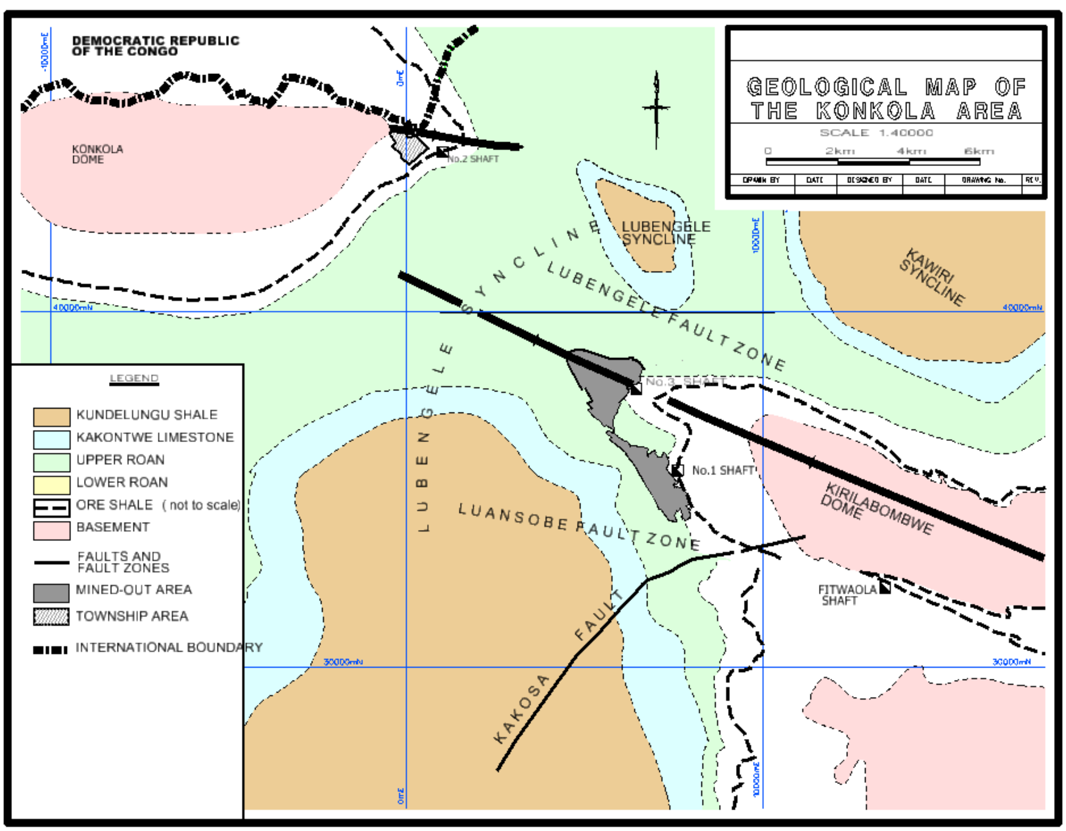


Figure 2. 5 Geological map of Konkola area (Mackay, 2000).

An analysis on the drillholes along the axis of the anticline and in situ measurements reviewed that the Kirilabombwe anticline plunges to the northwest at 10°–15° with a N75W strike of the fold axis concluded that: it is a tight and upright anticline with a sub vertical axial plane and an interlimb angle of 35°–45°. The prominent structures are the faults that occur on the western limb of the anticline at 2200mN and 2700mN position with movement of up to 60m. The effects caused by these faults are visible from surface and have been intersected at depth of more than 1 km from surface. Two other major faults are the Luansobe Fault cutting across the Orebody further south of the west limb dipping at 85 degrees to the North and the Lubengele Fault dipping at 79 degrees to the south on the north limb side. (Torremans *et al.*, 2013)

There are many other minor faults and folds that may be too small to show on the map which might affect the process of Mineral Resource estimation and mining in this area.

2.4.3 Mineralisation

Having a good understanding on the mineralisation of the deposit before commencing with the Mineral Resource Estimation process is beneficial as this insight improves the quality of the estimates. For instance appreciating how the mineralisation is spatially distributed may assist the resource estimator when checking for the assumption of stationarity as well as in the decision of domaining the orebody. Furthermore, this understanding can be drawn on in the interpretation of the behaviour of the experimental variograms and the selection of the best directions to model the spatial correlation of grades in the orebody under study. An example would be if the deposit experienced more than one mineralisation episode, this should show up in the experimental variogram and the variogram model can incorporate this phenomenon by having more than one structure in it (Dohm, 2018b). Several other behaviours observed in the experimental variogram such as cyclicity and trend can also be linked to the mineralisation pattern. This section explains the possible sources of copper mineralisation at Konkola, its distribution across the orebody, mineralisation episodes and the structures that control the mineralisation.

Since the early 1900s, several metallogenic hypotheses were proposed to try and understand the primary source of copper mineralisation on the Copperbelt province (Cailteux *et al*., 2005). The origin of the metal still remains speculative, with much of the debate centred around the following hypothesis: magmatic derived fluids, erosion products of the basement complexes, volcaniclastic sediments and hydrothermal fluids from the granites-granodiorite-tonalite bodies (Cailteux *et al.*, 2005; Van Wilderode *et al*., 2015).

Economic copper concentration at Konkola is restricted to the Ore shale unit and to adjacent parts of formations below and above the Ore shale. The mineralisation occurs as finely disseminated in the matrix of the host rock mainly as chalcocite, bornite and chalcopyrite (Annels, 1984). The deposition of the metal is suggested to be as a result of multiphase mineralisation process (Cailteux *et al.*, 2005; Selley *et al*., 2005) with the Supergene remobilisation constituting a last mineralisation phase (Van Wilderode *et al.*, 2015).

Structural features have a close relationship with higher concentrations of copper grades in fold hinges and at the intersections of regional faults with the mineralised stratigraphic units. This relationship can be observed from the higher grades where they are macro and micro scale structural features suggesting that they played a significant role in the mobilisation and subsequent concentration of metals (Torremans *et al*., 2013). They also suggested that the large faults observed at 2200mN and 2700mN area and the around the fold axis played an important role in grade distribution and supergene remobilisation. Figure 2.6 shows the distribution of the total copper across the orebody and its subsequent concentration around the fault zones.

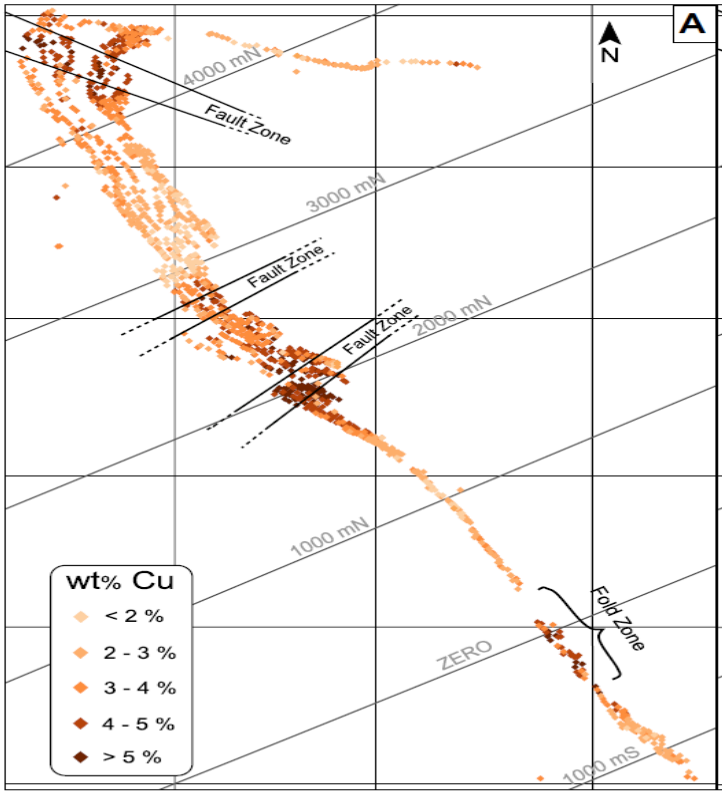


Figure 2. 6 Distribution of percent copper (%Cu) around the mine. After (Torremans *et al*., 2013)

2.5 Geological Modelling and Interpretation

The 3D geological models at Konkola mine constitute the geological and assay surfaces generated from geological and assay contacts respectively. The geological contacts are the contacts between two lithologies extracted from drillhole data, crosscut samples and mapped data whereas the assay contacts are defined by the cut-off grade from drillholes and crosscut samples. Since the drilling pattern at Konkola is not regular, it is practically impossible to model the geological and the assay surfaces explicitly by creating sections. The geology surfaces are modelled by extracting the points from the lithological contacts and the Digital Terrene Model (DTM) is created by a mathematical function using leapfrog software controlled by the extracted points. The two assay surfaces (AHW and AFW) are modelled at a cut-off grade of 1% TCu using hybrid method. The hybrid method uses both explicit and implicit modelling techniques. The assay file is manually coded with AHW for the cut-off on the hangingwall side and AFW for the cut-off on the footwall side.

An excerpt of the file is shown in Table 2.2. The points are extracted from the codes and a mathematical function is used to create the DTM for both assay surfaces. The major faults the 2200mN, 2700mN and these along the fold axis are modelled to represent a break in both geology and grade continuity. The extent of the boundary edge of the surfaces is controlled by the exploration holes drilled from surface. The modelled surfaces are used as geozones to constrain the blocks forming the foundation of Mineral Resource estimation.

Table 2. 2 Excerpt of a coded assay file.

BHID	SAMPID	FROM	TO	LENGTH	TCU	LITHO	OREZONE	Assay Code
CP685	KK203	55.75	56	0.25	0.98	OSU	0	
CP685	KK204	56	56.5	0.5	1.46	OSU	1	AFW
CP685	KK205	56.5	57	0.5	2.74	OSU	1	
CP685	KK206	57	57.5	0.5	7.84	OSU	1	
CP685	KK207	57.5	58	0.5	6.36	OSU	1	
CP685	KK208	58	58.5	0.5	6.26	OSU	1	
CP685	KK209	58.5	59	0.5	5.34	OSU	1	
CP685	KK210	59	59.5	0.5	5.62	OSU	1	
CP685	KK211	59.5	60.5	1	6.56	OSU	1	
CP685	KK212	60.5	61	0.5	5.2	OSU	1	
CP685	KK213	61	61.5	0.5	5.84	OSU	1	
CP685	KK214	61.5	62	0.5	6.14	OSU	1	
CP685	KK215	62	62.5	0.5	5.84	OSU	1	

3 Methodology and Description of the Theoretical Estimation Processes

3.1 Exploratory Data Analysis

Exploratory data analysis (EDA) must precede any form of work in geostatistical and geological modelling. This is to understand the characteristics of the data and increase confidence of the results obtained in the future process. To get a good understanding of the data, summarizing it into statistical parameters and graphs is the main practice used in EDA. A detailed EDA may start with sample verification and validation, carrying out descriptive statistics, plotting of Histograms and cumulative frequency curves for distribution analysis, trend analysis, data declustering and detecting outliers. Several authors have used EDA for different purposes, such as determining cut of grades (Glacken *et al.*, 2001; Sinclair, 1999; Chanderman, 2016), statistical analysis (Mpanza, 2015), domaining (Mandava,

2016) etc. Overall, carrying out EDA on the data set improves the quality of the variograms and final estimates (Dohm, 2018b)

Sinclair and Blackwell (2002) listed other benefits of carrying out EDA such as error recognition and data validation done on the raw data in the initial steps. They also noted that taking time to comprehensively understand the statistical and spatial characteristics of the variable of interest was very important. This included understanding the inter relationship between variables and checking for any systematic spatial variation such as in the grade distribution. They further said EDA could be used to check for the assumption of stationarity and to outline the geological domains that may require to be evaluated independently.

3.1.1 Geological Database

The author of this research report received a Microsoft Excel spreadsheet containing the drillhole data of Konkola Mine. The data originated from three sources namely Exploration diamond drillholes, Evaluation diamond drill holes and Pseudo drillholes. The commodity of interest is percentage Total copper (%TCu).

Exploration diamond drillholes are holes drilled from surface in the early stages of exploration and give an indication of the extent of the deposit. Evaluation drillholes are holes drilled from the mining extraction drives perpendicular to the orebody at a drilling spacing of 25m. Pseudo drillholes are created from crosscut samples that are converted to represent a drillhole. The orebody is sampled across the width, starting from the footwall side which is picked by the surveyor as the collar and ending in hangingwall picked as end of hole.

Data from the above-mentioned sources is captured in Excel into four files, the Collar file, Survey file, Geology file and Assay file. The collar and survey readings are plotted manually on the section plans and in plan-view to verify the coordinates, bearing and inclination before being signed off by the senior shaft geologist. The senior shaft geologist equally signs off the geology file and the assay files after confirmation of the assay QAQC results.

3.1.2 Data Validation

A requirement for reliable estimation is for it to be based on a clean data set (Dohm, 2018a). Database validations were carried out on all the samples at sampling average interval of 1m. The following validation exercises were undertaken.

- Check for outliers in terms of spatial location;
- Check survey data for bearing beyond 360 and inclination beyond ± 90;
- Check for missing data in collar file, survey file, geology file and assay file;
- Check for data duplication;
- Overlapping sample intervals;
- Consistence in geological coding; and
- Check that drillhole length is not less than the sampling length.

Outliers in spatial location, that is drillholes appearing in isolation were validated by confirming their coordinates. The locations of the drillholes were plotted on plan to check if there were any regions showing drillholes located in isolation from others as well as assist to determine the boundary limits. The plot also gave a clear picture of how the %TCu grade is spatially distributed and an indication for a decision on estimation domaining. Figure 3.1 shows a plot of the drillhole locations and the mine boundary limits. From this location plot, two surface drillholes on the southern side appeared to be isolated and far from known deposit limits. Verification of these two drillholes failed, it was not clear whether the drillhole positions were planned positions or whether their collar coordinates were captured incorrectly. The two drill holes were removed from the database, as no benefit could be seen in retaining them apart from having an increased number of samples on the one hand, and introducing unnecessary risk on the other, thus they were considered irrelevant since they are located beyond the study area of interest to this research.

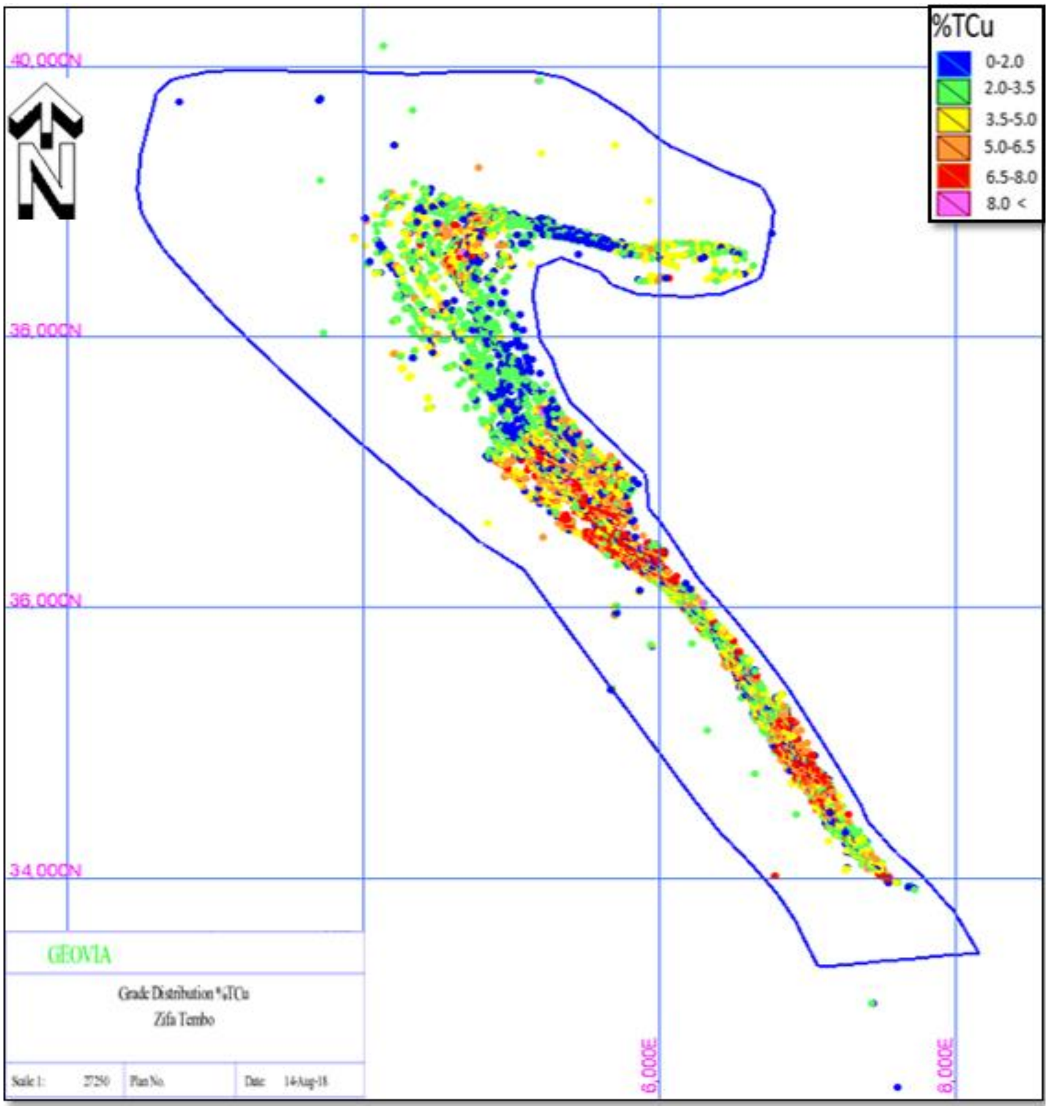


Figure 3. 1 Konkola drillhole locations highlighting the spatial distribution of the %TCu grades

3.1.3 Statistical Analysis

The application of statistical methods to metal grades and other attributes within a deposit is mainly concerned with the central tendency, dispersion of values, probability density functions (histograms), probability statements and simple correlations (Sinclair and Blackwell, 2002).

Central Tendency

The mean, median and mode are referred to as measures of the central tendency. The mean donated by ("μ") is the average value of the data set being analysed. It is that value every sample would have if the total value was shared equally amongst all the samples (Dohm, 2018a) .The mean is calculated using the formula.

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad 2$$

Where x_i is the sample values and *n* is the number of observations. The mean gives a measure of the central position of the data values and does not account for spread of data.

The median is the middle value within a data set when all the values are arranged in ascending or descending order. It is the fiftieth percentile of the data set and divides the data in half. It is actually a more reliable measure of central tendency for small number of observations than the mean (Sinclair and Blackwell, 2002). The formula for calculating the median is as shown below.

$$Me = value\ of\ the \left[\frac{(n+1)}{2}\right]^{th} observation\ of\ the\ ranked\ data \qquad 3$$

The mode is the value that occurs most often in the data set. This can be either the most occurring single value or the most occurring range of values. The mode can easily be checked by plotting histograms and the highest peak on the graph represent the most occurring values representing the mode. Modes are important in signaling the possible presence of complex distribution made up of two or more subpopulation and also in understanding outliers especially abnormally high values (Sinclair and Blackwell, 2002).

There is a strong relationship between these three measures of central tendency also referred to as the “middles”. In a situation where all the middles are similar, the result is a symmetrical distribution of data or a bell shaped. For data with a positve skew distribution the Mo < Me < Mean and when the Mean < Me < Mo the underlying probability distribution is negatively skewed (Dohm, 2018a).

Dispersion

Dispersion is the measure of how spread the data values are in a given data set. The degree of dispersion in a data set can be measured from the calculations of the range, variance and standard deviation. The range alone is unsuitable for defining dispersion because it only looks at the difference of the two extreme values the maximum and minimum and ignores the internal variability. Dispersion is therefore widely measured by variance and standard deviation. The calculation of the variance and the standard deviation is dependent on the mean as they measure the spread of data around the mean as the centre value. Having a majority of very low and high values away from the central value might symbolize high variance and deviation from the mean. The equation for calculating the variance is as shown below and the square root gives the standard deviation of the data set (Dohm, 2018a).

$$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(z_i - \overline{z})^2 \qquad 4$$

Where x_i represents any data value, $\overline{z}$ is the mean and n is the number of observations. Low variance and standard deviation signifies that the data values are closely related and clustered around the mean. The amount of spread within a dataset can also effects the shape of the distribution in terms of the kurtosis and Skewness.

Coefficient of Variation

The coefficient of variation CoV is the ratio of the standard deviation to the mean. It also gives a measure of spread of the data. A low (CoV<1) means that the data values are not too widely spread and may give a normal distribution. A high value (CoV >1) symbolizes a high variability in the data values and most cases data might be skewed. The CoV comes in handy when comparing variability between two or more datasets. Descriptive statistics were computed for the Konkola dataset. Table 3.1 shows the summary of the statistics.

Table 3. 1 Summary of the Descriptive Statistics (%TCu) Cu composites

Variable	Nsamples	Min	Max	Mean	Median	Variance	Std Dev	CoV
%TCu	15948	0	21.82	4.19	3.96	3.12	1.77	0.42

Normal Distribution

Also referred to, as the Gaussian distribution is the most widely used theoretical distribution in statistics. Its probability density distribution function is defined by the mean and standard deviation only, the skewness and kurtosis are constant. The normal distribution is defined by the equation:

$$f(x) = \frac{1}{\sigma\sqrt{(2\pi)}} e^{\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\}} \qquad 5$$

Where: $\boldsymbol{x_i}$ is any value in the data set, and $\boldsymbol{\mu}$ is the mean and $\boldsymbol{\sigma}$ is the standard deviation of the data set.

Given the mean and standard deviation of a normal distribution, probabilities can be determined by using the standardised normal distribution curve. A standardised value is created for each observation by deducting the sample average from it and then dividing that answer by the sample standard deviation.

Figure 3.2 shows the normal distribution curve and its probabilities representing areas under the curve in terms of percentages.

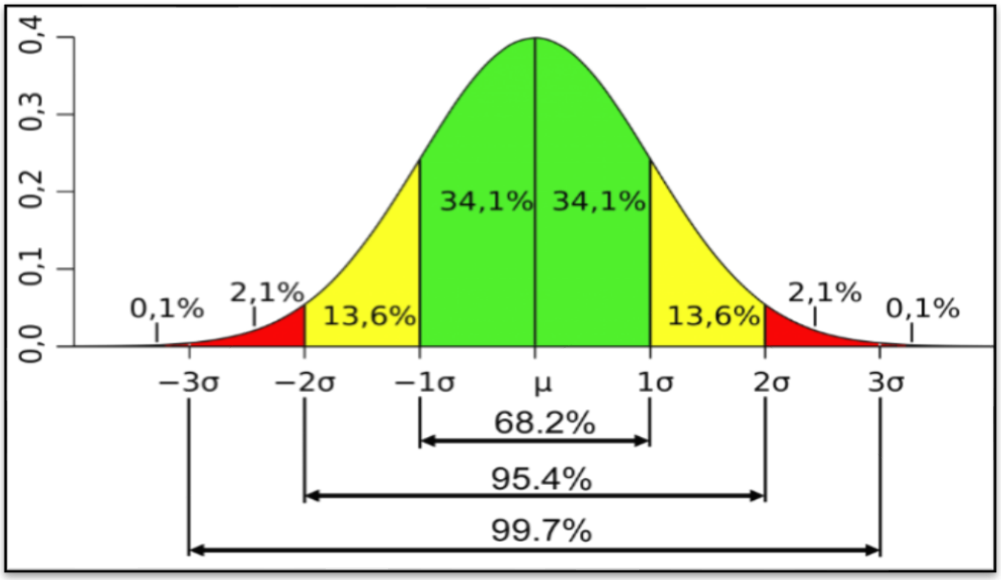


Figure 3. 2 Standardize normal distribution curve source (Dohm, 2018a)

The assumption of normal distribution can be tested through several techniques. One technique is comparing the three measure of central tendency. If the mean, median and mode are similar then the data could be having a normal distribution. The other method is to plot the distribution of the data to analyse its distribution visually/graphically. Plot of histograms, Box plots and cumulative frequency curves will depict the frequency distribution of the data and show if the data is normally distributed or not.

Histogram and Probability density plots

Histograms are graphs of frequency of a variable within a continuous uniform value interval known as the class interval. In mineral inventory studies, histograms can be useful in determining sampling and analytical errors, and in the determination of grade and tonnage above cut-off. A probability density function (PDF) is a continuous mathematical model or curve fitted to the shape of the histogram (Sinclair and Blackwell, 2002). The histogram shape provides information on data location, spread, skewness, presence of multiple modes symbolising sub populations and presence of outliers. (Dohm, 2018a).

A histogram of the Konkola Mine %TCu population was constructed and the outcome supports the descriptive statistics tabulated in Table 3.1. A probability density model was fitted to the histogram to represent a continuous distribution of data see Figure 3.3.

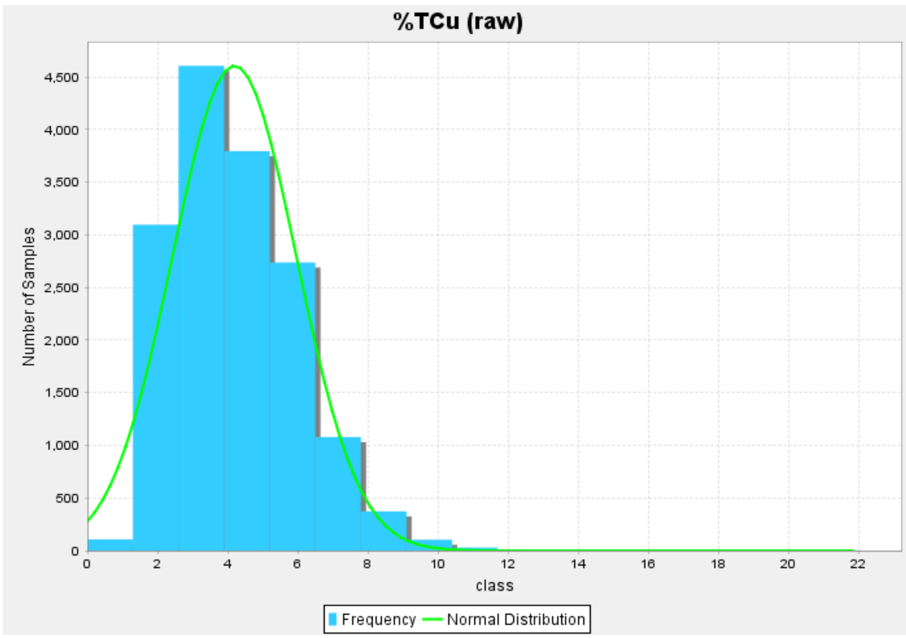


Figure 3. 3 Histogram and model for Konkola Mine copper %TCu dataset

Analysis was done on the calculated statistics Table 3.1 to determine how the data was distributed. Similarities between the mean and the median showed that the position of the mean is almost central depicting the behaviour of a Gaussian distribution. A relatively low CoV of 0.42 indicates that there is minimal dispersion in the data and supporting that the data could be normally distributed. The range highlights the big difference between the minimum 0.0 %TCu and the maximum 21.8 %TCu. A lower mean value of 4.2 %TCu showed that the majority of data was represented by the lower values and the small standard deviation of 1.77 %TCu showed that majority of the sample were clustered around the mean value, both observations are supported by this shape of the histogram. The analysis further revealed the presence of outliers, looking at how high the maximum value is in comparison to a low mean and small standard deviation. A percentile ranking was computed to check how the data is distributed as shown in Table 3.2 below. At 99th to 100th percentile, a jump in the %TCu value was observed from 9.05%TCu to 21.82%TCu. This showed that only 1% of the data could contain outliers.

Table 3. 2 Percentile ranking of the %TCu.

Percentile	%Tcu
10	2.14
20	2.60
30	3.03
40	3.47
50 (median)	3.96
60	4.45
70	5.03
80	5.68
90	6.51
95	7.30
97	7.91
98	8.35
99	9.05
100	21.82

Outliers

Sinclair and Blackwell (2002) define outliers as “Observations that appear to be inconsistent with the vast majority of data”. They can be either extreme low values or extreme high values. These values results from several factors that include errors in assaying or an indication of a subpopulation within a domain. In mineral deposits, the major concern is mostly with the extreme high values within a dataset resulting in the distribution having a positively skewed shape. The presence of outliers can cause a lot of problems, according to Rossi and Deutsch (2014), outliers can affect the basic statistics like mean and variance, correlation coefficient, and measures of spatial continuity (variography). The other major effect can occur during the estimation process using Kriging when an outlier value is assigned a negative weight, this may result in having incorrect estimates (Sinclair and Blackwell, 2002). Sinclair and Blackwell have outlined three approaches available for dealing with outliers. One option is cutting or capping of data. Reducing the values to some acceptable upper limit using experience or by using empirical cutting method to at least 95th percentile. Another approach is to omit outliers during the calculation of the experimental variograms and modelling thereof, but to use them in Ordinary Kriging estimation process. The last choice is to, in a case where the outliers represent a separate subpopulation, exclude them during estimation and regard them as being independent from the principal domain being estimated.

Determining of outliers is subjective and may differ from one practitioner to the other but there are universal steps that can be followed to assist, identify and analyse them. This is because outliers are unique values and can be statistically and spatially isolated from other values and action taken.

The flow chart provided by De-Vitry (2014) in Figure 3.4 was followed in identifying and dealing with outliers in this study. In the place of scatterplots, Box and whisker plots were used.

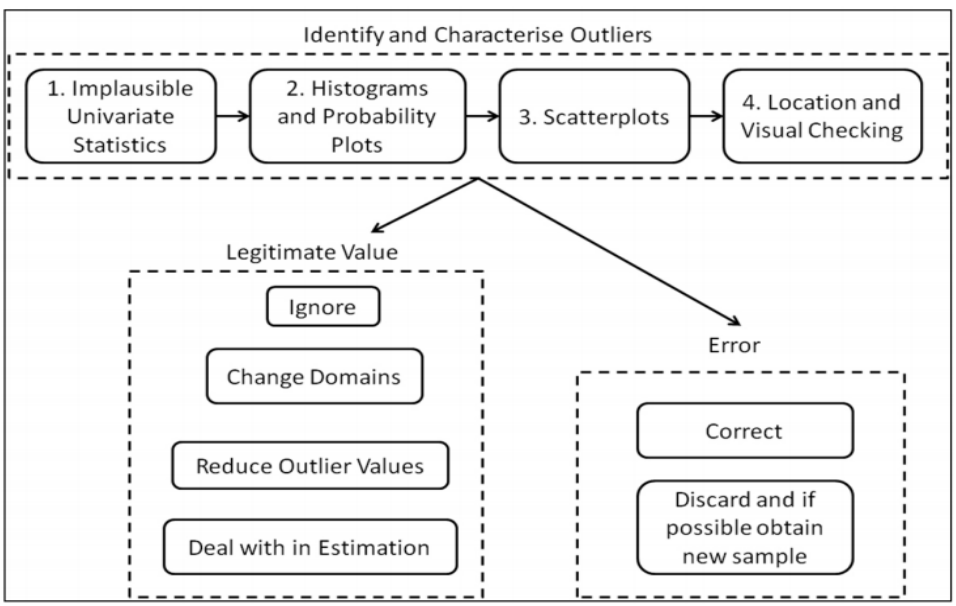


Figure 3. 4 Flow chart identifying and characterizing outliers (De-Vitry, 2014)

Outliers in many cases are removed from the data set during the variography analyses because they have the potential to reduce the quality of the variograms. These extreme values maybe used during estimations because they make the deposit viable.

For Konkola dataset the histogram in Figure 3.3 shows that samples with high values and low frequency pull the graph slightly to the right though the majority of the data is concentrated around the centre.

The box and whisker plot in Figure 3.5 gives a clear picture of the outlier values above Q4. A combined analysis from the percentile ranking, histogram and box plot was used to set the outlier cut off at 9.2 %TCu representing less than 1% of the total samples.

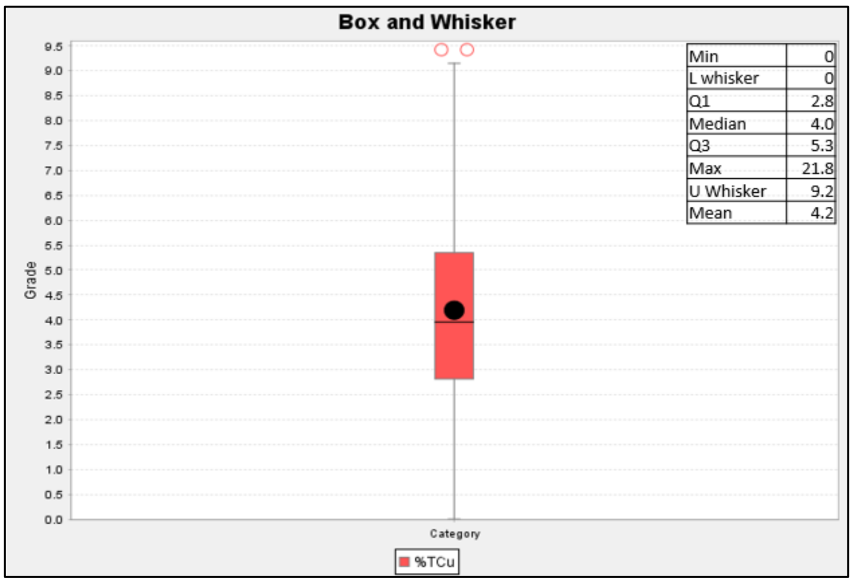


Figure 3. 5 Box and Whisker plot

Samples that were above the Q4 are falling within the outlier section. They will need to be domained, capped or the extreme value be cut to avoid producing variograms with abnormally high variability caused by only few samples.

The location of all the outliers identified in this manner are highlighted in Figure 3.6 with reference to other drillholes. The outlier values are coloured in red and are mostly concentrated around the areas affected by faulting which is expected as explained in section 2.4.3 under mineralisation.

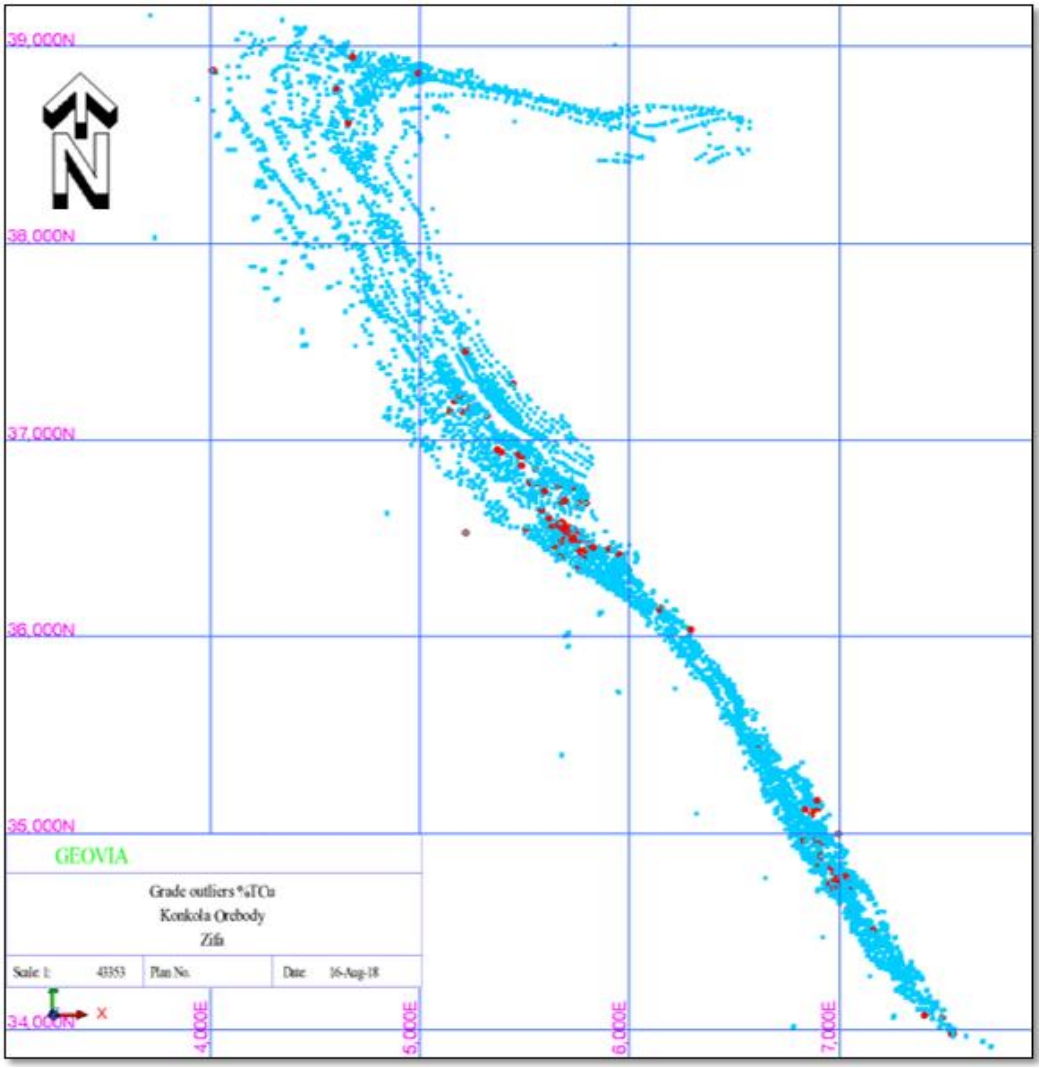


Figure 3. 6 Location of the TCu % outliers highlighted in red

3.1.4 Domaining

Domaining is a common practice in the mineral resource process. Deutsch and Wilde, (2011) define a domain as a subset of the deposit grouped together for common analysis. They are defined as volumes that are statistically and geologically homogeneous. In Mineral Resource estimation, domains are demarcated by boundaries in the form of strings, 3D surfaces, or solids. Domaining forms the foundation of Geostatistics as it improves the quality of variography (Sinclair and Blackwell, 2002; Chanderman, 2016, Dohm 2018b). In reality, most of the data will tend to have different zones of mineralisation within which the grade characteristics vary. If domaining is not applied to the deposit, it can lead to grade smoothing and eventually resulting in wrong estimates. The decision to domain an orebody for geostatistical estimation is influenced by, for example, having a mixed population which may result in having trend in the data or evaluating a deposit with varying geometry which might affect variography, or having different geological zones with different statistical and spatial characteristics. All of these factors will result in the creation of more spatially homogeneous domains and thereby improve stationarity.

Abzalov and Humpherys, (2002) did a comparative study on a Mesothermal Gold deposit in northern Canada where resources of the same zone were estimated after applying domaining and secondly without domaining. Results from their research showed that estimates obtained without domaining of mineralisation yielded a substantial error due to excessive grade smoothing.

Using data for analysis and estimation from similar rock volumes reduces the noise when doing variography and reduces over smoothing during estimations.

The Konkola orebody was divided into two-estimation zones; Zone1 and Zone2 based on the grade distribution and concentration shown in Figure 3.7.

Zone1 has high-grade concentration compared to Zone2. This also explains why most of the outlier samples are concentrated in Zone1 refer to Figure 3.6.

By analysing Zone1 and Zone2 separately the effect of outliers was reduced and their impact within Zone1 was minimised.

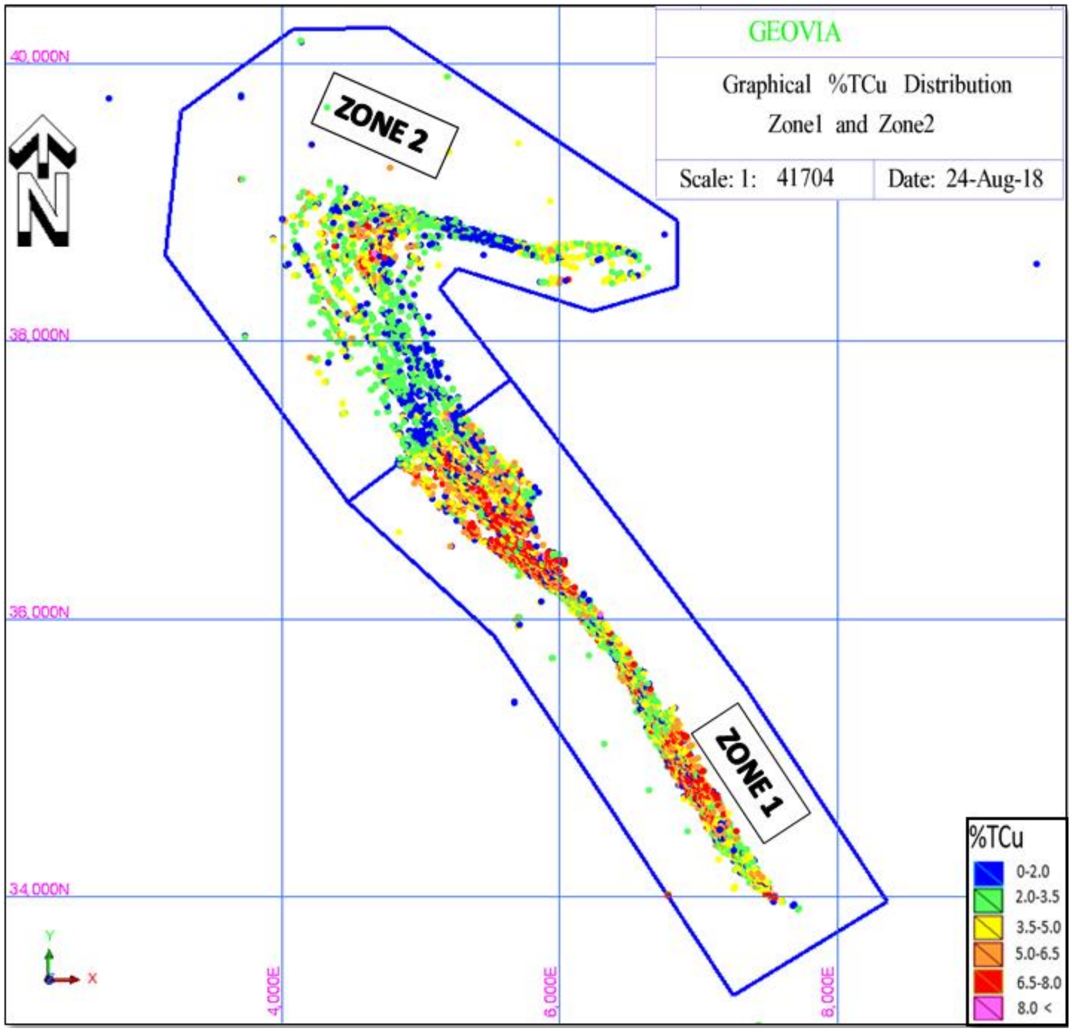


Figure 3. 7 Estimation domains: Zone1 and Zone2

To assess whether there was a statistically significant difference in distributions and mineral concentration of the two Zones, the %TCu descriptive statistics were calculated and are summarised in Table 3.3 and the corresponding %TCu histograms shown in Figure 3.8, were generated for the two individual zone.

Table 3. 3 Descriptive Statistics for %TCu in Zone1 and Zone2

Zone	Variable	Nsamples	Min	Max	Mean	Median	Variance	Std Dev	CoV
Zone 1	%TCu	10255	0	21.82	4.67	4.64	3.46	1.86	0.4
Zone 2	%TCu	5666	0.1	16.17	3.35	3.16	3.15	1.18	0.35

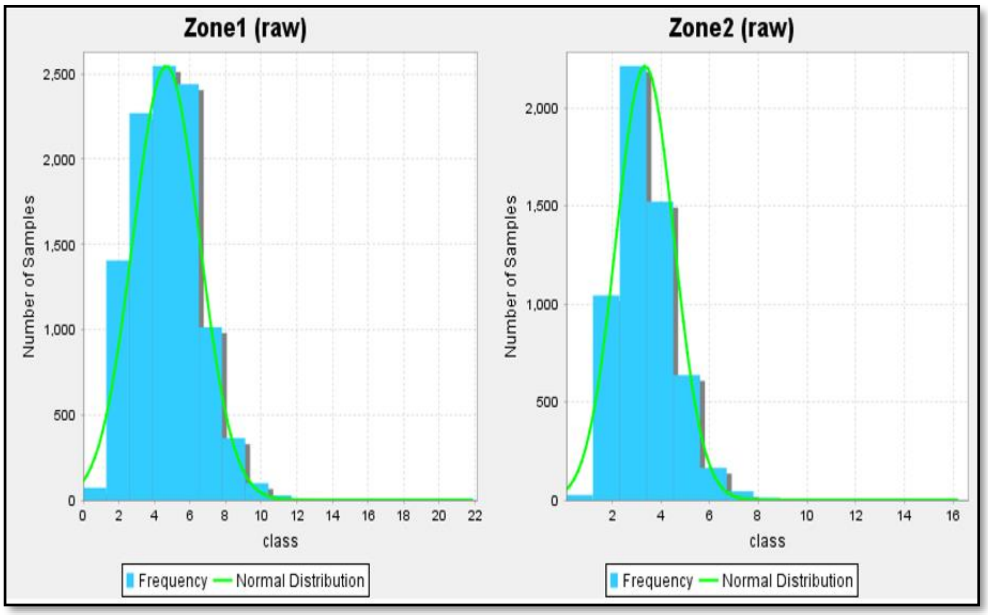


Figure 3. 8 %TCu Histograms and models for Zone1 and Zone2

From the summary statistics a difference in the mean values is observed, this difference is highlighted by the shift in the positioning of the histograms of Zone1 and Zone2 on the x-axis. The shape of the histograms are similar, however the highest frequencies in Zone1 occur between 3 %TCu and 8 %TCu and that in Zone2 between 2 %TCu and 5 %TCu. This shows that Zone1 has a higher and wider grade concentration compared to Zone2 which has a lower and narrower grade concentration. The box and whisker plot in Figure 3.9 below clearly confirms this observation, seen by shapes or positions of the box and whiskers for each zone.

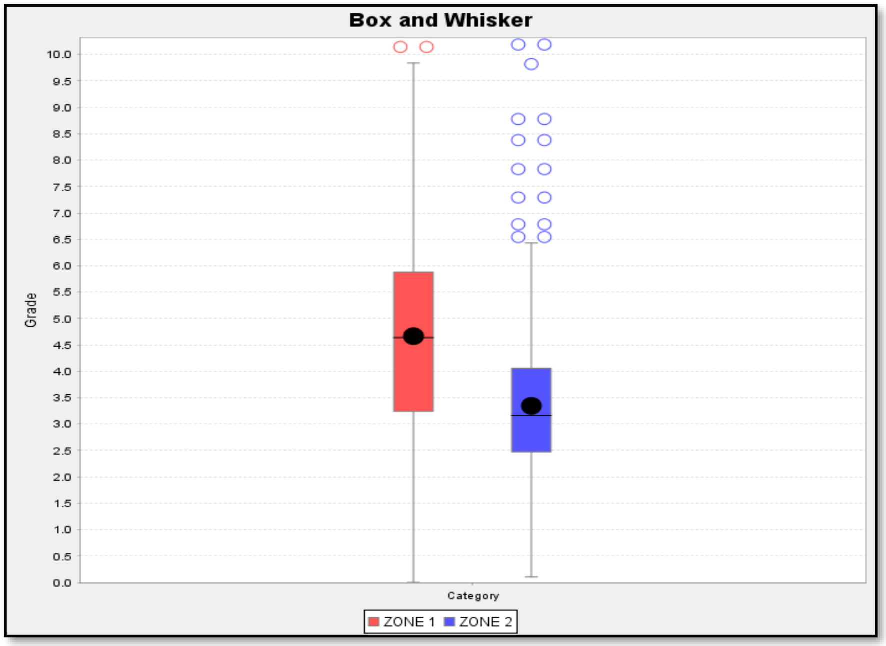


Figure 3. 9 The %TCu Box and Whisker plots for Zone1 and Zone2

The data in Zone1 has a higher dispersion than that of Zone2 therefore it is expected that the variogram for Zone1 to have higher variability when compared to that of Zone2.

Zone2 comprises of the two limbs of a fold therefore estimating the direction of greater continuity during variography will be difficult as the two limbs have different orientations. For the purpose of creating directional variograms, Zone2 was subdivided along the fold axis into two zones taking the total number of zones to three.

This is similar to the approach explained by Glass and Cornah, (2006) where a folded orebody was domained into limbs in order to define the orientation for the sake of variography. Individual variograms were then generated with orientation matching the dip and dip direction of the domains and the best variogram from the two fold limbs could be used to represent the both zones for the variable under study in this case %TCu. Figure 3.10 shows the three zones and their descriptive statistics summarized in Table 3.4.

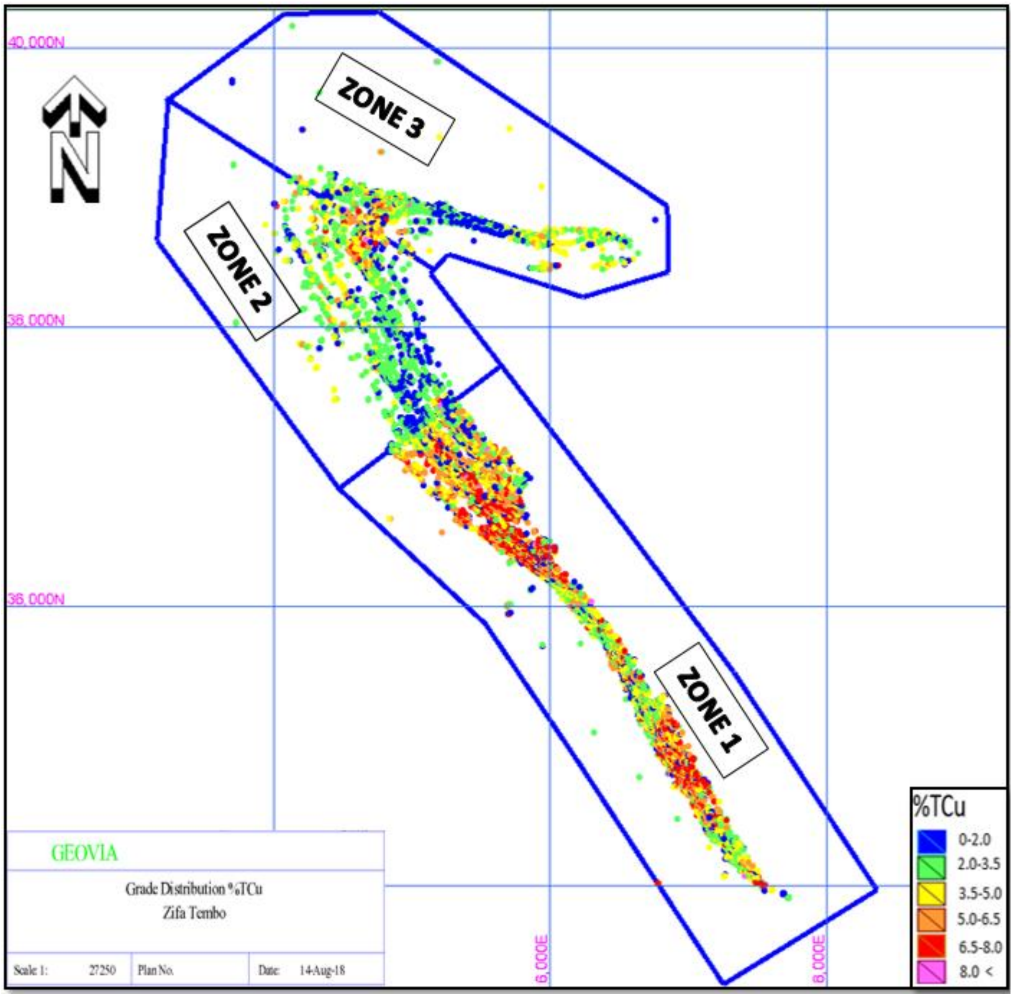


Figure 3. 10 Estimation and Structural domains: Zone1, Zone2 and Zone3

Table 3. 4 Descriptive statistics for the %TCu in the Zone1, Zone2 and Zone3

Zone	Variable	Nsamples	Min	Max	Mean	Median	Variance	Std Dev	CoV
Zone 1	%TCu	10255	0	21.82	4.67	4.64	3.46	1.86	0.4
Zone 2	%TCu	3322	0.1	10.88	3.28	3.08	1.42	1.19	0.36
Zone 3	%TCu	2344	0.76	16.17	3.43	3.29	1.36	1.16	0.34

The difference in grades between Zone1 and Zone2 and 3 is relatively high. Zone2 and Zone3 are very similar with mean values close and both have a low dispersion as can be seen from the descriptive statistics in Table 3.4 and the Box and whisker plot in Figure 3.11 below, confirm this interpretation graphically.

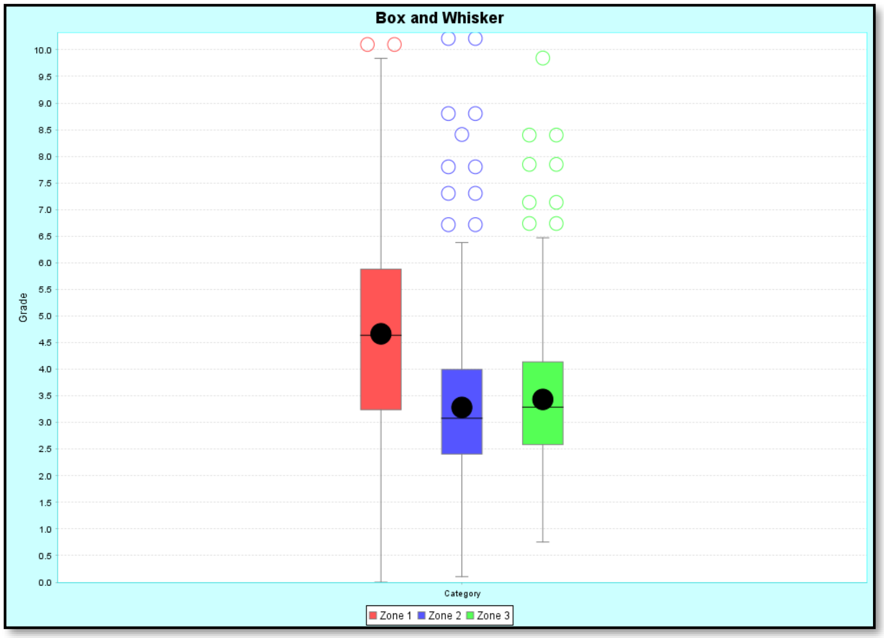


Figure 3. 11 Box and whisker plots for %TCu in the Zone1, Zone2 and Zone3

Though the Box and Whisker plots show outliers beyond 6.5%TCu for the two zones, these were not treated as extreme values as they were so close related to the other lower values and the outlier cut remained at 9.2%TCu as previously determined.

Three composite files were then prepared for each domain to use for the variography analyses. After domaining, the effect of the outlier values were reduced as the majority of them were confined to Zone1, which is the higher grade zone and thus keeping the variability in this zone within an acceptable range. Outlier values were retained and used in the spatial analysis and grade estimation

3.2 Geostatistics

This section focuses on the theory and application of geostatistical methods required to improve the understanding and measure of spatial variability within the deposit. Two data sets may have the same descriptive statistics but still be different in terms of spatial distribution or data roughness. Good understanding of the spatial variability within a data set improves prediction of unsampled areas and ultimately improve the accuracy of the resource model. Experimental and model variograms will be constructed in this section to produce 3D models of spatial variability and later quantify the variability to use in geostatistical interpolation.

The detailed theory of Geostatistics was first published by Matheron (1963). With its advancement over time, the purpose of modern geostatistical study in mining is to create high resolution numerical models that will use all available information to represent geologically realistic features (Boisvert *et al*., 2009). Before carrying out any serious geostatistical study, it is paramount that the theory of regionalized variables (Journel and Huijbregts, 1978; Isaaks and Srivastava, 1989; de Sousa, 1990) together with the four assumptions (Dohm, 2018b) on which all geostatistical techniques are based are well understood. Isaaks and Srivastava, (1989) defines a regionalized variable as one whose values are randomly distributed in space. These values have spatial locations, depend on each other, and specified by a probabilistic mechanism known as a random function.

The four assumptions to be satisfied before doing any geostatistical study are listed and described below (Dohm, 2018b):

1. Sample values must be measured with precision and be reproducible. This can be accounted for by administering repeats and duplicates;
2. Sample values are measured with accuracy and represents the true value of the sampled point. Level of accuracy can be checked by use of standards;
3. Sample collection is from a physically continuous and homogenous population of all possible samples. There should not be any sudden changes in the spatial characteristics to ensure estimation is done within known geological constraints; and
4. The values at sampled locations are related to values at unsampled locations.

In addition to the four assumptions, the principle of stationarity has to be satisfied.

Other factors to identify is the presence of outliers and trend in the data set, may affect the spatial variability analysis, if left unchecked.

3.2.1 Stationarity

The main objectives of doing a geostatistical research and modelling is to build numerical models, only after decisions relating to stationarity have been addressed. Boisvert and Deutsch (2011) defined stationarity as being a decision of how to pool available data for analysis. The assumption is that a pool of some data values within a given domain are representative of the entire domain. Geostatistical methods rely on this assumption, this is critical to ensure that there is representativeness and proper use of geostatistical tools available. According to Boyle, (2010), the assumption of stationarity is actually far more important in improving accuracy than that of determining optimal search radius, sample size, block size and block discretization. The level of stationarity may differ from one geostatistical interpolation method to the other; some may require strict stationarity (Simple kriging) where others may only require quasi-stationarity (Ordinary Kriging) which is assumed to exist in practice. Under strict stationarity, the mean of the random variable must be independent of location anywhere within the domain and under quasi-stationarity the variable is only constant within a limited distance known as the range (Journel and Huijbregts, 1978). Ordinary Kriging which is the interpolation method used in this research does not strongly emphasise stationarity; it depends on the neighbourhood (search range) to estimate the mean value and does not follow strict rules on stationarity.

An effective practice for achieving some level of stationarity is by domaining the data. The Konkola orebody was subdivided into three zones refer Section 3.1.4 to ensure that only similar data was used for both the variography and interpolation processes.

3.2.2 Variography

The process of mineral deposition results in a certain mineralisation pattern of spatial correlation, which is very important to the Mineral Resource evaluator to know and understand, prior to carrying out estimations. Therefore, the description and modelling of this spatial correlation pattern gives a better view of the mineralisation process and improves prediction of grade at unsampled locations

(Rossi and Deutsch, 2013). In order to be able to estimate the spatial correlation pattern, it is important to first understand the nature in which grade exists. Grade is a Random Variable (RV) whose uncertainty can be determined by a Random Function (RF). The RF is restricted to a RV that is within a deposit or domain that is considered stationary (Rossi and Deutsch, 2013), that is the RVs under consideration belong to the same statistical population. In Geostatistics, the tool mostly used to quantify the spatial correlation pattern of the mineralisation is the variogram. Barnes, (2004) defines a Variogram as a quantitative descriptive statistic represented graphically to characterize the spatial continuity or roughness of a data set. It defines the spatial variability between sample pairs within a given domain using the function:

$$2y(h) = \frac{1}{N(h)} \sum_{i=1}^{N(h)} [z(u_i) - z(u_i + h)]^2 \qquad 6$$

Where N(h) is the number of pairs, z(u_i) is the sample value at location u_i and $(u_i + h)$ is the second sample value at a location separated by the vector h.

The semi- Variogram serves many purposes during geostatistical estimation process as evidenced below:

- It provides a numerical and graphical measure of the continuity of the variable of interest within a deposit (Clark, 2009);
- The variogram can also be used in defining the block size and other QKNA parameters during block modelling (Glacken and Snowden, 2001);
- To verify the presence of trend in the data set (Deutsch and Wilde, 2011); and
- Can be used to determine optimum drilling grid for grade estimation.

When generating a semi variogram, practitioners should always validate the variogram with interpretations from the known geology (Dohm, 2018b). The variogram investigates and quantifies the geological information in numeric form for geostatistical purposes. In a case where a variogram is constructed with scarce data, the structural geological knowledge can be used to inform the local variograms

(Machuca-Mory *et al*., 2015). All effort is required to improve the quality of the variogram because it improves the estimation and simulation process.

3.2.3 Experimental and modelled Variograms

The variogram is the measure of geological variability over distance (Rossi and Deutsch, 2013). From the variogram the variability is measured as $\gamma(\mathbf{h})$ at a distance in a particular direction $\mathbf{h}$ see equation 6. The experimental variogram has two major components, the random component which gives measure of the nugget effect (C_0) and the structural component to which the range (a) is defined at a point it reaches the sill (C_1).

Three important steps have to be considered before calculating an experimental Variogram (Rossi and Deutsch, 2013).

- The data has to be properly understood from a geological perspective;
- A coordinate system has to be established because the variogram is computed in a coordinate system; and
- Domaining, Outliers and transformation of data should be considered.

Before setting up lag distances and directions of the exprimental semi-variogram calculations, it is cardinal to understand the drillhole pattern. The lag distance is usually set starting with the distance equal to the drillhole spacing or less. It is important to start with a smaller lag distance then steadily increase it until a better looking experimental variogram is selected. Keep in mind that maximum lag should not be more than half the length of the domain in any direction since the semi-variogram is only valid up to half the domain length. If the experimental semi-variogram is calculated for lags extending beyond this limit, the number of pairs in the calculation of the semi-variogram for theses longer lags reduces, resulting in unreliable estimates of the patial relationship for these lags and directions. In most cases it’s rare to find all paired samples at equal distance, a lag tolerance is used to control the capturing of the data at given lag distances.

The choice of direction of maximum continuity depends on several factors; The understanding of the geological interpretation (Dohm, 2018b), number of samples in the data set and software used (Rossi and Deutsch, 2013). If the deposit has anisotropy, three different directional distances will be generated by the variogram model that will became the main axes of the ellipsoid used during interpolation process.

Validating the experimental variograms with known geological information is important. Discrepancies that may arise between the known geology and the interpretation of the variogram model should be resolved before proceeding into Mineral Resource estimation. The four basic things to look for in variogram interpretation are cyclicity, trend, geometric anisotropy and zonal anisotropy (Rossi and Deutsch, 2013).

After calculation of the experimental variogram, a model is fitted on the experimental points to produce a continuous curve of the spatial variability. The model is important because Kriging and other geostatistical interpolators require a covariance or variogram value at all possible distances $(\mathbf{h})$ (Dohm, 2018b**.** The model will also guarantee that the Kriging variance is positive (Sinclair and Blackwell, 2002; Rossi and Deutsch, 2013) and smoothens out the fluctuations which could be as a result of sampling error (Sinclair and Blackwell, 2002**.** All the geological information observed from experimental variogram including nugget effects, anisotropy and trend should reflect in the modelled function $\gamma(\mathbf{h})$ (Rossi and Deutsch, 2013). There are several types of the variogram models including the Spherical model, Exponential, Gaussian and the linear models. The Spherical model is most commonly used model with the equation for a single structured with a nugget effect model shown below.

$$\gamma(h) = \begin{cases} 0 & if\ h = 0 \\ C_0 + C_1 \left[\frac{3h}{2a} - \frac{h^3}{2a^3}\right] & if\ 0 < h \le a \\ C_0 & if\ h > a \end{cases} \qquad 7$$

Where γ(h) represents variability, C_0 is the nugget effect, C_1 is the sill for structure one, a and h are the range and separation distances respectively.

For each of the three zones identified for Konkola, downhole variograms were constructed for estimation of the nugget effects see Appendix 7.1. Variogram maps were then generated to assist in determining the directions of maximum continuity long range at a low variability. Creating one variogram map for the whole deposit was impossible due to the different directions of continuity in each limb. See Appendix 7.2 for the variogram maps. Several experimental variograms were constructed in each zone and models fitted on them Appendix 7.3. The longest range or major (a_1) in this case representing grade continuity along strike was selected first, and then the semi major (a_2) was selected at 90 degrees or close to 90 degrees from a1 representing continuity down dip. The software aided the selection of the a_2. The selected axes were in tune with the expectations from geological interpretation of the area. Variograms along the vertical axis (a_3) to the orebody did not give sensible experimental variograms and their ranges were approximated with reference to the orebody thickness in each domain. Figures 3.12 to 3.14 show the experimental variograms and the fitted models from each of the three zones, the major: a_1 and the semi major: a_2.

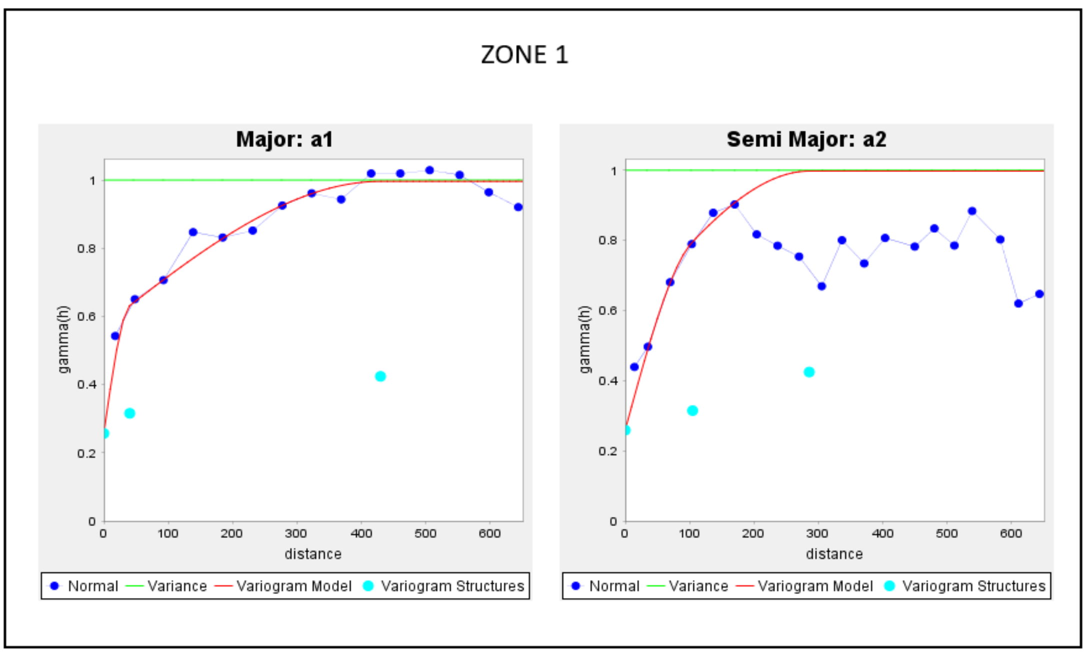


Figure 3. 12 Experimental variogram with a fitted model on Major and Semi Major for Zone1.

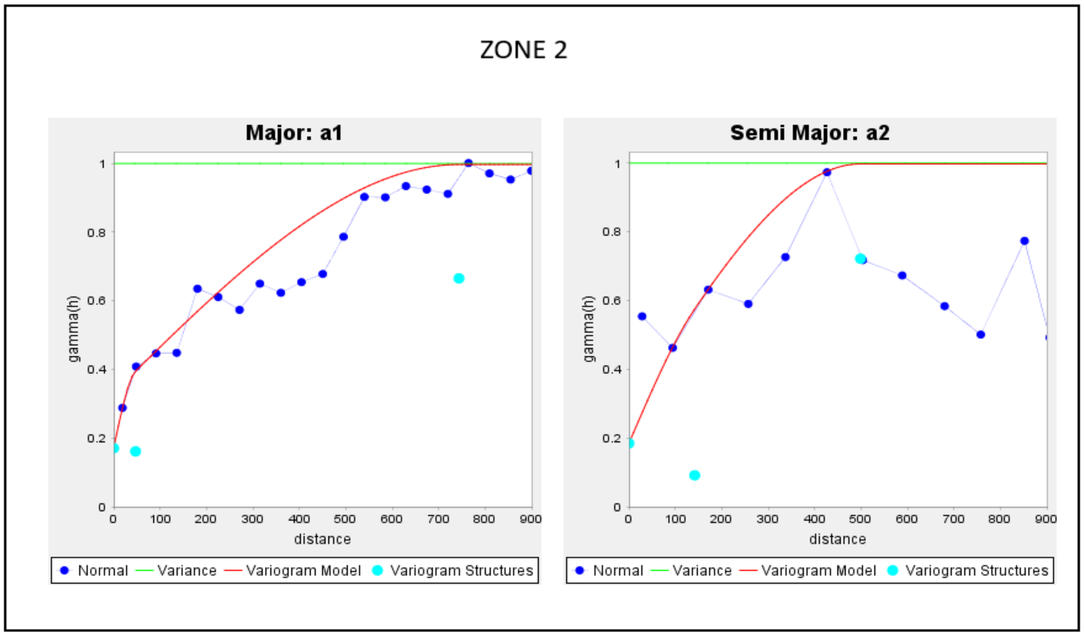


Figure 3. 13 Experimental variogram with fitted model on Major and Semi Major for Zone2.

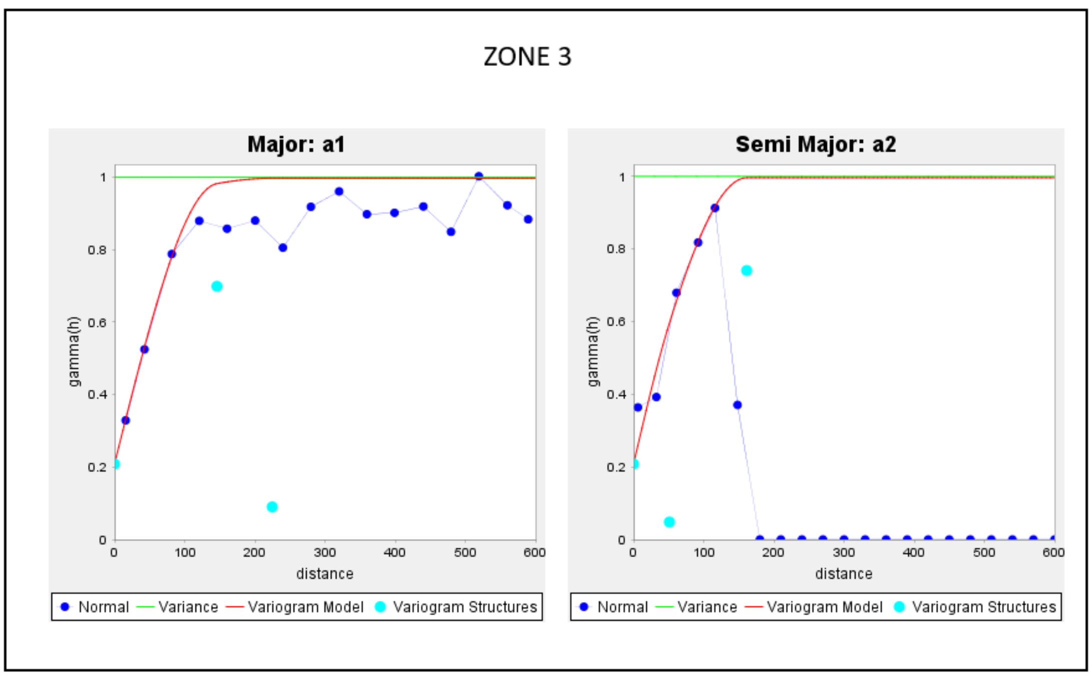


Figure 3. 14 Experimental variogram with fitted model on Major and Semi Major for Zone3.

The following observations were made from the variogram models.

- The variograms showed geometric anisotropy behaviour in all on the three zones. Zone2 has the longest range meaning it has highest spatial continuity and Zone3 has the shortest range meaning shortest spatial continuity. See Table 3.5 below for the summary ranges;

- The variograms showed relatively low nugget effect in all the zones see Appendix 7.1 for downhole variograms. Zone1 had a slightly higher nugget and this could be as the results of the 2200mN and 2700mN faults that according to literature Torremans *et al.,* (2013) played a major role in the redistribution and remobilisation of the mineralisation. This could have affected the uniform concentration of the minerals in this zone;

- The variogram models in all the zones were fitted using two structures. This could represent the multiphase mineralisation process experienced in this region (Cailteux *et al.*, 2005; Selley *et al.*, 2005);

- All the variograms stabilized at the sill or slightly below the sill which is a sign of no trend in the data except for semi major experimental variogram for zone 3 in Figure 3.14 which drop to zero (h) beyond the range of 150m. This is because Zone3 has only few samples down dip and beyond 150m there were no pairs thus the semi-variogram could not be calculated hence the zero values. The few high-grade outliers in Zone1 around the fault zone did not affect the quality of the variogram because of data robustness introduced by separating this zone. The importance of robustness in semivariogram construction has been explained by Sinclair and Blackwell (2002); and

The strike, dip and plunge, variograms showed that continuity was along the strike of the fold limbs and not down dip. This is in line with literature by Mwango (2011) in his report titled "structural and sedimentary controls of the copper-cobalt mineralisation at Konkola mine".

Table 3.5 below shows the variogram model parameters that were used in the estimation process.

Table 3. 5 Variogram model parameters of %TCu

							Range 1		Range 2	
Zone	Strike	Dip	Plunge	C0	C1	C2	X	Y	X	Y
1	327	55	-0.2	0.255	0.324	0.419	37.96	24.81	447.39	292.41
2	328	34	0	0.186	0.158	0.654	51.19	34.82	735.22	500.15
3	97	67	8	0.201	0.694	0.103	147.22	100.84	236.52	162.00

3.3 Quantitative Kriging Neighbourhood analysis

A Quantitative Kriging Neighbourhood analysis (QKNA) is conducted to minimize conditional bias that results from smoothing of grade during the Kriging estimation process. It is a mandatory step in setting up any Kriging estimate (Vann *et al.*, 2003). The process of interpolating grades from the point drillholes to blocks, results in conditional bias if the Kriging parameters such as block size, search radius, minimum and maximum number of samples and block discretization points are not optimum. Therefore, the main objective of QKNA is to determine what optimum combination of the kriging parameters is required to minimize conditional bias.

Conditional bias can be reduced by assessing measures which are calculated for each block within a block model. These conditional bias measures are SLOR and the KE and the parameters that influence them are the size of the estimation block, the search radius, number of samples and percentage of negative weights, block discretisation and KV. The weight of the mean in Simple Kriging did not play a role in this research report where Ordinary Kriging has been applied.

These measures and neighbourhood parameters have been discussed by several authors and are determined using a QKNA (Vann *et al.*, 2003; Hosken *et al*., 2006; Coombes and Boamah, 2015; Dohm, 2018b).

In this research, the SLOR and KE were assessed to identify the optimum block size, search radius and the minimum and maximum number of samples, least percentage negative weights and the block discretization points based on the Kriging Variance.

Slope of Regression

SLOR measures the bias between the theoretical true block grades and the estimated block grades (Hosken *et al.,* 2006). They explained that if a 1:1 relationship occurs between the true block grades and the estimated block grade then the slope approaches one. They further said that when the SLOR approaches zero then the estimated block shift towards the global mean grade and the difference between the true block grades and the estimated grades is high. The equation of the slope is expressed in terms of the covariance of the true block grade and estimated block grade and the variance of the estimated block as shown in equation 8.

$$Slope\ of\ regression\ =\ a = \frac{Cov(Z_v, Z_v^*)}{Var(Z_v^*)} \qquad 8$$

Z_V = true block grades for block volume V

Z_V^* = estimated block grades for block volume V

To get a SLOR close to one, there should be enough samples in the selection search during the estimation process meaning data should not be sparse. Boyle, (2010) recommends that if the data are sparse, the search should be increased until improvement in estimation and the SLOR is observed.

Kriging Efficiency

KE measures how well the histogram of the theoretical block grades matches the histogram of the estimated block grades (Hosken *et al*., 2006). The authors said that if the KE approaches 100%, it reflects a high quality estimation and correct classification at a given cut off. On the other hand, when KE approaches zero that is indicative of a poor estimate and high level of misclassification.

The equation for KE is expressed as:

$$Kriging\ Efficiency\ =\ KE = \frac{BV - KV}{BV} \qquad 9$$

BV = Block variance for block

KV = Kriging variance of the estimate

A systematic approach was followed in carrying out the QKNA in this research and is similar to that proposed by Hosken *et al*., (2006).

3.3.1 Block Size Optimisation

The final product of a geostatistical evaluation work is a resource/grade control block model that can be used to report in situ resource tonnage and grade estimates. Block models are made up of a combination of unit blocks or cells that have a centroid (coordinates at the centre of the blocks) which stores all the necessary attributes such as the grades, density etc. The decision on how far apart the centroids should be depends on the block size selected for the model. Hasty selection of a block size may result in conditional bias, affecting the final estimation results. It is therefore important to understand that the block size is critical especially in cases where a cut-off grade will be applied (Vann *et al*., 2003). A number of factors influences the ultimate selection of block size:

- Assessing Ordinary Kriging output for example SLOR and KE;
- Minimum mining width (Stope size or Bench height); and
- Drilling Spacing.

A drilling spacing of 25m x 25m x 10m was assumed for the Konkola orebody. A block discretization of 5m x 5m x 4m was selected with the minimum number of samples fixed at five and maximum at 100 and a search radius equal to the variogram ranges. In the QKNA process, tests were then conducted on a range of block sizes starting with the smallest block size of 12.5 x 12.5 x 10. As the rule of thumb, the smallest block size should not be smaller than half the drilling distance (Dohm, 2018b). The results of the test have been plotted in Figure 3.15 showing the SLOR and KE at different block sizes.

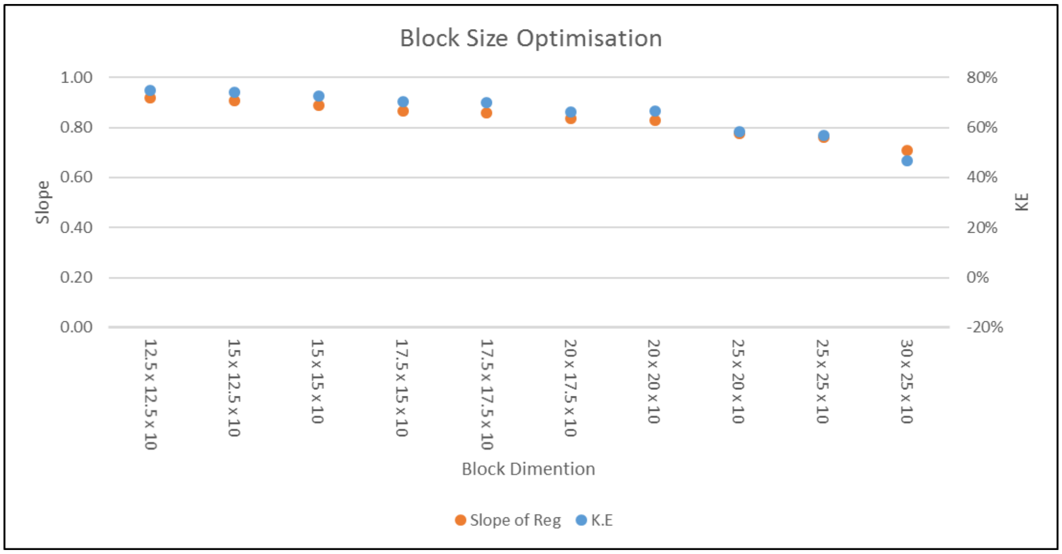


Figure 3. 15 Block size optimisation

A block size of 15 x 15 x 10 was selected as the optimum size. It is observed that from the smallest block size up to the selected optimal size there is very little change in the SLOR and KE, after that there is a drop in KE as block size increases. This block size also suits well with the mining stope sizes, which vary from 15m to 20m.

3.3.2 Search Radius Optimisation

All interpolation techniques that seek to estimate grade into a block or point depend on some kind of sample search procedure except of nearest neighbour method. The search range determines how many samples to include into the estimation though at times limited by the maximum number of samples. Most importantly is that it determines how far the sample search should go. There is danger in searching beyond uniform geological and mineralisation zones and this can cause serious errors in the final estimates. In determining the maximum search radius usually the variogram range is used as a guide for the limits (Khakestar *et al.*, 2013). The selected optimum radius can either be less than or equal to the variogram range. If the selected search radius is smaller than the variogram range, one must be mindful not to have it too restrictive as it can result in conditional bias. Similarly, if the search is unconstrained it may result in conditional bias by over smoothening the grade. Kriging is commonly referred to as a ‘minimum variance estimator’ but this holds only when the neighbourhood is properly defined (De-Vitry, 2003).

In the QKNA process, tests were carried out to determine the optimal search radius for each zone. The block size was kept at a constant of 15m x 15m x10m at a discretization point of 5m x 5m x 4m and the minimum number of samples to five and maximum to 100. Figure 3.16 below shows the plot of the results from the Ordinary Kriging for the SLOR and KE at different search radii Zone1.

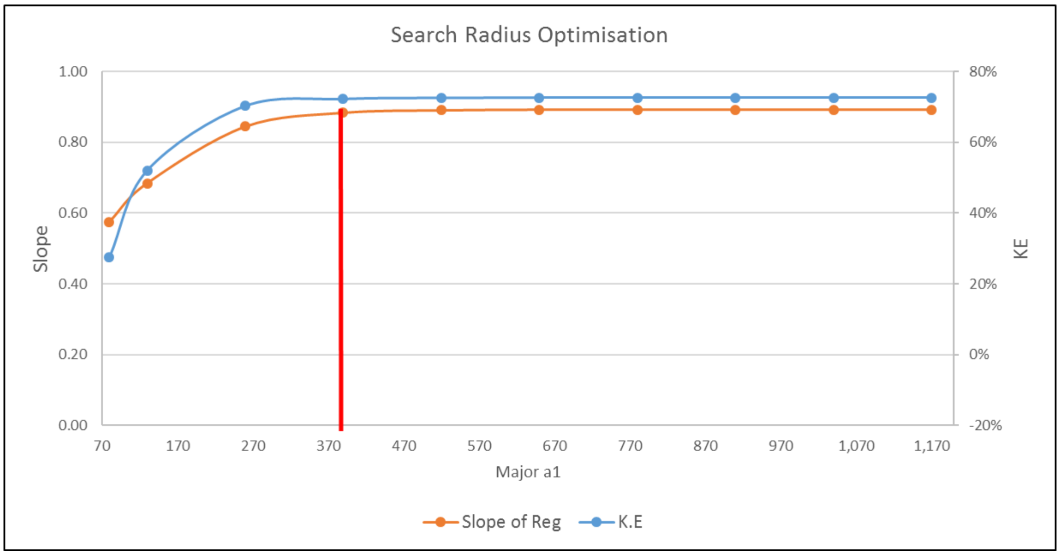


Figure 3. 16 Neighbourhood search radius optimisation Zone1

For Zone1, the selected optimal search radius is 390m x 255m x 7m. Beyond the 390m, there is no significant change in the SLOR or the KE therefore increasing the radius will not improve the estimation but instead force the ellipsoid to search in zones having different characteristics.

For Zone2, the selected optimal search radius is 520m x 350m x 7m with same explanation as that of Zone1, see Appendix 7.4 for the Zone2 and Zone3 plots. For Zone3, optimal search radii were identified as 370m x 250m x 7m but this is beyond the variogram range of 236m x 162m x 7m. The author decided to use the modelled variogram ranges as the optimum for Zone3.

3.3.3 Optimisation of the number of samples in the kriging Neighbourhood

When a constant search radius is applied to all the blocks or points being estimated, it is very important that the number of samples used in the estimation be regulated. An optimum minimum and maximum number of samples has to be defined so that only necessary required sample size is used. Blocks or points that may not reach the minimum number of samples are not be estimated and no extra samples are included beyond the maximum limit. Too few samples may increase the KV and too many samples may increase the number of negative weights and overall increase on computing time during interpolation. Increasing the number of samples beyond the optimal maximum can greatly affect the estimation results. According to a case study done by Boyle, (2010) on the Jura data set, a decrease in the estimation accuracy was observed as more samples were used beyond the optimum and smoothing of the estimated values increased.

In the QKNA process, tests were conducted to determine the optimal number of samples for each zone. The block size was kept at a constant of 15m x 15m x10m at a discretization point of 5m x 5m x 4m and the search radius equal to the variogram ranges for each zone. Figure 3.17 below shows the plot of the results from the Ordinary Kriging the SLOR, KE and negative weights at different number of samples.

For Zone1, the author selected a minimum of 12 and maximum of 46 as the optimal number of samples to be used in an estimation process. Samples below the minimum of 12 would give very low SLOR and KE and may ultimately give a wrong estimate. At the same time, including samples beyond 46 would not significantly improve the estimate as there is little improvement in terms of the SLOR and the KE but instead it will only increase the percentage of negative weights. Negative weights are not a threat if they represent in small proportion say $< 5\%$ of the total weight (Vann *et al.*, 2003).

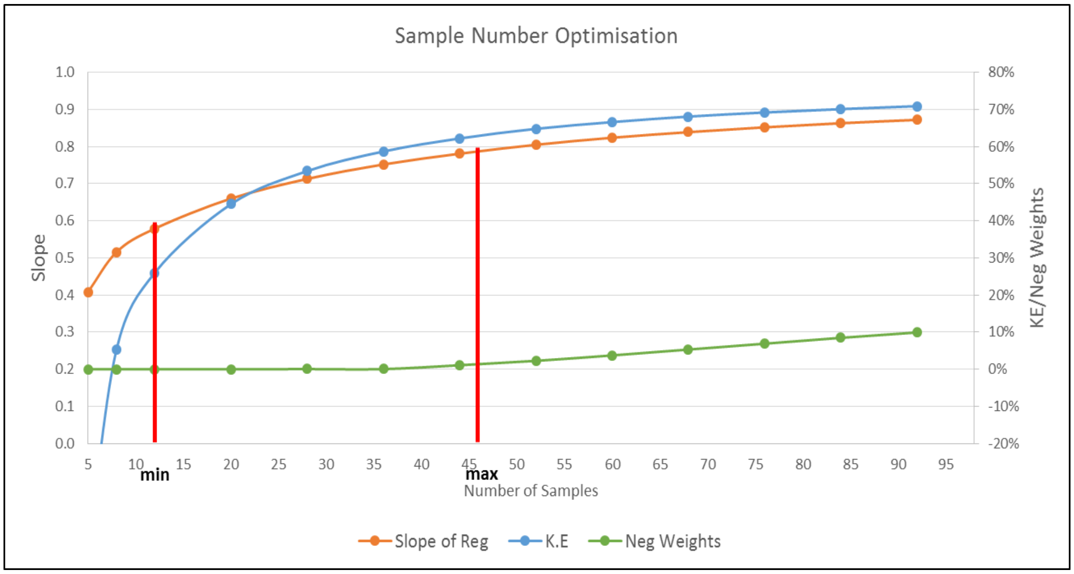


Figure 3. 17 Sample number optimisation Zone1

For Zones2 and 3 the author selected 10 and 12 as the optimal minimum, 40 and 44 as the optimal maximum number of samples see Appendix 7.5 for the plots.

3.3.4 Block Discretization Number Optimisation

Discretization of a block in kriging is used to calculate the average values of the point block of the covariance or variogram function given as $\bar{C}(x,V)$ or $\overline{\gamma}(x,V)$ (Vann *et al*., 2003). According to them, higher discretization are generally better with the only set back being the computing speed.

In the QKNA process, tests were carried out to determine the optimal number of discretization points for the optimal block size. The block size were kept at a constant of 15m x 15m x10m with a minimum of five and maximum of 100 number of samples and the search radius equal to the variogram ranges. Figure 3.18 shows the plot of the results from the Ordinary Kriging variance at varying block discretization points.

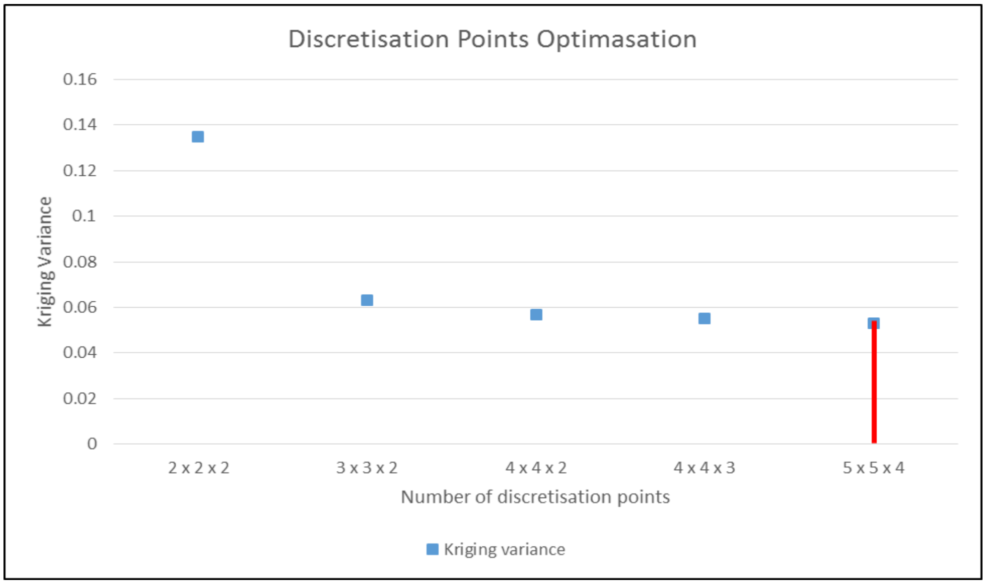


Figure 3. 18 Number of discretization point optimisation

A discretization point of 5m x 5m x 4m was selected of which five is the highest discretizing point that can be accepted in Surpac software version 6.9.

The final and optimal Kriging neighbourhoods for the different zones are summarised in Table 3.7 as determined from the Kriging neighbourhood analyses discussed in the previous subsections.

Table 3. 6 QKNA results

Zone	Block Size	Block Discretisation	Search Radius	Sample Min	Sample Max
1	15 X 15 X 10	5 X 5 X 4	390 X 255 X 7	12	46
2			520 X 350 X 7	10	40
3			370 X 250 X 7	12	44

3.4 Grade Estimation

In reality, only a small percentage of volume from an entire deposit gets to be sampled. The grade and other spatially correlated attributes must be estimated in the unsampled areas in order to have continuous attribute values at each point within a deposit. Grade estimation is very important because it enables segregation between waste and ore material and most importantly to predict the future tonnage and grade for planning purposes. Estimation processes vary from one deposit to another because of the difference and unique geological variability in each deposit. Classical and geostatistical studies precede the estimation process and are conducted to understand the spatial variability within the deposit, and select the appropriate estimation methodology.

The two types of estimates used are Global estimation and Local Estimation (Dohm, 2018a, 2018b). Global resource estimation is usually the first step in determining the viability of the project. According to Dominy *et al*., (2002), at this stage the objective is to obtain the global resource estimate and an estimate of the grade-tonnage curve within a deposit. In most cases, there is insufficient data for local estimation in the early stages. Local Estimation of resources takes place when there is sufficient data to allocate estimates to blocks or SMUs. These estimates are required at feasibility and pre-production planning stage for detailed mine design and mine scheduling.

This research report is considering the local resource estimation processes using traditional Ordinary Kriging on first model and the DA methodology on the second model. Detailed literature on the estimation method is documented under Literature review in Chapter one. To ensure that the estimates are correct, carrying out estimations within a zone of uniform mineral concentration is necessary. Zone1 and Zone2 were separated based on the difference in mineral concentration. In order to determine the type of boundary (soft or hard) to be applied between the two zones, Contact analysis must be conducted to decide which type of boundary to use.

3.4.1 Contact Analysis

Contact analysis is a technique used in deciding on data constraining during estimation. The decision on whether to restrict data to a particular zone or allow data interpolated across zones is critical. The definition and treatment of boundaries have implications on resource estimation such as lost ore, dilution or mixing of geological populations (Rossi and Deutsch, 2013). The Contact analysis results reveal the kind of boundary to use between zones either a soft or a hard boundary. Soft boundaries allows data from neighbouring zones be used during interpolation whereas hard boundaries restrict data to a specific zone. Sometimes the boundaries to use can be predicted from the geological knowledge, but it is important that it be confirmed with statistical contact analysis (Larrondo and Deutsch, 2005 cited in Rossi and Deutsch, 2013).

The contact analysis methodology followed in this research was along the methodology as the one outlined by (Rossi and Deutsch, 2013). They used trend analysis to determine what kind of boundary to apply between zones. The analysis is done near the boundary of each zone, because that is where data sharing between zones usually takes place, and restricted inwards by search radius. If at the contact line, the two trends from the zones meet nearly at the same point or grade and show at least similar trend near the contact then soft boundaries may apply. If at the contact line the trend from the two zones, meet at different points or grades and show different trends near the contact, hard boundaries may be the alternative.

The contact analysis for this research was done to identify the boundary type between Zone1 and Zone2. The statistical analysis of the box and whisker plots in Section 3.1.3 showed that two zones have different mineral concentrations. A trend analysis was done and the graph in Figure 3.19 shows the trend results from the two zones intersecting the contact line x= 0. The two zones intersect the contact line at different grades and show different trends away from the contact. The author decided to use a hard boundary approach between the two zones to avoid underestimation in Zone1 and overestimating Zone2.

A contact analysis for the contact boundary between Zone2 and Zone3 was not done as the two were divided on structural basis and they showed to have similar mineral concentration as seen from the box and whisker plots in section 3.1.3. The author applied a soft boundary between these two zones.

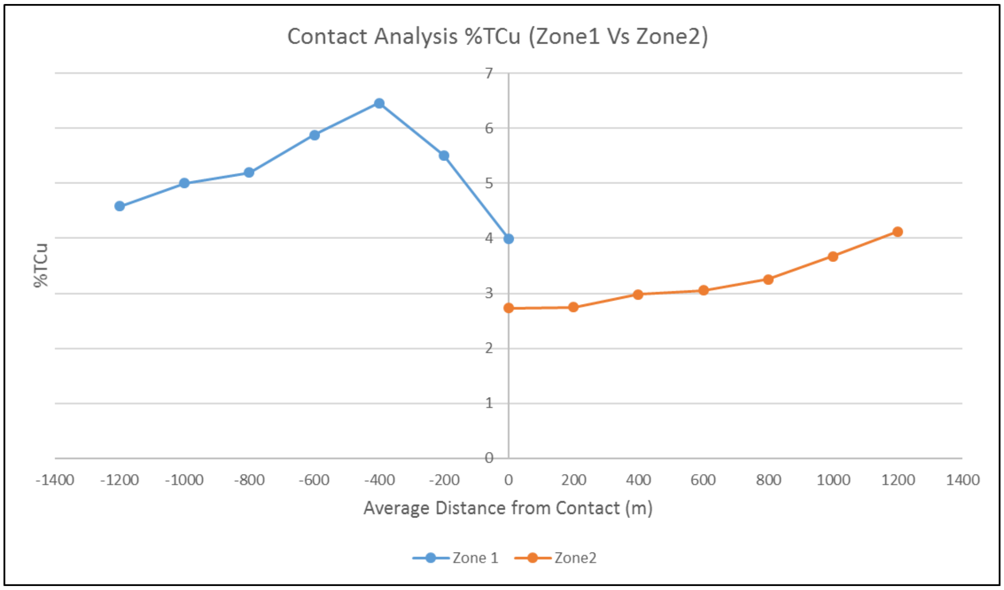


Figure 3. 19 Contact Analysis for Zone1 and Zone2 boundary

A block model was created to estimate TCu_OK using the traditional ordinary kriging with fixed search ellipses and another to estimate TCu_DA using the DA methodology for estimation. Literature on Ordinary Kriging and DA estimation methodology is documented in section 1.4. A systematic process on how to carry out the DA interpolation methods is also outlined in the same section.

4 Comparative Analysis of the Estimation Results based on Traditional OK and DA

This chapter focuses on a comparative analysis of the estimation results derived from the traditional OK and DA methods. Adopting a new interpolation method does not always mean an improvement in grade accuracy even if the proposed new method has a technological advantage over the current method as was the case with Mandava, 2016.

It was therefore important for the estimates from the proposed new DA method and from the current OK method to be compared against the input composite data to assess if there is any significant change. These comparative checks were done to assess which methodology resulted in more accurate and realistic estimates. Further checks were done to ascertain the financial benefit realised from the adoption of the DA methodology for Konkola mine.

4.1 Estimation Validation

Five estimation validation checks were performed; four statistical and one visual inspection test to validate the estimate results against the input composite sample data. For a fair comparison, the validation checks were done only on the blocks that contained both OK and DA estimates. The five validation methods used were: Global Statistics, Swath Plots, Scatter Plots, Distribution of Differences and Visual Inspection

4.1.1 Global Statistics total area

Global statistics were calculated to see how the overall statistical parameters from the estimates compare with the statistics from the input composite data. Descriptive statistics were generated from the OK and DA estimates and these together with the composite input data statistics are recorded in Table 4.1 below.

Table 4. 1 %TCu Global Statistics – all three zones combined

Variable	Nsamp	Min	Max	Mean	Stddev	CoV	%(Samp mean - Est mean)
TCu sample	15948	0.000	21.819	4.193	1.768	0.422	
TCu OK estimate	39062	1.767	7.897	3.857	1.071	0.278	8.01%
TCu DA estimate	39062	1.709	8.184	3.865	1.088	0.281	7.83%

The following observation were made from table 4.1.

- The estimates gave a higher minimum and a lower maximum values compared to the input composite data because of the change of support effect going from point to blocks in the estimation process and also due to smoothing effect caused by kriging process;
- The average grade from the estimates is lower than the one from the input composite data with a difference of 8.01% and 7.83% for the OK and DA

interpolation respectively. This is because of the smoothing effect from Kriging;

- The global estimates individually do however, compare well 3.857%TCu and 3.865%TCu for the OK and DA respectively, a difference of 0.008%TCu;
- The percentage difference between the global estimates using the OK and DA methodologies is insignificant at a 0.21%; and
- The standard deviations and CoV from the estimates is lower than that from the input composite data. This is to be expected due to the change in support effect which reduced variability between the blocks as compared to the sample to sample variability which is high.

The statistics for the composites in the individual zones were discussed in section 3.1.4. To assess the estimation methodology results obtained within the three zones individually Table 4.2 was generated and shows the statistics from the estimates and input composite data for each zone.

Table 4. 2 %TCu Global Statistics for the individual zones

Zone	Variable	Nsamp	Min	Max	Mean	Stddev	CoV	%(Samp mean - Est mean)
Zone1	TCu sample	10,255	0.00	21.82	4.67	1.86	0.40	
	TCu OK estimate	19,468	2.25	7.90	4.46	1.04	0.23	4.35%
	TCu DA estimate	19,468	2.16	8.18	4.48	1.05	0.24	4.07%
Zone2	TCu sample	3,322	0.10	10.88	3.28	1.19	0.36	
	TCu OK estimate	15,121	1.77	5.89	3.24	0.71	0.22	1.40%
	TCu DA estimate	15,121	1.71	5.72	3.25	0.75	0.23	0.97%
Zone3	TCu sample	2,344	0.76	16.17	3.43	1.16	0.34	
	TCu OK estimate	4,556	1.91	6.03	3.33	0.63	0.19	3.00%
	TCu DA estimate	4,556	1.99	5.59	3.29	0.61	0.19	4.21%

The following observations were made from Table 4.2.

- The difference between the kriged estimates and the sample data reduced when the zones are considered individually. The calculated difference between the estimated means and the sample means reduced to less than 50%

than that of the combined global statistics in Table 4.1. In Zone2 the means of the estimates and the samples were the closest;

- The DA estimates gave a closer comparison to the sample data for Zone1 and Zone2 whereas the OK estimates gave a better comparison for Zone3; and

- The percentage difference between the OK and DA with in the individual zones are 0.45% in Zone1, 0.31% Zone2 and 1.2% Zone3. Whilst these are larger than the difference on a combined global comparison, individually within the zones there have been overall improvements in both estimation methodologies which are related to the domaining discussed earlier in order to achieve homogeneity and stationarity, this increase is not considered to be of concern. The information from the global statistics only assisted to determine the accuracy of the methodology at a larger scale and any variations in estimates resulting from structures embedded with in the global scale could not be captured. At this stage, it was very difficult to tell which method was more accurate since the results between the estimates were close for both the combined global statistics and for the individual zones.

4.1.2 Swath Plots

Swath plots compare trends of estimates and sample data to determine how accurate the estimation is. It computes the mean grade of the estimates and sample data within a defined interval and compares them by producing trend in a chosen direction. Swath plots were constructed one for the various zones. The zones were analysed separately to cater for the variations in strike and also gave good resolution on the local changes. The Zone1 swath were oriented from south to north cutting along strike from 3400mN to 37500mN at an interval of 200m. The same orientation and interval length was used for Zone2 ranging from 37500mN to 3900mN. Zone3 has a different orientation with a strike trending east to west. The swath were aligned cutting across the strike from 4200mE to 4600mE at an interval of 200m. Figure 4.1 shows the swath orientation and spacing for all the three domains. The swath validation results for the three zones combined are plotted in Figure 4.2.

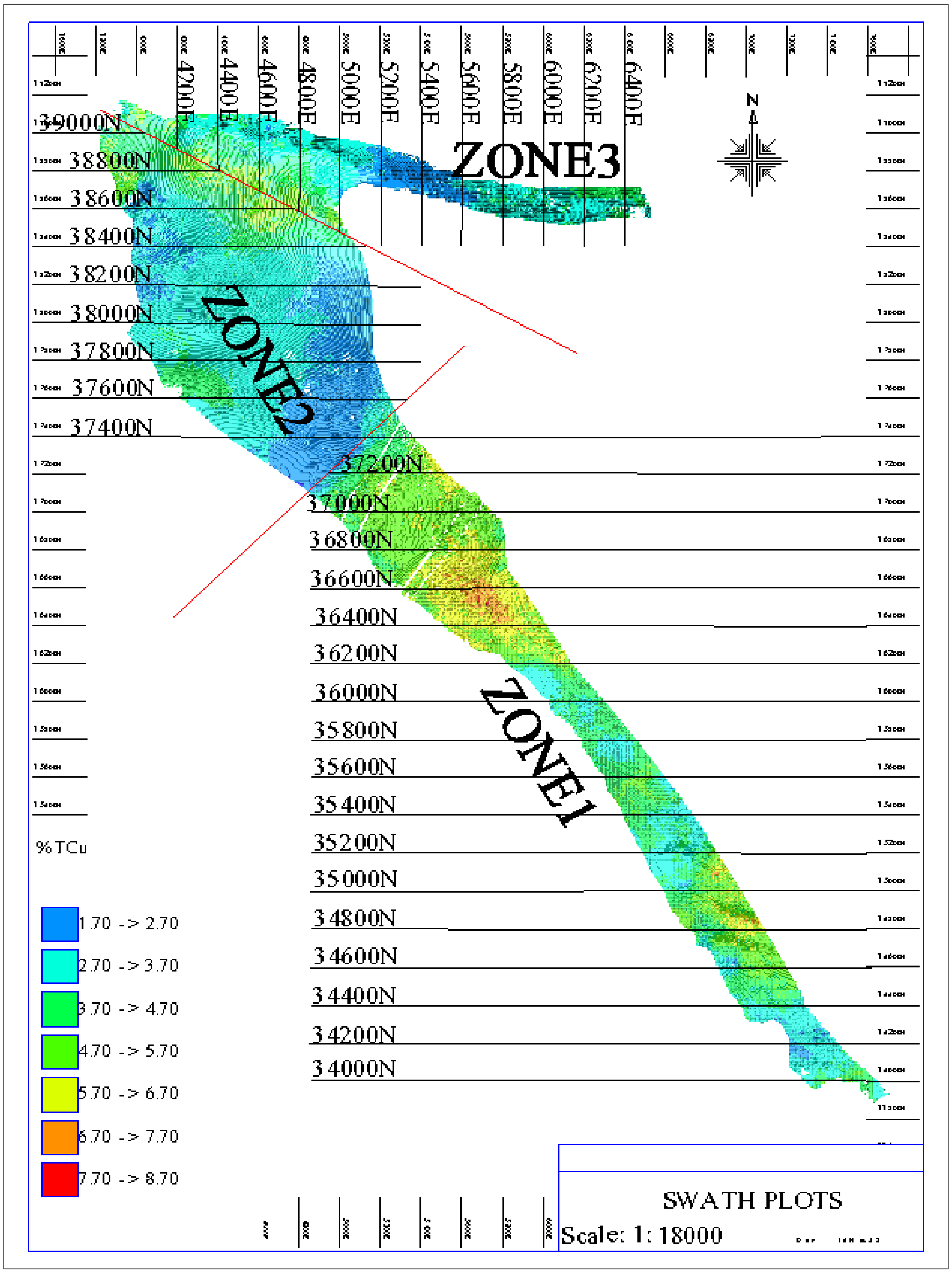


Figure 4. 1 Swath orientation and spacing

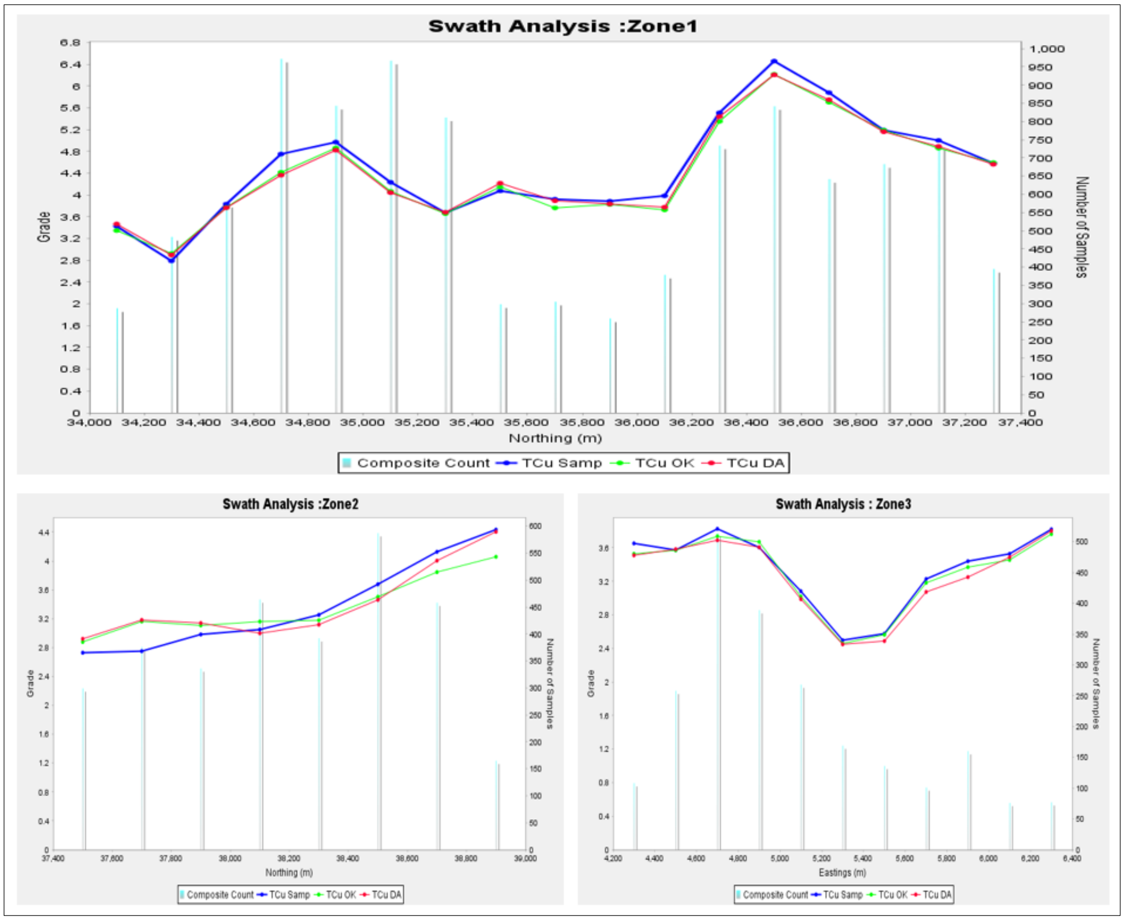


Figure 4. 2 Swath plots for Sample data vs OK and DA estimates.

The following observations were made from Figure 4.2.

- There is an overall close correlation between the estimates and the sample data revealing that the estimation from both methodologies are good. The only portion that did not give a good correlation was the southern and northern ends of Zone2 which showed a slight overestimation and underestimation of grade respectively.
- Zone1 is a close tie and it was very difficult to tell which method compared better with the sample data. For Zone2 the DA showed better results between 38800mN and 39000mN though it could not be justifiable due to a low number of samples. OK estimate in Zone3 showed a closer trend to the sample data which was in connection to the zone3 global statistics.

- The relationship between the OK and the DA swath was very tight, and it was still difficult to tell which method was more accurate at this point.

The swath plot interval of 200m was at a much smaller scale of analysis as compared to the global statistics. The plots assisted to determine accuracy at specific locations across the deposit. The two methodologies both gave a close trend to the sample data and it was difficult to actually tell which methods did better overall. There was no exact position that gave a significant difference between the two methods to justify accuracy.

From the swath plots results, it was still not easy to distinguish which methodology gave more accurate estimates. An attempt to reduce the interval spacing produced plots with very random sample trend which were not very useful. A better option was to extract the estimates and sample data at a smaller interval and represented it inform of scatter plots.

4.1.3 Scatter Plots

Scatter plots are simple but very effective way to determine the correlation between different datasets. The strength of the relationship is determined by observing how clustered together or scatter the points are. Clustered points mean good correlation and scattered points mean poor correlation between datasets. The relationship can be quantified by calculating the correlation coefficient R which ranges from -1 to +1 depending on the kind of relationship between the datasets being examined. R value close to +1 mean a positive relationship and a value approaching -1 indicate a negative correlation between datasets. A linear regression line y=x is inserted for the bias fit between the two data sets.

The mean values were extracted at every 20m interval throughout the deposit to produce three data sets containing sample values and estimates from the OK and DA interpolation. Two scatter plots were generated for the samples vs OK estimates and for samples vs DA estimates. A linear regression line was inserted, and correlation coefficients calculated. The two scatter plots are shown in Figure 4.3.

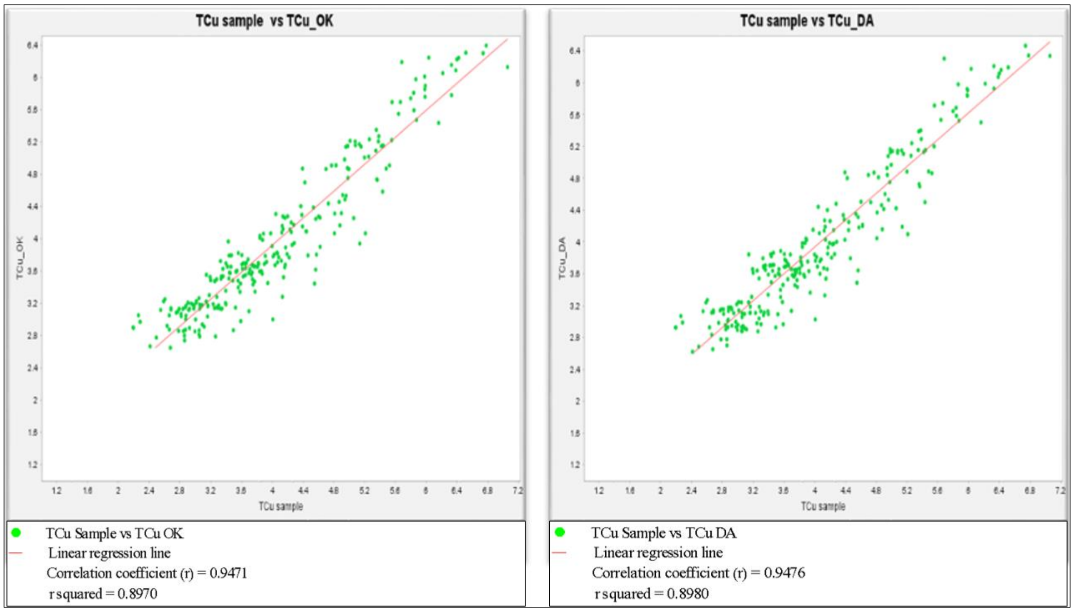


Figure 4. 3 Scatter plot Sample data vs estimates, OK on the left and DA on the right

The following observations were made from Figure 4.3.

- Both scatter plots show a strong relationship between the estimates and the samples. Sample vs OK gave R of 0.9471 and sample vs DA gave R of 0.9476;
- No biasness was observed between the sample and estimates as the scatter points plotted along the line of regression; and
- The DA gave a better R value with a 0.005% difference which was insignificant to ultimately conclude whether the DA is a better method than the OK.

Even after reducing the scale to a smaller interval of 20m, there was still very little difference between the estimates of the two methodologies. The DA gave a slight better R but the difference of 0.005% in R between the two methodologies was not significant to make any justifications. It was still very difficult to make a decision on which one was a more accurate methodology based on the scatter plots. Reducing the interval from 20m to 10m did not significantly affect the difference between the R values from both estimates.

4.1.4 Distribution of Differences

The distribution of differences is expressed as a relative frequency polygon were the relative frequency plots on the y axis and the x-axis is the class midpoint of the differences. If the mean value for the distribution plots at zero or close to zero with a narrow sharp and a high relative frequency, then there is very little difference between datasets in this case the estimate values are close to the input sample values.

The sample data and block estimate average grade were extracted at every 10m interval to produce three datasets, sample, OK and DA. The average OK and DA estimate values were then subtracted from the average samples for the corresponding interval to produce two datasets of differences. Relative polygonal plots were then generated from the datasets as shown in Figure 4.4.

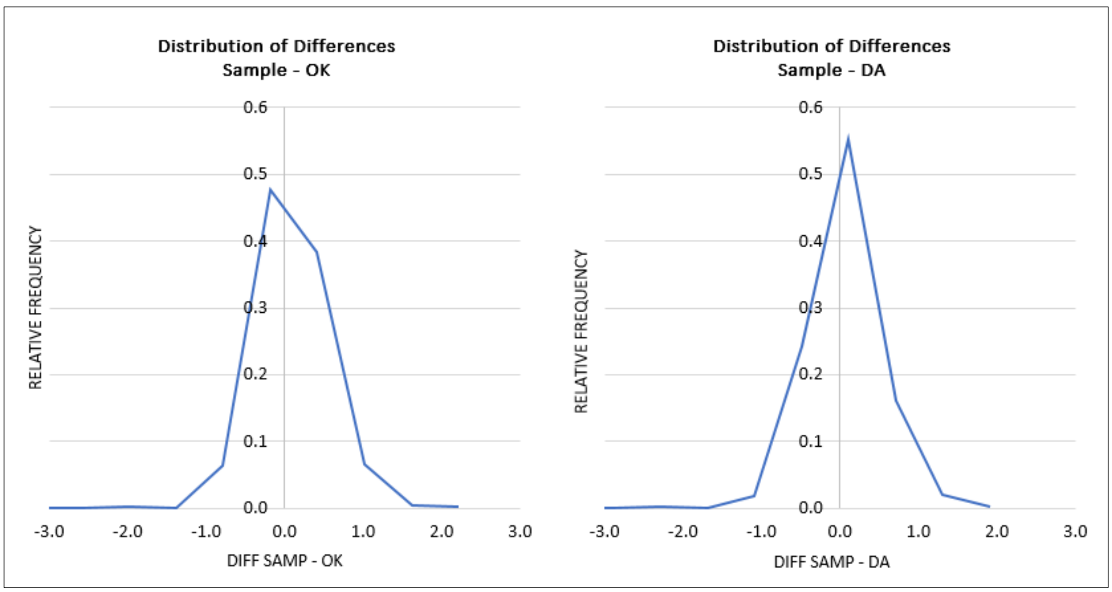


Figure 4. 4 Distribution of Differences for samples and estimates.

The following observations were made from the plots

- Both plots show mean values close to zero indicating that the majority of the estimates and the sample data are similar to each other; and
- There is, however, a marked difference between the shapes of the two individual difference distributions. The DA difference has a higher relative modal frequency (0.55) positioned just to the right of 0, this distribution is

more peaked. The OK difference distribution is broader and lower modal relative frequency of 0.48 just to the left of the zero position.

This visual comparison of the difference distributions shows a significant difference between the two estimation methods. This showed that by analysing the distribution of differences between the average of samples in the DA block and the OK block estimates at the local block scale i.e. at a closer resolution it is possible to distinguish a difference between the two methodologies. These results showed that The DA search OK estimates were more accurate compared to a static search OK estimates at a closer scale. The above comparison only revealed which of the two methods had more accurate estimates but did not look at the spatial distribution of the estimates. The spatial distribution was checked using the visual inspection process described below.

4.1.5 Visual Inspection of the spatial distribution of estimates

Visual inspection is an important validation method as it helps to identify spatial distribution anomalies in the estimate that cannot be picked up from statistical checks, which ignore the position of the data and the blocks. The spatial distribution of grade estimates are checked with spatial distribution of the sample grades and also verified against what is expected from the literature on the deposit mineralisation. Another validation point is to lookout for an artificial break in the spatial grade distribution due to the influence of the alignment of the ellipsoids.

The spatial grade distribution, the OK static search and DA search estimates were plotted and checked against the sample distribution and to identify any artificial break in estimated grade continuity. To ensure compatibility between samples and the two estimates, the same grade intervals have been applied as shown in the legends of Figure 4.5 and Figure 4.6 for the OK static search and DA search, respectively.

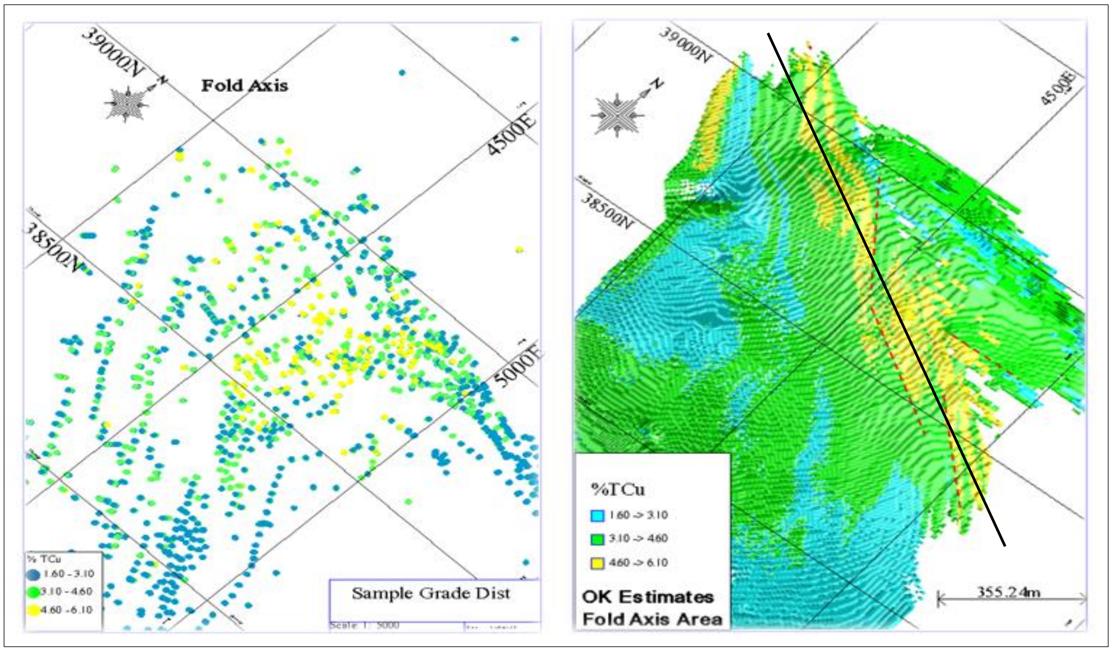


Figure 4. 5 Grade distribution Sample vs OK static search estimates

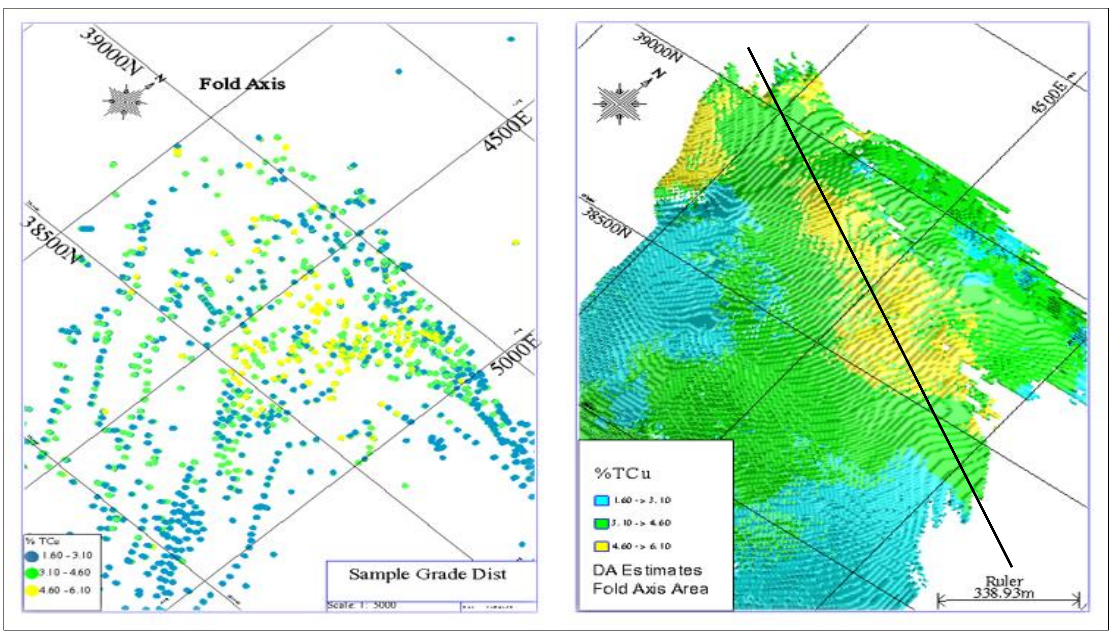


Figure 4. 6 Grade distribution Sample vs DA search estimates

The following observations were made from the visual inspections.

- The spatial distribution of the OK static search estimates does not compare well with that of the sample spatial distribution. There are artificial breaks in grade shown as alternating lines of high and low grades. The breaks have been emphasised in red dotted lines in Figure 4.5;

- The DA search estimates showed a smooth spatial distribution of the grades which corresponds with that of sample grades;
- Elongated grade stripes aligned in the direction of the search ellipse are noticeable in the spatial distribution of the OK static search estimates. This phenomenon is not present in the spatial distribution of the DA search estimates;
- The OK method gives a spatially different picture from what is to be expected from the sample distribution;
- It is observed from this spatial presentation of the grade estimates that they were to some extent affected by the orientation of the ellipse in the OK estimation process;
- The fold axis which separated the two zones must have had an influence on the OK estimates as it separated the two search ellipse with different orientations. The two fixed orientated search ellipsoids reflect grade estimates as strips aligned in the same direction;
- The fold axis did not have any influence on the DA estimates because of the ability for the search ellipse to change direction and follow mineralisation continuity;
- The DA ellipse was able to curve and follow the trend of the fold. The DA gave a favourable outcome because in reality the fold axis is an imaginary line and should not have an effect on the grade distribution rather the effect should be across the entire fold zone not a line; and
- Therefore, the OK method is not suitable for the areas affected by folding resulting in changes in the strike and dip.

Around the fault zones between 2200mN and 2700mN a high-grade area, the OK estimates resulted in spatially elongated grades areas aligned to the direction of the search ellipsoid see Figure 4.7 (left) below.

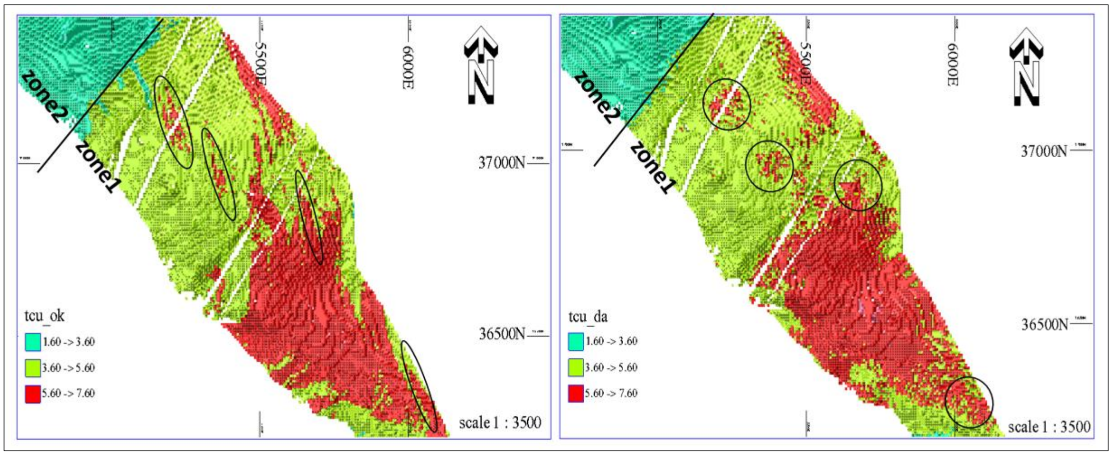


Figure 4. 7 Spatial Grade distribution OK (left) and DA estimates (right)

The dip around this area is shallower than the rest of Zone1 because it is closer to the fold axis area where the orebody is flat. The average oriented search ellipse used in the OK was dipping steeper, the kriging neighbourhood defined by it failed to capture relevant down dip samples and only some on-strike samples, this caused the spatially strip like grade distribution elongated in the direction of the search ellipse. In comparison, the distribution of the DA search estimates followed the orientation of the mineralisation, because this methodology is able to adapt to changes in the dip and therefore able to capture samples down dip as well as along strike during the estimation. The DA estimates did not result in the artefacts introduced by the traditional OK estimates Figure 4.7 (right).

Getting the spatial distribution of the estimated grades right is fundamental, it shows the flow of the mineralisation which is important to mine planning. In this case using OK method resulted in overestimating some low grade blocks as a result of stretching of the grade distribution. It can be concluded that using the DA search interpolation method gives an improved and therefore a better and realistic grade distribution compared to the traditionally used OK interpolation.

4.2 Financial benefit from the use of DA method for estimation

Mining companies are often looking for effective and efficient new techniques that will help improve productivity and ultimately increase profits. New improved techniques, if properly utilised may assist the company gain financially by reducing production cost and still be able to execute the task as planned before. In short, management focusses on maximising the output results with minimal inputs. The cost of acquiring information especially drillhole data is very high. The drilling information though costly, is necessary to reduce risk during Mineral Resource estimation. Therefore, an interpolation technique that utilises the sample data correctly, that is in a relevant and appropriate way, in the estimation process may be preferred to maximise outputs at a fairly lower cost and not result in inappropriate mine planning for example:

Tests were done to establish how adopting the DA would benefit the company financially as compared to the OK. Two test were done to investigate the following:

1. If the DA method utilised sample data effectively compared to the OK methodology to help cost save on acquiring too much information; and
2. If the DA had a higher output in terms of the metal tonnes compared to OK for the same number of samples in both interpolations, because more blocks were estimated using this methodology.

Histograms were plotted to assess data usage between the two methodologies. Both OK and DA used the maximum number of samples (46) on most of the estimated blocks. Figure 4.8 below is the histogram for the number of samples used by DA and OK methodologies for Zone1. See Appendix 7.6 for Zone2 and Zone3 histograms.

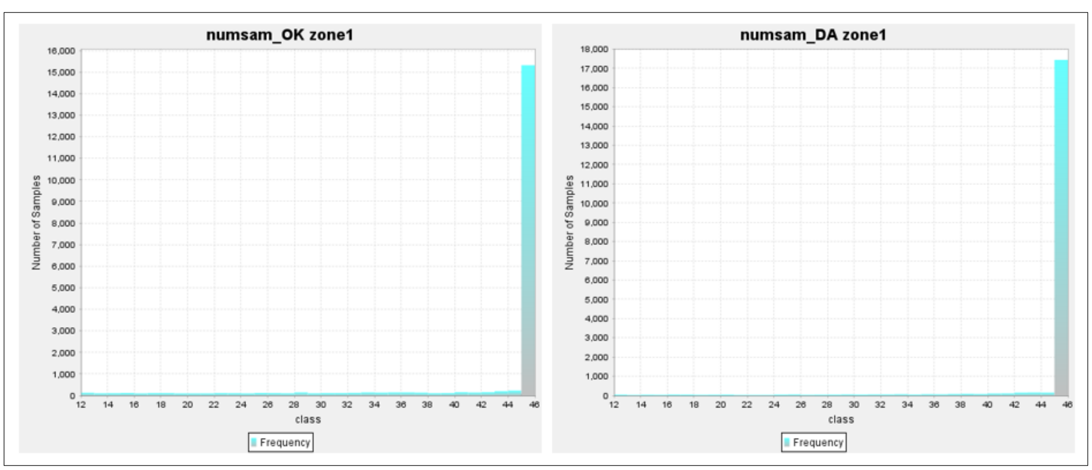


Figure 4. 8 Number of samples Zone1

The total number of samples used in the estimation which accessed only the maximum number of samples was 15,316 and 17,436 for OK and DA respectively. The DA used an extra 2,120 samples for maximum number of samples interpolation for Zone1 only. This was attributed to its dynamic nature that allows the ellipsoid to meander through complex geology and increase the ability of capturing more data during an interpolation process. The rigidity nature of the traditional OK ellipsoid applied reduced its potential to fully utilise the information during interpolation process. Assuming the number of samples required for an interpolation was set to 46 samples, OK method would not account for the 2,120 samples after the estimation. It was noticed that the OK method would require more information than the DA to achieve a similar task.

The effect of data usage by the two methodologies was further analysed using the Lagrange Multiplier values Figure 4.9. Low Lagrange values indicate that the blocks have sufficient samples in the Kriging neighbourhood and a high Langrage values indicate that the block have limited information in the Kriging neighbourhood and more weight should go to the mean and Simple Kriging might be a better option (Dohm, 2018b). Therefore an interpolation methodology that produces a lower Lagrange values have the ability to capture sufficient data during the estimation process.

The distribution of the Lagrange values for the OK and DA method were plotted to establish which method gave a lower Lagrange value across the distribution.

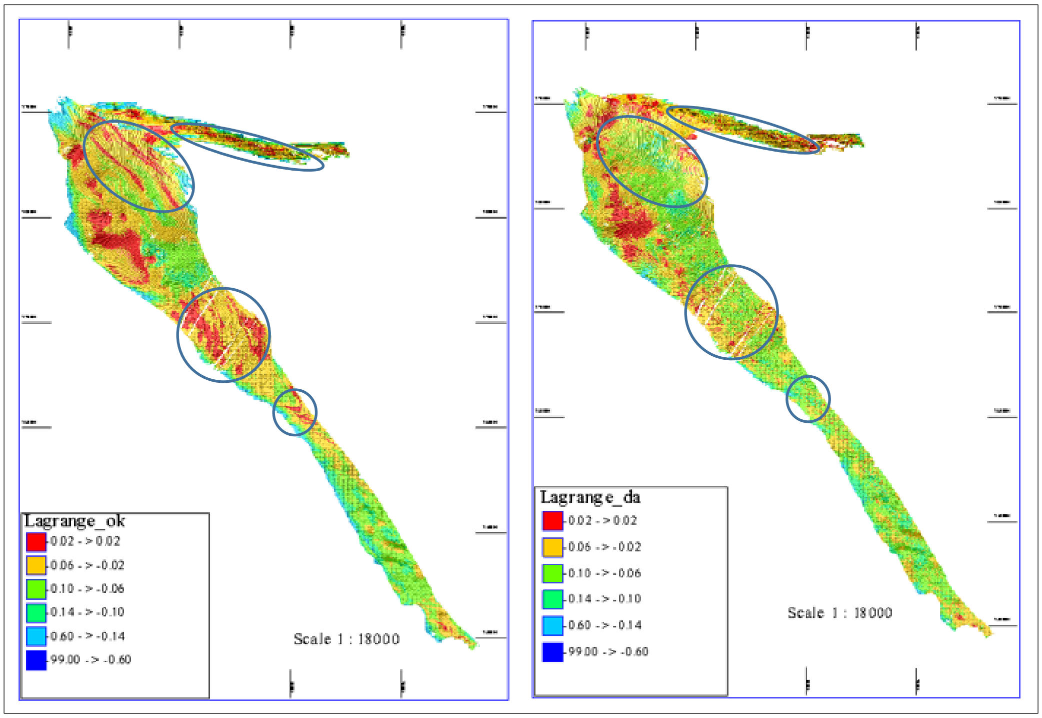


Figure 4. 9 Lagrange distribution for OK (left) and DA (right)

From the plots, The DA methodology had lower Lagrange values compared to the OK methodology. Areas with rapid changes in structural orientations such as the fault zone, fold axis area and the north limb gave distinctive high Lagrange values for the OK than the DA. This was because the OK ellipsoid was unable to capture as many samples in these areas due to its rigid nature of not adapting to changing structural orientation. The DA showed favourable results as the Lagrange values were kept low even in areas with rapid changes in orientation and highlights the advantages of following this estimation methodology.

The test on affective data usage favoured the DA methodology, the DA method would therefore assist the company in cost saving because with the same amount of samples it performed better in terms of sample utilization as seen from the Lagrange values.

A second test was conducted to determining how much copper metal tonnes would be realised from DA method taking into account its ability to maximise data usage. The estimated tonnes and grade were generated from the OK and DA estimated blocks. Table 4.3 shows the tonnes, grade and %TCu metal from the estimated blocks of the two methodologies including the extra tonnes gained from DA estimates.

Table 4. 3 Tonnes and Grade for OK and DA

Method	Estimated Blocks	Tonnes	%Tcu	Tcu Metal
OK	41,762	106,148,273	3.84	4,076,094
DA	50,639	126,614,534	3.82	4,836,675
Extra DA Tonnes	**(8,877)**	**(20,466,262)**	**3.72**	**(760,582)**

The comparisons done between the DA and OK methodologies were within the first pass search radius to maintain the same level of confidence in the estimation process.

The DA estimated 4,836,675 tonnes Cu metal compared to the OK which estimated 4,076,094 tonnes Cu metal. This showed that with the same amount of data, same variogram and optimal Kriging neighbourhood parameters and within the same level of confidence, DA method produced more Cu metal tonnes than the OK method by over 760,582 tonnes. It is likely that these extra tonnes will be realised because of a better grade estimation methodology implemented thereby extending the life of mine for Konkola mine.

The OK technique estimated 8,877 less blocks than the DA resulting in fewer tonnes. To determine what could have caused loss in tonnes for the OK methodology, a section was cut at 5100mE across the two block model. A comparison was made by highlighting the estimated blocks for both OK and DA methodology.

The OK method left gaps which meant blocks around those portions were not estimated. The gaps were seen to be around the fold hinge where the two fold limbs intersect. The portions have sufficient data but because of changing structural orientation, the traditional search ellipse (refer to figure 1.1) which were aligned to the average global orientation of the limbs were unable to estimate the blocks around the hinge zone. The DA had all the blocks estimated because the ellipsoids are dynamic and not fixed and are able to rotate depending on the block orientation.

From this research it is clear that the ability of DA interpolation to maximise on information usage will assist Konkola Mine to save cost on the need to drill more drillholes and also realise more tonnes and copper than if OK methodology was employed. Figure 4.10 below shows a cross section view of the estimated blocks for the traditional OK and the DA methodology.

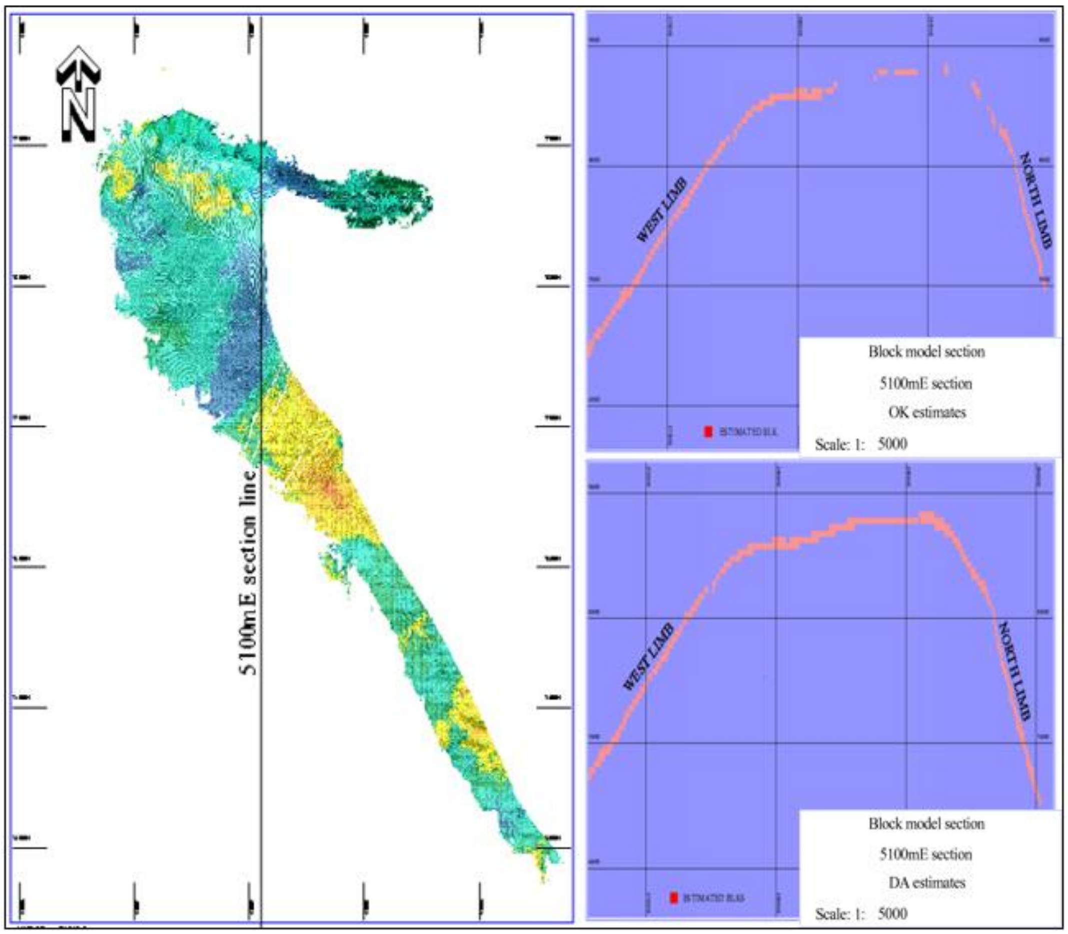


Figure 4. 10 Cross section view of estimated blocks

5 Conclusion and Recommendations

Carrying out Mineral Resource estimation in folded and undulating orebodies has always posed a challenge to the resource geologist. Structural complexity has to be well understood and represented in 3D geological models as surfaces or solids. The resource block model is constrained in the geological models of complexity and the individual blocks of the resource block model take up different orientations depending on the complexity of the geological model. When it comes to grade interpolation, it maybe be challenging if the block model has blocks of varying orientation due to structural complexity and a fixed search ellipsoid is applied. The DA methodology has proved to be a better option when carrying out interpolation in such orebodies as it offers a most effective, efficient and fast way of grade estimation.

Konkola Mine has been using OK methodology for its resource estimation despite having an orebody which is folded with a huge variation in dip and dip direction. The author decided to employ the DA method on the orebody by carry out a study if there be any significant improvement compared to the current OK methodology. Grade was interpolated into the blocks using OK method (TCu_OK) and using DA (TCu_DA). The results from the interpolations were compared with the input composite data to determine which methodology gave more accurate estimates. Five comparison check methods where used; Global statistics, Swath plots, scatter plots, distribution of differences and visual inspections.

Even though results from the Global statistics, Swath plots and scatter plots on most test favoured the DA method, the difference was insignificant as the scale used for the spatial comparison was too big to capture the differences between the two methods. The final statistical analysis done using the distribution of differences was able to highlight a valid difference between the two methodologies with the DA estimates comparing better to sample data than the OK. Apart from the statistical comparisons, visual inspection proved that the DA method was a better interpolation method for this orebody than OK. The DA grade distribution compared well with the sample distribution and no artificial breaks or spread in the grade distribution due to the influence of the rigidity of the search ellipsoid were observed as was the case with the traditional OK methodology. The OK estimates showed strips of grade that were clearly as a result of rigid search ellipsoid. The OK grade distribution was seen to be affected by the fold axis where the two ellipse from the west and north limb intersect which was not the case with the DA method. These results showed that the DA method produces estimates which are closer to sample grades and an improved grade representation as compared to the OK methodology. Adopting DA interpolation method would mean having more realistic planning and reduced risks in the ore extraction that may result from grade uncertainty. A better grade distribution from the DA method will greatly improve mine planning and scheduling and cut down on surprises because what will be mined will relate closer with the real in situ distribution.

Other tests were done to determine the financial benefits of adopting the DA methodology as the main interpolation technique. It was observed that the DA had better usage of information because of its dynamic nature with the ability to capture more information better that OK. The cost of acquiring data can be very high and therefore adopting a more efficient and effective interpolation methodology to make maximum use of the available data is paramount. This methodology should also be used to determine where future drilling might be most beneficial by looking at the Kriging efficiency, Slope of Regression and kriging variance of pseudo holes thereby also managing drilling costs more effectively and reducing risks.

Using the same number of samples, Variogram and Kriging neighbourhood parameters, DA had many blocks estimated compared to OK. The poor sample “capturing” from the traditional (fix ellipsoid) OK methodology resulted in some blocks around the fold hinge not being estimated therefore having a lower tonnage compared to DA. Using the DA method realised an extra 20 million tonnes at 3.72% TCu that is 0.76 million tonnes of copper metal in the resource estimate, that was previously ignored or not known.

The benefits of adopting DA methodology were significant and beneficial compared to the OK method. The author recommended the adoption of DA interpolation method for the Mineral Resource Estimation of copper at Konkola Mine. The author further recommends its adoption for grade control models as well to ensure a realistic grade distribution for short term mine planning.

6 References

Abzalov, M. Z. and Humpherys, M. (2002) 'Resource Estimation of Structurally Complex and Discontinuous Mineralization Using Non-linear Geostatistics: Case Study of a Mesothermal Gold Deposit in Northern Canada', 11, p. 11.

Annels, A. E. (1984) 'The geotectonic environment of Zambian copper-cobalt mineralization', *Journal of the Geological Society*, 141(2), pp. 279–289. doi: 10.1144/gsjgs.141.2.0279.

Armstrong, M. (1998) *Basic linear geostatistics*. Berlin: Springer.

Armstrong, R. A., Master, S. and Robb, L. J. (2005) 'Geochronology of the Nchanga Granite, and constraints on the maximum age of the Katanga Supergroup, Zambian Copperbelt', *Journal of African Earth Sciences*. (Recent Advances in the Geology and Mineralization of the Central African Copperbelt), 42(1), pp. 32–40. doi: 10.1016/j.jafrearsci.2005.08.012.

Barnes, R. (2004) 'Variogram tutorial', *Golden Software, Inc*.

Bell, G. D. and Reeves M. (1979) 'Kriging and Geostatistics: A Review of the' Litera'ture Available in English', (269), p. 11.

Binda, P. L. (1994) 'Stratigraphy of Zambian copperbelt orebodies', *Journal of African Earth Sciences*, 19(4), pp. 251–264. doi: 10.1016/0899-5362(94)90013-2.

Binda, P. L. and Mulgrew, J. R. (1974) 'Stratigraphy of copper occurrences in the Zambian Copperbelt', *Annales de la Société géologique de Belgique*. Available at: https://popups.uliege.be/0037-9395/index.php?id=3486 (Accessed: 13 June 2018).

Boisvert, J. B. and Deutsch, C. V. (2011) 'Programs for kriging and sequential Gaussian simulation with locally varying anisotropy using non-Euclidean distances', *Computers & Geosciences*, 37(4), pp. 495–510. doi: 10.1016/j.cageo.2010.03.021.

Boisvert, J. B., Manchuk, J. G. and Deutsch, C. V. (2009) 'Kriging in the Presence of Locally Varying Anisotropy Using Non-Euclidean Distances', *Mathematical Geosciences*, 41(5), pp. 585–601. doi: 10.1007/s11004-009-9229-1.

Bowen, R. and Gunatilaka, A. (1976) 'The Zambian Copperbelt', *Science Progress (1933-)*, 63(249), pp. 87–109.

Boyle, C. (2010) 'Kriging neighbourhood analysis by slope of regression and weight of mean – evaluation with the Jura data set', *Mining Technology*, 119(2), pp. 49–58. doi: 10.1179/037178410X12741755140804.

CAE Datamine corporate Limited (2014) 'CAE Datamine Corporate Limited. Dynamic Anisotropy'. CAE Mining Documentation for Studio 3, Version 3.21.

Cailteux, J. L. H. *et al.* (2005) ‘Genesis of sediment-hosted stratiform copper–cobalt deposits, central African Copperbelt’, *Journal of African Earth Sciences*. (Recent Advances in the Geology and Mineralization of the Central African Copperbelt), 42(1), pp. 134–158. doi: 10.1016/j.jafrearsci.2005.08.001.

Cardwell, J., Inc, F.-M. and Cartwright, A. (2016) ‘Dynamic Unfolding-Complex Geology Case Study Of Tenke-Fungurume Mining District Deposits’, p. 5.

Chanderman, L. (2016) *3D geological modelling and mineral resource estimate for the FE2 gold deposit, Sadiola mine, Mali*. Thesis. Available at: http://wiredspace.wits.ac.za/handle/10539/20173 (Accessed: 19 June 2018).

Chanderman, L., Dohm, C. E. and Minnitt, R. C. A. (2017) ‘3D geological modelling and resource estimation for a gold deposit in Mali’, *Journal of the Southern African Institute of Mining and Metallurgy*, 117(2), pp. 189–197. doi: 10.17159/2411-9717/2017/v117n2a10.

Clark, I. (1979) *Practical Geostatistics*. England: Applied Science Publishers Ltd.

Clark, I. (2009) ‘Statistics or geostatistics? Sampling error or nugget effect?’, p. 6.

Coombes, J. and Boamah, P. (2015) ‘Local Kriging Neighbourhood Optimisation’, in *Africa Australia Technical Mining Conference 2015*, p. 27.

Deutsch, C. V. and Wilde, B. J. (2011) ‘The Decision of Stationarity in Modern Resource Estimation’, p. 17.

De-Vitry, C. (2003) ‘Resource classification – a case study from the Joffre-hosted iron ore of BHP Billiton’s Mount Whaleback operations’, *Mining Technology*, 112(3), pp. 185–196. doi: 10.1179/037178403225003564.

De-Vitry, C. (2014) ‘Identifying and Dealing with Outliers in Resource Estimation’, p. 9.

Dohm, C. E. (2018a) ‘MINN 7007 Geostatistical methods in mineral resource evaluation lecture notes’. University of the Witwatersrand, Johannesburg.

Dohm, C. E. (2018b) ‘MINN 7006 Geostatistical methods in mineral resource evaluation lecture notes’. University of the Witwatersrand, Johannesburg.

Dominy, S. C., Noppé, M. A. and Annels, A. E. (2002) ‘Errors and Uncertainty in Mineral Resource and Ore Reserve Estimation: The Importance of Getting it Right’, *Exploration and Mining Geology*, 11(1–4), pp. 77–98. doi: 10.2113/11.1-4.77.

Garlick, W. G. and Brummer, J. J. (1951) ‘The age of the granites of the Northern Rhodesian copperbelt’, *Economic Geology*, 46(5), pp. 478–497. doi: 10.2113/gsecongeo.46.5.478.

Glacken, I. M. and Gray, D. B. (2011) ‘Resource estimation at the Kylylahti copper-gold-cobalt mine, Outokumpu, Finland - challenges and solutions’, *Fennoscandian Exploration and Mining* p. 30.

Glacken, I. M. and Snowden, D. V. (2001) ‘Mineral resource estimation’, *Mineral resource and ore reserve estimation—the AusIMM guide to good practice. The Australasian Institute of Mining and Metallurgy, Melbourne*, pp. 189–198.

Glass, H. J. and Cornah, A. J. (2006) ‘Unfolding the Luce Deposit to Improve Variograms’, *the International Mining Geology Conference*, p. 8.

Gnamien, C. (2017) *How to perform Dynamic Anisotropy in Surpac, Discover, Model and Harness our Natural and Urban Environments*. Available at: http://blogs.3ds.com/geovia/perform-dynamic-anisotropy-surpac/ (Accessed: 12 May 2018).

Hitzman, M. W. (2000) ‘Source basins for sediment-hosted stratiform Cu deposits: implications for the structure of the Zambian Copperbelt’, *Journal of African Earth Sciences*, 30(4), pp. 855–863. doi: 10.1016/S0899-5362(00)00056-7.

Hosken, J., Haren, E. and Winchester, A. (2006) ‘Resource Modelling in an Evolving Mine — CSA Mine, Cobar, New South Wales’, *th International Mining Geology Conference*, p. 14.

Isaaks, E. H. and Srivastava, R. M. (1989) *Applied Geostatistics*. New York: Oxford University Press.

Journel, A. G. and Huijbregts, C. J. (1978) *Mining Geostatistics*. Academic Press. Available at: https://infoscience.epfl.ch/record/27687 (Accessed: 23 April 2018).

Kampunzu, A. B. *et al.* (2009) ‘Sediment-hosted Zn–Pb–Cu deposits in the Central African Copperbelt’, *Ore Geology Reviews*, 35(3), pp. 263–297. doi: 10.1016/j.oregeorev.2009.02.003.

Key, R. M. *et al.* (2001) ‘The western arm of the Lufilian Arc in NW Zambia and its potential for copper mineralization’, *Journal of African Earth Sciences*. (African Renaissance and Geosciences), 33(3), pp. 503–528. doi: 10.1016/S0899-5362(01)00098-7.

Khakestar, M. S. *et al.* (2013) ‘Determining the best search neighbourhood in reserve estimation, using geostatistical method: A case study anomaly No 12A iron deposit in central Iran’, *Journal of the Geological Society of India*, 81(4), pp. 581–585. doi: 10.1007/s12594-013-0074-y.

Konkola Copper Mines (2001) *Konkola Geology and Geotechnology*. Internal Konkola Copper mines.

Konkola Copper Mines (2006) ‘General Konkola Geology’. Internal unpublished.

Konkola Copper Mines (2007) ‘Geology of Konkola & Mining Applications’. Internal unpublished.

Konkola Copper Mines (2008) ‘Location of Konkola Mine in Southern Africa, Zambia’. Internal unpublished.

Machuca-Mory, D. F., Rees, H. and Leuangthong, O. (2015) ‘Grade Modelling with Local Anisotropy Angles: A Practical Point of View’, in *37th Application of Computers and Operations Research in the Mineral Industry (APCOM 2015)*.

Mackay, C. . . (2000) ‘Geological map of Konkola’ .Internal unpublished.

Mackay, C. . . (2000) ‘Konkola Stratigraphy’ .Internal unpublished.

Mandava, S. M. (2016) *Finding the optimal dynamic anisotropy resolution for grade estimation improvement at Driefontein Gold Mine, South Africa*. Thesis. Available at: http://wiredspace.wits.ac.za/handle/10539/20591 (Accessed: 24 March 2018).

Master, S. *et al.* (2005) ‘Provenance ages of the Neoproterozoic Katanga Supergroup (Central African Copperbelt), with implications for basin evolution’, *Journal of African Earth Sciences*. (Recent Advances in the Geology and Mineralization of the Central African Copperbelt), 42(1), pp. 41–60. doi: 10.1016/j.jafrearsci.2005.08.005.

Matheron, G. (1963) ‘PRINCIPLES OF GEOSTATISTICS’, 58, pp. 1246–1266.

Matheron, G. (1967) ‘Kriging or polynomial interpolation procedures’, *CIMM Transactions*, 70, pp. 240–244.

McArthur, G. J. (1988) ‘Using geology to control geostatistics in the Hellyer deposit’, *Mathematical Geology*, 20(4), pp. 343–366. doi: 10.1007/BF00892983.

McGowan, R. R., Roberts, S. and Boyce, A. J. (2006) ‘Origin of the Nchanga copper–cobalt deposits of the Zambian Copperbelt’, *Mineralium Deposita*, 40(6–7), p. 617. doi: 10.1007/s00126-005-0032-8.

Milesi, J. P. *et al.* (2006) ‘An overview of the geology and major ore deposits of Central Africa: Explanatory note for the 1:4,000,000 map “Geology and major ore deposits of Central Africa”’, *Journal of African Earth Sciences*. (The Precambrian of Central Africa), 44(4), pp. 571–595. doi: 10.1016/j.jafrearsci.2005.10.016.

Morrison, R. S. and Grant, C. L. B. (2012) ‘RIO GRANDE CU-AU-AG PROJECT, NORTHWEST ARGENTINA’.

Mpanza, M. (2015) *A comparison of ordinary and simple kriging on a PGE resource in the Eastern limb of the Bushveld complex*. Thesis. Available at: http://wiredspace.wits.ac.za/handle/10539/18366 (Accessed: 19 June 2018).

Mwango, C. (2011) *DETERMINING THE STRUCTURAL AND SEDIMENTARY CONTROLS OF COPPER-COBALT MINERALISATION AT KONKOLA MINE AREA*. Thesis. The University of Zambia.

Porada, H. (1989) 'Pan-African rifting and orogenesis in southern to equatorial Africa and eastern Brazil', *Precambrian Research*, 44(2), pp. 103–136. doi: 10.1016/0301-9268(89)90078-8.

Rainaud, C. *et al*. (2003) 'A cryptic Mesoarchaean terrane in the basement to the Central African Copperbelt', *Journal of the Geological Society*, 160(1), pp. 11–14. doi: 10.1144/0016-764902-087.

Ronald, E. C. (2018) 'Rules of Thumb for Geological Modeling'. *SME Annual Comference*, Australia. Available at: https://www.srk.co.za/en/publication/na-rules-thumb-geological-modeling (Accessed: 20 June 2018).

Rossi, M. E. and Deutsch, C. V. (2013) *Mineral Resource Estimation*. Springer Science & Business Media.

Selley, D. *et al*. (2005) 'A New Look at the Geology of the Zambian Copperbelt', *Society of Economic Geologists, Inc.*, 100th. Available at: https://eprints.utas.edu.au/755/ (Accessed: 9 May 2018).

Sinclair, A. J. (1999) 'Exploratory Data Analysis: A Precursor to Resource/Reserve Estimation', *Geological Engineering, Department of Earth and Ocean Sciences The University of British Columbia*, (British Columbia, Canada).

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

de Sousa, E. . (1990) *Impact of geology on ore grade estimation of a porphyry copper deposit*. The University of Arizona. Available at: https://repository.arizona.edu/handle/10150/277264 (Accessed: 20 June 2018).

Steel, R. W. (1957) 'The Copperbelt of Northern Rhodesia', *Geography*, 42(2), pp. 83–92.

Straskraba, V., Sharma, D. and Naish, E. (2012) 'Konkola Mine Dewatering Study', p. 12.

te Stroet, C. B. M. te and Snepvangers, J. J. J. C. (2005) 'Mapping Curvilinear Structures with Local Anisotropy Kriging', *Mathematical Geology*, 37(6), pp. 635–649. doi: 10.1007/s11004-005-7310-y.

Sweeney, M. A. and Binda, P. L. (1994) 'Some constraints on the formation of the Zambian Copperbelt deposits', *Journal of African Earth Sciences*, 19(4), pp. 303–313. doi: 10.1016/0899-5362(94)90016-7.

Sweeney, M. A., Binda, P. L. and Vaughan, D. J. (1991) 'Genesis of the ores of the Zambian Copperbelt', *Ore Geology Reviews*, 6(1), pp. 51–76. doi: 10.1016/0169-1368(91)90032-3.

Torremans, K. *et al.* (2013) 'Remobilisation features and structural control on ore grade distribution at the Konkola stratiform Cu–Co ore deposit, Zambia', *Journal of African Earth Sciences*, 79, pp. 10–23. doi: 10.1016/j.jafrearsci.2012.10.005.

Unrug, R. (1983) 'The Lufilian Arc: a microplate in the Pan-African collision zone of the Congo and the Kalahari cratons', *Precambrian Research*, 21(3), pp. 181–196. doi: 10.1016/0301-9268(83)90040-2.

Unrug, R. (1988) 'Mineralization controls and source of metals in the Lufilian fold belt, Shaba (Zaire), Zambia, and Angola', *Economic Geology*, 83(6), pp. 1247–1258. doi: 10.2113/gsecongeo.83.6.1247.

Van Wilderode, J. *et al.* (2014) 'Metal sources for the Katanga Copperbelt deposits (DRC) insights from Sr and Nd isotope ratios', *Geologica Belgica*, 17(2), pp. 137–147.

Van Wilderode, J. *et al.* (2015) 'Metal sources for the Nkana and Konkola stratiform Cu–Co deposits (Zambian Copperbelt): Insights from Sr and Nd isotope ratios', *Ore Geology Reviews*, 67, pp. 127–138. doi: 10.1016/j.oregeorev.2014.11.011.

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', in *5th International Mining Geology Conference*. Bendigo, Australia. Melbourne: Australian Inst Mining & Metallurgy, pp. 215–223.

Wendorff, M. (2003) 'Stratigraphy of the Fungurume Group - evolving foreland basin succession in the Lufilian fold-thrust belt, Neoproterozoic-Lower Palaeozoic, Democratic Republic of Congo', *South African Journal of Geology*, 106(1), pp. 17–34. doi: 10.2113/1060017.

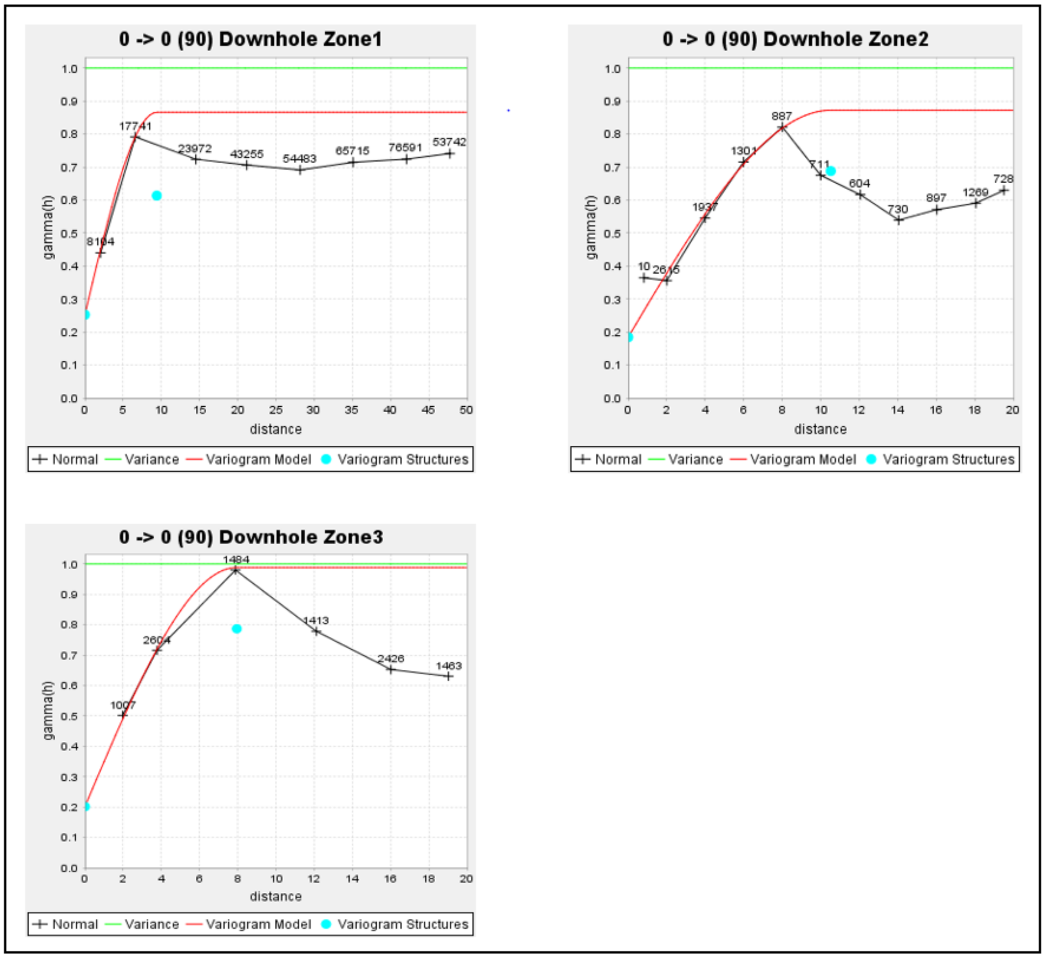
Wendorff, M. (2005) 'Sedimentary genesis and lithostratigraphy of Neoproterozoic megabreccia from Mufulira, Copperbelt of Zambia', *Journal of African Earth Sciences*. (Recent Advances in the Geology and Mineralization of the Central African Copperbelt), 42(1), pp. 61–81. doi: 10.1016/j.jafrearsci.2005.08.010.

Woodhead, J. (2013) *The Neoproterozoic Roan Group in the Zambian Copperbelt: Sequence stratigraphy, alteration and mineralization*. Ph.D. Colorado School of Mines. Available at: https://search.proquest.com/docview/1367082408/abstract/9E744B34D3EF4910PQ/1 (Accessed: 10 May 2018).

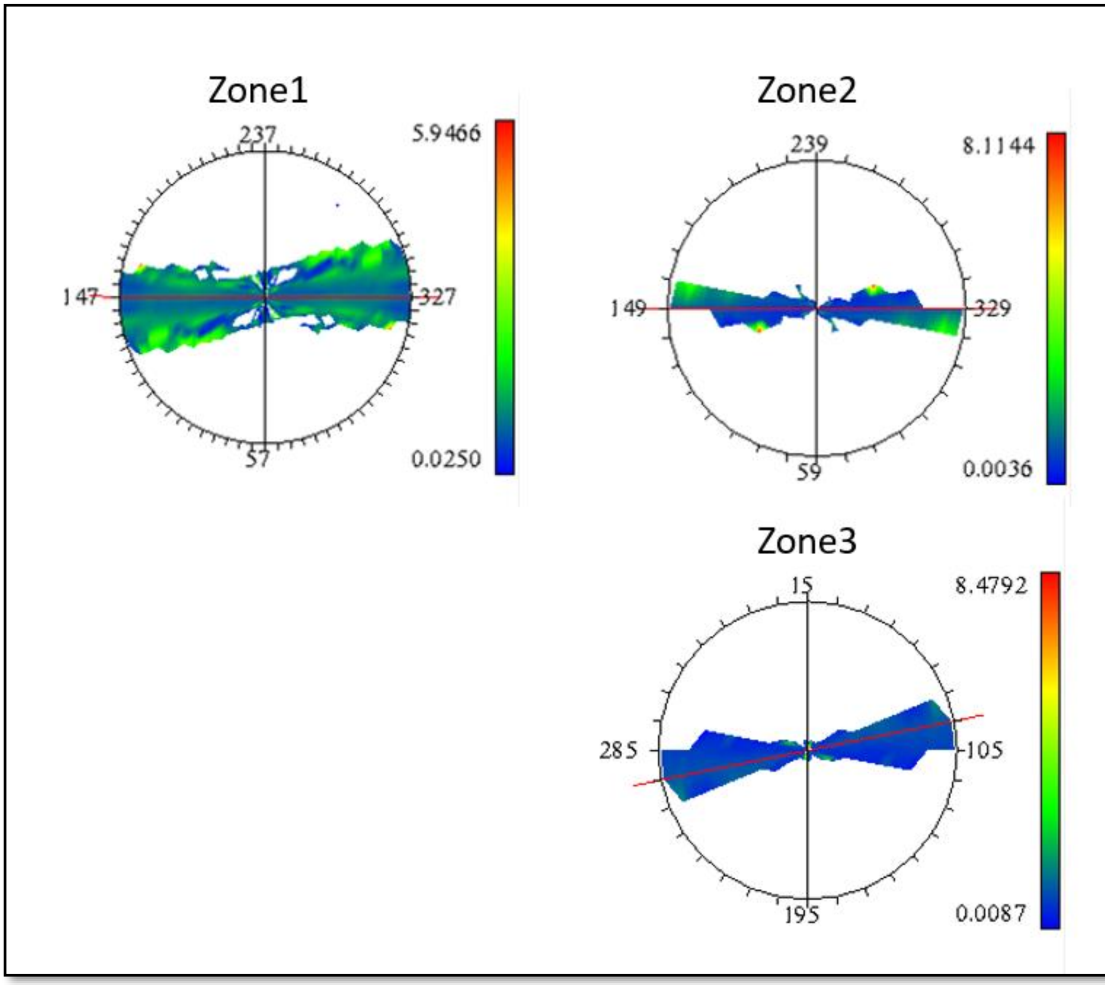
Zabrusky, K. and Assoc, G. (2013) 'Using Dynamic Anisotropy to Improve Resource Estimation', p. 3.

7 Appendices

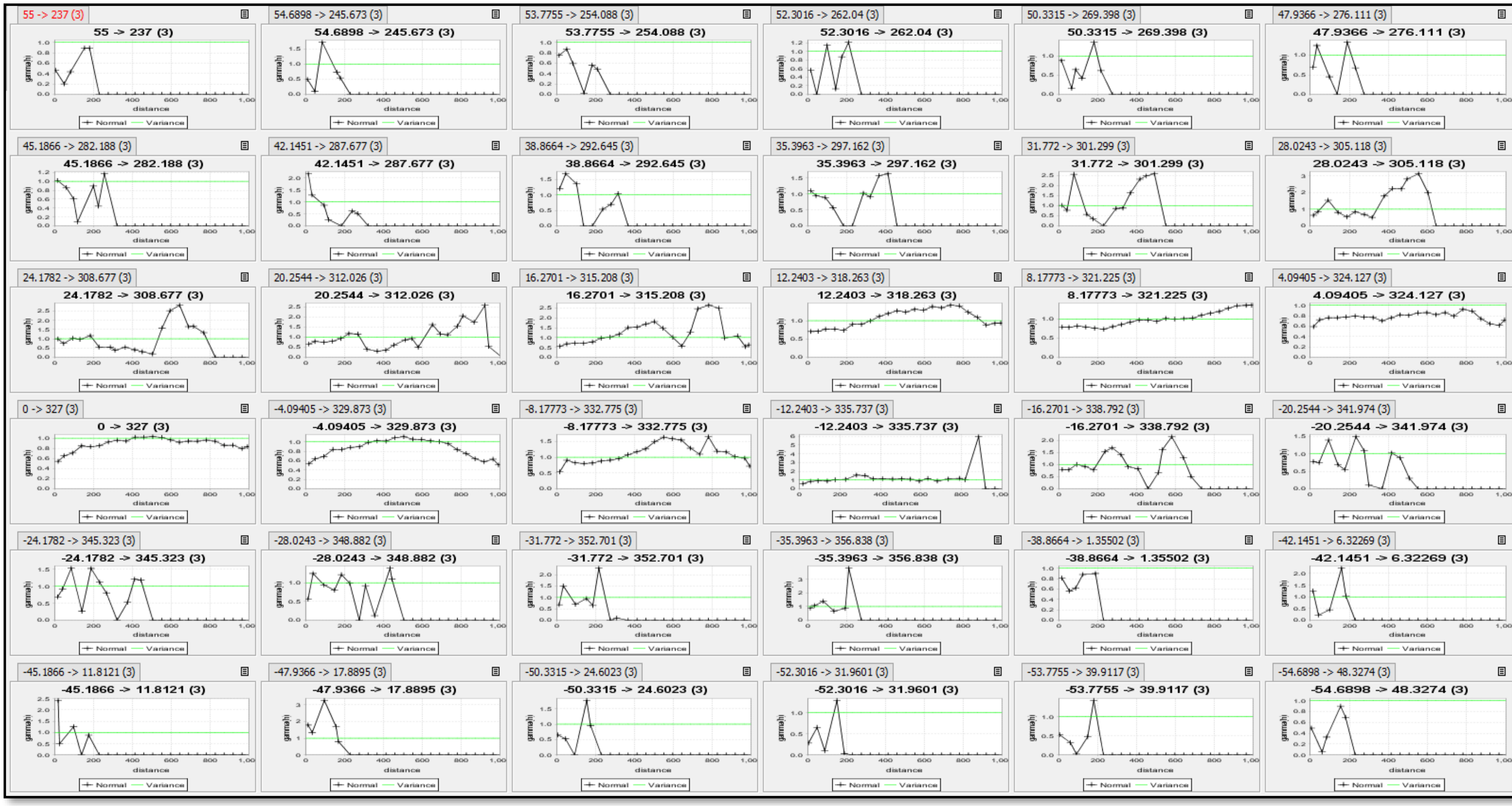
Appendix 7.1: Downhole Variograms



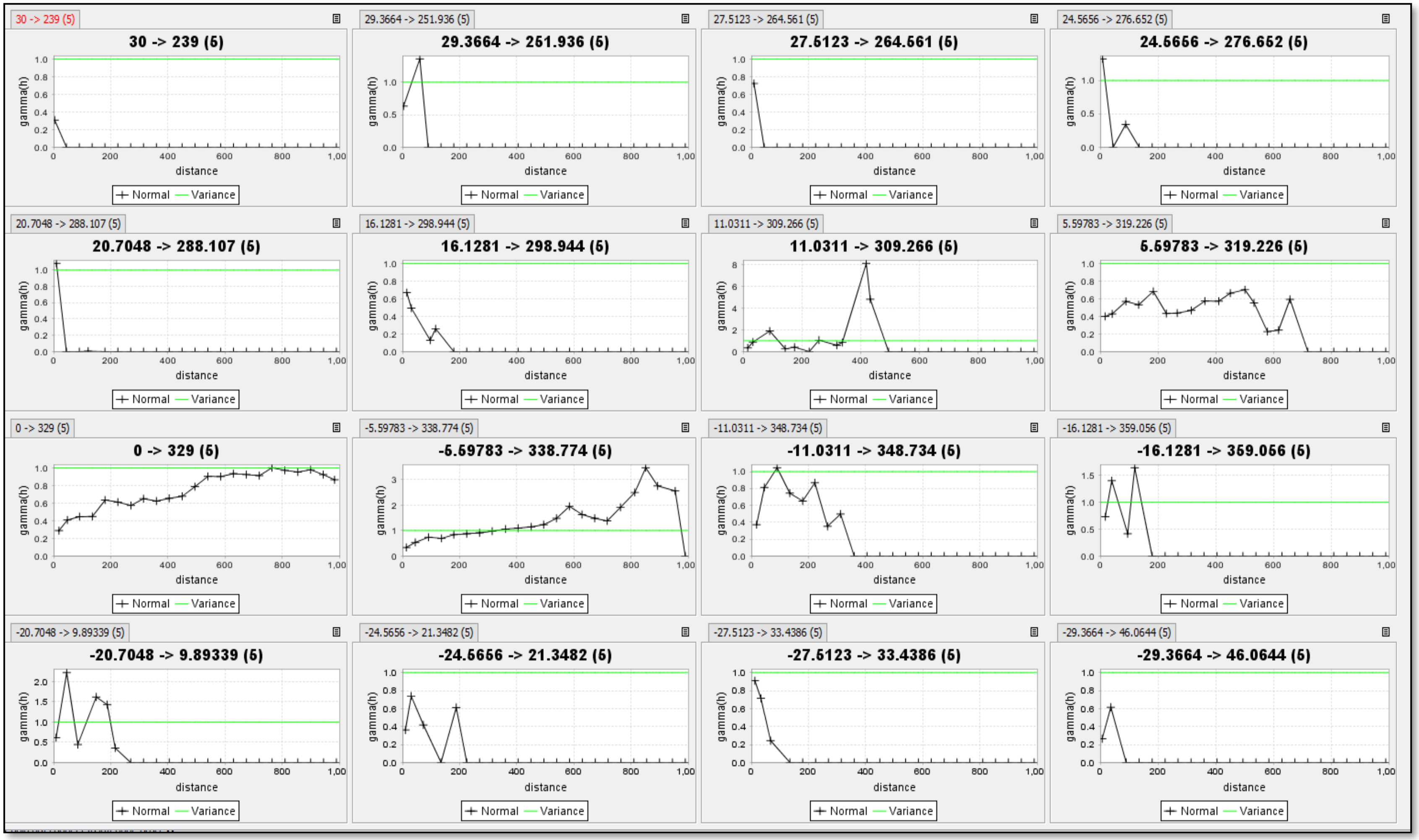
Appendix 7.2: Varmap



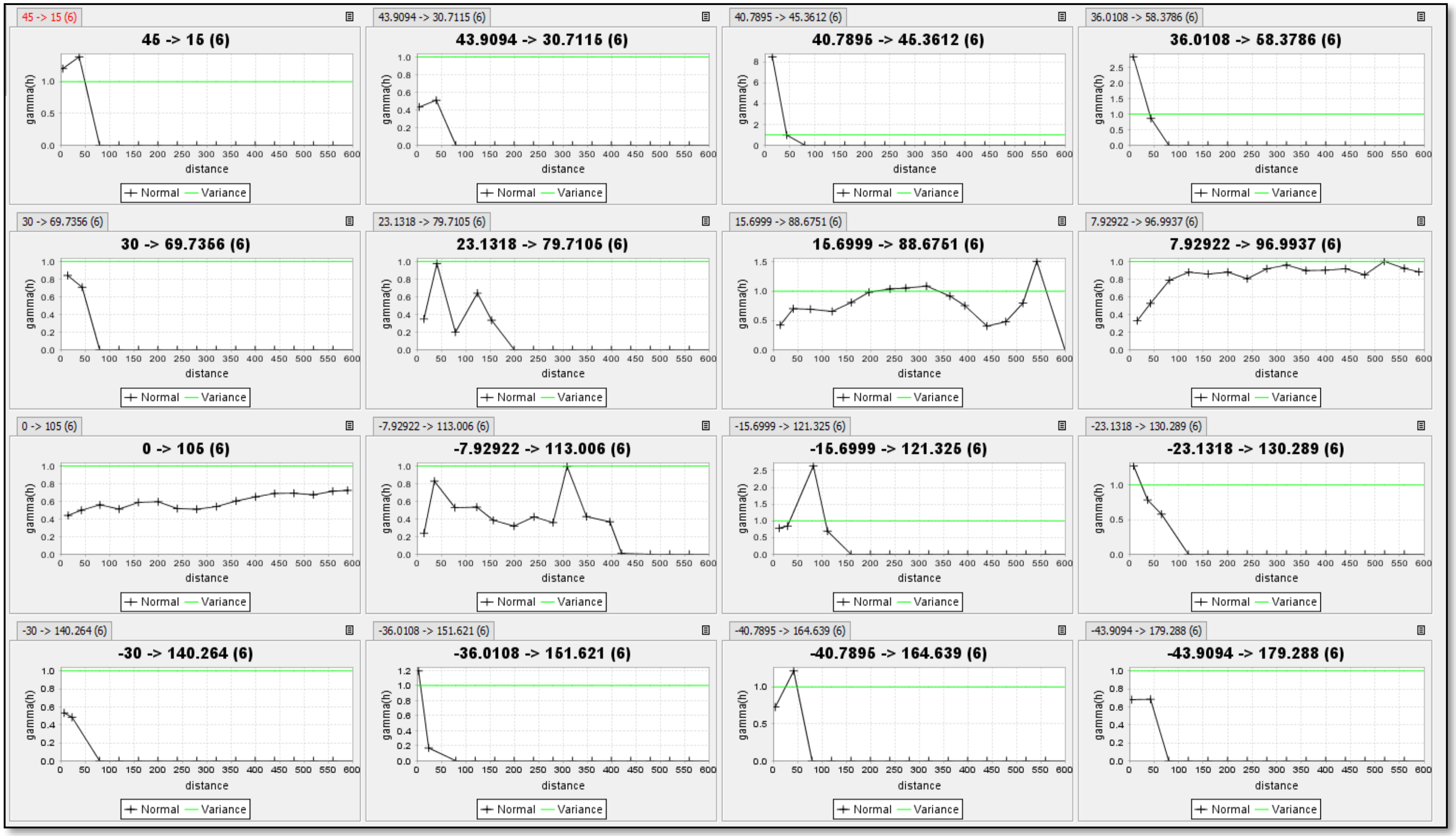
Appendix 7.3: Zone 1 Directional Variograms



Appendix 7.3: Zone 2 Directional Variograms



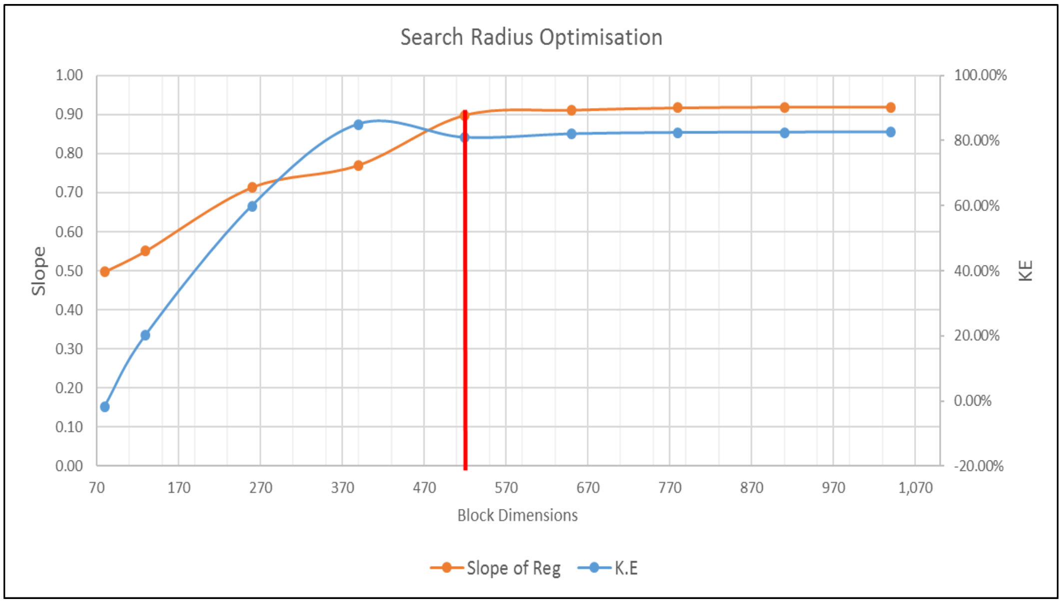
Appendix 7.3: Zone 3 Directional Variograms



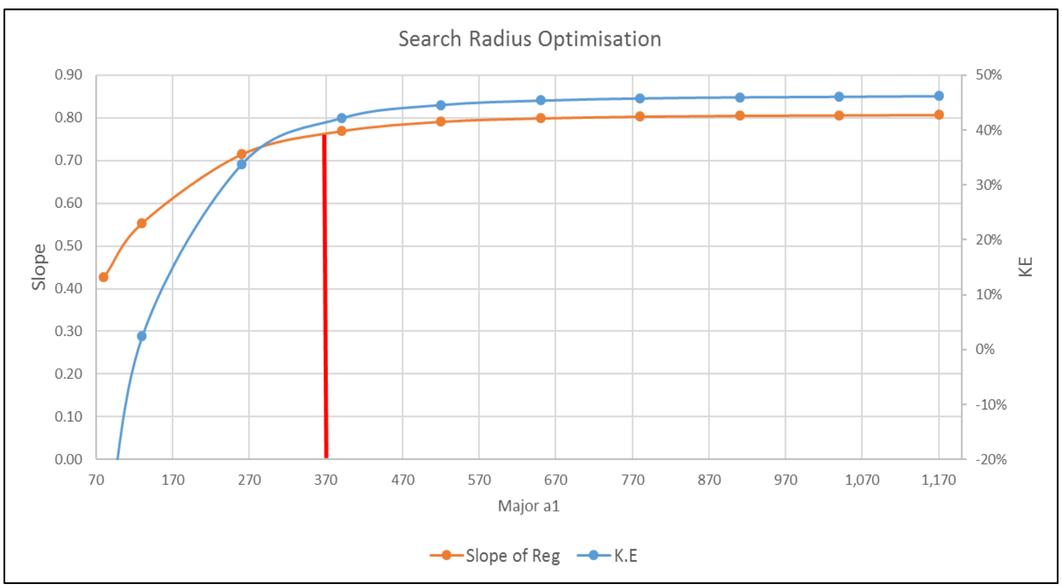
Zone3

Appendix 7.4: Search Radius Optimisation

Zone2

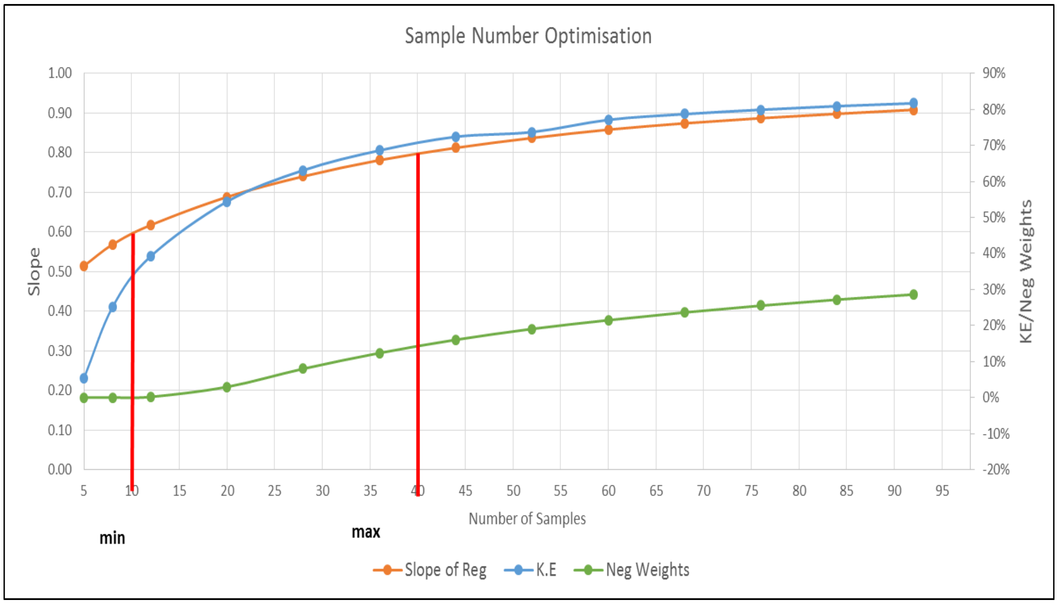


Zone3

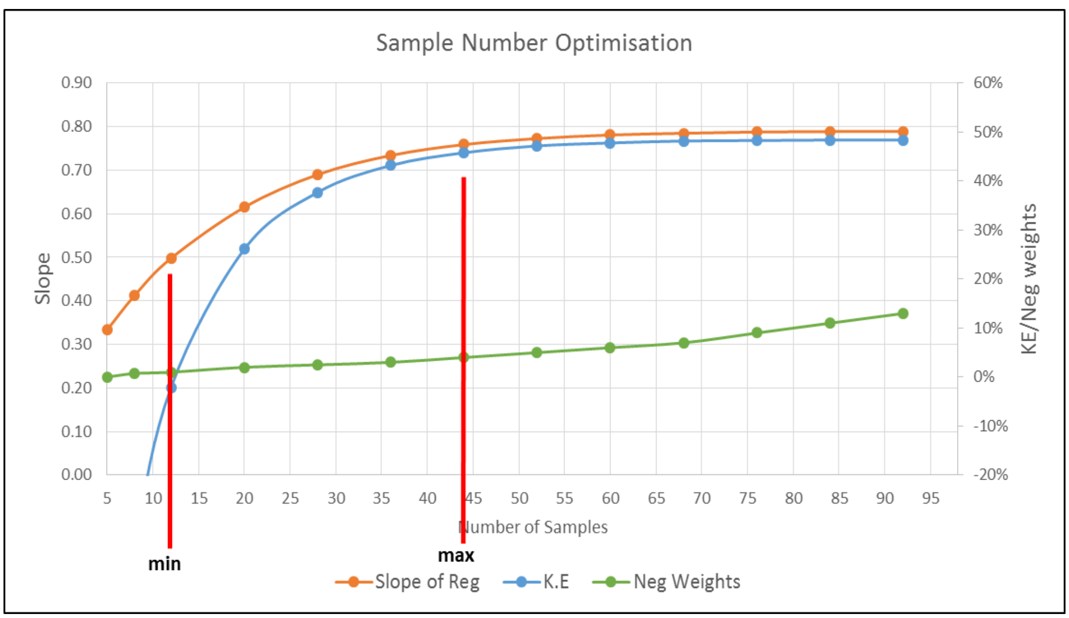


Appendix 7.5: Sample Number Optimisation

Zone2



Zone3



Appendix 7.6: Histograms for Number Samples