School of Mining Engineering

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

A REVIEW AND ASSESSMENT OF THE APPROPRIATENESS OF THE MINERAL RESOURCE ESTIMATION AND CLASSIFICATION PRACTICES, AS CURRENTLY APPLIED TO THE MG1 CHROME SEAM ON A BUSHVELD COMPLEX CHROME MINE

Andre Hanekom

Student number:886823

Supervisor: Prof Christina Dohm

A research report submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science in Mining Engineering.

Johannesburg, 2020

DECLARATION

I declare that this report is my own, unaided work. I have read the University Policy on Plagiarism and hereby confirm that no plagiarism exists in this report. I also confirm that there is no copying nor is there any copyright infringement. I willingly submit to any investigation in this regard by the School of Mining Engineering and I undertake to abide by the decision of any such investigation.

Furthermore, I declare that I have obtained authorisation with regards to the research study by the company the research is conducted on.

30th of October 2020

André Hanekom | Date

ABSTRACT

The applicability of both the Mineral Resource estimation and classification practices of the MG1 chrome seam on a Bushveld Complex mine are addressed in this research. The Growth technique (a 2D gridding algorithm) available in Geovia Minex™ software, currently used for resource estimation. Mineral Resource classification is based on the application of fixed radii (150m, 300m and 600m for Measured, Indicated and Inferred Resources respectively) to verified MG1 chromitite borehole intersections. The Competent Person can at his/her discretion, manually adjust classified Mineral Resource boundaries resulting from the radii for resource declaration. These practises stem from experience gained over many years of mining the MG1 chromitite resource. Establishing formal methodologies supported by research and comparative studies for MG1 chrome resource estimation and classification are the focus areas for this research investigation. The benefit of having technical support for the resource estimation and classification practices is that this will assist the Competent Person (CP) in his/her justification for estimation and classification methodologies in the resource declaration of the mine, a requirement of the Mineral Resource reporting codes. Having formal backing for these practices is considered value adding to the mine.

Growth technique estimation is compared to alternative estimation methodologies namely Inverse Distance Weighting (IDW) and Ordinary Kriging (OK). The fixed radii resource classification procedure is weighed up against published Mineral Resources classification approaches found in the resources industry. Within the current sampling configuration IDW and Ordinary Kriging estimation results were globally similar to those of the Growth technique. Locally however, IDW to the power two and OK produced more representative estimates.

Mineral Resource classification methods based on geostatistical parameters and measures confirmed that the fixed borehole confidence radii used for resource classification are applicable. Spatially the geostatistical classification approach resulted in a more sensible representation of the Mineral Resource categories. In conclusion the influence and impact of geological factors on resource classification are stressed. The development and implementation of a Mineral Resource classification scorecard approach is recommended, as such would result in a transparent, defendable, and robust classification methodology meeting mineral Resource Reporting Code requirements.

ACKNOWLEDGEMENTS

First and foremost, I want to thank God for blessing me with this opportunity and providing me with the knowledge to complete this research project.

Furthermore, I want to thank my family, friends and colleagues for their support and believing in me throughout the process of this research project. I also want to thank the mining company which granted me permission to conduct this study, making use of the relevant software, and providing me with the data for this research.

I want to acknowledge the following individuals for their contributions:

- Professor Christina Dohm (University of the Witwatersrand), for her guidance, assistance, support and patience, and challenges which kept me determined to complete this research project.
- My wife, Leani Hanekom, for all her love, support, patience and for motivating me.
- The Superintendent of Geology which worked for the mining company for preparing the data for this research project and documentation that explains the Resource estimation and classification procedure of the mine, including technical inputs.
- Justin Glanville, for technical advice and guidance, including inputs towards data conversions and macro’s which assisted me in the analysis of the technical part of the research.
- Antonio Umpire, for providing technical reviews and software guidance.
- Isobel Clark, for reviewing and providing guidance on variography.
- Felix Walraven (Seequent Pty Ltd) for providing software licenses for Leapfrog® and Datamine® for the use of this research project.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

APPENDIX

LIST OF UNIT SYMBOLS

UNIT	SYMBOL
centimetre	cm
Chromium	Cr
Chromium(III) oxide	Cr_2O_3
Coefficient of determination	R^2
grams per cubic centimetre	g/cm^3
Iron	Fe
Iron(II) oxide	FeO
meter	m
Million tonnes	Mt
Million years	Ma
More than	>
percentage	%
silicon dioxide	SiO_2
Trademark	™
Registered trademark	®

LIST OF ABBREVIATIONS

ABBREVIATION	DEFENITION
2D	Two dimensional
3D	Three dimensional
ASX	Australian Securities Exchange
B.L.U.E	Best Linear Unbiased Estimation
BC	Bushveld Complex
BV	Block Variance
CAD	Computer-aided design and drafting
CDF	Cumulative Distribution Function
COV	Coefficient of variation
CP	Competent Person
CR:FE	Chromium to Iron ratio
CVV	cross-validation variance
CW	Channel Width
DHS	Drill Hole Spacing
DIFF	Difference
EDA	Exploratory Data Analysis
GPS	Global Positioning System
ICP-OES	Inductively coupled plasma - optical emission spectrometry
IDW	Inverse Distance Weighting
IDW2	Inverse Distance Weighting to the power 2
IDW4	Inverse Distance Weighting to the power 4
IND	Indicated
INF	Inferred
IRUPs	Iron-rich ultramafic pegmatites
ISO	International Organization for Standardization
JORC	Joint Ore Reserves Committee
JSE	Johannesburg Stock Exchange
KE	Kriging Efficiency
KV	Kriging Variance
LG1	Lower Group one
LG2	Lower Group two
LG6	Lower Group six
LG7	Lower Group seven

ABBREVIATION	DEFENITION
MG1	Middle Group one
MG2	Middle Group two
MG3	Middle Group three
MG4	Middle Group four
MINTEK	Council for Mineral Technology
MRE	Mineral Resource estimation
N	North
N/A	Not applicable
NNW-SSE	North North West - South South East
NR	Neighbourhood restrictions
NZX	New Zealand's Exchange
MAX	Maximum
MIN	Minimum
MEAS	Measured
OK	Ordinary Kriging
PGE	Platinum Group Elements
PGM	Platinum Group Metals
QA/QC	Quality assurance and Quality control
QQ	Quantile-Quantile
RBF	Radial Basis Function
RC	Reverse Circulation
RCI	Resource Classification Index
RLS	Rustenburg Layered Suite
SABS	South African Bureau of Standards
SAMREC	The South African Code for the Reporting of Exploration Results, Mineral Resources and Mineral Reserves
SANAS	South African National Accreditation System
SARM	South-African Reference Materials
SG	Specific Gravity
SOR	Slope of Regression
STANDEV	Standard Deviation
UG1	Upper Group one
UG2	Upper Group two

1 INTRODUCTION

The data used in this research study is considered confidential and reporting of results is drafted in such a manner that the details and origin of the information remains confidential. The company's confidentially is respected by not disclosing the specific location, or specific project description throughout this research report the abbreviation "MCo" refers to "the Mining Company". Furthermore, any internal documentation, reporting or research information provided by MCo and used in this research study is referenced in such a manner to not breach the confidentiality agreement. The intellectual property on which the research study was conducted is retained by MCo.

MCo agreed to make geological and borehole data available in order to compare the mine's estimation and classification practices with other methods using the same data set, on condition that the confidentially agreement is respected. This permission implied that apart from data access, information on practices had to be accessed through interaction with relevant stakeholders at the mine

1.1 Project Background

The research project was conducted on one of MCo's underground chrome mines that extracts chromitite ore, for producing beneficiated chrome, including ferro-chrome for the local market and international export markets. The mining right for mineral extraction is owned by MCo. Again respecting the confidentiality a Google map image, indicating the general area in which the MCo project is located in the North-West province, east of Rustenburg and west of Pretoria appears in Figure 1.

The project is situated in the western Bushveld Complex (BC) and is underlain by the Rustenburg Layered Suite (RLS), which hosts the Middle Group chromitite seams that are of interest for chromitite ore extraction. The two main chromitite seams mined underground for economic value are the Middle Group one (MG1) and Middle Group two (MG2) seams. Underground mining of the MG1 and MG2 chromitite seams are predominantly by means of hybrid-conventional mining for the MG1 and bord and pillar mining for the MG2. The chromitite seams are generally homogeneous in terms of mineralisation and grade, with the MG1 seam, generally higher in grade.

Figure 1: Satellite image: general area of the research project indicated by the red circle (Google Maps , 2020).

1.2 Estimation and Classification Methodologies in Place at MCo

MCo's Mineral Resource estimation and classification practices at the time of this research study stems from years of practical experience and empirical knowledge of the chromitite resources in the Bushveld Complex(BC) gathered and defined by geology and mining professionals from exploration to resource estimation through to life of mine planning.

Estimation

The Growth technique is a proprietary algorithm within Geovia Minex™ software; currently the software package of choice for Mineral Resource estimation and classification at MCo. This estimation method is based on a two dimensional (2D) gridding algorithm, that calculates best-fitting surfaces for stratiform deposits, considering regional trends while honouring drillhole data. The technique is applied to the Cr_2O_3%, SiO_2%, FeO%, Cr:Fe ratio, Specific Gravity (g/cm^3, and MG1 Seam Thickness(m) variables for MG1 resource estimation.

Classification

The current Mineral Resource classification methodology, based on prescribed empirical borehole radii for the delineation of the chromitite resource categories relates to the borehole grid spacing. As the drilling grid expands, the radius from seam intersections of verified drilled borehole locations increases and consequently the resource confidence decreases. For a Measured Resource, a 150m radius is typical, a 300m radius for an Indicated Resource and a 600m radius for an Inferred Resource. The Competent Person can manually adjust the resource confidence categories for closer borehole spacing based on his/her own discretion.

Comparative Studies

The methodologies for resource estimation and classification have evolved within the mining industry with advancement of the technological age, advanced software applications allowed for the application of spatial estimation techniques as opposed to classical approaches. Although MCo recognised this development and have adopted modern estimation and classification methods, technical comparative studies confirming the current resource estimation and classification methodology have not been carried out.

1.3 Research Project Objective

The intension of MCo comply with the requirements of the SAMREC(2016) and JORC(2012) reporting codes for Exploration Results, Mineral Resources and Mineral Reserves, specifically that the Competent Person (CP) should be able to defend their choice of estimation and classification methodologies employed in the Mineral Resource declaration of a company.

The objective of this project research is to address the MCo's aim of adherence to the reporting codes and to provide the CP with defendable researched Mineral Resource estimation and classification guidelines and recommendations based on acceptable industry practices. Furthermore, the study will assess the appropriateness of MCo's Mineral Resource estimation and classification approach, in comparison to alternative estimation methods (IDW & OK), and classification methods based on geostatistical studies, by using the same data set. The "same data set" refers to the data that was used in the most recent Mineral Resource and classification, 2017 end year reporting of MCo.

The goal is to either confirm the appropriateness of current resource estimation and classification approaches or to propose different methodologies based on researched practices of Mineral Resource estimation an classification. The results of the study could also assist other chrome mines within the BC in approaches towards Mineral Resource estimation and classification.

1.4 Problem Statement

Firstly, the MCo currently uses the Growth technique for Mineral Resource estimation, a commonly applied method in the coal industry. The appropriateness of this estimation technique has not been established through comparative studies of other estimation methods (e.g. IDW or OK), in the project area being considered.

Secondly, the borehole radii mineral resource classification approach (similar to the coal industry), has been entrenched as a standard for several years, and have also not been compared to other alternative methods (e.g. geostatistical methods), used in the mining industry.

1.5 Research Hypothesis and Assumptions

Applying statistical and geostatistical techniques and analyses, as opposed to the current methodology of a growth algorithm for estimation and the application of fixed radii for resource classification categories, can improve the resource estimation confidence. This is expected to have a positive impact on the MG1 resource classification. This does not necessarily mean that there will be more resources in the higher confidence categories, but rather that the confidence in estimates within all the resource categories will be improved in terms of confidence measurement or determination.

1.6 Research Motivation

A general lack of published research regarding the estimation and classification of chromitite resources, established by the detailed literature search and review of estimation and classification methodologies in the mining industry was a significant driving force in the motivation for the investigations carried out by this research.

The value of the research lies in a benefit to the CP, compiling or reviewing the MG1 chromitite resource statement for the mine, who will be able to muster support for their choices of resource estimation and classification practices based on the outcomes of the research.

1.7 Research Questions and Methodology

The methodology followed throughout this research study is based on a quantitative approach, in conjunction with industry research, including internal documentation supplied by MCo. Due to the confidentiality agreement with the company, references of any internal literature, reports or information used, is not provided in this research study. The research report is structured to incorporate a review of the Mineral Resource estimation and classification of the MG1 chromitite seam, by using comparisons of known industry-standard estimation and classification methods, with the current methods employed by MCo. The comparative results were not statistically measured for significant differences and was rather compared with logical conclusions.

The key questions this research aims to answer are as follows:

- Irrespective of the use of geostatistical parameters for resource estimation, are other factors such as geological parameters influencing the confidence in the resource estimation?
- Is the Growth estimation methodology as used MCo applicable for the MG1 orebody and can it provide measurable or quantifiable estimation confidence?
- Is there merit in applying alternative estimation methods such as Ordinary Kriging (OK) and IDW, to the relevant variables (grade, seam width, and Relative Density), i.e. do these methods provide estimates that are closer to reality? Is there an underlying spatial variability in terms of grade, seam width and SG in the MG1 seam?
- Are the predetermined radii sizes for resource estimation applicable for the declaring the current resource confidence associated with the orebody?
- How do statistical, geostatistical, geological and (or) scorecard approaches compare to the current resource classification practise in place at MCo?

The methodology followed to answer the research questions and address the objectives of the study is listed below:

- Conduct a literature review and assessment of the current Mineral Resource estimation techniques, and classification practices applied to the MG1 chromitite seam at the mine.
- Assess the geological setting (regional & local) and the main geological factors that influence the resource estimation confidence conducted at the MCo. This was achieved by a literature review of the BC geology and supported by a numerical indicator modelling conducted in Leapfrog® Geo software.

- Investigate via an Exploratory Data Analysis(EDA) the underlying statistical distribution of the relevant variables used for estimating the MG1 resource, which is a crucial factor of determining an applicable Mineral Resource estimation technique.
- Analyse spatial variability and continuity of the variables used for Mineral Resource estimation based on a literature review of variography including the calculation and modelling of variograms, also apply Leapfrog® Geo numeric modelling (Isoshells) to enhance this analysis.
- Carry out comparative statistical and geostatistical analyses of the Growth estimation technique, including the classification methodology used by MCo. In principle, comparisons was also conducted by using a Mineral Resource classification score card approach.

1.8 Research Project Outline

This research project consist of 10 chapters, followed by the Reference list and an Appendix.

Chapter 1 offers an introductory background to the research project. Commencing with the limiting confidentiality aspect of the project and how it is addressed. Followed by a summary of current estimation and classification practices of MCo. Proceeding with the research objective namely to assess MCo's Mineral Resource estimation and classification practices and to either confirm or provide recommendations based on acceptable industry practice whilst adhering to reporting codes. The two fold problem is stated, the research hypothesis and assumptions are presented. The research is motivated by the value add of the outcome and benefit expected for the CP generating the Mineral Resource declaration for MCo. Finally, the research questions and methodology are discussed.

Chapter 2 provides an holistic overview of the Mineral Resource estimation and classification practices within the mining industry. The importance of reviewing the appropriateness of these practices is highlighted as they can have an major impact on the efficiency, productivity and financial wellbeing of a mine.

In Chapter 3 the Geological setting and the MCo's data regime is reviewed, background of the data used within this study is also discussed. The MCo's

Geological modelling procedures are reviewed, in accordance to Mineral Resource estimation and classification practices. The 3D Geological modelling methodology conducted in Leapfrog® Geo by the researcher, is presented in comparison with MCo's current geological structural model.

Chapter 4 elaborates on the Exploratory Data Analysis conducted to gain understanding of the underlying grade distribution and continuity of the relevant variables used in the Mineral Resource estimation and classification at MCo. Analysis and investigation on domaining, stationary and influences of geological complexities on the data conducted are argued.

Chapter 5 provides a high level literature overview of variography, the semi-variogram model, and the spatial analysis conducted for this research, with concluding results. The "two thirds" variogram range of influence classification method, is also compared with MCo's current Mineral resource borehole radii criteria.

Chapter 6 describes the block modelling and estimation process followed, and the determination of a search neighbourhood using a quantified Kriging neighbourhood analysis. The results of applying alternative estimation techniques (IDW & OK) in comparison to the Growth technique are also discussed.

Chapter 7 describes the main influencing factors affecting the MG1 Resource classification practices currently employed by MCo.

Chapter 8 summarises the Mineral Resource classification comparison results, conducted by using geostatistical parameters.

Chapter 9 concludes the research findings based of comparisons conducted on MCo's current Mineral Resource estimation and classification practices. Furthermore, the advances and disadvantages of the Growth technique are discussed, and the findings of the research questions of this research study are also addressed.

Chapter 10 summarises the recommendations based upon the conclusions and outcomes of this research project. Furthermore, guidelines to improve the current Mineral Resource estimation and classification practices of MCo are also discussed.

2 LITERATURE REVIEW

The literature review of this study is focused on providing an holistic overview of the Mineral resource estimation and classification practises within the mining industry. Furthermore, an overview of the estimation techniques that were compared for this study is also described.

2.1 Resource Estimation, Classification and Reporting

Resource estimation is critical within a mining company and used to determine performance, describe risk and allow informed decisions to be made (Snowden, 2001). The generation of Ore Reserves is underlain by the estimation of Mineral Resources. It is therefore critical for resource estimations to be reliable to provide a level of confidence in day-to-day operations and in feasibility studies. Geologists and Engineers that conduct these estimates should be mindful of the errors and uncertainty associated with estimations (Dominy et al, 2002).

The most critical goal of resource estimation is to predict future grade and tonnage of resources that may be mined, in other words, the final estimation for the purpose of distinguishing between ore and waste. Mining companies must live up to production expectations and deliver adequate returns to investors who provide funding. Therefore, the emphasis is on local precision and exactitudes of estimates, including the realistic expected value that could be recovered (Deutsch & Rossi, 2014).

Noppé (2014), explains that mining is inherently a risky type of business from technical, environmental, social, including uncertainties economically with regards to an exploration prospect to a feasible project advancing to a developed mine, that is associated with operating, market and safety risks. The risk in a project can better inform internal and external stakeholders with improved transparency, consistency and balanced interpretations of technical confidence. Therefore, minimum standards, recommendations, and guidelines for public reporting of Exploration Results, Mineral Resources and Mineral Reserves are specified by International reporting codes.

Although the Reporting codes provide guidelines on more specific matters in terms of estimation and classification, the guidelines remain non-prescriptive and rely on the judgement of the Competent Person (CP) that reports the estimates (Njowa, 2008).

The SAMREC and JORC codes have been included in the listing rules of securities exchanges (ASX, JSE and NZX), that are associated with specific requirements for exploration and mining companies that report to the relevant exchanges (Noppé, 2014).

Furthermore the reporting codes (SAMREC and JORC), make recommendations, provide guidelines and set minimum standards and criteria for Mineral Resource estimation and classification.

The researcher, therefore, believes that it is critical to consider SAMREC 2016, specifically Clause 24 covering the Reporting of Mineral Resources and Table 1 Section 4, which emphasises the geological model interpretation, the nature and appropriateness of the resource estimation method and resource classification technique.

MCo aims to comply with the SAMREC reporting Code. Figure 2 below is the SAMREC (2016) framework for the classification of tonnage and grade estimates, reflecting the geoscientific confidence and associated factors of technical and economic evaluation.

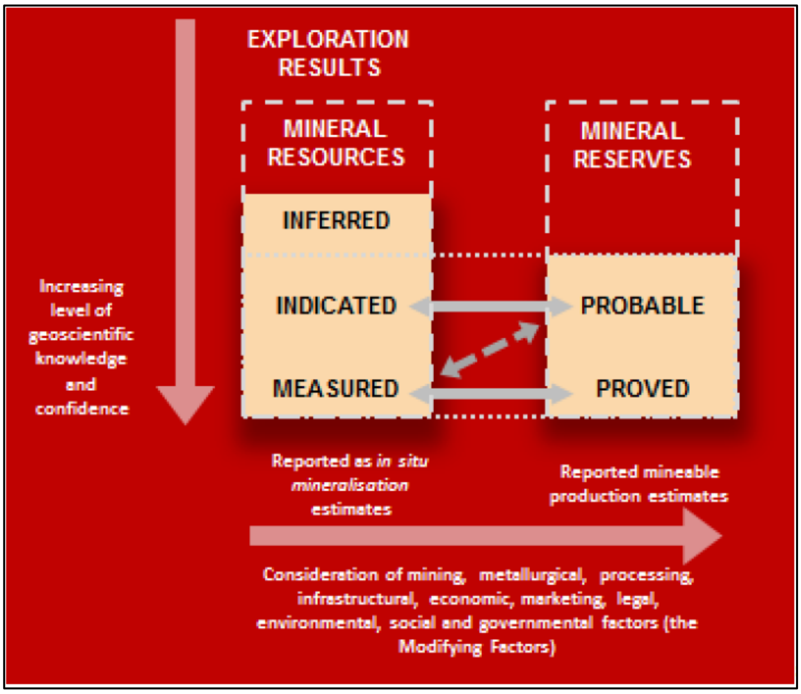


Figure 2: Linkages between Exploration results, Mineral Resources and Mineral Reserves (SAMREC, 2016).

Mineral Resource reporting Codes, such as the SAMREC code, do not describe how Mineral Resources should be classified, and only requires the CP to describe the criteria and methods that were used in order to classify Mineral Resources into different categories of confidence. However, the criteria and methods used, should adhere to the guidelines per definition of the different classification categories (Measured, Indicated and Inferred), on the basis of data quality, geological and grade continuity.

This still leads to subjective decisions of classifying a Mineral Resource and would depend solely on the criteria compiled by the Competent Person and (or) mining company, hence the reason for proper documentation and justification required (Emery, et al., 2004). The underlying difficulty of quantifying the extent of confidence associated with a Mineral Resource estimate has resulted in various and different methods, terminology, and definitions, with mining companies drafting their own independent classification standards (de Souza, et al., 2010).

De-Vitry (2003) points out a valid reason for this in stating that:

> *" … no prescribed criteria and rules will work for all situations or even between different ore types within the same deposit"*.

2.2 Factors Impacting Mineral Resource Estimation

There are many variables and disciplines influencing the precision of estimation all of which are important to achieving accurate resource estimation results. This includes, but is not limited to mining, metallurgy, geostatistics and geology mineralisation prior to resource estimation and realistic geological interpretation, including block modelling (Snowden, 2001).

Dominy et al (2002) state that reliable information and high-quality data is critical to sound investment and operational decisions, they also highlight the importance of the transparency of the estimator with regards to the inherent risks of the estimation.

Micon International (2016) highlights four main factors that have an influence on resource and reserve estimation and are causes of mine failure. These are identified as Geology in the estimation; Orebody characterisation; Top cutting of outlier assays and grade interpolation. Factors also affecting estimation, are poor data quality used to define the Mineral Resource, difficulties with regulating the amount and density of exploration data that is used to estimate the Mineral Resources and define the Mineral Resource confidence categories.

The inability of mine production to reconcile with Mineral Reserve estimates in terms of tonnage and grade are often associated with mine failure. Errors with regards to these measures are unavoidable. However, by applying appropriate estimation procedures, the expectancy of estimates produced by professionals could be within 10 percent of reality (Sinclair & Blackwell, 2002).

In summary, the literature review of the above three authors brings focus to the importance of understanding the reliability of and confidence in all elements playing a role in Mineral Resource assessment. Lacking this insight and appreciation could lead to compromised Mineral Resource estimation and classification, including consequential inaccurate mine planning, estimation of operational costs and capital expenditure, leading to compromised Mineral Reserve estimates.

2.3 Resource Estimation Methodologies

One of the fundamental decisions during the process of resource estimation is the selection of the appropriate estimation method. Inappropriate estimation methods could result in errors of ±50% associated with the estimate. The estimation method of choice should be based on the geology, grade distribution complexity and degree of high-grade outlying values (Dominy et al, 2002). Isaaks & Srivastava (1989) emphasise- that no single estimation method is appropriate for all Mineral Resources.

Furthermore, it is important to understand the capabilities associated with the method that is used. As an example, polygonal estimation methods contain one fixed biased answer and are more suitable for producing volume-weighted global mean grade estimates. The IDW technique is an unbiased estimator; it is a purely geometric technique and it is impossible to determine an estimation error variance as estimates only depend on the distance between samples and point to be estimated.

A geostatistical technique, namely kriging, provides the best linear estimate possible with obtainable data (Dohm,2015), and minimises the error variance of the estimation (Matheron,1963).

The appropriateness of an estimation technique is related to estimation goal Deutsch & Rossi (2014) mention for example if the goal is simplicity and reproducibility, then IDW estimation may be suitable. Should the goal be to reveal large scale geologic trends then both block kriging and IDW could be appropriate.

Considering that the goal determines the resource estimation technique, a review of the Growth method, Ordinary Kriging and Inverse Distance Weighting (IDW) techniques, which are in general applicable to chromitite resource estimation, follows.

2.3.1 Growth technique

The Growth technique is considered as a general-purpose gridding method available in Geovia Minex™ software, which was designed for the purpose of geology and mine planning solutions for coal, including other stratified orebodies (Dassault Systèmes, n.d.).

Dassault Systèmes GEOVIA Inc. (2016) describes the Growth technique as

> *"… a proprietary 2D gridding algorithm that calculates the best-fitting surfaces for strataform deposits, taking into account the regional trends while honouring the drillhole data, given the appropriate gridding parameters. The growth technique is suited to modelling borehole data, contour strings or spot heights and can handle features such as faults, trend lines (ridges) or discontinuity lines (creeks, gullies)."*

The Growth modelling technique is predominantly used in conjunction with gridded seam models. Irregular spaced data configurations are used to estimate attributes at grid values that are regularly spaced. The gridded model represents a deposit as a succession of layers and is appropriate for layered ore bodies, for example coal; bauxite; laterites and phosphate deposits (Surpac Minex Group, 2005).

Surpac Minex Group (2005) cites Batcha & Reese (1964); Crain (1970); Jones et al (1986), and states that the Growth technique occurs as a two-staged process. The first stage consists of surrounding the known data by four mesh points (nodes) on a grid. The second stage grows away from the initial four mesh points and estimate the remaining grid nodes by growing the mesh outwards. As the process continues the original points are ignored and only estimated points are used to fill the mesh points. A few passes are required until all the grid points have estimated values.

The Growth technique is predominately used for modelling surfaces of coal seams, including estimation of coal quality, in the mining industry.

2.3.2 Alternative Estimation Techniques

Sinclair and Blackwell (2002) call attention to the fact that in any given situation where alternative estimation methods deliver different numeric grade results, then these results can generally be used for comparative purposes.

A brief review of the alternative estimation techniques commonly used within the Chrome industry namely Ordinary Kriging (OK) and Inverse Distance Weighting to the power 2 (IDW2) are therefore described in the sub-sections that follow. These estimation techniques were also used to compare MCo's current estimation method.

2.3.2.1 Ordinary Kriging

Deutsch et al (2014) state the following:

> *"… early computerised OK techniques were developed by Krige, Sichel and others in South Africa. Matheron formalised the methods for mining resource and reserve estimation and named it kriging after the South African pioneer Danie Krige".*

OK is a geostatistical interpolation method that delivers local estimations. It is known as a "best linear unbiased estimator" (B.L.U.E). The estimates are "linear", as OK aims to estimate weighted linear combinations; attempts to equalise the mean error to zero, being "unbiased"; and referred to as "best", as OK tries to minimise the variance, associated with the estimation errors (Isaaks & Srivastava, 1989).

OK makes use of a weighted average approach with regards to neighbouring samples to interpolate an "unknown" value at a specific location. The weights are improved by the use of the semi-variogram model, describing the inter-relationship of known and unknown values, including the location of sample values. Furthermore, the OK technique provides a "standard error", and has the option to measure levels of confidence in the estimate, (Geostokos (Ecosse) Limited, n.d.).

2.3.2.2 Inverse Distance Weighting

Hengl (2007) cites Shepard (1968) stating that the IDW interpolation method is possibly one of the oldest techniques in spatial prediction.

Inverse distance methods are closely related to weighted average methods. The method is grounded on the calculation of weights for samples related to the distance from the samples to a specific point or block to be estimated. Weights are calculated according to the inverse of the distance between a known sample value and estimation point. To ensure that the estimate is globally unbiased, the sum of the weights are standardized to one. The weights decline based on the inverse a specific power (exponent) of distance. The Inverse Distance squared ($1/d^2$) technique is typically employed with attributes associated with uniform variation, for example, coal beds, in-situ bulk density values and strata-bound deposits (Deutsch & Rossi, 2014).

The IDW technique ($1/d$, $1/d^2$, $1/d^{2.7}$, $1/d^3$, etc.) is one of the traditional and most widely used Mineral Resource estimation methods, that considers point samples on which properties such as grade is estimated on a regular grid. This method is often critiqued for being subjective, however it remains popular as it produces results relatively close to geostatistical estimates, which has a rational theoretical basis for mine valuation (Sinclair & Blackwell, 2002).

One of the major shortfalls of the IDW technique, is that it cannot provide a measure of accuracy or precision (Myers, 1994), as opposed to geostatistical estimation methods. Gentile, et al. (2012) highlight pros and cons of the IDW technique which are presented in Table 1.

Table 1: Pros and Cons of the IDW technique (Gentile, et al., 2012).

Pros	Simple and intuitive Computationally fast
Cons	The choice of the interpolation parameters are empirical The interpolation is always exact – no smoothing Sensitivity to outliers and sampling configuration (clustered and isolated points) No estimation of interpolation errors (deterministic)

The most commonly used IDW power functions for Resource estimation to the second or third power, the choice is somewhat subjective (Glacken & Snowden, 2001).

Babak & Deutsch (2008) and Weber & Englund (1992) discuss several reasons why the IDW technique may be preferred over Kriging techniques and found that in several comparative studies the IDW estimates performed better. Although the IDW method is considered as an unbiased method, it does not account for spatial correlation (variography) and does not attempt to minimise the estimation variance, that Kriging does.

Another issue in using IDW is the decision of search neighbourhood parameters, however if used in conjunction with variography and a QKNA process, it can be resolved, as used in this study.

2.4 Resource Classification Review

The final task after resource estimation is the resource classification as it is required to report the level of confidence associated with the Mineral Resource (Glacken, & Snowden, 2001). The classification describes whether the Mineral Resources have enough confidence to be considered assets (Deutsch & Rossi, 2014).

The JORC code aims to guide Mineral Resource classification through guidelines such as the requirement for a Competent Person to base the classification results on as many objective factors as possible (Glacken & Snowden, 2001). Resource classification needs to be transparent and disclose all material issues for the benefit of all stakeholders (Snowden, 2001).

These requirements ultimately aim to address the subjective debate with regards to classification resulting in misclassification. Subjectivity is also influenced by the lack of an easy and established method to measure the confidence of varying classification approaches (Arik, 2002).

Furthermore, there seem to be unreasonable expectations of the resource model, due to an industry trend of using statistical descriptions of uncertainty, to supplement traditional resource classification criteria (Deutsch & Rossi, 2014).

2.4.1 Classification Practices

Some common Mineral Resource classification practices include utilising drill holes and samples near each block, the kriging variance (KV) method which provides an index of the data configuration and the use of radii to estimate blocks (Deutsch & Rossi, 2014).

The KV is known as a useful criterion and an objective measure for resource classification, geostatistical confidence with respect to the data configuration and it is a good indicator of overall sample spacing due to dependency on the arrangement and continuity of samples around the estimated block (Glacken & Snowden, 2001).

The KV classification method makes use of the cumulative probability (CDF) or the histogram of the kriging variance to assign resource confidence categories to the resource (Arik, 2002).

Silva & Boisvert (2014) proposed a new classification technique, calculating the cross-validation variance (CVV) during block kriging, and eliminating drillholes (one or more) that contains the highest weights and classify the block by using the resultant kriging variance.

Snowden (2001) specifies a comprehensive list of traditional and geostatistical Mineral Resource classification assessments or measures with related advantages and disadvantages. The list below only summarises some of the assessments of confidence using different aspects:

- The semi-variogram: measuring the anisotropy of the mineralisation, and assessment of confidence can be conducted with regards to drill hole spacing in relation to the range of influence.
- Number of samples per block: classification based on the number of samples within a search ellipse of a specified block.
- Distance: is useful for deposits that are isotropic (same variability in different directions), by using the average distance of samples from an estimated block.
- Kriging efficiency (KE%) and Regression slope: these measures can be used to investigate the appropriate block size during estimation, as well as to regulate the confidence of block estimates. In the case of a perfect estimation, the KE will be 100%, with the Regression slope being equal to 1.

Arik (2002) proposed the Resource Classification Index (RCI) that could be effective for resource classification, and utilises a combined variance, to combine various desirable classification measures into one.

Silva & Boisvert (2014) also highlight that many authors namely Wawruch and Betzhold (2005), Dohm (2005), Dominy et al (2002), and Snowden (2001), suggest using conditional simulation for resource classification, that presents an improved approach for accessing uncertainty compared to the KV and other methods. Deutsch et al (2006) however, recommend that conditional simulation should only be used as a supporting tool and that the classification criteria should remain geometric for final results.

Silva (2015) states that the most common Resource classification techniques used are geometric techniques, and although there are various types of geometric measures used the most popular are Drill hole spacing (DHS) and Neighbourhood restrictions (NR).The general principle of the DHS technique is the use of spacing between drill holes in order to classify blocks close to a block under consideration. The NR technique is based upon the distance of samples close to the classifying blocks and constraints associated with the number, including the configuration of samples within a search radius.

Deutsch, et al. (2006) suggests that geometric techniques (i.e. DHS and NR), should be based on thresholds such as standard industry practises of a country; geological setting; experience from comparable deposits: a calibration with uncertainty measured by geostatistical calculations and skilled judgement of the CP.

2.5 Reality of Mineral Resource Estimation in the Mining Industry

Glacken, & Snowden (2001) emphasise that future resource estimation will be influenced by technology and more sophisticated estimation algorithms. Deutsch & Rossi (2014) highlight that automation of many steps in the resource estimation process means less trained professionals might be required, which could be an advantage seeing there are already relatively few highly trained professionals for resource estimation. Furthermore, some of the other benefits include repeatability and transparency as well as real-time diverse data type collection, incorporation and processing of resource modelling, (Deutsch & Rossi, 2014; Glacken & Snowden, 2001).

Some disadvantages of the automation of resource estimation include unrealistic geological models, possible mistakes and a false sense of confidence being portrayed. These authors believe that professionals and software providers should become better equipped to address these disadvantages as well as the uncertainty associated with resource estimation, (Deutsch & Rossi, 2014).

3 GEOLOGY AND DATA COLLECTION

3.1 Regional Geology

There are three main mineral commodities that are mined from the layered mafic rocks of the RLS, of which the most important is the Platinum Group Elements (PGE), followed by chromitite and then vanadiferous magnetite. The RLS is estimated to contain 80% of the worlds PGE reserves (Morrissey, 1988 cited in Maier and Barnes,1999).

The mining area in this study is underlain by the mafic and ultramafic rocks of the Bushveld Complex (BC). The saucer-shaped BC intruded the sedimentary rocks of the Transvaal Supergroup, 2055–2060Ma, largely along an unconformity between the Magaliesberg quartzite of the Pretoria Group and the overlying Rooiberg felsites (Cheney and Twist (1991) cited in Hunt, 2006).

The BC hosts more than 80% of the world's Chromium and Platinum Group Elements (PGE) deposits (Crowson, 2001 cited in Cawthorn, 2010), and is recognised as the largest layered intrusion on earth (Von Gruenewaldt,1977) cited in Manyeruke (2006).

The BC is comprised of three suites of plutonic rocks, namely the mafic and ultramafic Rustenburg Layered Suite(RLS), the Rashoop Granophyre suite and the Lebowa Granite Suite (Von Gruenewaldt et al, 1985).

The RLS consists of an approximately 9km thick succession of layered mafic and ultramafic rocks, that are exposed in 5 major limbs; the Eastern, Western, the far-western limbs, the Northern (Potgietersrus) limb and the Bethal (Southern) limb (Kinnaird et al, 2004). Figure 3 shows the locations of the limbs.

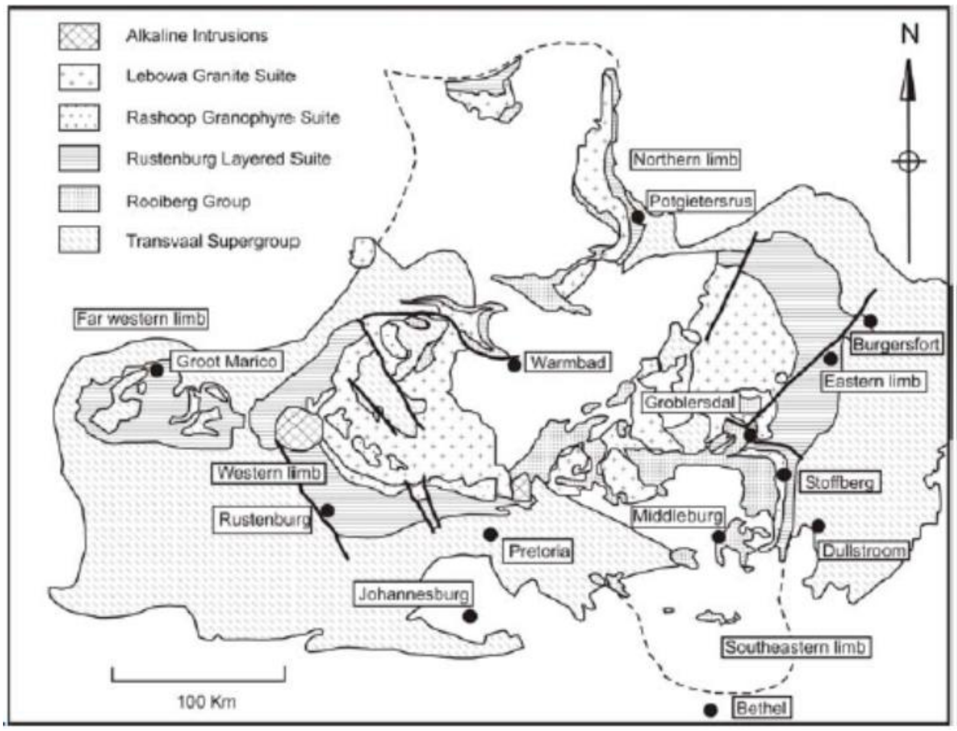


Figure 3: Simplified map of the Bushveld Complex showing the location of the various limbs (Kinnaird et al, 2004).

The RLS can be subdivided into five major zones known as the Marginal, Lower, Critical, Main and Upper Zones (Figure 3, after Kinnaird et al, 2002).

Layers of chromitite were deposited throughout the Critical zone, generally at the base of the crystallisation cycles. Chromitite seams are divided into Lower, Middle and Upper Groups. The Lower and Upper Group seams occur in the Lower and Upper Critical zones respectively, with the Middle Group chromitite seams that are in between the boundaries of the Lower and Upper Group chromitite of the Critical Zone. Due to the chromitite layers occurring in a succession, the seams get named according to their location, with numbers starting from the bottom up. The Lowermost Group gets named LG1 followed by LG2 to LG7 in the Lower Group (consisting of 7 layers), progressing to MG1, MG2, MG3 and MG4 (consisting 4 layers) in the Middle Group, and ends on two layers in the Upper Group UG1 and UG2, followed by the Merensky reef (SRK consulting, 2008).

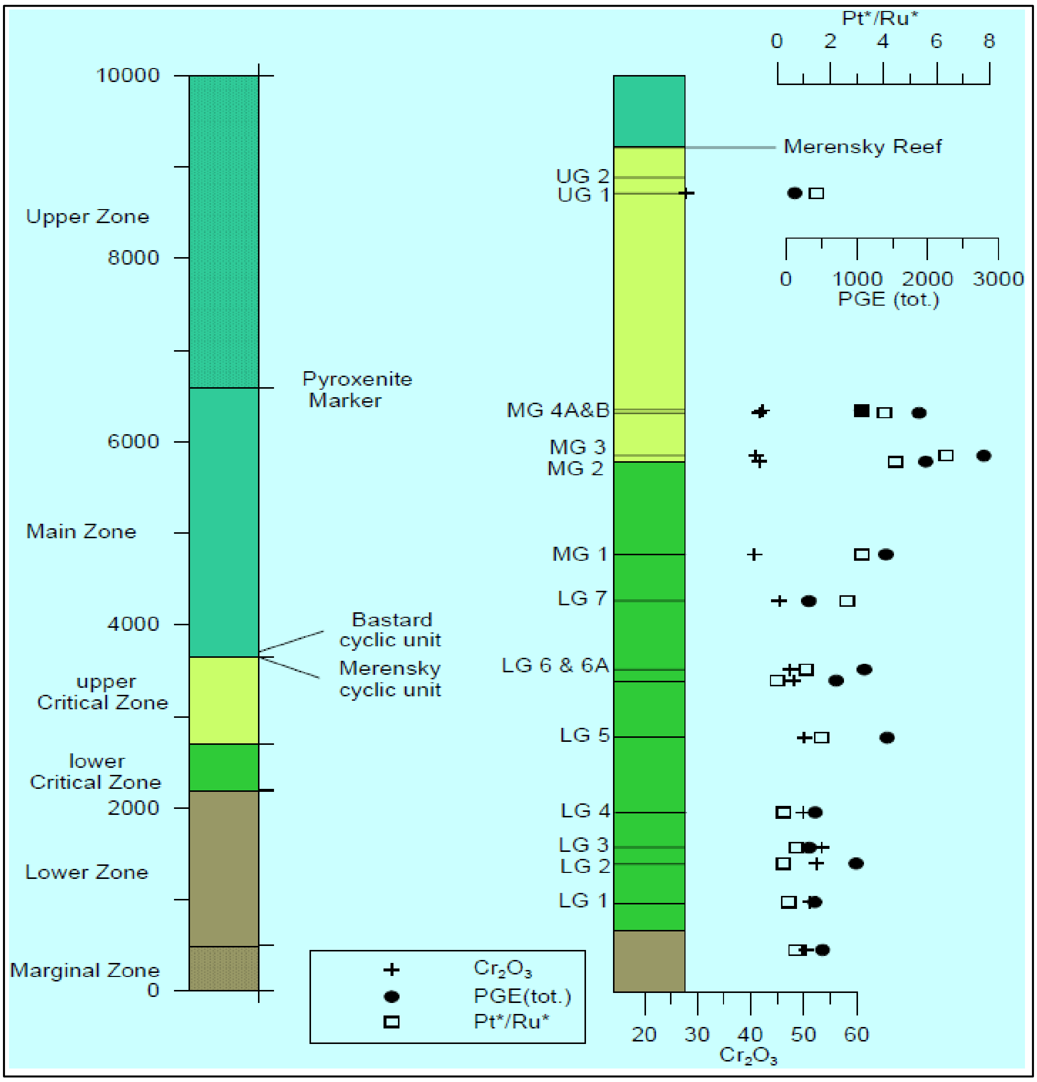


Figure 4: Typical Stratigraphic column of the Rustenburg Layered Suite with general zone thicknesses; major chromitite layers of the Critical zone, with Cr_2O_3 and PGE compositional data (column on the right) based on Scoon and Teigler (1994). (Kinnaird et al, 2002).

The chromitite layers predominantly mined for the extraction of chromite content is LG6 and MG1 to MG4. Generally, the LG6 and MG1 are associated with the highest chromite content being mined in the BC. The bottom layer of the sequence, the Marginal zone, is associated with noritic rocks, overlain by the Lower Zone (lithological units of dunites, harzburgites and pyroxenites), the Critical Zone (cyclic units of chromitite, pyroxenites, norites, and anorthosite), the Main Zone (cyclic units of norites and gabbronorites), and the Upper Zone (layers of magnetite, anorthosite, troctolite, ferrogabro to diorites). (Kinnaird et al, 2002).

The Critical Zone only occurs in the Western and Eastern Limbs and its enrichment in the platinum group elements (PGE), relative to the marginal rocks, culminates in the formation of the world-famous Merensky Reef and UG2 reefs, producing close to 60% of the World's PGM supply. The Merensky Reef is a feldspathic pyroxenite with a thin basal chromitite stringer which is associated with the highest PGM contents. The UG2 comprises of a main chromitite layer, carrying most of the mineralisation, followed by a poorly mineralised pegmatoidal pyroxenite footwall. The Critical Zone is thus of utmost economic importance and contains chromitite layers carrying between 50 and 85% chromite. The best Cr: Fe (Chrome to Iron ratio) values are found in the lowest layers, which currently produce about 40% of the World's chromium (Saager, 2005).

3.2 Project Geology

The mine's lease area is located within the Western Limb of the BC. The rocks associated with the Lower and Upper Critical Zone of the Complex underlies the project area, with chromitite seams interlayered with norite, anorthositic norite, mottled anorthosite and pyroxenite. The Marginal zone is also present within the project area and is associated with quartzite xenoliths. This represents the transgressive relationship between the Rustenburg Layered Suite and its floor. Distinct undulations such as the Spruitfontein and Kookfontein upfolds within the quartzite sedimentary floor, subdivide the South-Western BC into the Brits, Marikana, Rustenburg and Boshoek sectors which could be responsible for the lateral variations in the stratigraphy, chromitite thicknesses including chemical characteristics (CAE, 2013).

MCo chromitite deposits are situated in the Marikana section of the BC (Figure 5).

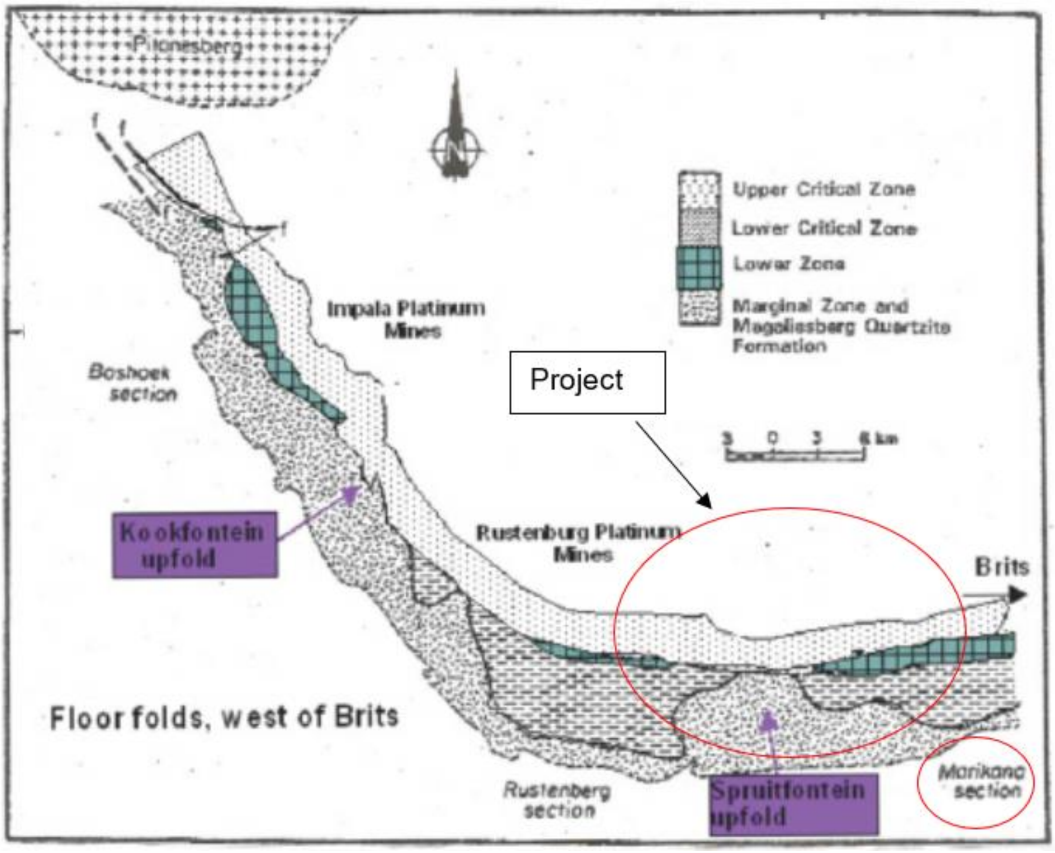


Figure 5: Floor folds in the Magaliesberg Quartzite Formation in the south-western Bushveld Complex, west of the property (modified after Davey, 1992 cited in Dube, 2010).

3.1.2 Stratigraphy

On the project area, there are sub-outcrops of chromitite seams belonging to the Middle Group chromitite layers within the RLS and are overlain by 0.5m to a few meters of black turf. Figure 6 represents the general stratigraphy underlying the project area.

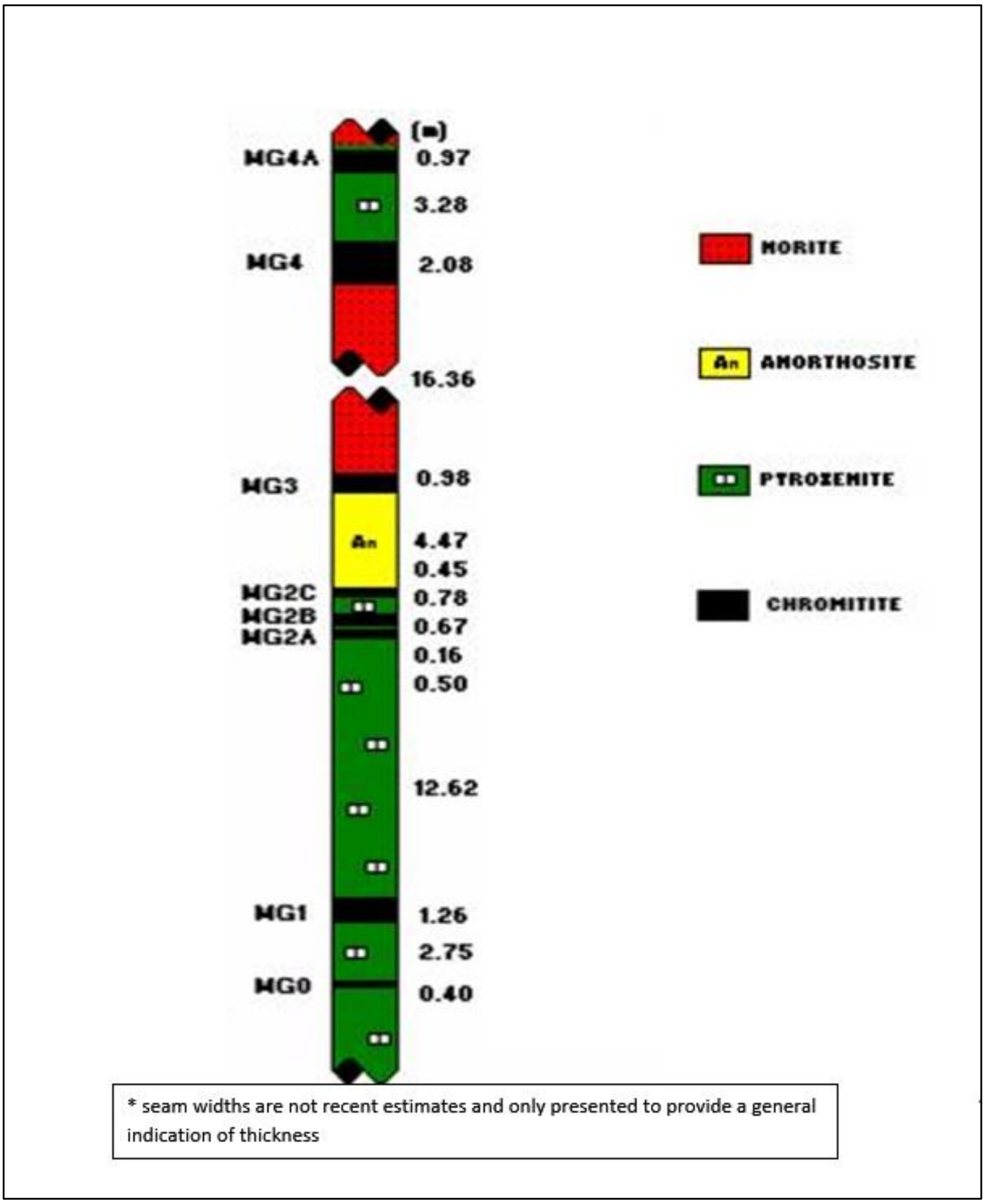


Figure 6: General Stratigraphy underlying the project area (MCo, n.d.).

3.3 Data collection

The borehole database, that incorporates collar, survey, stratigraphy, lithology and assay data was provided by MCo in the form of csv files, exported from Geobank Micromine® data management software. The borehole database dates back to 1999. Prior to exporting and handing over the borehole data to the researcher, MCo conducted both a data validation in Geobank and a seam validation in Minex software. The resource estimation for chromitite grade is based on surface exploration borehole data only.

The total number of boreholes within the database received from MCo is 196 surface boreholes (Figure 7) consisting of wireline diamond and percussion drilling, including deflections. Note to comply with the confidentiality on the location of the Project area coordinates are not shown in Figure 7.

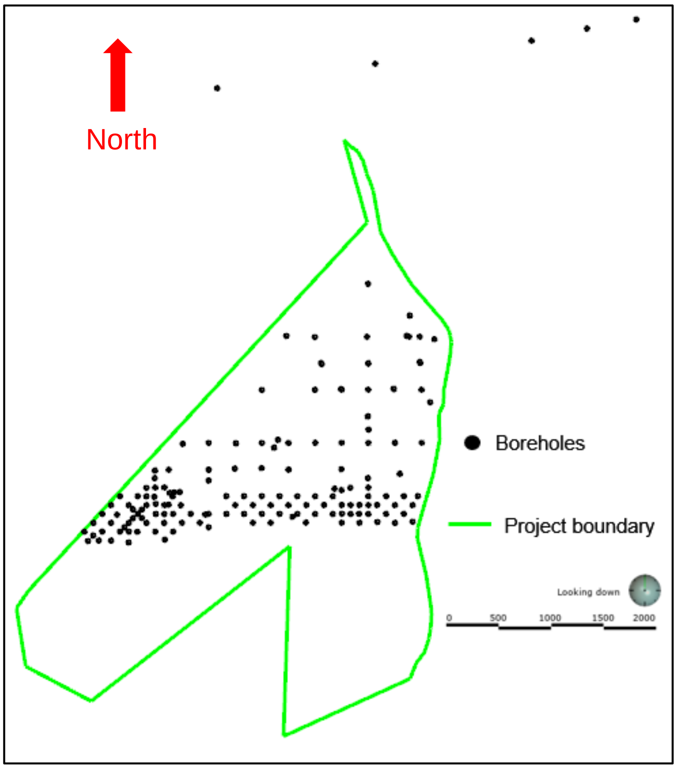


Figure 7: Borehole collars from available surface drilling data provided by MCo.

The main chromitite variables under consideration are Cr_2O_3%, SiO_2%, FeO%, Cr to Fe ratio, Specific Gravity(g/cm^3) and chrome seam width. Statistics were calculated for all the variables. However, the objective of the research is to improve confidence in the Mineral Resource estimate and classification, therefore, the focus has been on the economic driver (Cr_2O_3%), Specific Gravity(g/cm^3) and seam width(m) of the MG1 chromitite being the relevant variables for the resource grade and tonnage estimates.

Additional data such as, validated underground survey pegs; top contact MG1 off-sets by means of survey equipment, and interpreted geological structural plans, were also provided by MCo.

3.3.1 Drilling Techniques

The Borehole database generally comprises of wireline diamond drilling of BQ size (36mm diameter) mother holes and single deflections of TWB size (45mm diameter) core. The drilling of deflections was initiated from 2008 and comprise of approximately 24% of the diamond drilling that was conducted. Deflections were drilled for additional assay confirmations, including geotechnical and metallurgical test work. Reverse circulation (RC) drilling was also conducted in 2000, with 52 boreholes drilled in the opencast area of the property, however the drilling information was only used for orebody and structural delineation, and not deemed representative for Resource estimation by MCo.

Contracts with drilling contractors specifically stipulate more than 95% core recovery and not less than 99% within the economic mineralised zones.

3.3.2 Collar Positions

Final borehole collar positions were conducted with calibrated survey instrumentation, with a total station and differential GPS. The measurements were configured within the geomatic software of the instrumentation to automatically convert all data from WGS84 to LO27 coordinate system.

3.3.3 Down Hole Surveys

Down-the-hole surveys were conducted for approximately 31% of the Boreholes, which excludes RC drilling. The average deviation of the surveys is less than two degrees and a maximum of less than four degrees from vertical, that is considered, acceptable.

3.3.4 Geological Logging

MCo has standard logging codes in place for capturing data into a Geoscientific Information Management system, Geobank Micromine® software. However, a formal logging procedure is still within a final drafting phase.

Detailed geological information is captured and the chromitite mineralisation of economic importance is captured as “Economic Zones” (EC Zone) that is used for Resource estimation. The level of logging that is conducted includes lithologies, mineralisation, alterations, core bedding angles and geotechnical data if available. According to records within the database, about 50% of the borehole core from

1999 to 2006 drilling is in core storage. Drilled, and hardcopy logging documents for the drillhole database is safely stored for cross-reference if needed. Borehole core from 2006 to the most recent exploration program, is all (100%) in storage, with supporting hard copy documentation available.

3.3.5 Sampling

According to internal company reports of 2003, the sampling protocol that was followed on historical boreholes(mother holes) of the MG1 chromitite seam was to split the seam into two individual samples on the internal chromitiferous disseminated pyroxenite layer, and further split into half-core for assaying. A diamond rotary saw is used to cut and split the core. The MG1 chromitite layer is separated from adjacent waste rock by cutting it at the top and bottom contacts. Consistently one half of the core was sampled for assay analysis, and the other half retained in the core tray and allocated the same sample number as on the sample tickets, included in the plastic bags used for the assay sample. The protocol specifies that internal waste or partings more than 4-5cm in thickness would have to be sampled individually for assay analysis.

Deflections are sampled with a similar procedure, however if there were no deflection drilled, the mother hole chromitite intersection would have been sampled as a quarter core. Deflections would typically be used for friability analysis; two half core samples or if requested full core samples will be analysed. The same sampling protocol has been followed up to the latest exploration drilling projects.

The bagged samples are placed in a larger sample bag which contains all samples for one borehole. Each sample bag is adequately tagged with a sample identification number, as well as the larger sample bag containing all the samples. Subsequently, a laboratory request form for analysis is completed, upon delivery at the laboratory and cross-reference checks are conducted together with the laboratory Superintendent, prior to signing acceptance.

3.3.5.1 Sample Preparation and Analysis

MCo make use of an on-site laboratory that prepare and analyse all sampling that is obtained from exploration projects or underground. The Laboratory adheres to all the requirements of the South African Bureau of Standards (SABS) Standard ISO 17025: 1999 specifications in order to maintain international standard operating procedure and to retain accreditation. Furthermore, the company's laboratory is also accredited by The South African National Accreditation System (SANAS).

Inductively Coupled Plasma Optical Emission Spectroscopy (ICP-OES) is the analysis method that is used for determining percentages of Cr_2O_3, SiO_2 and FeO, of which an additional wet chemical analysis is conducted for Cr_2O_3.The Cr:Fe (ratio) is determined from the Cr_2O_3% and FeO% analysis.

The sample preparation and analysis is comprehensively documented in the June 2004 Mineral resource and Reserve report from the company, which complies to the SAMREC code.

3.3.6 Bulk Density

Lipton and Horton (2014) mention three fundamental inputs to a Mineral Resource estimate, namely grade, volume and bulk density. The importance of density stems from the fact that tonnage is estimated as a product of volume and density. Furthermore, grade estimates usually get weighted by tonnage, for reporting, which has a direct impact on the validity of grade.

Makhuvha et al (2014) also highlight that density have an impact regards to operational factors, such as mine planning; mine design; equipment selection and operational performance. The authors also point out essential procedures for mining and exploration projects such as selecting the appropriate method for density determination; comparing two or more techniques and quality control measures, to reduce risk and improve operational performance.

MCo uses Specific Gravity (SG) as a measure for density that is used for Mineral resource estimation, to report tonnage. The SG measurements are conducted at the company's laboratory and are reported together with the chemical analysis conducted for grade elements on the certificate of analysis. Records of the procedure for the specific method used for SG determination could not be obtained, however internal documentation from 2004, stated that an Archimedes method was used.

3.3.7 Database Integrity, Quality and Validation

Several authors (Assibey-Bonsu, 2016), (Chanderman, 2015), (Duggan, et al., 2017) and (Snowden, 2001) emphasise the critical importance of database integrity, quality and validation throughout the initial stages of Mineral resource estimation and classification. The integrity of a Mineral Resource estimation database is directly proportional to the reliability and confidence of the estimation results. Errors are considered to accumulate, due to the fact that geological interpretations and Mineral Resource estimations are grounded on the initial sampling database (Minnitt, 2014 cited in (Chanderman, 2015)).

The database integrity of MCo is upheld by ensuring that external and internal audits are frequently conducted on the drill hole database, procedures, and random checks on geological logging compared to physical observations of the borehole core. The company employs competent trained staff to ensure the quality of the data obtained is maintained, and by having transparent guidelines instated within the geological department.

Although the data received from MCo was validated using the Geobank® (database management software) and Geovia Minex™, the author of this research study re-checked and validated the database prior to Mineral Resource estimation and throughout the geological modelling process.

The researcher carried out additional validation by carrying out cross-reference checks and due diligence was conducted on the following:

- Zero values, missing, duplicated or erroneous collar coordinates
- Reconciliation of collars and the surface topography
- Overlaps, gaps, duplicates, negative values of borehole intervals, including sampling, especially the mineralised zone (MG1)
- Outlier, missing, zero values or anomalous assay results within the mineralisation zone (MG1) based preliminary histograms, and normal probability plots
- Visual inspections with regards to the borehole data in relation to geological structures that could have an influence on the mineralised intersections and assay results
- Visual inspections of elevation difference with regards to MG1 intersections

The collars coordinates of the boreholes were deemed acceptable, however during reconciliation with the surface topography two borehole collars were found to have a more than 2m difference, that is outside the acceptable margin. Subsequent to investigation, it was found that the topography available had survey data of a waste rock dump that influenced the reconciliation, and the collars were accepted as is.

3.3.7.1 Quality Assurance and Quality Control (QA /QC)

The SAMREC code (2016) guidelines for Quality Assurance and Quality Control QA/QC states that the Competent Person should be able to:

> *"… demonstrate that adequate field sampling process verification techniques (QA/QC) have been applied, e.g. the level of duplicates, blanks, reference material standards, process audits, analysis, etc*."

The company's laboratory is accredited to ISO 9000, and conforms to a Quality Assurance system. The company has well documented QA/QC procedures, as it is standard practise at the laboratory.

However, no documentation on a QA/ QC protocol with regards to the field sampling process, prior to sending samples for assay at the laboratory for historical borehole core samples were supplied by MCo. More recent records do however show a drive towards implementing control samples, such as blanks and standards into the sample stream. Records were obtained for 12 borehole samples assayed for Cr2O3% in 2017, where 18 blank and 12 standard samples were included in the sample batches (Figure 8 and Figure 9). Blank samples comprise of pure quartzite, and standards are certified reference material, SARM 146, prepared and distributed by MINTEK.

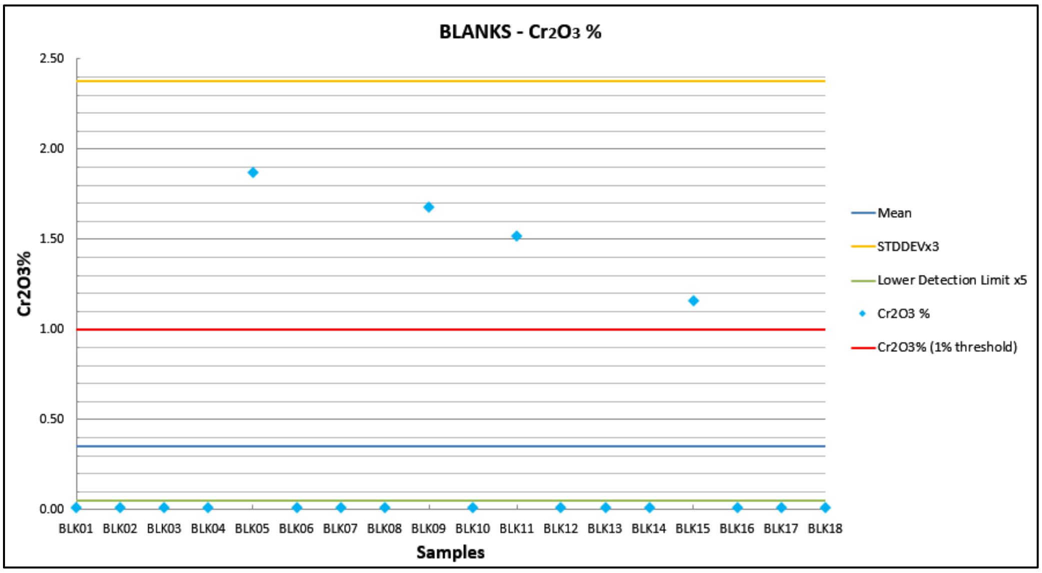


Figure 8: Sample blank analysis for Cr_2O_3% with QA/QC thresholds.

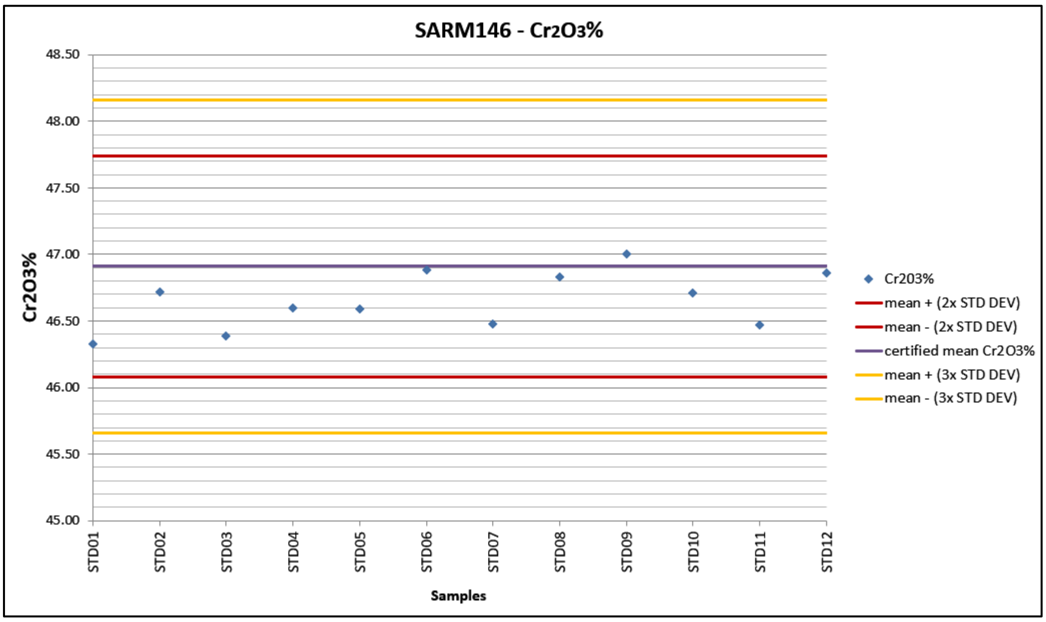


Figure 9: SARM146 sample analysis for Cr_2O_3% with QA/QC thresholds.

Blank and standard sample analysis is used to determine contamination, and accuracy respectively with regards to the analytical process of a laboratory. Standard practice in the chrome industry allows for a one percent threshold in terms of blank samples for Cr_2O_3% analysis. Standard samples or certified reference material analysis usually represents a good reflection of the accuracy of overall sample batch or batches, if results are within at least two standard deviations from the certified mean. Standard samples are also used to test the biasness of the analysis and good practice is for the results of the laboratory to be within 5% difference of the certified mean value.

Based on the limited records found, it is evident that the laboratory reflects acceptable accuracy and biasness towards the 12 boreholes that were assayed. However, in terms of the contamination analysis, less than 80% of the blanks passed the 1% Cr_2O_3 threshold. This indicates that the company should further investigate to the origin and preparation of the quartzite material used as the blanks, as this material is not certified. Further investigation with regards to the laboratory procedures internally should also be investigated.

3.4 Geological Modelling

Chanderman, et al. (2017) considers a geological model of an orebody prior to Mineral Resource Estimation (MRE) and Classification as a fundamental process, as it acts as the limits in which estimates are defined. Thus, MRE and classification fundamentally depend on the confidence of a model and a good understanding of the geology of an orebody, as it impacts the interpretation and the analysis process of conducting a Mineral Resource evaluation.

MCo generally uses a two-dimensional platform (CAD and contouring software), and to some extent three-dimensional interpretations when updating an ongoing 2D Geological structural model, based on historical drilling information; geophysical surveys; underground mappings; underground survey pegs and three-dimensional MG1 seam contours generated from the data. The MG1 seam contouring is created in Surfer Golden software® and (or) Geovia Minex™ to assist with geological interpretations, and dip regime of the orebody. The 2D geological structural model and MG1 contours is updated as new information is obtained through underground drilling, annual exploration, including updated underground mappings from mining advance.

The models that are used for Mineral Resource estimation (MRE) and classification consists of a combination of the 2D geological structural model, to incorporate an estimate of the geological loss, and a 3D gridded MG1 seam model that is generated in Geovia Minex™, to report volume. Furthermore, the models are also used for interpretation during resource classification, of structures that could have an influence on the confidence of the classification. The economic zone, which consists of MG1 borehole intersections, and relevant underground data of the MG1 seam, forms the basis of the 3D MG1 seam model.

The 3D gridded MG1 seam model consist of meshes, that are interpolated from borehole and other relevant data, by using the Growth technique. A borehole seam interpolation is used to insert seam intervals to complete the stratigraphic sequence for each borehole before generating model seam roof and seam floor grids (meshes). This ensures that there are no missing seams in the boreholes and prevent the crossing of gridded meshes. The MG1 seam model, does however, not take into account the geological structures when conducting interpolations. This could have an effect on the dip regime interpretations, and possibly reporting of the MG1 volume.

3.4.1 Geological model

For this research a 3D geological model of the MG1 roof (top contact) was constructed in Leapfrog® Geo (Figure 10) based on current and historical data of various sources listed below:

- Surveyed topography
- Existing 2D geological structural model of MCo
- 3D underground surveyed pegs and MG1 top contacts
- Validated MG1 borehole intersections

Leapfrog® uses a Fast-Radial Basis Function (RBF)^{TM} algorithm (Spragg, 2013), to implicitly create interpolated meshes of triangles from the input data, in 3D space.

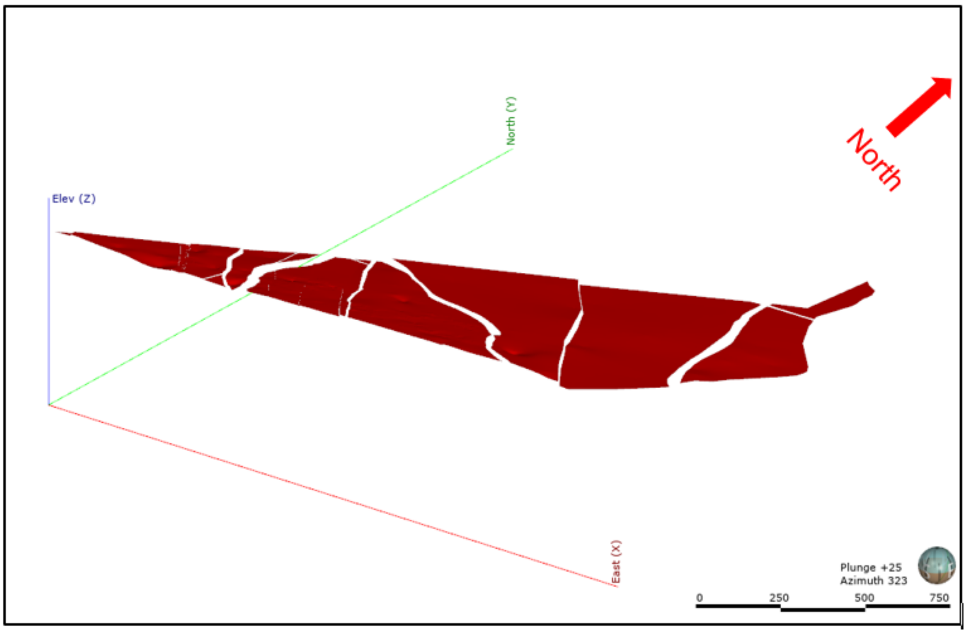


Figure 10: Orthogonal view of the interpreted MG1 top contact of the 3D geological model.

The 3D geological model was constructed to assist with the following:

- Confirmation and review of the current structural interpretation of MCo
- Orebody delineation and dip regime
- Influence of geological complexities that can affect grade continuity
- Geological loss and data influence associated with geological structures
- Conversion for MG1 drillhole seam intersection data, from apparent to true thicknesses using the MG1 top wireframe

The mineralisation of the MG1 orebody was modelled within definite hard boundaries of the exterior country rock, pyroxenite, that represent the footwall and hanging wall units.

In carrying out the geological modelling phase it became clear that the strike of the MG1 chromitite is generally east-west, dipping 15^0 to the north-northeast and north-northwest. Whilst the seams are assumed to be planar localised undulations do exist. Steep dipping depressions, known as pothole structures, occur in the project area, these tend to decrease or excessively increase the thickness, and locally increase the dip of the seam. The pothole occurrences are observed in both the borehole core and underground mapping data incorporated into the 3D geological model. Major known geological structures intersected and interpreted within the project area are faults, dykes and pothole structures. MCo's interpretation of the geological structures generally correlate well with the 3D geological model that was constructed (Figure 11).

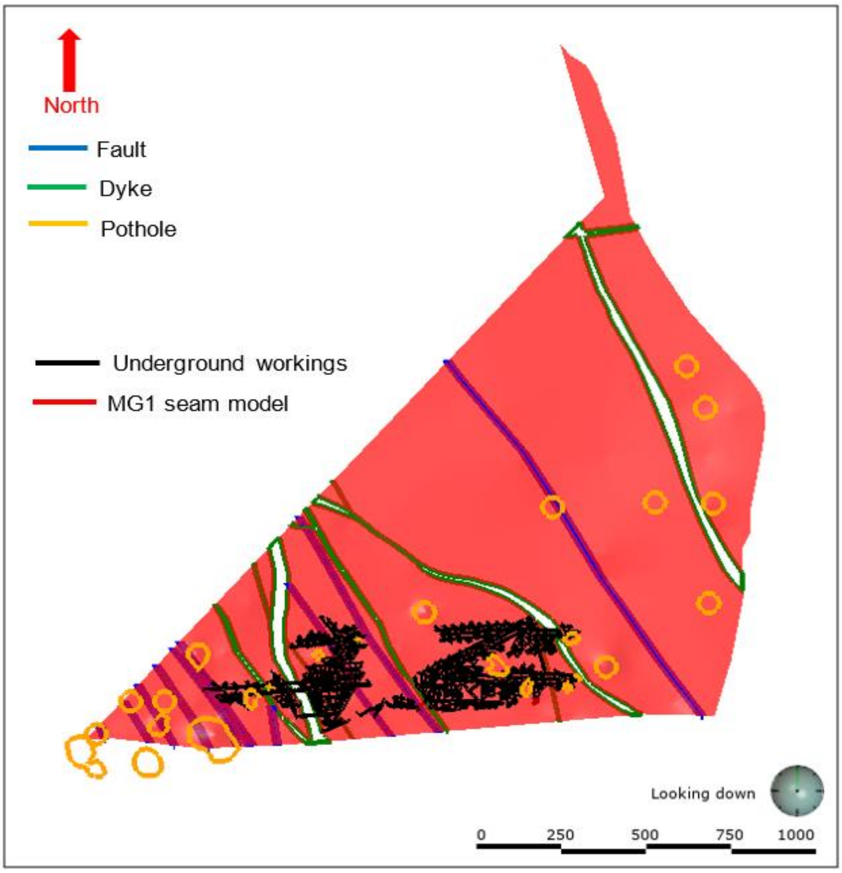


Figure 11: 3D Geological model overlain by MCo's major geological structural interpretation (plan view).

3.4.2 Geological structures

The major geological structures present within the project area, that could have a potential influence on geological and grade continuity are Faults, Dykes, Potholes and Iron-rich ultramafic pegmatites (IRUPs) and are detailed in the sub-sections to follow. Add “IRUPs” to the abbreviation list the you do not have to do it in the IRUP section below.

Major Faults:

Major faults or fault zones within the project area can be described as fault structures or zones that displace the chromitite seam(s) more than or equal to two meters in elevation. Generally, the faults that have been intersected and interpreted from geological modelling is normal (dip-slip) faults, with the occasional reverse fault intersection. Associated with these faults are a number of smaller dip-slip faults (fault zones) with throws less than 2m. The major faults within the project area range from 2-6m displacements, with one ±22m downthrow fault to the east of the property. The major strike direction of the faults is North West-South East dipping North-East or South-West respectively.

The faults are commonly associated with shear zones, dense sympathetic jointing, slickensides, alteration (clay minerals – serpentine, chlorite, talc) and water presents (seepage/ discharge). These conditions and fault displacements contribute to zones of geological loss within the MG1 chromitite seam.

Dykes:

The dykes interpreted from the geological modelling and intersected in underground workings are later stage igneous intrusions that replace the chromitite seams with a generally pyroxenitic (dolerite) rock mass, causing a geological loss in terms of mining. Pilanesberg age dykes trending NNW-SSE was determined by previous geophysical modelling and opencast mining on the project area. The dykes generally trend in a similar direction as the faults and conjugate. Minor sills associated with these dykes that intruded through weakness planes of the bottom contact of the MG1 seam are evident from underground mapping.

The dykes “pinch” and “swell” along its length (dip and strike) and sometimes bifurcates into thin branches, with thicknesses of ±1-20m. The dykes that were intersected in underground workings are associated with minor to moderate alteration, more severe alteration with the presence of water. Steep seam “drags” resulting in reduced seam thicknesses of minimum (±0.50m) or maximum increased thickness of (±2.0m) have been observed in underground workings that are associated with the influences of dykes.

Potholes:

Other structural features that are exposed within the project area in the underground workings are potholes, which are large “dish-or-pear“ shape structures with diameters estimated between 30 to 80m and a depths varying between 1m and 16m. Many Geologists generally describe potholes as synmagmatic circular depressions or slumps (Hoffman, 2010). Furthermore Hoffman (2010) highlights that

> *“… in Mineral Resource modelling, potholes may be characterized either as known losses, where the data acquisition activity has allowed reasonable definition or as unknown losses, where there is an expectation that potholes will be present with some statistical proportion”.*

The main characteristics of potholes within the project area, observed in underground workings and geological modelling, that impact economic extraction of the ore are listed below:

- Associated poor rock mass conditions due to high density of jointing and alteration of the pyroxenite host rock, that leads to uneconomical dilution when mined with mechanized machinery. Furthermore, also associated with safety risks that result in unfavourable mining conditions.
- Steep apparent and true dips of the MG1 seam, measured up to ±30^{0}.This leads to off-seam mining, uneconomical ore:waste ratios and decreased ore extraction.
- Steepening of the MG1 seam within areas close to pothole structures, termed “seam rolls”, which can prevent feasible extraction of ore.
- Reduced seam widths (±0.30m), “splitting”, and “pinching” of the MG1 seam, resulting in large areas of total geological loss.

Internal company reports from 2004, mention that no regional trend has been established regarding the occurrence of potholes. However, in 2017 the MCo’s Geology team, attempted to improve the predictions by a applying the methodology suggested by Hoffmann (2010), by including an analysis of strike/dip regime contours.

Hoffmann (2010) and a Geology department report from 2017 concluded that the size and local occurrence of potholes are highly unpredictable, and require sufficient data from underground workings, exploration/underground drilling or geophysical seismic surveys to accurately estimate/predict the influence on the Mineral Resource.

Even using all the sources of relevant data in the geological model, there will be large areas of the unmined Mineral Resource that will be associated with uncertainty. Hence, conducting a thorough “pothole influence” analysis in conjunctions with other methods, is crucial for estimating geological loss and influence. It is also important to consider a level of uncertainty when declaring the Mineral Resource in classification categories.

IRUPs :

Cawthorn, et al.(2018) consider IRUPs, as rocks primarily consisting of clinopyroxene olivine and magnetite, that intrude/cut layered successions irregularly, and are usually associated with sharp contacts. Due to their magnetic characteristics Aeromagnetic surveys are useful to identify the areas that could potentially influence economical chromitite seams. IRUPs can cause total geological loss, including deformation of chromitite seams. According to an internal company report in 2003, minor occurrences of IRUPs have been observed within the project mining area, however, could be exposed throughout the life of mine. Underground mapping and borehole data used for geological modelling also confirmed that currently there is no presence of major IRUPs, that cause geological loss or uncertainty with regards to the MG1 Mineral Resource.

4. EXPLORATORY DATA ANALYSIS (EDA)

The initial process, prior to resource estimation is an exploratory statistical approach, in order to understand the underlying characteristics of the related data and investigating stationarity of the geology associated with spatial continuity of grade, lithology, mineralogy, including alteration (Ortiz & Emery, 2006). Stationary refers to geological domains that are generally isotropic and homogeneous. The nature of the tabular MG1 orebody is vertically bound by prominent chromitite mineralisation within lithology that does not contain significant mineralisation and is also generally homogeneous within the mineralisation zone itself. However, continuity can vary along dip and strike of the orebody, that can influence the statistical analysis of the data, and if variant across specific areas, should be treated as separated domains. MCo considers the MG1 orebody to be estimated as a single domain, and the exploratory data analysis was conducted based upon that principle.

The main aim of the statistical analysis was to gain an understanding of the general distribution of the Cr_2O_3%; SiO_2%; FeO%; CR:FE (ratio), SG and true thickness (seam width) relevant to the estimation of the MG1 Chromitite seam .Descriptive statistical analyses were carried out to identify outliers or irregularities in the borehole database. This was done to ensure that the geological modelling, including the block model estimation, is not influenced by local variations due to geological structures or unrealistic assay values. Furthermore, the results of the statistical analysis were used to investigate the appropriate resource estimation technique to be utilised for a comparative review of the current practice at the mine.

4.1 Data Selection and Representativeness

The final drill hole database used for the exploratory data analysis, resource estimation and classification was based on the representative data selection criteria of MCo to ensure that the investigation conducted in this research study is carried out on the same data and that results would be directly comparable.

MCo considers borehole data nonrepresentative for resource estimation and classification based on the following criteria:

- Diamond drilling of MG1 intersections that are less than 40m from surface are deemed to be in the weathered zone of the orebody

- Percussion drilling within the opencast area of the mining perimeter
- MG1 intersections that are influenced by geological structures (potholes; dykes; faults and IRUPs)
- variables that are indicated to be erroneous or outlying (based on statistical analysis)

The number of acceptable boreholes based on the MCo selection criteria and used for statistical analysis of the different variables of interest are shown in Table 2.

Table 2: Number of boreholes used for statistical analysis

	Cr_2O_3%	SIO_2%	FeO%	CR:FE	SG	Seam Thickness (CW)
Number of boreholes	91	91	91	91	72	73

4.2 Compositing and Descriptive Statistics

Composting of originally borehole sampled grade values is usually conducted prior to resource estimation, however, it is not a mandatory requirement. Generally, resource estimation software requires the user to ensure that input data is of constant support, meaning that sample lengths are distributed equally according to grade. Original sampled variables consist of lengths that are usually not homogenous and can consist of internal waste; incomplete intervals; small scale analysis and high variability. Compositing homogenises and decreases the variability of samples to an appropriate data scale, which also relates to more robust geostatistical analysis, including variography (Deutsch & Rossi, 2014).

The MG1 sample data was composited based on the total length of each seam intersection, prior to statistical analysis. This method is known within the chrome industry and also part of the company’s procedure. The final validated composite values are then used throughout the resource estimation process. The implication of this practice is that there is no real grade vertical variability within the seam.

The histogram in Figure 12 presents a summary of the un-composited data, i.e. all the samples that were cut according to the protocols discussed in **Section 3.3.5**.

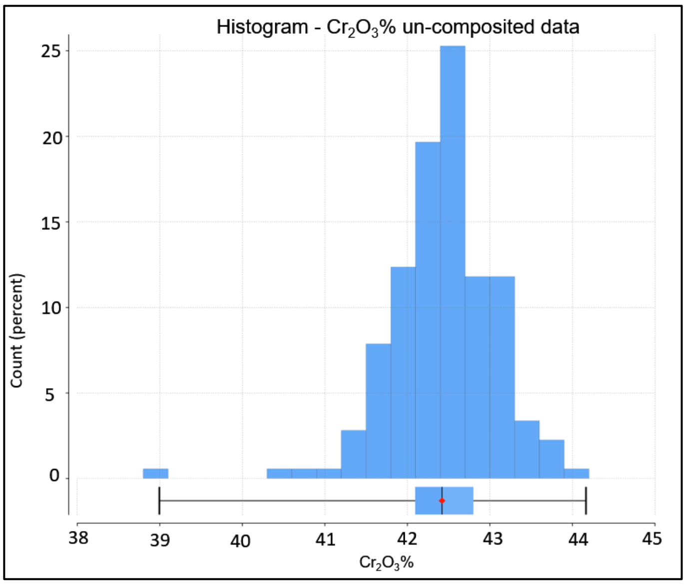


Figure 12: Un-composited Cr2O3% sample data.

The results subsequent to composting is presented in Figure 13, i.e. variable length composite that would include internal waste for the main economic variable Cr_2O_3%.

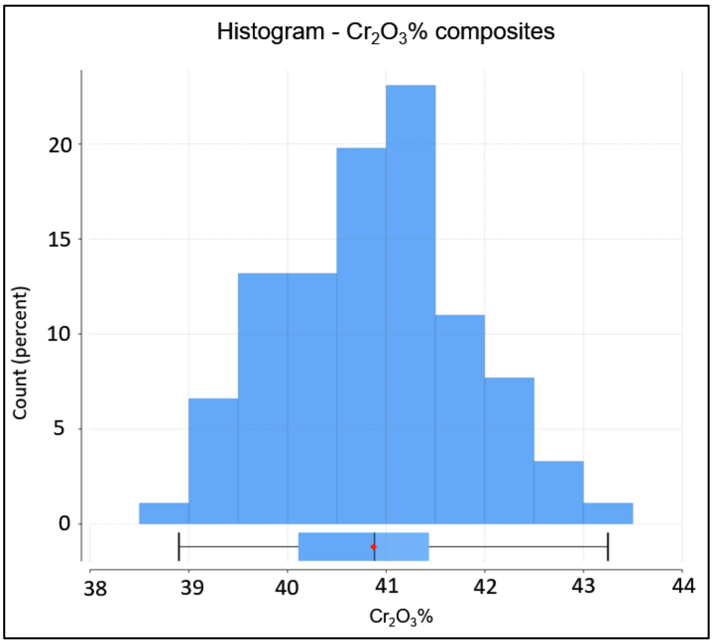


Figure 13: Composited Cr2O3% sample data.

The descriptive statistics for the composited and un-composted of the relevant variables are presented in Table 3.The true channel width (CW) of each selected MG1 borehole intersection, were calculated during the compositing process using the geological modelled surfaces (wireframes), to obtain estimated true dips, that were used for conversion calculations form the apparent drilled intersection lengths.

Table 3: Descriptive statistics of the un-composted and composited borehole data.

UN-COMPOSITED DATA STATISTICS												
VARIABLE	**RECORDS**	**SAMPLES**	**MISSING VALUES**	**MIN**	**MAX**	**RANGE**	**MEAN**	**VARIANCE**	**STANDDEV**	**SKEWNESS**	**KURTOSIS**	**COV%**
LENGTH(m)	179	179	0	0.08	1.50	1.42	0.65	0.03	0.17	0.50	8.55	26
CR_2O_3%	179	178	1	33.99	44.33	10.34	40.84	1.52	1.23	-0.96	4.81	3
FEO%	179	178	1	21.00	25.80	4.80	24.10	0.52	0.72	-1.08	2.57	3
SIO_2%	179	178	1	3.08	14.38	11.30	6.84	1.54	1.24	2.20	12.08	18
CR:FE	179	178	1	1.36	1.67	0.31	1.49	0.00	0.05	0.29	1.18	3
SG	179	140	39	3.61	4.41	0.80	4.12	0.02	0.14	-0.67	0.85	3
COMPOSITED DATA STATISTICS												
VARIABLE	**RECORDS**	**SAMPLES**	**MISSING VALUES**	**MIN**	**MAX**	**RANGE**	**MEAN**	**VARIANCE**	**STANDDEV**	**SKEWNESS**	**KURTOSIS**	**COV %**
LENGTH(m)	91	91	0	0.22	1.60	1.38	1.27	0.04	0.21	-2.33	6.78	17
CR_2O_3%	91	91	0	38.90	43.25	4.35	40.87	0.90	0.95	0.18	-0.45	2
FEO%	91	91	0	21.62	25.42	3.80	24.09	0.38	0.62	-1.27	2.67	3
SIO_2%	91	91	0	4.71	9.27	4.56	6.82	0.67	0.82	0.35	0.48	12
CR:FE	91	91	0	1.40	1.67	0.27	1.49	0.00	0.04	0.89	3.61	3
LENGTH_SG(m)	72	72	0	0.22	1.60	1.38	1.26	0.05	0.22	-2.21	6.03	18
SG	72	72	0	3.77	4.36	0.59	4.12	0.02	0.12	-0.38	-0.44	3
True CW (m)	73	73	0	0.66	1.56	0.90	1.26	0.03	0.18	-1.88	3.42	14

Observing the descriptive statistics, it is evident that there is a general reduction in the variability, range, and coefficient of variation (COV) across all the variables from un-composited samples to composited samples and the number of records also reduced. The shape of the distribution of the main variable Cr_2O_3% also transformed from a negatively skewed to a more normal shaped distribution, as expected (Figure 13). The homogeneity of the orebody can be noted in the fact that the mean and COV value of un-composited data does not differ significantly from the composited data. On average, it can be observed that there are about 2 individual samples per MG1 borehole intersection, and the mean length roughly double subsequent to compositing. Furthermore, the means of the un-composited and composited Cr_2O_3% values remained similar, with a reduction in variance, which is to be expected from the process of compositing the samples.

From the COV values of all variables it can be deduced that the distributions are relatively symmetrical, and several estimation methods will be applicable for Resource Estimation, this interpretation is based on Table 4 compiled by Noble (1992).

Table 4: Rules for analysing COV (modified after Noble , 1992).

COV (%)	Interpretation
0 - 25	Simple symmetrical grade distribution. Resource estimation is easy, many methods will work.
25 -100	Skewed distributions with moderate difficulty in resource estimation. Distributions are typically lognormal.
100 - 200	Highly skewed distributions with a large grade range. Difficulty in estimating local resources is indicated.
Above 200	Highly erratic, skewed data or multiple populations. Local grades are difficult or impossible to estimate.

4.3 Graphical representation of the data

4.3.1 Histograms

One of the most basic statistical tools to analyse data graphically is by use of a histogram (Deutsch & Rossi, 2014). The histograms of the composited data for the relevant variable are given in Figure 14 . Furthermore, the histograms were also used to identify outliers, and local changes in the distribution that could assist in the investigation of geological and (or) grade domains, for Resource estimation, if required.

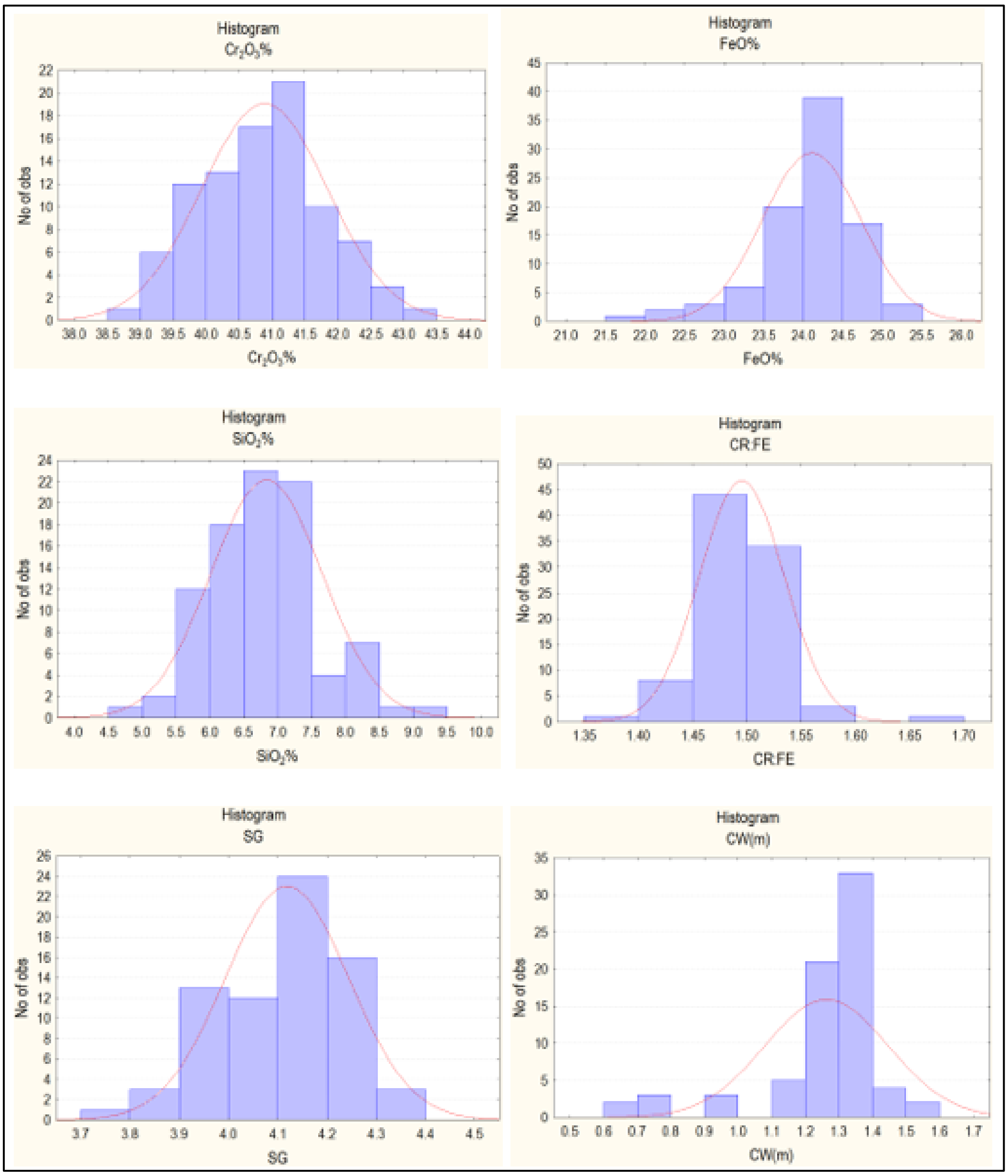


Figure 14: Histograms and fitted normal distributions for Cr_2O_3%, FeO%, SiO2%, CR:FE, SG and Channel/Seam Width from left to right and top to bottom respectively.

Based on the histogram plots and descriptive statistics the following conclusions were drawn:

- Cr_2O_3 %: Normally distributed
- FeO %: Negatively distributed
- SiO_2 % and CR:FE: Slightly positively distributed
- SG: Slightly negatively distributed
- Channel width: negatively distributed

The histograms for CR:FE and CW, Figure 14 indicate noticeable outliers, of high and low values respectively. This could be due to geologically related influences or random outliers inherent within the orebody and will be investigated in the sections to follow.

4.3.2 Normal probability plots

Probability plots can be used to easily identify deviations from normality and also assist in identifying inconsistencies within a dataset (Revuelta, 2018).

Figure 15 presents the normal probability plots for all the relevant variables. Deviations from a straight line in these plots identify gaps within the distribution which can be preliminary indications of possible population differences for domaining and (or) grade capping. Grade capping is a method to constrain values above the pullulation threshold, resetting values to the threshold value (Deutsch & Rossi, 2014).

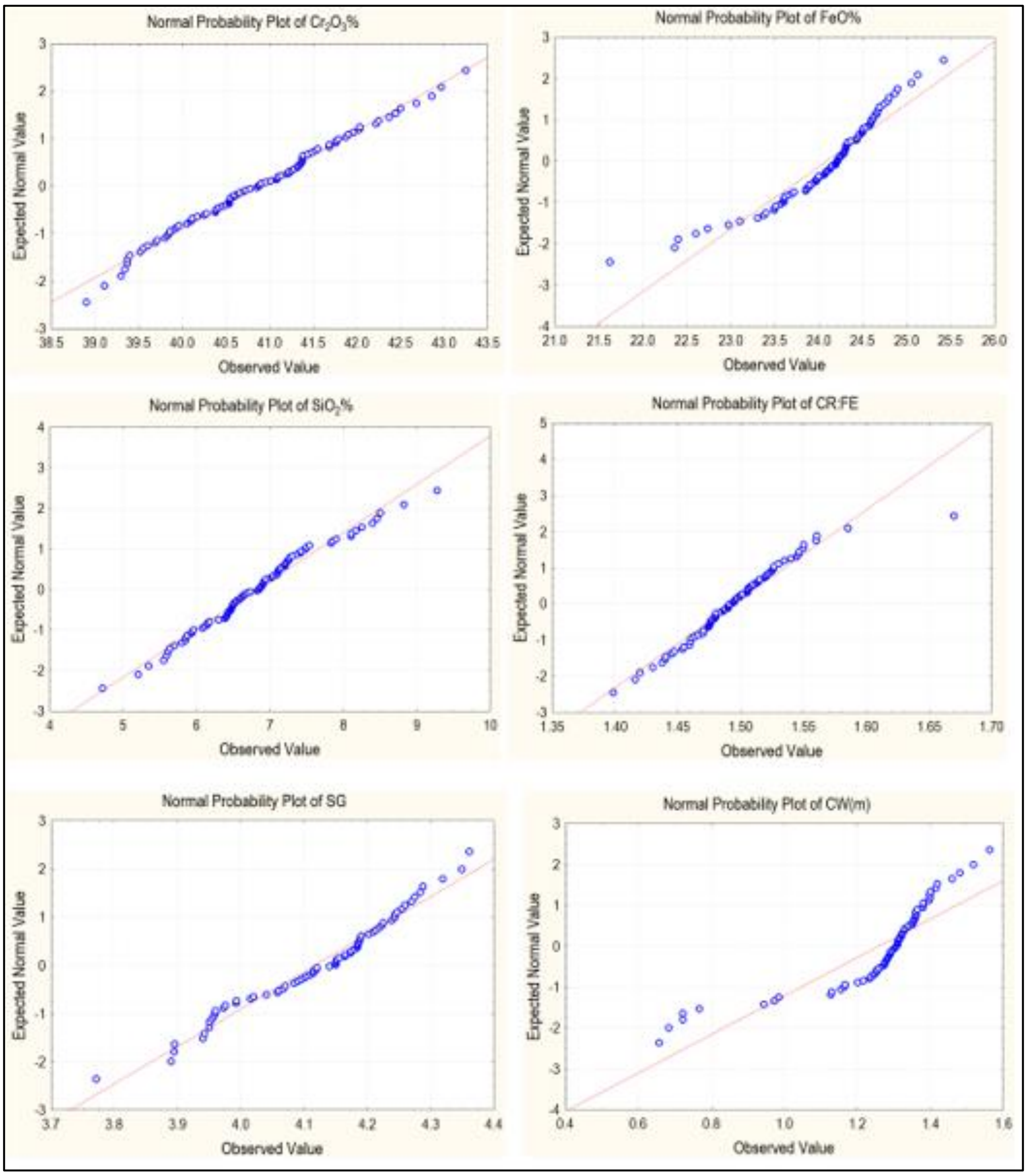


Figure 15: Normal cumulative probability plots for Cr_2O_3%, FeO%, SiO2%, CR:FE, SG and Channel/Seam Width.

Based on the normal probability plots, and visual inspections with regards to the outliers and deviations from a Gaussian distribution in relation to geological structures (mainly potholes, dykes, and faults) the following were concluded:

- **Cr_2O_3%; FeO%; SiO_2%; SG -** Lower and upper bound values are largely influenced by borehole intersections within or in close proximity of faults, dyke or pothole structures.
- **CR:FE** - A result of Cr_2O3% and FeO%, outliers were detected in boreholes located >700m outside the project area.

- **CW –** A distinct group of eight low values, less than 1m were identified, of which five values could be associated with a geological structural influence. The remaining three values could be associated with underlying structures which have not been delineated due to a lack of supporting borehole and underground data.
- Based on the current data plots, the deviations and differences in populations are fairly random in terms of location, and do not constitute in forming distinct domains, and rather governed by geological influences.
- Due to the relatively few composited samples and the low variability in the variable distributions, and low COV values observed in Table 3, grade capping is not appropriate in this instance.

The geological influenced data was temporarily removed from the selected borehole database in order to investigate the impact on the statistics (Table 5).

Table 5: Composite data statistics (geological influenced intersections removed).

VARIABLE	RECORDS	MIN	MAX	RANGE	MEAN	VARIANCE	STANDDEV	SKEWNESS	KURTOSIS	COV %
CR_2O_3%	77	39.30	42.97	3.67	40.87	0.77	0.88	0.21	-0.59	2
FEO%	77	23.10	25.13	2.03	24.18	0.18	0.42	-0.22	-0.12	2
SIO_2%	77	5.21	8.45	3.25	6.79	0.47	0.68	0.13	0.26	10
CRFE	77	1.40	1.56	0.16	1.49	0.00	0.03	-0.25	0.21	2
SG	60	3.89	4.36	0.47	4.12	0.01	0.12	-0.18	-0.74	3
True CW (m)	65	1.13	1.56	0.43	1.31	0.01	0.08	0.22	1.10	6

It is evident that subsequent to the removal of the geologically influenced intersections the data distributions of all the relevant variables are more symmetrical and closer to normality, as expected. This elementary analysis confirms the notion that Faults, Dykes, Potholes and IRUPs do have an influence on the mineralisation.

4.4 Domaining

According to (Glacken & Snowden, 2001) and (Chanderman, et al., 2017) the process of domaining should occur subsequent to creating a sound geological model, where domains have been identified. In the simplest term, a domain can be referred to as a volume or area which contain similar mineralisation characteristics with regards to outside the specific area, in this case, the domain.

Domains can be classified as areas that also consist of similar continuity in relation to geology and (or) value, which is usually grade or thickness. Geological and grade domains are not always similar, although there could be a relationship. Sinclair and Vallee (1994) cited in Sinclair & Blackwell (2002) refer to two categories of continuity in Mineral Resource estimation, which are geological continuity and value continuity. Domain boundaries are commonly defined by assay and geological information (Sinclair & Blackwell, 2002).

Glacken and Snowden, (2001) highlight that frequently there are situations where the mineralisation domains are embedded within a geological unit, meaning that the resource grade model is constrained completely by the geological modelling.

This is true for this specific research project with regards to the MG1 chromitite unit. The chromite mineralisation is constrained by the Middle Group 1 geological unit, representing the domain for Mineral Resource estimation. However, economic and product beneficiation recovery-related characteristics, including geological structural influence could result in different domains being created based on strike or dip direction of the orebody. This research project did not cover all the details of the related attributes, as the current Mineral Resource estimation of MCo classifies the MG1 orebody as a single estimation domain. Furthermore, the Mineral Resource classification of MCo is mainly based on the borehole intersections of the main economic variable Cr_2O_3% and is associated with various radii sizes to represent resource confidence.

4.4.1 Stationarity

Chanderman (2015) indicates that geostatistics depend on the assumption that an area that is being estimated should be stationary. Stationary can be referred to as a domain that is homogeneous; without a dominant trend; constant continuity; without extreme outliers of grade and represents a single population (Coombes, 2008).

Swath plots were used to investigate stationarity of the three variables mostly influencing the Mineral Resource estimation, namely Cr_2O_3%, Channel width (CW) and Specific gravity (SG). Swath plots, also known as sectional plots, are specified width slices which can be used to plot composite averages of each slice on a graph. The swaths are usually created through various directions of an orebody, indicating the spatial distribution of a specific variable and can assist in verifying stationary domaining. Swath plots are commonly used as a validation method for comparing estimated block and sample grade distributions, (Webster, n.d.).

Slices of 120m and 180m were used for Cr_2O_3%, CW and SG composites in X (North), and Y (east) directions respectively (Figures 16-18).

The data support for the swaths plots could be considered limited, however, the results indicate that the value distribution within the single domain used is fairly consistent. Although there are identified anomalies, it is concluded that these are either as a result of the few observations in a specific swath (more likely) or are associated with possible geological influences based on the position of the borehole intersections with regards to major geological structures (faults and dykes).

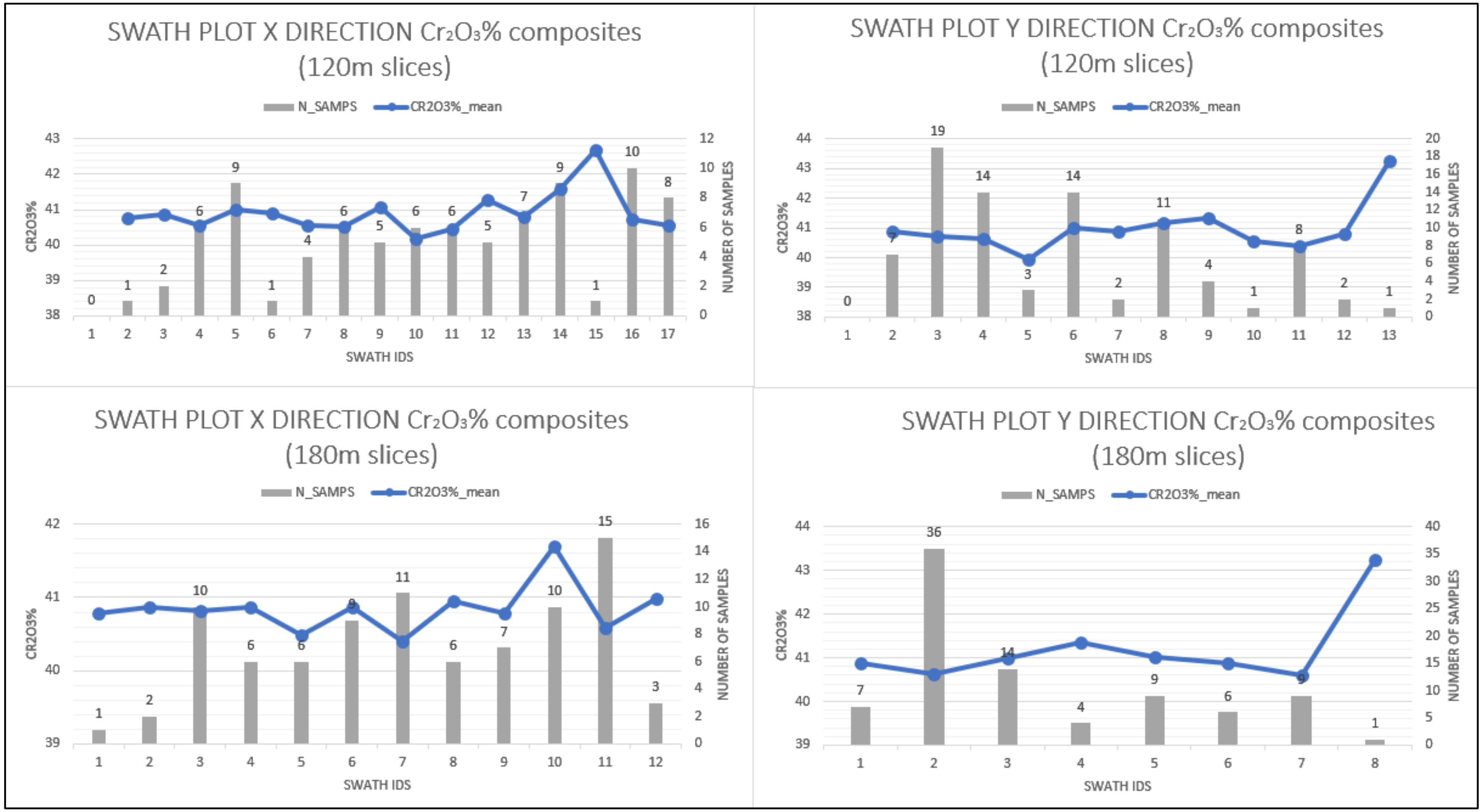


Figure 16: Swaths plots for Cr2O3% sample composites.

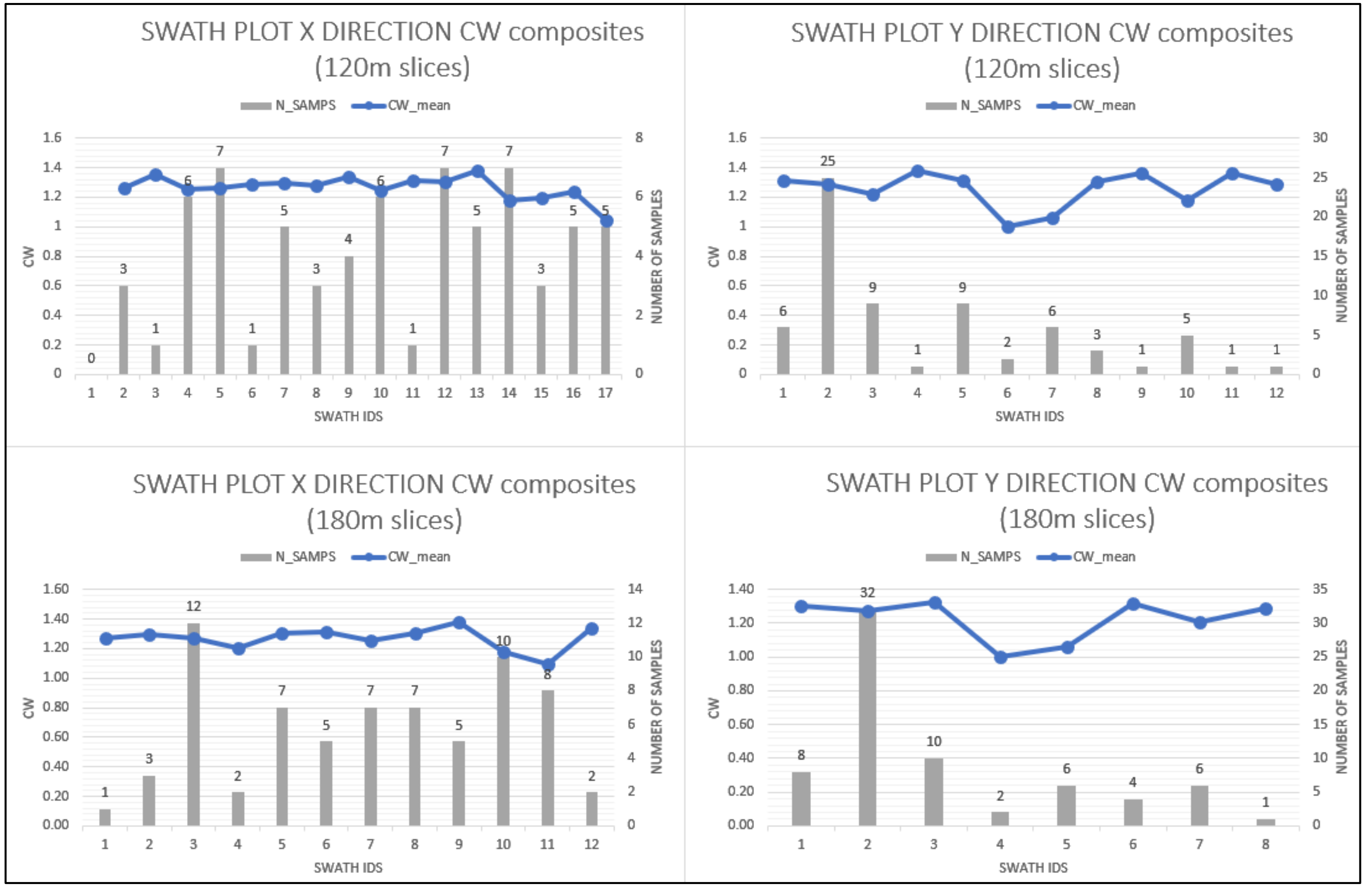


Figure 17: Swaths plots for CW sample composites.

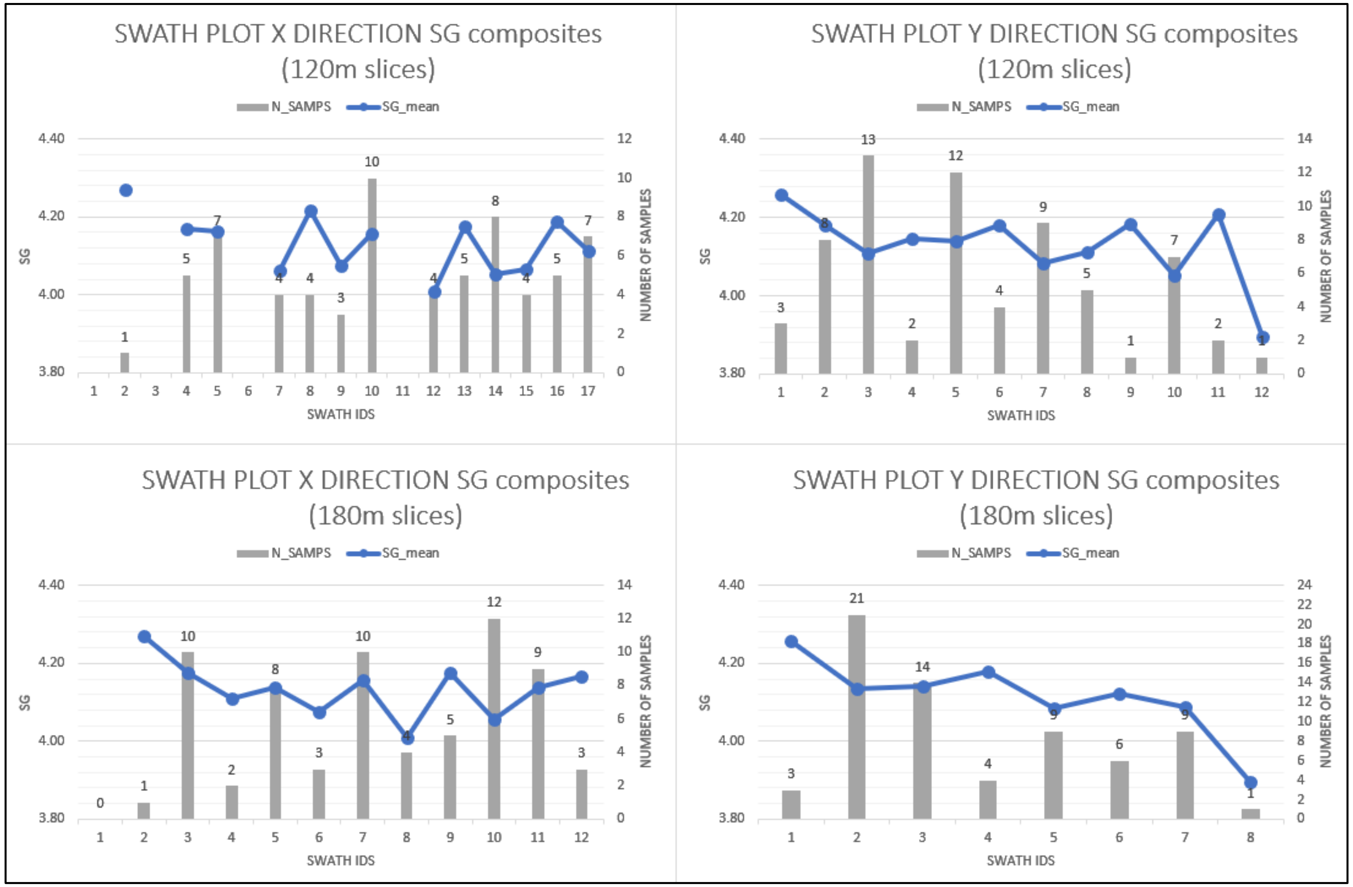


Figure 18: Swaths plots for SG sample composites

5. VARIOGRAPHY (SPATIAL ANALYSIS)

The research project utilises Ordinary Kriging (OK); a geostatistical method for spatial grade estimation; for comparison of the reliability and appropriateness of the current Mineral Resource estimation and classification practices of MCo. The OK estimation process not only produces a block estimate (Z_K*) but also the minimum estimation variance (σ_K^2), which reflects the confidence in the estimate, at any location in the focus area (Dohm, 2015).

The spatial relationship of relevant variables needs to be estimated and modelled as a requirement for any geostatistical estimation method, by means of a semi-variogram (Morgan, 2011). Weights that are assigned to samples in the Kriging estimation process which is based on the use of the semi-variogram model, associated with the continuity in two or three dimensions of the variables under consideration (Mpanza, 2015).

Apart from the requirement of the semi-variogram model in geostatistical estimation algorithms, it is also a tool to quantify and investigate the underlying spatial variability of the variables that are considered for estimation (Gringarten & Deutsch, 2001). In the simplest description for a semi-variogram, is defined by differences in grade, or a numeric variable, that is plotted in relation to the distance of a sample population (Coombes, 2008).

It should be emphasised that prior to variography thorough Exploratory Data Analysis must be conducted, that includes the establishment of domains, if present [Coombes (1997) and Snowdengroup(2017a)].

5.1 The Semi- variogram and variogram model

According to Sinclair & Blackwell (2002) the fundamental application of the semivariogram, is that it i) acts as an autocorrelation function that quantifies the average continuity of grade in three-dimensional space and ii) the isotropic or anisotropic nature of the grade distribution can be defined which is a crucial concept regardless of the estimation technique that is utilised. The anisotropy can be measured mathematically by the use of a semivariogram (Snowden, 2001), that can then be applied in geostatistical estimations.

Geostatistical techniques all stem from the basis of the theory of regionalised variables, that was developed by a French mathematician, Georges François Paul

Marie Matheron, and his theory of regionalised variables can be sited in Matheron (1963). Geostatistical algorithms aim to use the spatial relationship between variables, calculated by the semi-variogram, in order to apply a form of weighting towards the estimation of a point or block with an unknown value (Glacken & Snowden, 2001).

The function γ(h) represents the semi-variogram and is half the squared difference in value of sample pairs which is separated by a lag distance (h). The values of the experimental variogram (γ*(h)) can be calculated based on different lag distances (h) by the formula:

$$\gamma^*(h) = \frac{1}{n_h}\sum_{i=1}^{n_h}\big(Z(x_i) - Z(x_i + h)\big)^2$$

$Z(x_i)$ is the regionalised variable value at a sample point x_i

$Z(x_i + h)$ is the value of another point at a lag distance (h) from point x_i

n_h is the number of sample pairs for a specific distance h

The semi-variogram is calculated in different directions to measure variability, which increases as the spacing between samples increases (Deutsch & Rossi, 2014).

The experimental variogram values ($\gamma^*(h)$) are plotted against h on a graph and a model is fitted to represent an approximation of a smoothed mathematical function (Figure 19).

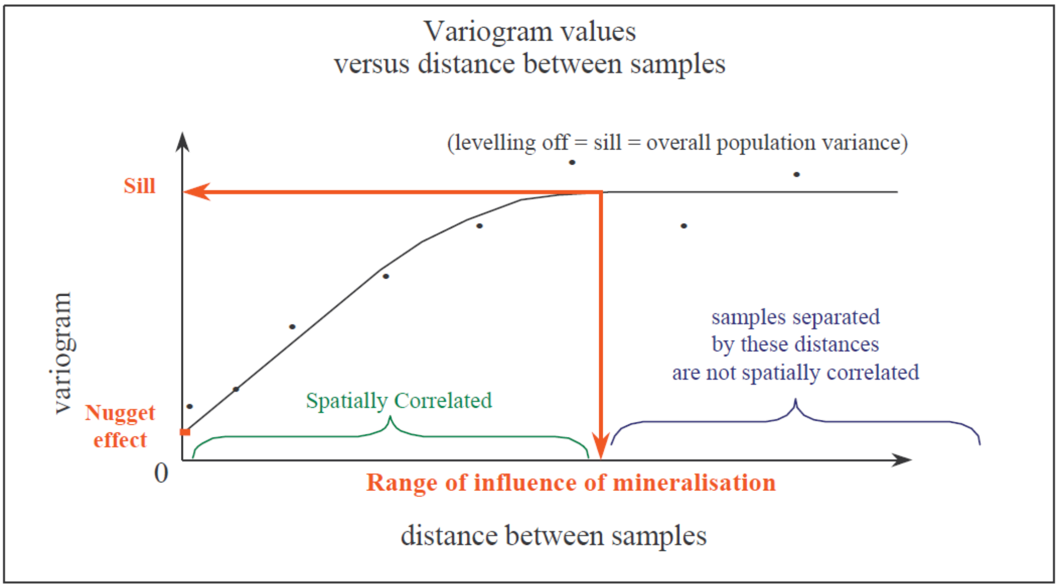


Figure 19: Experimental semivariogram with a spherical model (Snowden, 2001).

The three main components of the fitted semivariogram model are described by (Bohling , 2005) and (Snowden, 2001):

- Sill: The value of the modelled semivariogram, where the graph levels and is typically equal to the population variance.
- Range: the range at which the lag distance of the semivariogram approaches the sill value. The values that are beyond the range can be considered to be spatially uncorrelated.
- Nugget: Theoretically the value at the origin of the semivariogram should be equal to zero. The nugget or also referred to as the nugget effect is the intrinsic variability, including the sample variability at a zero-lag distance.

There are various variogram models types, represented by different mathematical functions and used in geostatistical applications, the most frequently used for Mineral Resource estimation is however the spherical model (Sinclair & Blackwell, 2002).

A single structured spherical variogram model (Figure 20) was also used in this research and is represented by this formula defined in the equation: `

$$\gamma(h) = \left\{ \begin{array}{cc} 0 & if\ h = 0 \\ C_0 + C_1 \left[\frac{3}{2}\left(\frac{h}{a}\right) - \frac{1}{2}\left(\frac{h}{a}\right)^3 \right] & if\ 0 < h < a \\ C_0 + C_1 & if\ h \geq a \end{array} \right\}$$

C_0 = the nugget effect, that represents local, short-range geological variability, including subsampling; analytical and sampling variability. According to Bohling (2005) , *"the nugget represents variability at distances smaller than the typical sample spacing, including the measurement error."*

C_1 = the structural component of the model, and also referred to as the sill component.

$C = (C_0 + C_1)$ = the total sill, which theoretically is the total variance of the sample data.

a = the range (or range of influence), which represents the increase of the distance of the average variability from zero to C_1, or from C_0 to the total sill.

h = the lag distance or also referred to as the sample spacing.

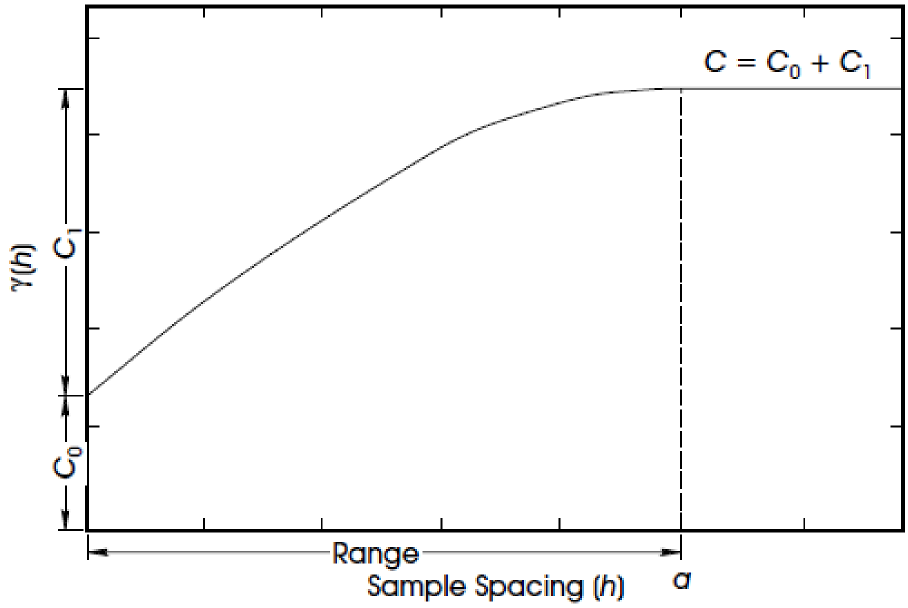


Figure 20 : Components of the spherical model (Sinclair & Blackwell, 2002).

5.2 Variography of variables under study

According to Gringarten & Deutsch (2001) an understanding of the variogram in three-dimensional space is necessary to completely identify geological continuity. Furthermore, different directions of continuity should be tested to be consistent with geological deposition, including accurate quantification of the spatial variability for algorithms associated with geostatistical estimations. Variogram values can be plotted in various directions and then subsequently contoured for an easier method of viewing and interpreting variograms (Coombes, 2008).

Variogram contours can assist in identifying the maximum direction of continuity, which is usually associated with the lowest variability in the longest range. Recent developments in Resource estimation software have made this process easy to plot, for example, Supervisor® and Leapfrog Edge®, that was also used for this study with regards to variography.

The numeric modelling functionality in Leapfrog , a Radial Basis Function (RBF) interpolation method, was used throughout the variography analysis to assess the spatial continuity with regards to the distribution of the variables. Grade shells in the form of isosurfaces (RBF contour surfaces) were created for the relevant variables Cr_2O_3%, CW and SG, and are presented in Figures 21-23, respectively.

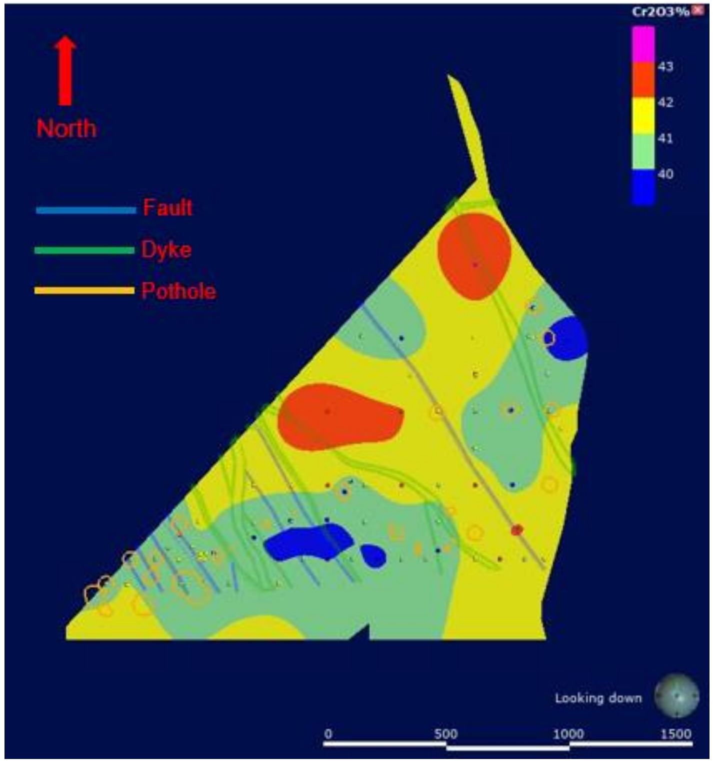


Figure 21: Isosurfaces for Cr_2O_3%.

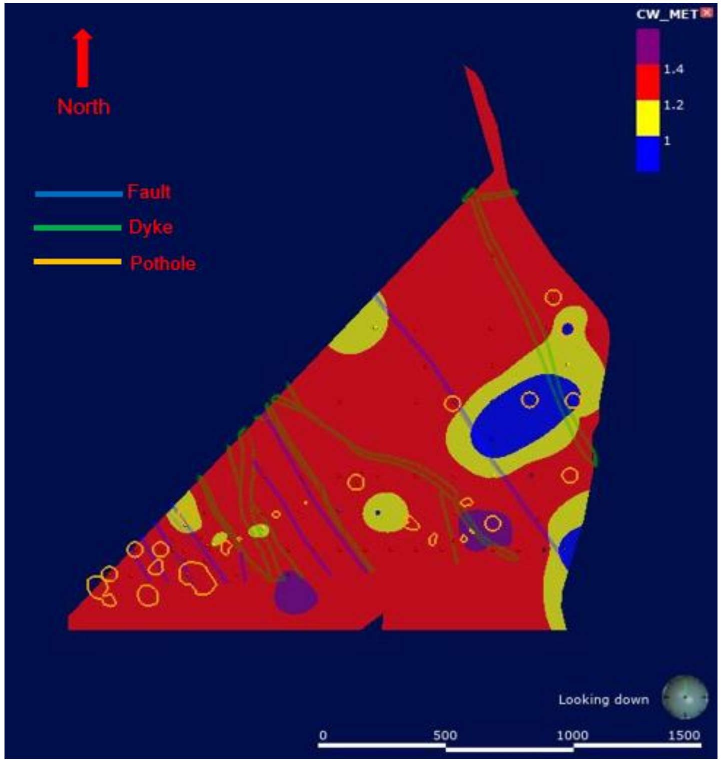


Figure 22: Isosurfaces for CW.

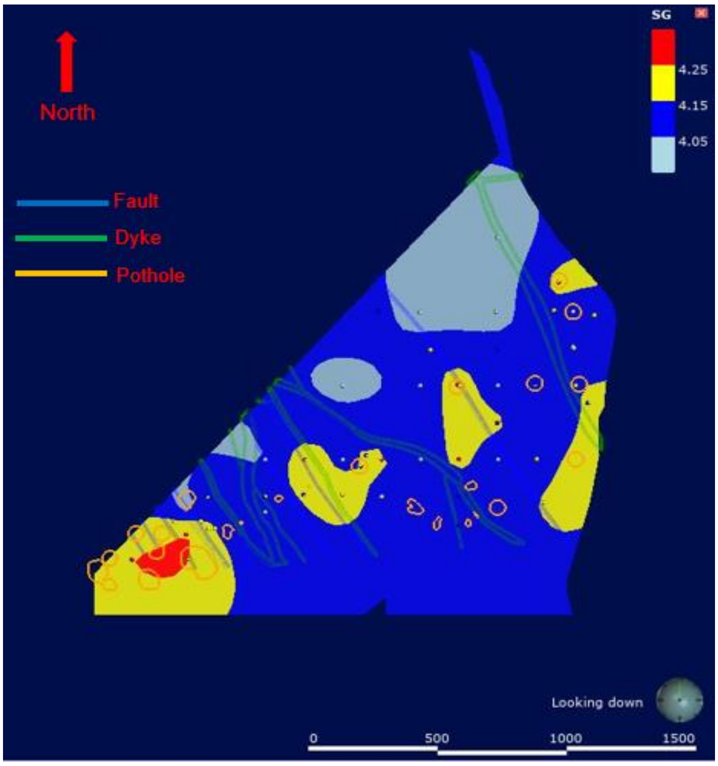


Figure 23: Isosurfaces for SG.

Based on the results of the isosurfaces of the relevant variables, it is evident that there is no prominent continuity direction. Furthermore, based on the current sample support, it was also observed that the spatial continuity is not related to geological structures. However, geological structures do have an influence on the distribution of the variables with regards to a post-depositional sense. It is possible to argue that based on the initial EDA, swath plots and isosurfaces that domaining should be further investigated, especially for Cr_2O_3% and CW, as domains will impact the variogram analysis. There can, however, also be strong geological structural influences that could be associated with the grade distribution characteristics.

The decision of treating the sample data of the three primary variables (Cr_2O_3%, CW and SG) as a single domain was established in **Chapter 4**, and the experimental semi-variograms from the data were calculated for the domain.

Standardised experimental semivariograms were calculated in different directions, both grade capping as well as cutting were applied to the Cr_2O_3% variable. Due to the few data available it was however not possible to identify any preferred direction of continuity for any of the three variables and therefore, omni-directional semivariograms spherical variograms models were fitted to the experimental semivariograms for the three variables (Figures 24-26).

Omni-directional variograms can also be referred to variograms that are isotopic, the spatial variability of the variable is the same in all directions. The variogram is considered to be isotropic, where the calculated semivariogram is not dependent on the direction of the lag distance (Krige, 1981).

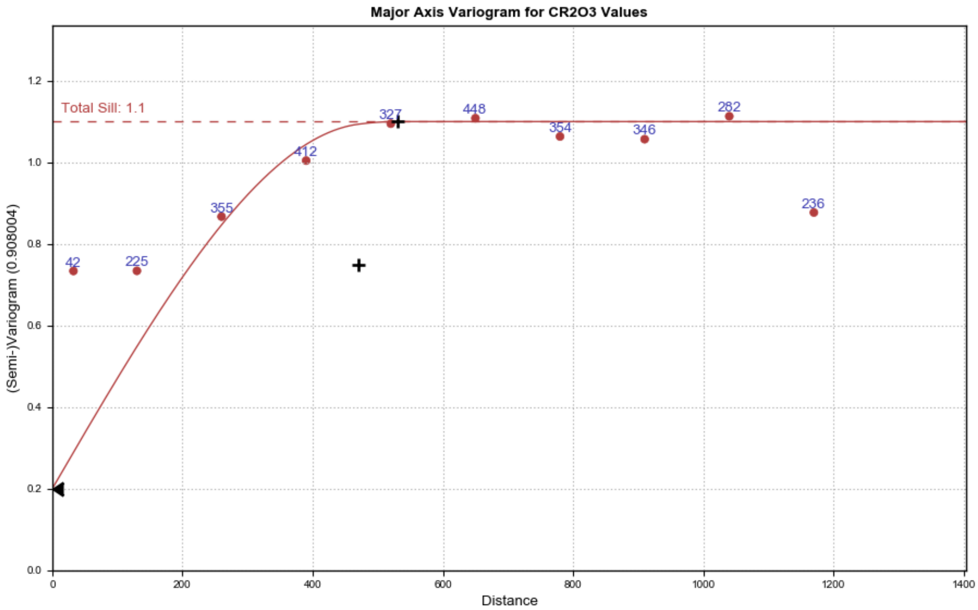


Figure 24: Spherical Semivariogram model for Cr_2O_3%.

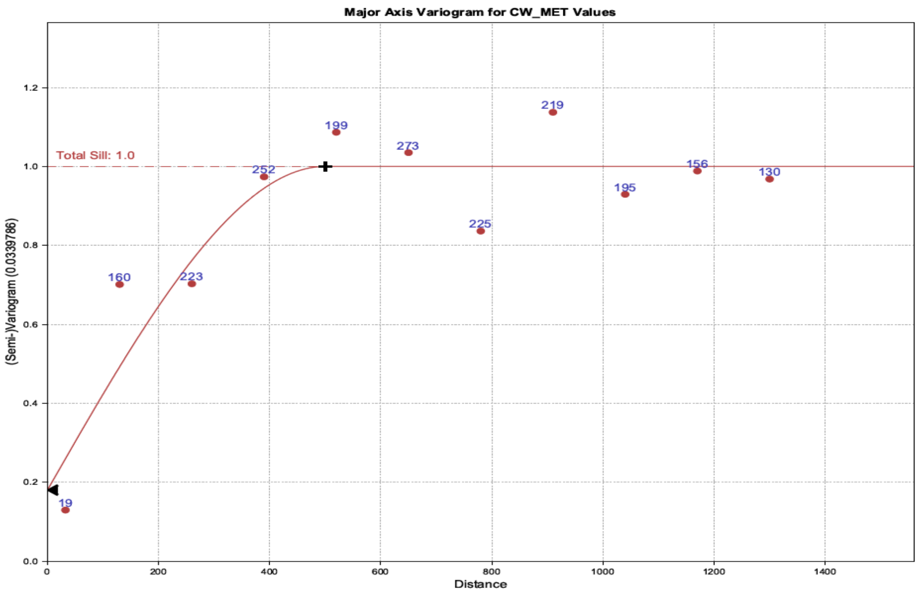


Figure 25: Spherical Semivariogram model for true channel width (m).

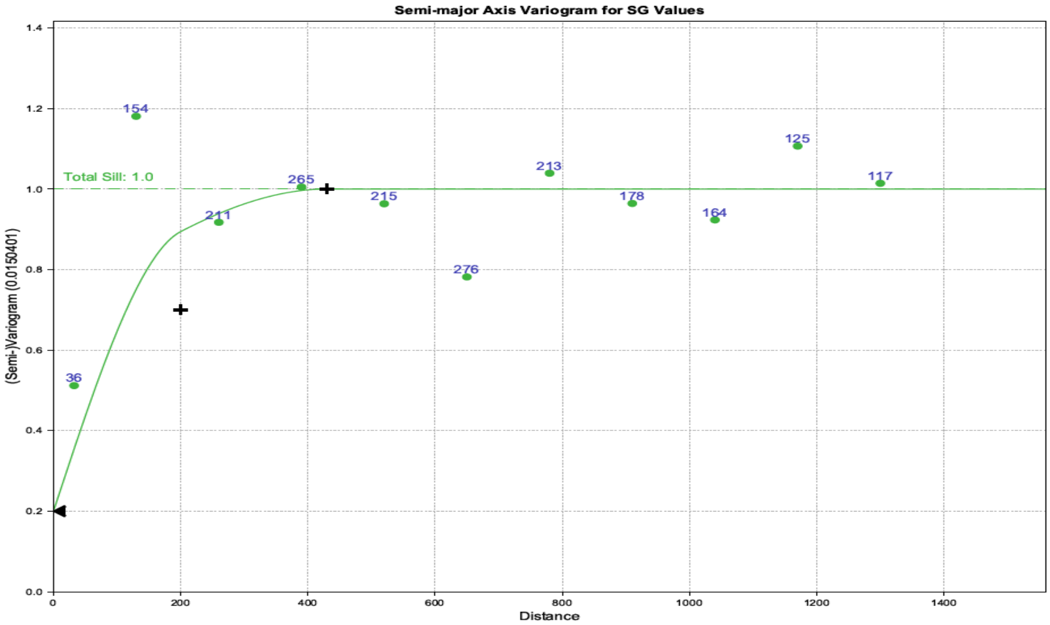


Figure 26: Semivariogram with spherical model for SG.

Double structured spherical semivariogram models were fitted to the Cr_2O_3%, and SG(g/cm^3) and a single structured semivariogram model was appropriate for the CW(cm), the model parameters are presented in Table 6. The percentages in brackets represent the ratios of each variability component to the total sill (C) of the semivariogram model.

Table 6: Parameters of modelled spherical variograms for Cr_2O_3%, CW and SG.

Variable	Nugget Effect C_0 (C_0/C)%	1st Structure Sill C_1 (C_1/C)%	2nd Structure Sill C_2 (C_2/C)%	1st Structure Range a_1	2nd Structure Range a_2
Cr_2O_3%.	0.20 (18%)	0.55 (50%)	0.35 (32%)	470	530
CW	0.17 (17%)	0.83 (83%)	-	500	-
SG	0.20 (20%)	0.50 (50%)	0.30 (30%)	200	430

The general rule of thumb is to model the semi variogram to the sample variance, which if the variogram is normalised, to a sill value of 1. However, in the event that the total sill is more than one, it means that experimental sample variance is more than the sample variance of the data. According to Morgan (2011) in the case where the experimental semivariogram contains a minor difference greater than the sample variance, the semi-variogram should be fitted to the sill of the experimental semivariogram.

Morgan (2011) concludes on this statement, by stating that:

> *"… the sample variance is calculated assuming random, independent samples (which is generally not the case – the samples are spatially correlated.)".*

The standardised experimental sill for the Cr_2O_3% (Figure 24) is greater than one. Therefore a Sill greater than 1 was modelled for this variable.

The variations of experimental variogram values that were observed in all (Cr_2O_3%, CW and SG) the semivariograms, is most probably associated with a lack of sample data and large sample/ borehole spacing.

Morgan (2005) emphasises that

> *"… the most important aspect of the fitted semi-variogram model is the nugget effect and the slope near the origin."*

and also refers to Armstrong (1998) which states that

> *"… the behaviour of the semi-variogram at and near the origin has a significant influence on kriging results, as well as their stability".*

The researcher also reached this conclusion from a practical exercise executed during a geostatistical course at the University of the Witwatersrand (Dohm,2015).

Due to the lack of closely spaced borehole data, with an average spacing of ±130m, and limited deflections, a limited amount of sample pairs close to the origin of the semivariograms was available. This reality had a subsequent influence on the estimation of the modelled nugget effects for the relevant variables (Cr_2O_3%, CW and SG).

It could be argued that the modelled nugget effects are higher than expected in a Bushveld Complex chromitite environment. Although the nugget effects are subjective, especially for Cr_2O_3% and SG, the variograms provide a good indication of the range of influence associated with the spatial variance (or correlation) of the variables considered.

5.2.1 Variogram Model Range of Influence and Resource Classification

Dohm (2004) mentions a method based on the range of influence of the variogram model as proposed by Snowden (1996) and that was at the time often used for Mineral Resource classification, that is:

“Resources are classified as Inferred when drill holes are further apart than the range of influence of the variogram. The drill spacing at which a distinction between Measured and Indicated is made is based on a rule of thumb and is taken as the distance equivalent to two-thirds of the total variability i.e. two-thirds of the sill of the variogram model”.

However, Dohm (2004) clearly states that ranges of the variogram are not considered to be adequate for all resource classification situations, especially in the Witwatersrand Gold environments where high nugget effects, and short variogram ranges are commonly encountered.

This two thirds the range of influence classification methodology has been observed to be applied for Chromitite and Platinum Mineral Resource classifications and was sited in African Rainbow Minerals (ARM) (2008), including Canadian Aviation Electronics (CAE) (2013) annual Mineral Resource and Reserve reports.

There is thus some merit in using this technique, as a foundation, although one should also consider other factors, such as geological complexities and the Competent Person’s judgement and experience. Furthermore, it appears that the technique would only be useful in highly homogeneous orebody environments, with long range variogram models, zero nugget and not associated with a high frequency of geological complexity.

Isaaks & Srivastava (1989) mentions “in fitting this model (spherical model) to a sample variogram it is often helpful to remember that the tangent at the origin reaches the sill at about two-thirds of the range”. The researcher is of the opinion that the technique is based upon the fact that most of the spatial correlation is generally captured within two-thirds of the theoretical spherical variogram and could serve as a means of confidence, depending on the characteristics of the orebody, and should consider geological complexities.

The “two-thirds” classification technique was compared to MCo’s current classification standard (Table 7). It is evident that MCo’s classification radii are more conservative, likely for good practical reasons. The risk of unknown or unidentified geologically complex or pothole influenced areas are too high to allow for declaration margins such as ±350m and 530m borehole radii for Measured, including Indicated Mineral Resources respectively.

Table 7: Comparison between two-thirds variogram range technique and the mining company’s standard for Mineral resource classification.

Confidence classification	Confidence radii (m) - two thirds method	Confidence radii (m) - mining company	%Diff
Measured	353	150	136%
Indicated	530	300	77%
Inferred	>530	600	-
*Variogram range for Cr_2O_3% = 530m			

6. BLOCK MODELLING AND ESTIMATION

MCo utilises a 2D gridding algorithm, known as the Growth technique, described in **section 2.4** of this research report, for estimation. The technique requires a gridded mesh, of which the mesh size is determined by the estimator, and as a starting point Dassault Systèmes GEOVIA Inc. (2016) recommends using one-quarter to one-fifth of the sample data spacing. MCo uses a mesh size of 25m x 25m for estimating the three variables (Cr_2O_3%, CW and SG) within the Geovia Minex^{TM} software.

In this research report two other estimation techniques (OK & IDW) are used for comparison to the Growth technique, based on estimated block models created in Leapfrog® Edge.

6.1 Block Model Size and Search Neighbourhood

Snowdengroup (2017b) considers the parent block size used in a Mineral Resource model to be one of the most important parameters, as it influences the quality of grade estimates, especially when using OK. Furthermore, Chanderman (2015) highlights the fact that Kriging aims to minimize the estimation variance, however this can only be achieved when the search neighbourhood is properly defined.

The search neighbourhood for OK comprise of the parent block size; minimum and maximum number of samples considered; search range and point discretisation of the estimated parent block. The search neighbourhood can also be considered as the “input or estimation parameters” for a kriging estimate, which also includes a variogram model, discussed in detail by Coombes (2008) and Amwaama (2018).

Yamamoto (2005) indicates that linear estimation methods, such as OK and IDW, inherently have a smoothing effect that leads to conditional bias. Conditional bias is well documented in Deutsch (2007), and in simple terms, it refers to the occurrence that the expected true values of the blocks not being equal to estimated grades. The influence of the smoothing effect is dictated by the continuity of mineralisation (variogram model); number of samples used in the OK estimate and the search criteria established for the kriging neighbourhood (Deutsch, 2007).

Vann, et al. (2003) describes a well-known method for quantitatively assessing a kriging neighbourhood, which assists in minimising conditional bias and optimising the kriging estimation parameters, prior to the estimation. The method known as Quantified Kriging Neighbourhood Analysis (QKNA), has the objective to determine a search neighbourhood and block size combination, to achieve conditional unbiasedness by assessing measures of the following criteria: Slope of Regression (SOR); Kriging Efficiency (KE); weights of the means for a simple Kriging; Kriging weights (which includes proportion of negative weights) and Kriging variance.

Kriging efficiency (KE) and Slope of regression (SOR) are derived from the following formulas (De-Vitry, 2003) :

$$KE = (BV - KV)/BV$$

$$SOR = (BV - KV + \mu)/ (BV - KV + 2\mu)$$

Where:

BV is the Block variance (theoretical variance of blocks within the estimation domain).

KV is the Kriging variance

μ the LaGrange multiplier (used in solving the OK matrix system)

The use of the SOR and KE as a criteria for measuring the conditional bias is well documented in literature by Deutsch (2007) ; Sinclair & Blackwell (2002) ; Coombes (2008) ; Vann, et al. (2003); Deutsch, et al. (2014) and Nowak & Leuangthong (2016), whom all describe the detailed Geostatistical background in a mathematical sense. Nowak & Leuangthong (2016) reviews the use of the SOR and KE as measures in defining the optimal kriging neighbourhood and highlights that both these measured should be handled with caution, which is supported by the case study on an epithermal gold deposit in British Columbia.

The QKNA process proposed by Vann, et al. (2003) was used in this research project to inform the selection of appropriate block size, minimum and maximum number of samples, including the dimensions of the search range combinations that contain the least conditional biasness.

Vann, et al. (2003) recommends testing a range of block sizes with a range of data configurations that are well informed, less well informed, and poorly informed. The margins that best define conditional unbiasness are:

- A SOR and KE that are equal to one or expressed as a percentage of 100%

- Negative weight proportion of less than 5% of the total kriging weights
- Analysis of the Kriging Variance, or also known as the estimation variance and attempt to obtain a minimum variance with regards to the other measurement criteria

The initial block size that was considered in this report prior to QKNA for the OK and IDW estimation was based on the composite data configuration of the relevant variables (C_2O_3%, CW, and SG). The sample composite spacing is on average 130m, and 60m x 60m block size was considered as a baseline for QKNA, based upon the industry standard for blocks not to be smaller than ½ the drill hole spacing (Coombes, 2008).

6.1.1 Quantified Kriging Neighbourhood Analysis (QKNA) results

The QKNA was conducted using a trial version of Supervisor® software on the sample composites for Cr_2O_3%, as it is considered as the main variable of this study. The variogram is a critical input for a QKNA (Snowdengroup, 2017b), and similar variogram model parameters were used in Supervisor®, as modelled in Leapfrog Edge® for Cr_2O_3%. The initial selected block model size (60mx60m) were tested together with a range of different block sizes, however the 60m x 60m block size was deemed representative and used throughout the QKNA process.

The kriging neighbourhood parameters that were established during the QKNA process based on the measurement criteria is shown in Table 8. The search radius has been determined by the modelled Cr_2O_3% semivariogram presented in **Table 6** (Section 5.2) for all the data configurations.

Table 8: Kriging neighbourhood parameters based on QKNA.

Kriging neighbourhood parameters - based on QKNA				
Data configuration	Search Range	Min samples	Max samples	Discretisation
Well informed	530m	4	12	4x4x2
Less well informed	530m	6	15	4x4x2
Poorly informed	530m	4	12	4x4x2
* 60m x 60 m x 2m Block sized used based on QKNA				

6.2 Estimation Comparisons and Analysis

In order to analyse the appropriateness of MCo's Mineral Resource estimation method, namely the Growth technique, comparisons were conducted with known industry estimation techniques. The Mineral Resource estimation techniques used for comparisons were OK and IDW. This is not to say that estimation techniques used for comparison are more appropriate, however, it is merely used as a measure of the algorithm commonly used to estimate chromitite deposits in the Bushveld Complex.

Only the Cr_2O_3% variable was used for the comparison as assumption has been made that if alternative methods are used for comparisons for the other variables (CW and SG), the same conclusions can be established based on different tested algorithms.

Various scenarios were considered to achieve similar results as obtained from the Growth technique, and comparisons with the original search neighbourhoods established from QKNA results. Table 9 reflects different variogram parameters and Table 10 the different search neighbourhoods considered in the comparison process.

Estimation comparisons were conducted on a 60m x 60m x1m block size, in 2D space. The estimated gridded meshes conducted in Geovia Minex^{TM}, were converted into 25m x 25m block models, and subsequently regularised into 60mx 60m block models for comparable visualisation and statistical analysis in Leapfrog® Geo/Edge software. The conversions were conducted in the Datamine Studio RM®.

Table 9: Tested estimation scenarios, with parameters used for comparison towards the Growth technique.

Scenario	Scenario code	Model type	Nugget	Structure 1 (Sill)	Structure 2 (Sill) (Sill)	Structure 1 (Range-Major)	Structure 1 (Range-Semi-major)	Structure 1 (Range-minor)	Structure 2 (Range-Major)	Structure 2 (Range-Semi-major)	Structure 2 (Range-minor)
1	IDW2	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
2	IDW4	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
3	OK_1	Spherical	0	0.75	0.35	470	470	50	530	530	50
4	OK_2	Spherical	0.2	0.55	0.35	470	470	50	530	530	50
5	OK_3	Spherical	0.2	0.55	0.35	470	470	50	530	530	50
*Variogram models are normalised											

Table 10: Variogram model parameters, used in estimations comparisons towards Growth technique.

Estimation search neighbourhoods for Cr_2O_3%											
Scenario	**Scenario code**	**Estimation type**	**Search ranges (Search 1)**	**S1 Minimum no of samples**	**S1 Maximum no of samples**	**Search ranges (Search 2)**	**S2 Minimum no of samples**	**S2 Maximum no of samples**	**Search ranges (Search 3)**	**S3 Minimum no of samples**	**S3 Maximum no of samples**
1	IDW2	Inverse distance weighting to the power 2	Max:530 Int:530 Min:N/A	4	12	Max:1060 Int:1060 Min:N/A	4	10	Max:2650 Int:2650 Min:N/A	3	8
2	IDW4	Inverse distance weighting to the power 4	Max:2500 Int:2500 Min:N/A	1	5	N/A	N/A	N/A	N/A	N/A	N/A
3	OK_1	Ordinary Kriging	Max:530 Int:530 Min:N/A	4	12	Max:1060 Int:1060 Min:N/A	4	10	Max:2650 Int:2650 Min:N/A	3	8
4	OK_2	Ordinary Kriging	Max:530 Int:530 Min:N/A	4	12	Max:1060 Int:1060 Min:N/A	4	10	Max:2650 Int:2650 Min:N/A	3	8
5	OK_3	Ordinary Kriging	Max:530 Int:530 Min:N/A	6	15	Max:1060 Int:1060 Min:N/A	4	12	Max:2650 Int:2650 Min:N/A	3	10
* Block size used : 60m x 60m x1m (2D estimation) , expansion factors used for Search 2 = 2 and Search 3= 5, bottom / top capping was not applied.											

The estimation statistical analysis was conducted on a volume-weighted approach with regards to the block model estimate comparison, with equal dimension in the z-direction (height) of the block size, which is one meter.

However, tonnage-weighted statistics were tested for some of the estimation tests, and insignificant differences were found, compared to a volume-weighted approach.

6.2.1 Estimation results, comparisons and validation

Throughout the comparison of the estimation results the differences were calculated by subtracting the Growth techniques results from an alternative estimation method, then dividing by the Growth technique and converted to a percentage by multiplying by a 100 to obtain a percentage difference.

Various authors such as Webster (n.d.), Glacken & Trueman (2014) and WSP (2015) recommend common methods of validation for Mineral Resource estimates of which the following were used to validate and compare the different estimation scenarios with the Growth technique:

- Visual comparison of block model grades and input data
- Comparing estimate and input data declustered means
- Using alternative Resource estimate algorithms and comparing descriptive statistics and grade distribution graphically by using histograms, QQ Plots, including scatter plots.
- Swath plots (sectional plots) comparing averages of input composite data and block model estimates

The spatial results of the Cr_2O_3% block model estimation scenarios considered together with declustered composites are shown in Figure 27.

The Cr_2O_3% grade distribution based on volume percentage of the block model estimates are summarised with bar charts in Figure 28.

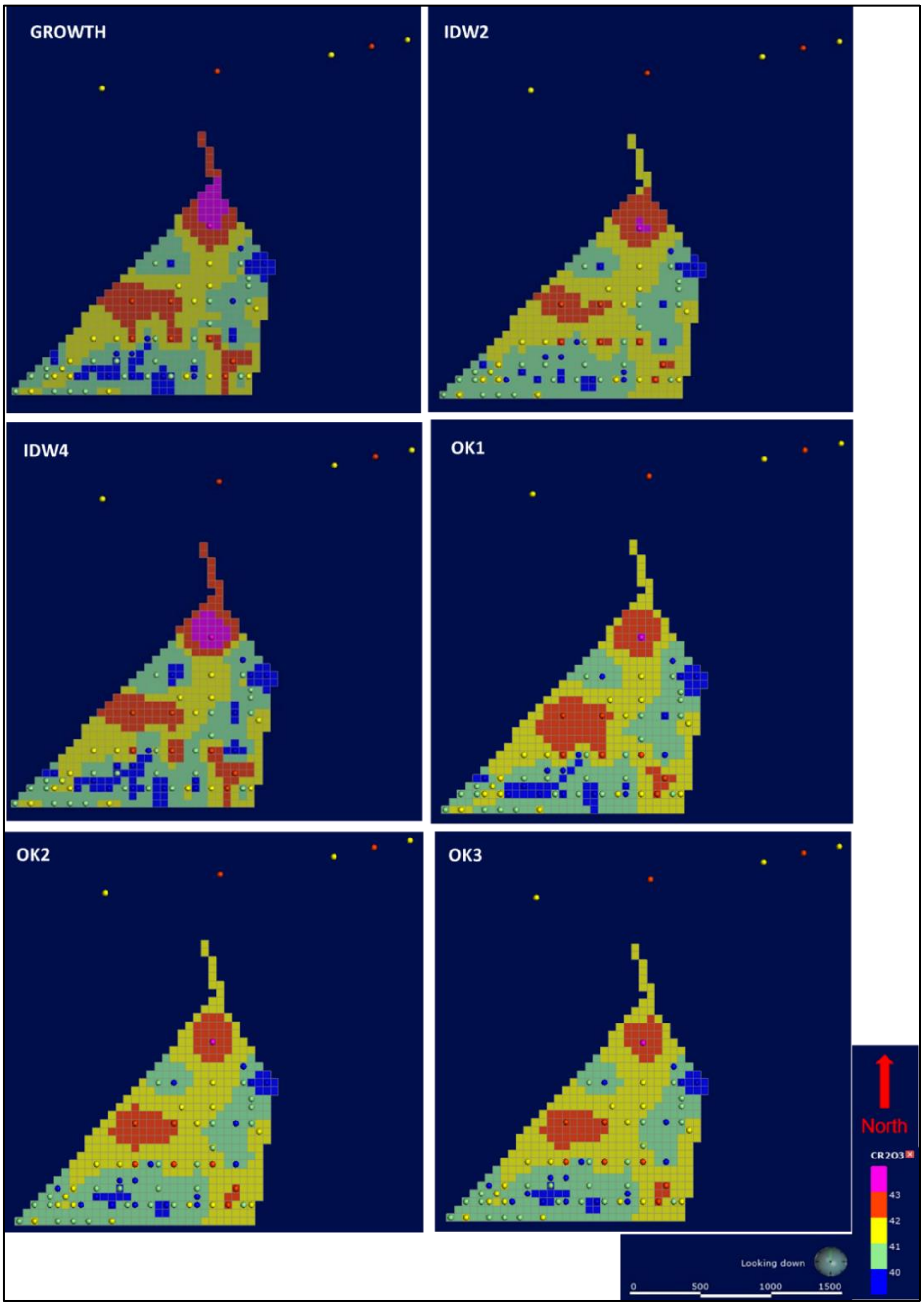


Figure 27: Cr2O3% block model estimates (Growth technique and alternative methods)

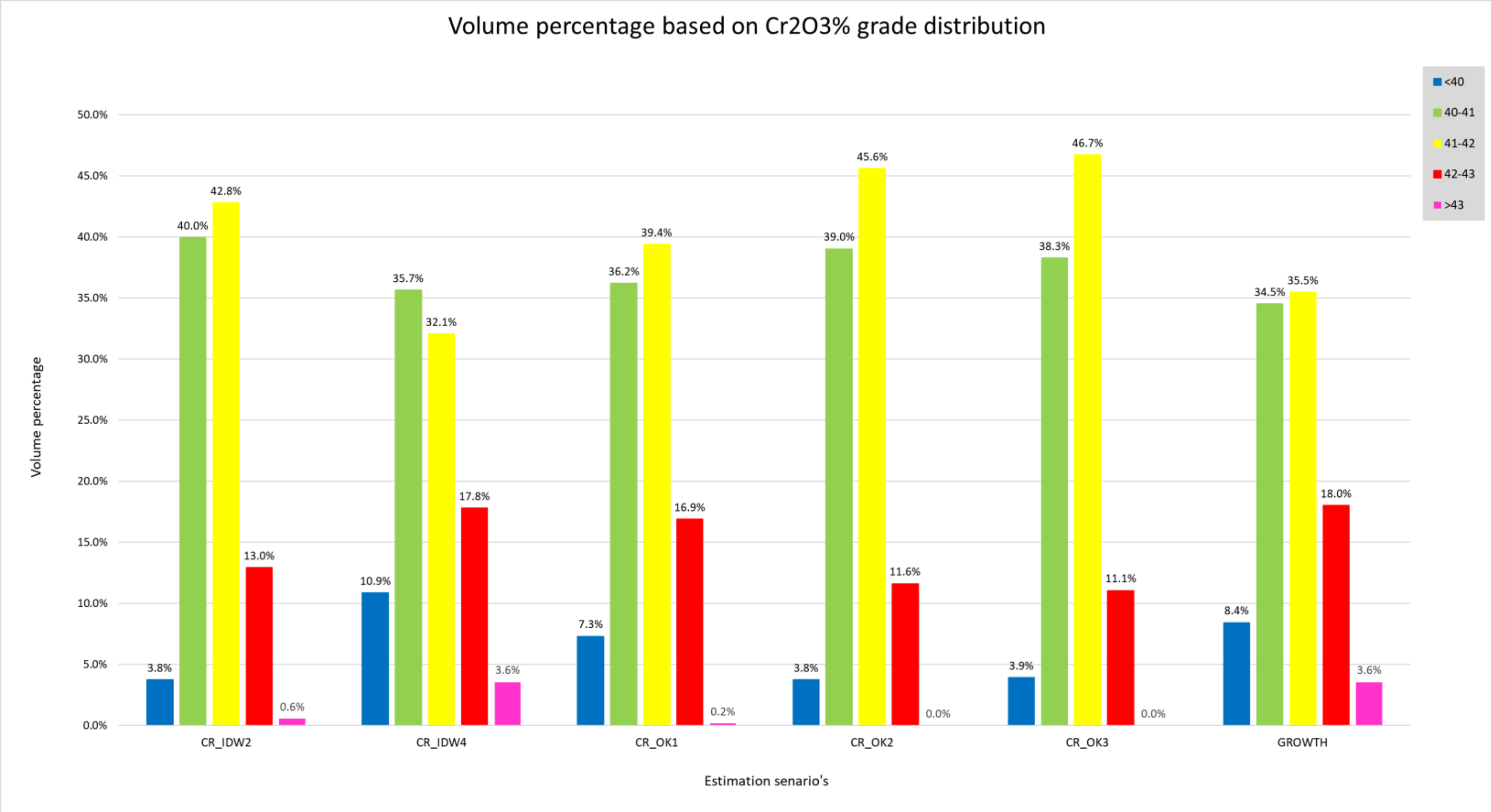


Figure 28: Volume percentage based on Cr_2O_3% grade distribution of the estimation scenarios

.

Based on the general visual inspection of the Cr_2O_3% grade estimates and declustered composites (Figure 27), all the estimations methods honour the input data to an acceptable level. However, the Kriging estimates that were conducted with variograms with 18% nugget effects (OK_2 & OK_3), over smooth the grade estimates relevant to the input data. The over smoothing, is associated with the effect that the variogram model has on the weight distribution of samples used to estimate a block. In this case the over smoothing effect is observed when a higher nugget effect is used for the variogram model, as appose to OK_1 results with a zero nugget effect. Furthermore, increasing the minimum and maximum number of samples for the Kriging neighbourhood of OK_3, did not have a significant impact on the estimate.

Visually the grade distribution of the Growth technique and the inverse distance weighting to the power of 4 are similar and this was confirmed by the volume grade distribution plot (Figure 28). Both these methods are sensitive to high or low-grade samples that are sparely spaced and creates a “smearing” effect of low or high-grade zones.

The observation confirms that increasing the power of the IDW algorithm, the estimated value starts receiving the value of the closest sample composite, resulting in an estimate that is similar to a Polygonal method (Diadato & Ceccarelli (2005) cited in Babak & Deutsch (2008) or Nearest neighbour method (Glacken & Snowden, 2001). This means that in the event that there are low or high-grade composite samples sparsely spaced from surrounding data, the estimated values around the sample will receive a high or low grade until the surrounding data is closer to a block that requires estimation.

Glacken & Snowden (2001) highlights that most resource estimation techniques, are associated with a grade smoothing interpolation and can be categorised into non-geostatistical (IDW) and geostatistical (Kriging) estimation methods.

Based on the visual observation for the IDW2, compared to IDW4 and Growth technique, the “smearing” effect is mitigated by IDW2, and grades are smoothed more conservatively.

Three Ordinary Kriging estimation scenarios were conducted (Figure 27), in order to test the effect of different search neighbourhood parameters and using a variogram with a zero nugget effect for OK_1.

Due to the limited amount of close-spaced data the nugget effect initially modelled at 18%, can be considered as subjective, as Chromitite deposits in the BC are known for low nugget effects (<5%). The grade distribution of the OK_1 estimates, using a variogram model with zero nugget effect, visually appears to represent grade trends of the input data better than with the other estimation comparison scenarios, including the Growth technique.

Glacken & Trueman (2014) states that for understanding the global performance of the Resource estimation during validation, the declustered sample mean, should be similar to the estimation mean. The block estimates variance, should also show reduction as appose to the sample data variance.

The declustered mean for the Cr_2O_3% composites was determined with a declustering tool available in Leapfrog® Edge (Leapfrog3d-Mining and Minerals team, 2019), and an ellipsoid approach based on the general spacing of the data was used. The declustered mean for the composite data was estimated to be 41.11% Cr_2O_3, and the differences in percentage compared to the estimate means are shown in Figure 29.

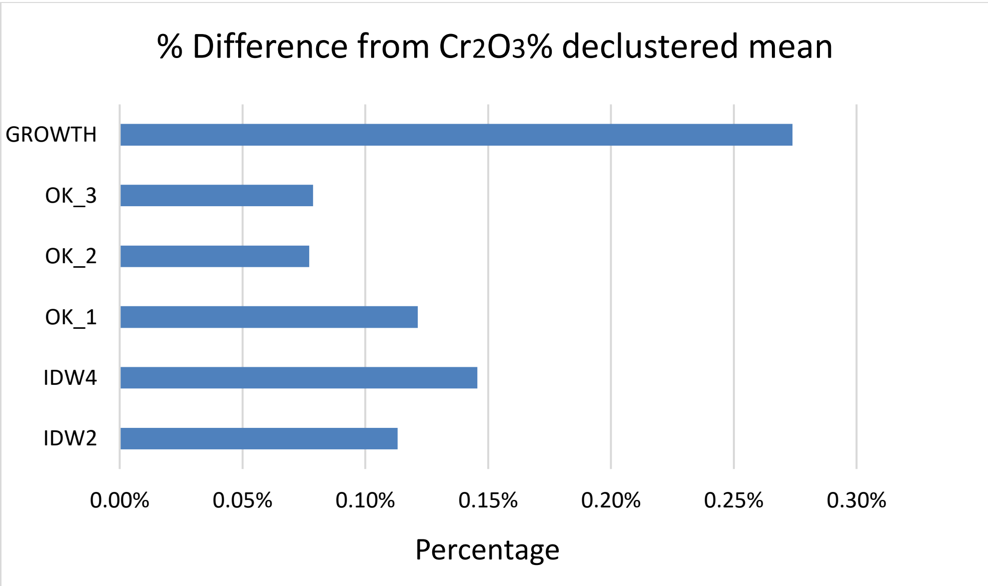


Figure 29: Percentage difference of Cr_2O_3% block estimate means and the declustered composite sample mean.

Although the Growth technique estimated mean difference is the highest, the estimate means are within 0.5% difference of the declustered sample mean, which is deemed acceptable.

The descriptive statistics of the block model estimates and the sample composite data are presented in Table 11.

Table 11: Statistics of the estimation methods and sample composites.

Descriptive statistics of block model estimates - Cr_2O_3%										
Method	**Volume**	**Mean**	**Standard dev**	**COV**	**Variance**	**Min**	**Lower quartile**	**Median**	**Upper quartile**	**Max**
IDW2	1918800	41.15	0.735	0.018	0.541	39.18	40.65	41.10	41.61	43.22
IDW4	1918800	41.17	0.944	0.023	0.891	38.91	40.45	41.11	41.75	43.25
OK_1	1918800	41.16	0.809	0.020	0.655	39.28	40.55	41.13	41.73	43.02
OK_2	1918800	41.14	0.672	0.016	0.451	39.60	40.64	41.18	41.63	42.69
OK_3	1918800	41.14	0.670	0.016	0.448	39.60	40.63	41.18	41.63	42.69
GROWTH	1918800	41.22	0.909	0.022	0.826	39.14	40.56	41.12	41.82	43.23
Descriptive statistics of Cr_2O_3% sample composites										
Cr2O3% composites	N/A	40.87	0.953	0.023	0.908	38.90	40.11	40.88	41.43	43.25

Generally, the statistics compare well between the block estimates, the alternative estimation technique means are within 0.5% of the Growth technique mean. Reduction in the variance from the original composites is also noted, however minimal (<10%) with regards to the Growth technique and IDW4, as appose to the Ordinary Kriging technique, including IDW2 scenarios that reduced more than 25%. Base on the statistics, a global bias is observed for all the block estimates, of over estimating, if compared to the composite mean. This could be the effect of the sparse sample data that was used for the estimation process, however as mentioned, the global performance are better measured by using the declustered mean of the composites. Slightly higher coefficient of variation (COV) was noted from the Growth and IDW4 estimates, compared to IWD2 and Ordinary Kriging results. This can be attributed , as the global means of all the block estimates that are almost similar, however the standard deviations are higher for the Growth and IDW4, which will result in higher COV values.

The reduction in the variance is explained by Isaaks & Srivastava (1989):

> *"This reduced variability of estimated values is often referred to as smoothing and is a consequence of combining several sample values to form an estimate".*

Isaaks & Srivastava (1989) also highlights in an exercise conducted, that the polygonal method that only uses a single sample, had estimates that are unsmoothed.

Glacken & Trueman (2014) states that when a lower power is used in inverse distance (i.e. IDW2), the greater the smoothing, and the higher the power (i.e IDW4), the estimate approaches a nearest neighbour method, as observed in Table 11.

Rezaee, et al. (2011) also mentions the smoothing effect associated with OK estimates:

> *"OK estimates do not reproduce the sample histogram because of reduced variance as a consequence of the smoothing effect. In the OK estimation process low values are overestimated and high values underestimated making the estimated histogram narrower than the sample histogram*."

Morgan (2005), conducted an exploratory comparison by using the polygonal, IDW2, and OK methods, and also confirmed the smoothing effect. However, Morgan (2005), clearly states the advantages of Kriging of being the best linear unbiased estimator, and provides a KV, as a measure of quality of the estimation. Furthermore, Morgan (2005) cites Journel & Huijbregts (1978), which states that "reproducing spatial variability is not the goal of kriging estimates, but rather the goal of geostatistical simulations".

The histograms of the Cr_2O_3% estimation results for the different estimates are shown in Figure 30 and the histogram of the Cr_2O_3% input data on which the estimations are based on appear in Figure 31 for further comparison of results.

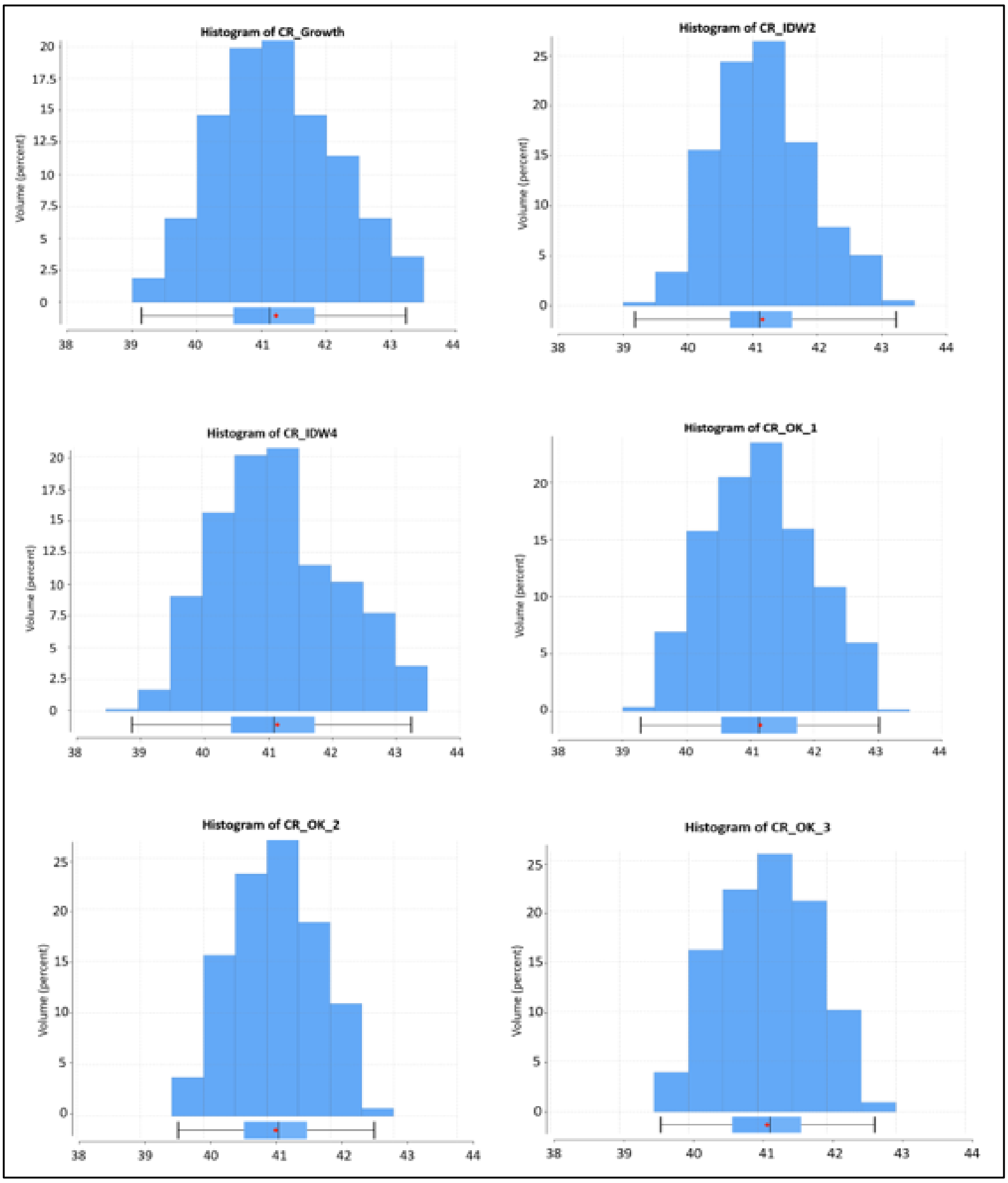


Figure 30: Histograms of the Cr_2O_3% block estimate scenarios.

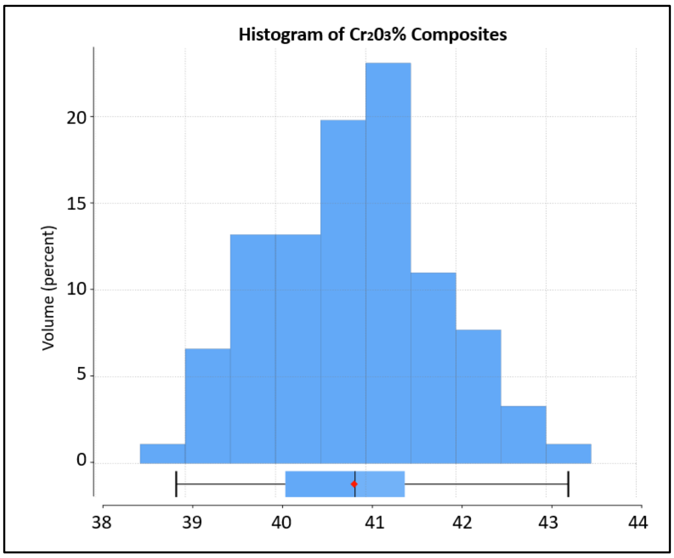


Figure 31: Histogram of original sample input data (Cr_2O_3% composites).

The kriging results with a higher nugget (OK_2 & OK_3) reduced the variance of the estimates more than the other estimates, including the input data, however it overly smoothed the grade distribution of the estimates.

This highlights the importance of accurately fitting the nugget-effect and slope near the origin of the variogram model, due to the significant influence towards kriging results (Morgan, 2005).

The Growth and IDW4 estimates underlying grade distribution is similar and compares the best with the input data distribution, with minimal reduction of variability, based on the histograms and statistics. The IDW2 and OK_1 grade distributions have more similarities, with the smoothing effect confirmed (Table 11), with reduction in the variability.

The grade distribution of the alternative estimation techniques was also compared with the Growth technique grade distribution by the use of Q-Q plots (Figure 32) and scatter plots (Figure 33) to investigate correlation.

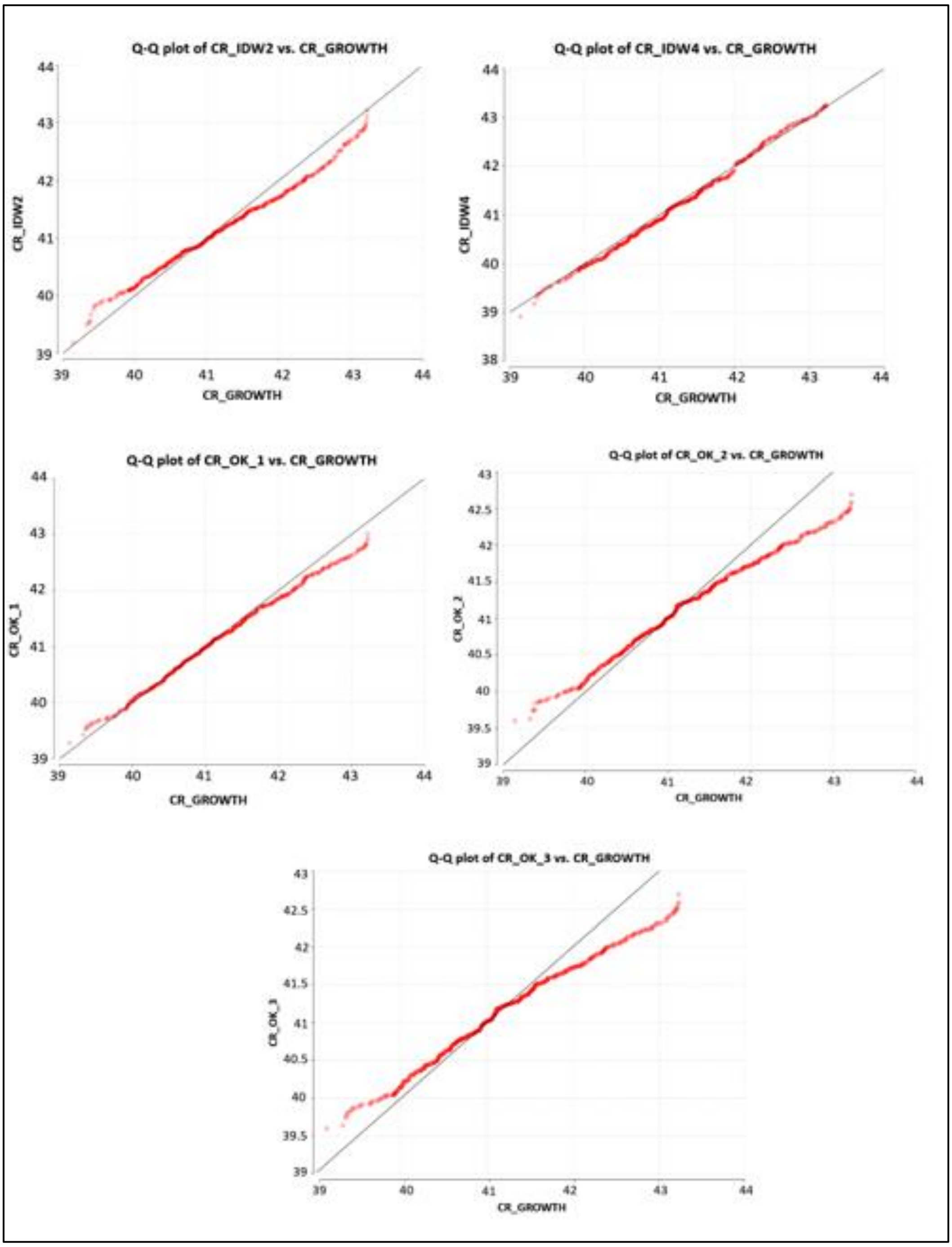


Figure 32: Q-Q Plots of the Growth technique estimate versus the alternative estimation methods.

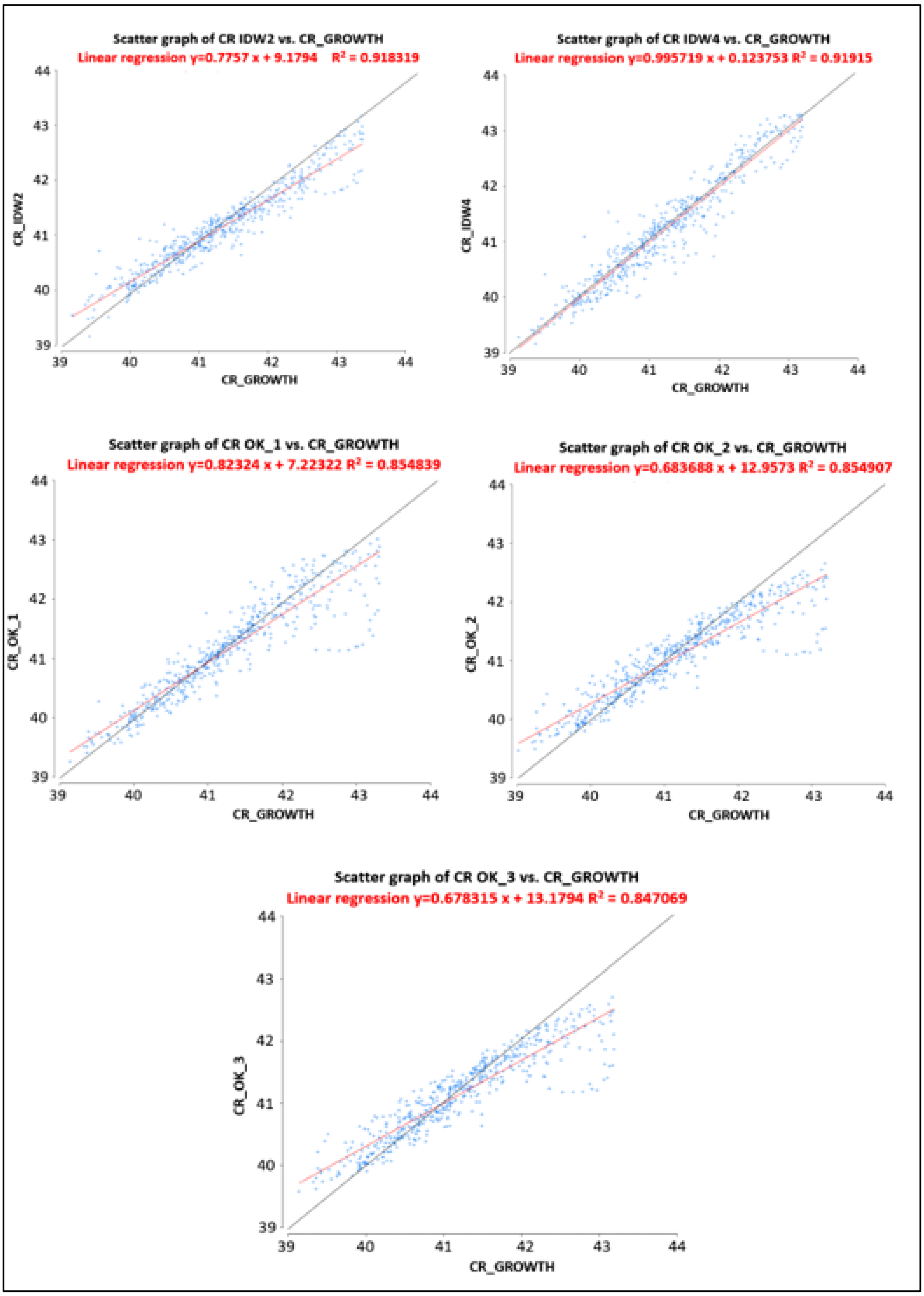


Figure 33: Scatter Plots of the Growth technique estimate versus the alternative estimation methods.

The results confirm the grade distribution similarities of the Growth and IWD4 grade estimates, including a good positive correlation (R^2 >90%) between the estimated values, with a narrow scatter envelope between the values. The scatter correlation between the growth and IDW2 estimates also presents a positive correlation of >90%, however the scatter envelope starts to increase towards the high grades, and effect is more prominent with regards to the Ordinary kriging estimates, although still presents a positive correlation of >80%.

The effects of smoothing and variance reduction from the IWD2 and Kriging estimates can be seen in the differences of grade distributions compared to the Growth estimate distribution. Higher grade distribution is observed in the upper-quartiles for the Growth estimates and vice-versa on the lower-quartiles for low-grade distribution, compared with IDW2, including Ordinary Kriging distributions.

Swath plots were generated in 120m slices through the estimated block model grades, which included the sample composites in a North-South and East-West direction **(Appendix A:1).**

Generally, it is recommended to use swaths/slices that are equal to the block model size, however due to a lack of composite data, the slices were multiplied by a factor of two, to capture more data within a swath. Swath plots are used to compare two datasets (Webster, n.d.), and could also indicate “smearing” or smoothing of high grades (Leuangthong & Nowak, 2015). A swath plot represents the averages of the grade estimates and composite data at various swath/slice intervals that are then plotted on the same graph. Chanderman (2015), also states that the purpose of the swath plot is to investigate gross over or under underestimation associated with the block model estimates.

Due to the limited amount of sample composites that are captured in a swath interval, the swath plot interpretations can be somewhat subjective, nonetheless the swath plots were also used to compare the grade trends between the growth and alternative block estimates. Generally, the average differences based on the swath intervals for all the estimates, compared well to the composite values and the means are within 1%, which is considered acceptable. Consistent overestimation was noted in the swaths plots for all the estimated grades, probably due to the effect of a lack of sample numbers available, as well as sparse spacing of data along swath intervals.

However, the swaths plots do provide a grade trend comparison between the growth estimates and alternative estimation methods. As previously observed, it is evident that Growth and IDW4 generally possess the same grade trends, with minor differences, with regards to the swath plots.

The Ordinary Kriging estimates do appear to smooth the grade trend at places; however, minor differences were noted with grades slightly higher and lower than the Growth estimates. The IDW2 grade estimates are consistently lower than the Growth estimates and globally appears to follow the grade trends of the composite data the best of all the estimated grades.

Based on the estimate validation and comparisons, the following is surmised; globally the means of the estimates appear to be similar leading to the conclusion that the estimation methodologies considered do not differ significantly on a global scale. However, local variation is observed between the estimates compared, which is revealed by the differences in the variance of the estimated grade distributions of the blocks.

6.2.2 Comparison of Estimation Techniques within the MCo Resource Classification

In order to compare local variation of the grade estimates, and the impact of the estimates when applying MCo's resource classification method were to be used, the estimates are reported according to MCo's resource classification perimeters (Table 12). The estimate via the growth method, was obtained directly as reported by MCo using Geovia Minex^{TM}. In order to obtain tonnage for the alternative estimates, CW and SG were estimated using the IDW2 technique, to discount the influence of variogram modelling.

Table 12: Estimated Cr_2O_3% grades and tonnages of all estimation methods within MCo's defined resource classification perimeters.

	RESOURCE CLASSIFICATION				
	MEASURED	INDICATED	INFFERED	TOTAL	
IDW2	41.18	41.70	41.67	41.27	Estimated Cr_2O_3% -Tonnage weighted
IDW4	41.18	41.81	42.02	41.29	
OK_1	41.21	41.79	41.22	41.29	
OK_2	41.19	41.70	41.22	41.26	
OK_3	41.19	41.68	41.22	41.26	
GROWTH	41.22	41.91	42.36	41.35	
*ALTERNATIVE (Mt)	6.57	1.13	0.22	7.92	Tonnes
MCo (Mt)	6.68	1.14	0.24	8.06	
%DIFF TONNES	-2%	-1%	-8%	-2%	
* The tonnage for all alternative estimates (IDW2,IDW4,OK_1,OK_2,OK_3) are equal					

The percentage grade difference between the Growth estimate for each Resource class that is based upon the results of table 12, is presented in Table 13.

Table 13: Grade (Cr_2O_3%) percentage differences of the Growth estimate compared to the alterative estimates as per MCo's resource classification perimeters.

	Cr2O3% difference compared to GROWTH – Tonnage weighted				
RESOURCE CLASSIFICATION	IDW2	IDW4	OK_1	OK_2	OK_3
MEAS % DIFF	-0.1%	-0.1%	0.0%	-0.1%	-0.1%
IND % DIFF	-0.5%	-0.2%	-0.3%	-0.5%	-0.6%
INF % DIFF	-1.6%	-0.8%	-2.7%	-2.7%	-2.7%
TOTAL % DIFF	-0.2%	-0.1%	-0.1%	-0.2%	-0.2%

The greatest % tonnage differences between the alternative estimation methods and the Growth technique are observed in the Inferred category, these percentages are considered to be within a margin of acceptance.

It might be argued that the choice of applying a different estimation technique (IDW2), to estimate the variables that account for tonnage (SG and CW) and this could affect the tonnage estimation. However, MCo's resource classification perimeters were used to report the Cr_2O_3% differences between the Growth estimates based on volume as well, with a fixed block model height and the volume results are given in Table 14. The conclusion reached based on Table 13 remain unchanged and the biggest difference is with the Inferred Resource category.

Table 14: Alternative estimated (volume weighted) Cr_2O_3% percentage differences compared to the Growth estimate as per MCo's classification perimeters.

	Cr2O3% difference compared to GROWTH – Volume weighted				
RESOURCE CLASSIFICATION	**IDW2**	**IDW4**	**OK_1**	**OK_2**	**OK_3**
MEAS % DIFF	-0.1%	-0.1%	0.0%	-0.1%	-0.1%
IND % DIFF	-0.6%	-0.3%	-0.4%	-0.6%	-0.7%
INF % DIFF	-1.5%	-0.7%	-2.6%	-2.6%	-2.6%
TOTAL % DIFF	-0.2%	-0.1%	-0.2%	-0.2%	-0.2%

The differences in grade per resource class, compared to the Growth estimates, can also be logically considered as insignificant, with regards to the Measured and Indicated Resource classes. However, the most difference is observed in the Inferred Resource class, where data is sparse, and the IWD2 and the OK results have less of a "smearing" effect on the grade estimate. The close resemblance of the IDW4 and Growth method is observed in the Inferred class and is due to the fact that the IDW4 generally mimics the Growth technique. The comparison did not include the total geological losses for reporting, and only included the geological losses associated with major dykes, as applied by MCo, from the classification perimeters.

The Resource classification perimeters of MCo (Figure 34) are determined by a combination of pre-determined MG1 Chromitite intersected borehole radii (150m for Measured; 300m for Indicated; 600m for Inferred) and the resource estimator's judgement where confidence can be overruled by the general standard, based upon complex geological influences, unexpected grade trends, or dip regimes, where confidence is uncertain. This judgement call can be observed in the top part of the Mineral Resource, East and West with regards to an Inferred Resource classification.

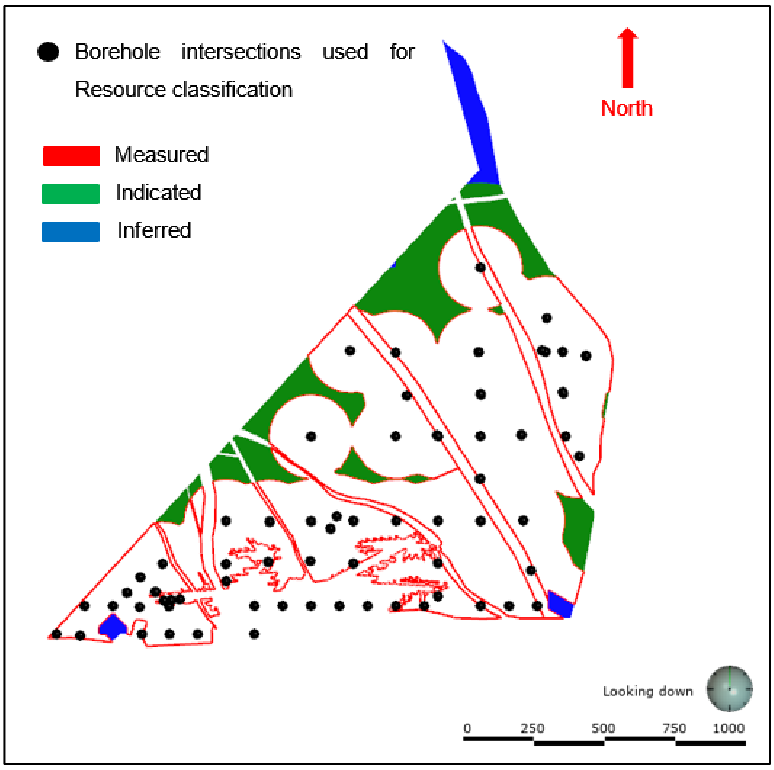


Figure 34: MCo's resource classification for the current sample data configuration.

7. FACTORS THAT CAN INFLUENCE THE MG1 RESOURCE CLASSIFICATION

This chapter describes the main influencing factors that can affect the MG1 resource classification practices that are currently employed by MCo.

7.1 Non-numeric Factors Relevant to Mineral Resource Classification

Mineral Resource classification at MCo is a function of the prescribed search radii associated with the resource categories and the adeptness of the CP to adjust the resource class boundaries based on their personal knowledge and experience. In the research process four additional factors that can affect the resource classification boundaries have been identified. Three of these are inherent to the MG1 Chromitite deposition, all three require additional drilling information to confirm interpretation confidence and the fourth is related to the value of historic information. The factors are:

- Areas of geological complexity: usually associated with Potholes Faults, Dykes and IRUPs, modelling of the size and shape thereof can have an influence on the estimated resource and reserve tonnages.
- Grade continuity and apparent outlier values: the spatial positions of outlier intersections can impose, uncertainty particularly in the areas of their occurrence within the resource.
- Sudden changes in the dip regime or seam thickness of the orebody: often associated with geological structures such as Potholes confirm can influence confidence in the modelling and the orebody delineation and consequently the resource classification .
- Historical mining knowledge of the Mineral Resource: gathering available information, of known underground or opencast mining, and applying this knowledge to the resource classification can lead to the increase in confidence or reduction of uncertainty in the three topics discussed above.

Potholes are the most unpredictable geological structures due to the fact that these vary in size, dimension, including direction and can be located anywhere within the chromitite borehole intersection grid. The best method for confirmation of pothole delineation is a combination of underground workings, underground and exploration drilling and/or seismic information (if available).

The bulk of the resource area often only has exploration drilling available from which predictions of potholes can be projected. Pothole structures are usually thinning or increasing seam thickness, other indicators are the reduction of internal layering with regards to the overlying Chromitite layer (MG2), outlier grade trends, increased dip regimes and increasing internal waste layering within the MG1 chromitite layer. MCo generally use a ±30m radius around a borehole intersection suspected to have intersected a pothole structure when only exploration data is available, and as additional drilling is carried out and information becomes available the structure delineation becomes more detailed.

The information made available from MCo’s borehole database, included previously estimated potholes plotted on structural maps, underground mappings and dip regime wireframes, that were used to construct a possible pothole influence zone model. The current pothole map was scrutinised and for the purposes of this research, a pothole influence model was created (Figure 35). The model was derived from Leapfrog Geo® numeric RBF indicator interpolation functionality (Leapfrog, n.d.).Construction of the model is based on borehole intersections that have been declared as potholed intersections, and further refined based upon underground mappings, the MG1 seam dip regime, decreased interseam thickness, and thinning/increasing seam thickness.

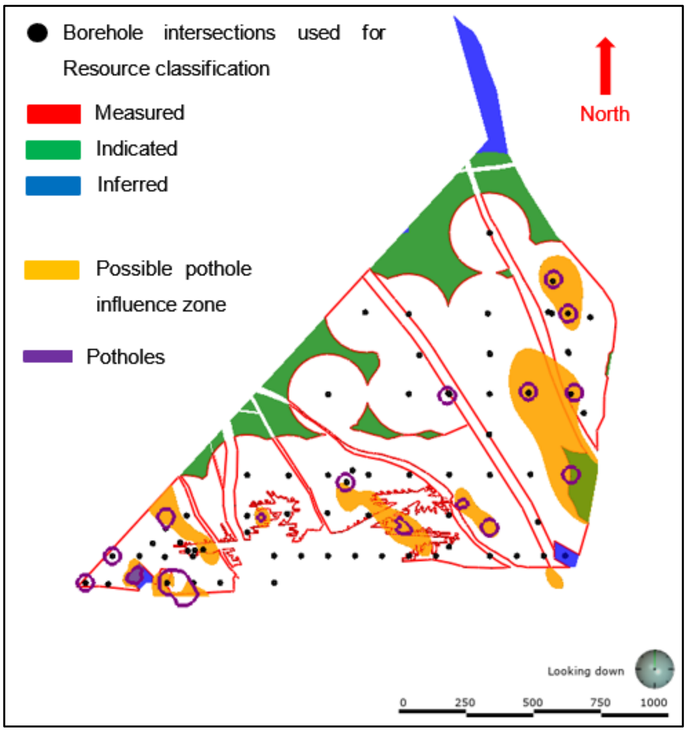


Figure 35: Possible pothole influence zones in the project area.

MCo does account for potholes, faults, dykes and IRUPs (when and where encountered), with a the application of a geological loss factor, to mitigate the effect these structures on the estimated tonnage of the declared Mineral Resource statement.

However, about ±80% of the possible pothole influence zones are within the Measured category of the resource. A question that can be raised is whether there is adequate data and geological knowledge/confidence available to support and justify the declaration of all of these areas as Measured. Furthermore, bearing in mind that high confidence does not mean high grade. The potholes will have an influence and effect on the reserve classification and consequently on the mine planning. Another point of observation that is debatable, is the allocated ±30m radius applied around pothole intersected boreholes in sparsely drilled areas, as in some areas this pothole prediction may not be applicable and the size could be increased.

7.2 Borehole Radii Approach in Resource Classification

The guidance that the SAMREC code (2016) provides for declaring a Measured Mineral Resource are the following :

> *"A Measured Mineral Resource requires that the nature, quality, amount and distribution of data are such as to leave the Competent Person with no reasonable doubt that the tonnage and grade of the Mineralisation can be estimated to within close limits and any variation within these limits would not materially affect the economics of extraction. This category requires a high level of confidence in, and understanding of, the geology and the controls on mineralisation".*

> *"A Measured Mineral Resource estimate should be of sufficient quality to support detailed technical and economic studies leading to Mineral Reserves which can serve as the basis for major development decisions".*

Geological influences, such as potholes do have an effect on the economics of ore extraction, as it will potentially amount to a higher geological loss or overly diluted grade of the resource, which results in areas that are economically unmineable. However, the more prominent point to be observed is the effect that geological continuity can have on resource classification , if the classification method used, does not adequately cater for geological or grade continuity between data points.

Technically it is more difficult to account for geological continuity than for chromitite grade continuity and more reliance would be on the judgement of the CP based his/her experience and interpretation of the data available. Although MCo's standard practice allow room for the CP to exert their own judgement when making informed decisions in areas that do not conform to the general standard resource classification, there is still a risk of only accepting the pre-determined classification radii, if not thoroughly interpreted or reviewed. The risk is that the Resource classification can result in a "spotted dog" effect (Figure 36).

As early as 2006, Stephenson, et al. (2006) stressed the importance recognising the geological and grade continuity in Mineral Resource classification:

> *" Spotted-dog resource classifications should be unacceptable to both geologists and mining engineers. A final smoothing step to produce resource classifications commensurate with a realistic level of*

geological and grade estimation confidence should be seen as a necessary and integral part of the resource estimation process".

Stephenson, et al.(2006) further argue that "spotted dog" classification may be contradictory to reporting codes and mentions the SAMREC code, and further emphasised that:

"all of these standards discuss continuity of geology and grade in terms of drillholes plural, implying correlation between drillholes, not around individual drillholes".

The SAMREC code (2016), states that for a Measured Resource*,*

"geological evidence is derived from detailed and reliable exploration, sampling and testing <u>and is sufficient to confirm</u> geological and grade or quality continuity between points of observation".

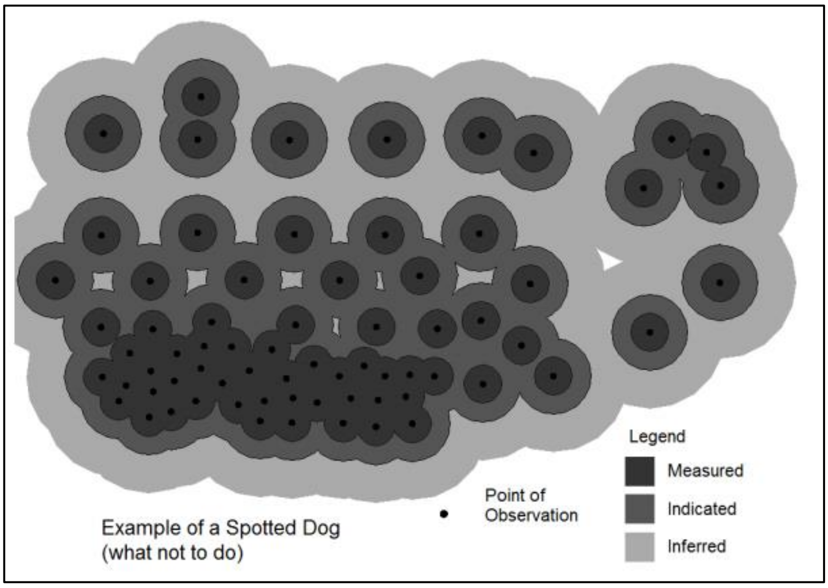


Figure 36: Example of a "spotted dog" – what not to do (Guidelines Review Committee (JORC), 2014).

The JORC Guidelines Review Committee (Guidelines Review Commitee (JORC), 2014), in the Australian Guidelines For The Estimation and Classification of Coal Resources considers the "spotted dog", as a poor practice:

"… a Resource estimate classification which displays the poor practice of estimating Measured, Indicated and Inferred Resources over disconnected circles of influence around individual Points of Observation or along a line of Points of Observation".

This concern has been raised by other authors such as Nengovhela (2018), Lewis (2018) and Stephenson, et al. (2006).

Nengovhela (2018) emphasises the risk of practitioners applying default software suggestions for resource confidence and this has led to less focus being put on the importance of geology in Mineral Resource classification:

> *"The advent of computers for geological modelling and the increased application of geostatistics in estimating Mineral Resources has seen most practitioners limiting the assignment of confidence to the suggestions made by software package algorithms. This has further seen a reduced focus on the impact geology has on the confidence of an estimated block, which is something that industry needs to address".*

Although MCo does not make use of geostatistics to determine confidence, the underlying issue is associated with a set methodology or recipe, that could deter focus on interpretation and impact of geology on the confidence of a Mineral Resource, if not properly addressed by the CP.

Lewis (2018): Highlights consequences of ignoring geological continuity in using radii around borehole intersections and questions the credibility of those who claim competence in doing so. Lewis (2018) also cautions against this practices as it could have detrimental effects on Mineral Reserves estimates:

> *"A 'Spotted Dog' output is potentially misleading since fundamental requirements, such as continuity of geology and mineralization between drill holes, and the imprecise nature resource estimation, have been ignored. As such, it undermines the credibility of the responsible QP's (Qualified Person) claim to competence and relevant experience in the commodity or type of deposit".*

Lewis (2018), further argues that:

> *"… mis-classified resource estimates can subsequently cause substantial problems for engineers undertaking a mine design and applying modifying factors to the resource estimates to produce Mineral Reserve estimates".*

MCo's resource classification approach does not lead to a "spotted dog" effect where close drillhole spacing, allows for the overlapping of classification radii, however areas where spacing increases, the effects of the “spotted dog” is present. Furthermore, the radii approach for classification, cannot and does not cater for the impact of geological continuity (i.e. pothole influence zones or geological complexities), and for this it would have to rely on the experiential judgement and interpretation of the CP.

Resource classification based upon a minimum borehole spacing based on coal quality data, is a common practice in Coal Resource reporting based upon the SANS 10320:2004 (Figure 37), in conjunction with the SAMREC Code.

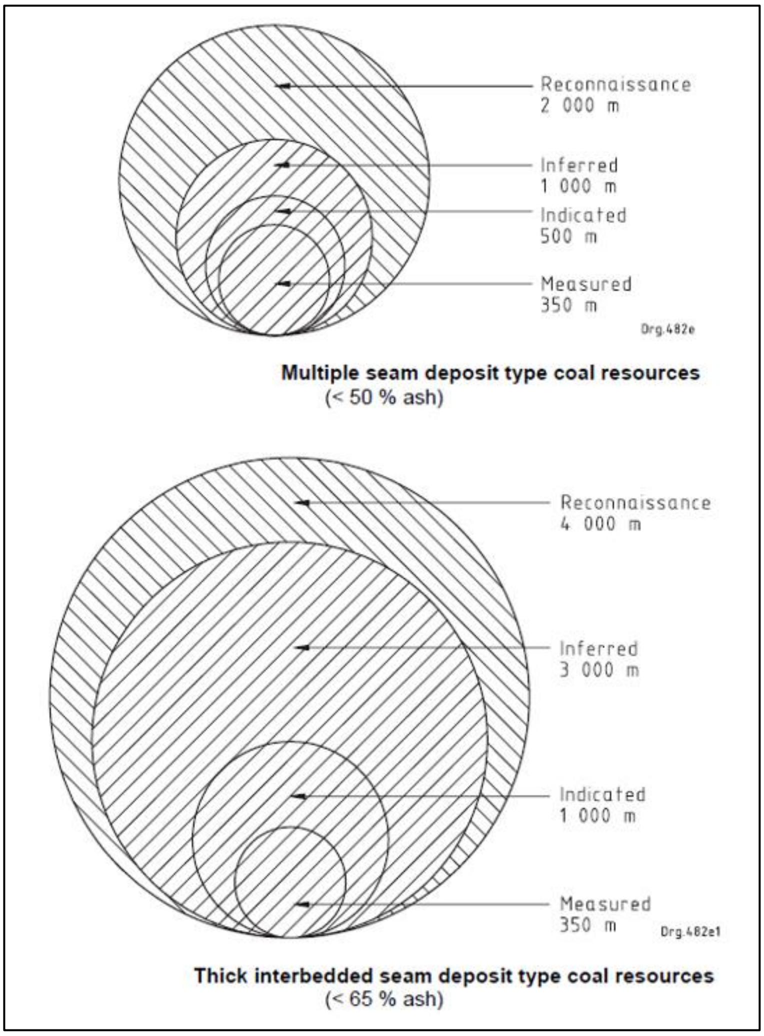


Figure 37: Minimum borehole spacing for each Coal Resource classification category for the various South-African coal deposit types (SANS 10320:2004 cited in Hancox & Pinheiro, 2017)

Stephenson et al.(2006) highlights that

> "*Competent Persons for Mineral Resources must keep in mind the purpose of their work and should use their experience and judgment to avoid or smooth out "spotted dog" classifications, providing a result commensurate with the level of geological and resource".*

An example of an Exarro Mineral Resource statement of classifying Coal resource based upon the SANS 10320:2004 classification guidelines, where a Competent Person's judgement was used and mitigated the 'spotted' dog effect can be seen in Figure 38. Exarro also uses Geovia Minex^{TM} for Resource Estimation and Classification, with a distance-gridding functionality, that is adapted with hand-drawn polygons to adhere to the CP's understanding of the geological continuity for classification (Exxaro, 2015).

Figure 38: Example of a Coal Resource classification based upon SANS 10320:2004 (Exxaro, 2015).

The functionality of the borehole distance gridding in Geovia Minex^{TM} can be best described by GEOVIA (2014) and the use thereof for Mineral Resource classification by Mitra (2017).

The borehole distance gridding functionality creates distance contours around individual boreholes, based upon specified distances. An example is shown in

Figure 39 of three increasing distances (red; green and blue), around individual boreholes. In the event that such criteria based on radii are accepted for a Mineral Resource classification, the classification can easily start representing a “spotted dog” effect.

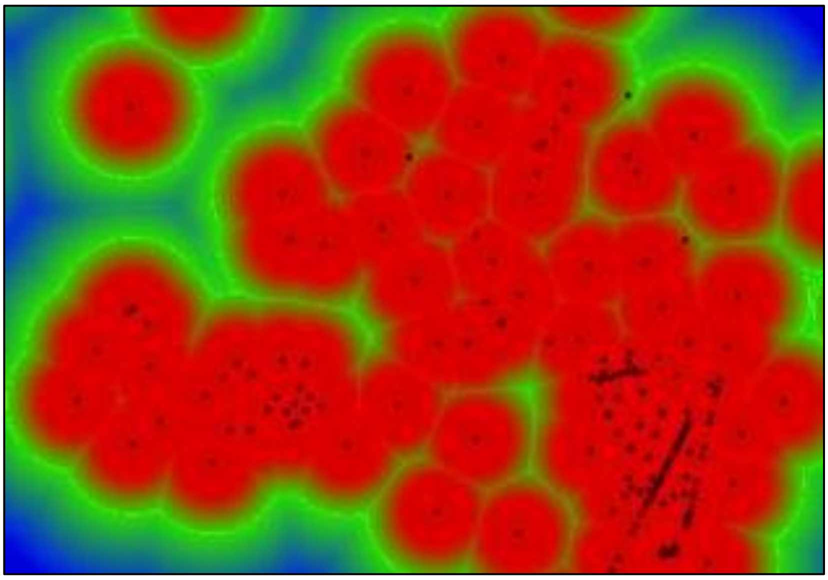


Figure 39: Example of the borehole distance gridding functionality in Geovia Minex™ (GEOVIA, 2014).

8. APPROPRIATENESS OF MCO'S MINERAL RESOURCE CLASSIFICATION

There are various Resource classification techniques that are globally used by Resource estimation practitioners, some of the more commonly techniques used were discussed in **section 2.5.1** of this research report.

The use of point data density based upon a borehole intersection spacing or radii criteria, in conjunction with geological continuity (considering complex geological areas) for classifying Mineral Resources, is not uncommon in the Chrome industry. A recent Mineral Resources and Mineral Reserves statement of using point data spacing criteria in Western Bushveld Complex for MG1 was observed in Merafe Resources (2018). Sinclair & Blackwell (2002) considers the "distance from a sample site" method as inadequate, if not used in conjunction with other parameters and leads to cylindrical shapes that are difficult or impractical to use in practice.

In other chromitite Mineral Resources and Mineral Reserves statements, such as African Rainbow Minerals (ARM) (2016), Resource classification was conducted by considering geological and geostatistical parameters. Mining companies, such as Anglo American have entrenched a scorecard based approach to classify Mineral Resources, incorporating a range of factors that can influence uncertainty and confidence (Anglo American, 2017).

8.1 Classification Based on the "two thirds" of the Range Method

The "two-thirds" range of the variogram classification technique mentioned in **section 5.2.1**, is visually compared to MCo's resource classification approach in Figure 40. The "two-third" technique was applied solely on the variogram ranges and did not account for geological complexities, neither were manual (hand-made) adjustments made.

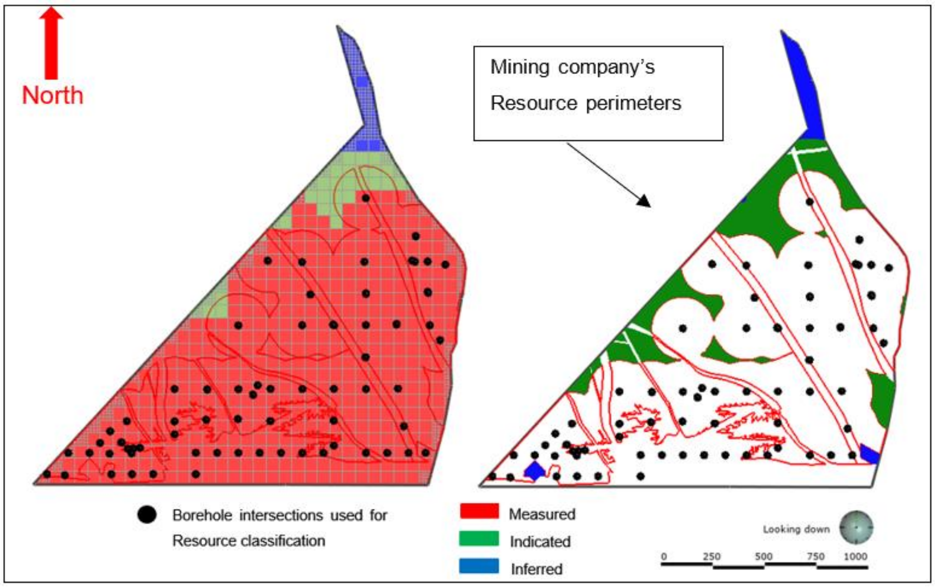


Figure 40: Visual comparison between the "two thirds" (left) and MCo's (right) Resource classification approaches.

Although the "two thirds" technique would require some manual adjustments, it can be concluded that MCo's resource classification approach is more conservative, however it is considered to be appropriate.

Based on the critique by Stephenson et al.(2006) and Sinclair & Blackwell (2002), it would be however more appropriate and practical to manually override the radii perimeters to produce a classification that is more similar to the Exarro (2015) approach shown in the example Figure 38, where a more realistic interpretations of the geological and grade continuity have been incorporated in the classification boundaries.

8.2 Classification Based on Kriging Input and Output Parameters

Using the input parameters and output measures of a Geostatistical estimation process have become common in classifying Mineral Resources, as these assist with providing an indication of uncertainty associated with an estimate, which can be difficult to determine solely by the CP's interpretation of geological and grade continuity.

Using the kriging input and output measures also creates a sense of standardisation in mining company's resource classification practices, as the interpretations can be documented and aim to adhere to the transparency of Mineral Resource reporting. However geostatistical input parameters, including output measures are still just estimates and cannot replace the final judgement, interpretation and experience of the CP or estimator. Hence all these factors/measures should be combined when classifying Mineral Resources.

The basis of geological influence is the most important and generally takes primacy over Mineral Resource confidence that is based on mathematical indicators (Snowden, 2001). Glacken & Snowden (2001) highlight that resource classification should in most cases be a combination of criteria, numerical and geological measures, with a manual interpretation and an override by the CP on the final classification.

8.2.1 Kriging Variance, Kriging Efficiency and Slope of regression

The advantage that a Kriging estimate has over non-geostatistical estimations is that it provides a measure of quality of the estimation, providing a minimum error variance, that is known as the Kriging Variance (KV). Snowden (1996) explains that the *"kriging variance represents the expected value of the squared error between the actual grade and the estimated grade"*.

The KV can be useful as criteria for resource classification, as it is dependent on the sample configuration and continuity (the semivariogram) associated with an estimated block, however independent of the actual grade estimates (Glacken & Snowden, 2001).

There are numerous ways of using the Kriging variance for resource classification that has been proposed by various authors such as Arik (2002) , Emery, et al. (2004) and Silva & Boisvert (2014). Dohm (2004) explains that the KV can be calculated without producing an estimate, as the KV calculation only depends on the semivariogram model, the sampling grid and block configuration of the block to be estimated. For this reason the author did not find the use of the KV in resource classification surprising and provides a reasoning for the popularity of this practice:

> *"Measured Mineral Resources arise from interpolated blocks, which have lower kriging variances and therefore higher confidence associated with them. Indicated Mineral Resources occur when blocks are extrapolated, this means that these blocks have higher kriging variances and thus a reduced confidence is associated with them. Any blocks extrapolated beyond the range of influence of the variogram are classified as Inferred blocks".*

Arik (2002) and Mwasinga (2001) suggests a basic method to establish the resource classification classes by using the cumulative histogram or cumulative probability (cdf) of the KV, to derive classes based on visual inspection or predefined criteria. Major changes in the shape of the histogram and cdf can be used a guide to establish the different classes of confidence. Arik (2002) though suggest calibrating the categories based on production data (if available) or previous experience with regards to the orebody.

The cdf of the KV values for the OK_1 estimate was used to establish resource classification thresholds, using the above methodology. The cumulative log probability graph of the KV is show in Figure 41 and the thresholds identified in Figure 41 are presented in Table 15.

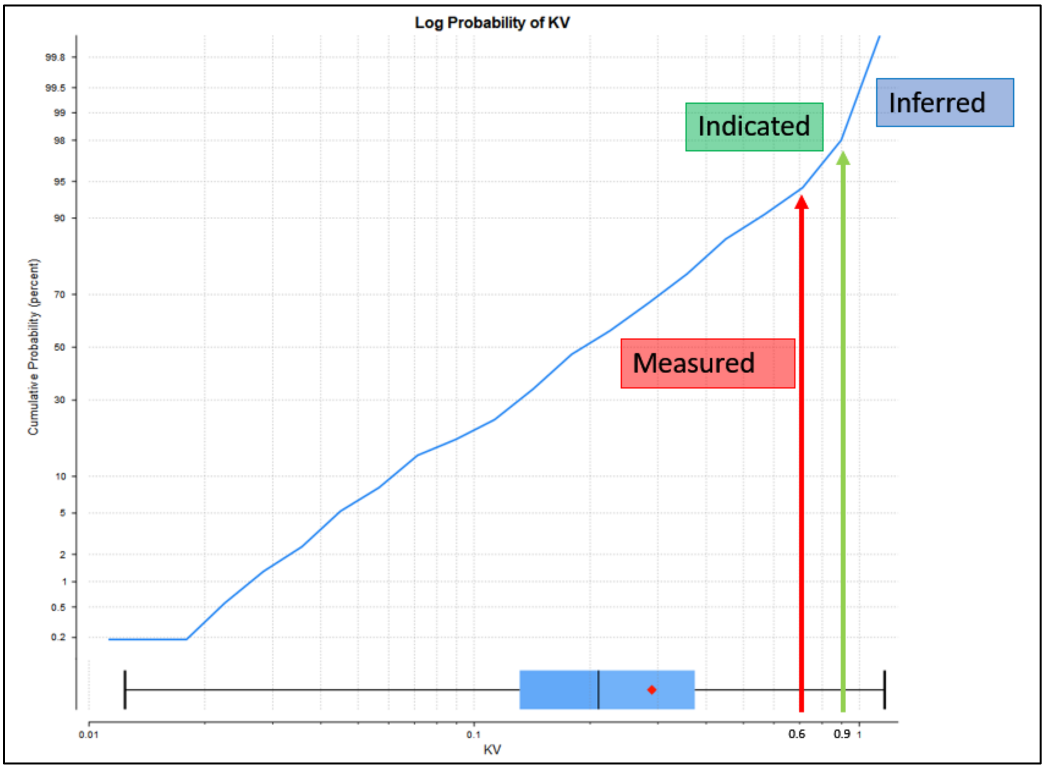


Figure 41: Resource classification criteria based upon the cumulative log probability of the KV values of OK_1.

Table 15: OK_1 Kriging variance classification criteria based on Figure 41.

Resource classification	Kriging variance
MEASURED	< 0.6
INDICATED	0.6 - 0.9
INFFERED	>0.9

The resource classification criteria based the OK_1 estimation KV (Table 15) is compared to MCo's resource classification perimeters in Figure 42.

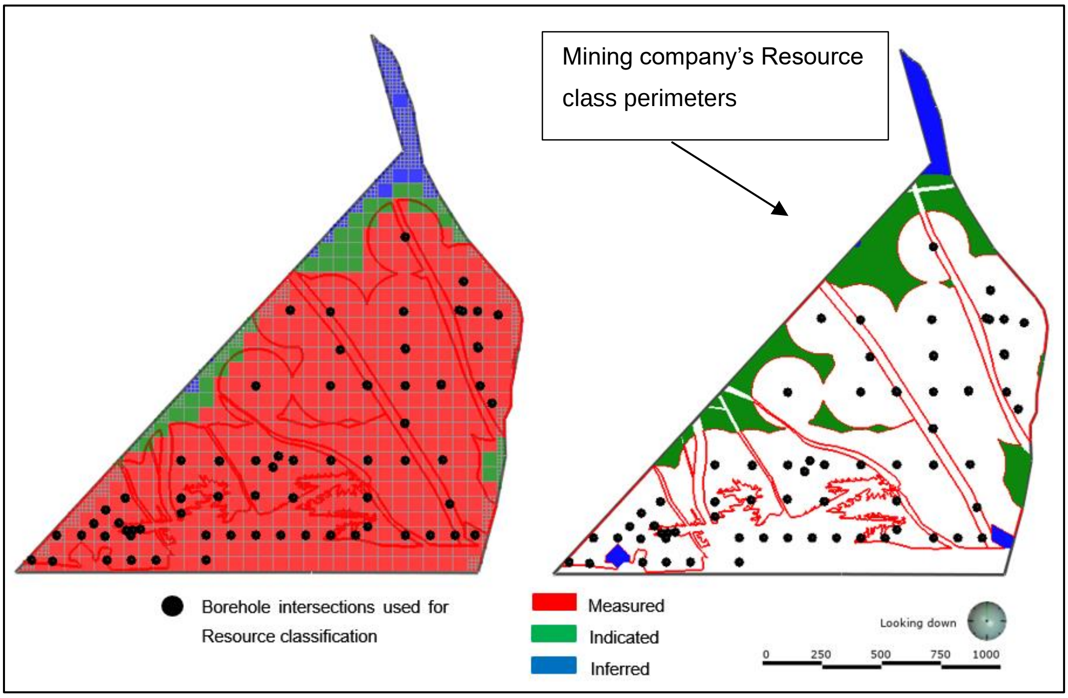


Figure 42: Resource classification criteria based on KV(left) compared to that of MCo (right) resource classification perimeters.

Based on visual observation (Figure42) the resource classification using the KV, measured category spatially overlaps relatively well with the measured category (white perimeter outline) of MCo. However, due to the nature of KV, that relies the sample configuration artefacts are created on the edges of the mining perimeter for the inferred category, requiring some manual adjustments, should this methodology be applied.

An additional criterion was introduced to the criteria specified in Table 15, added incorporated the range of influence of the variogram. If the block estimates were within the range of influence of the variogram it would be considered to be classified as Indicated, any estimate beyond the variogram range and a KV value more than 0.9, was classified as inferred. This resource classification comparison with the resource classification perimeters is presented in Figure 43.

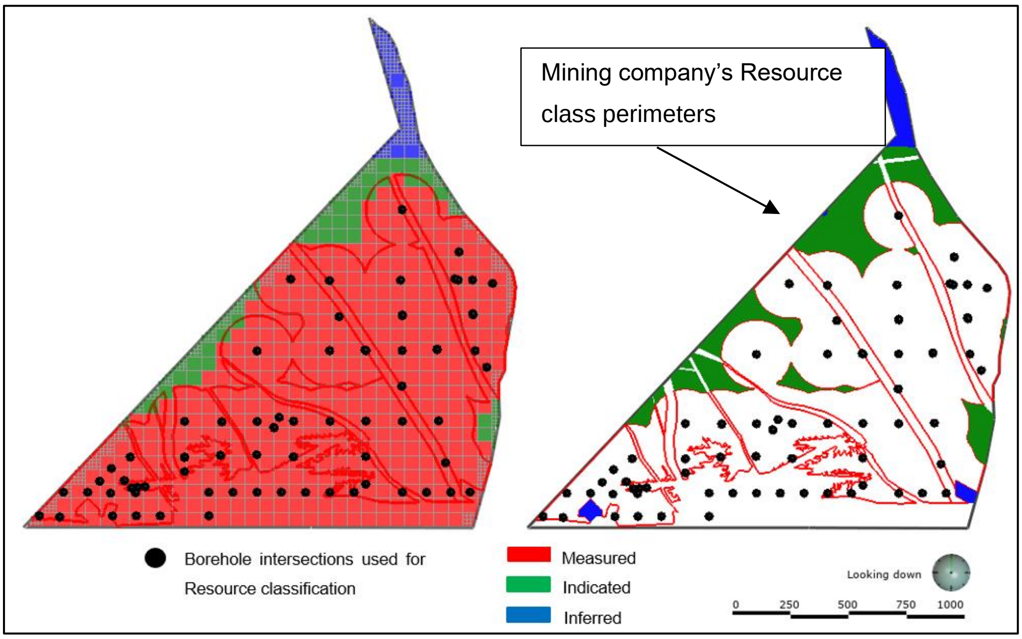


Figure 43: Resource classification criteria based on KV and variogram range of influence compared to the MCo resource classification perimeters.

Generally, the incorporation of the variogram range of influence, together with the KV produced a spatially more realistic resource classification result, and closely resembles the underlying MCo resource classification.

Based on some 70 cases, of various ranges of spatial and data patterns (Figure 44), Krige (1996) concluded that in this instance a correlation (87.5%) between the Kriging Efficiency and Slope of Regression was observed. Furthermore that poor efficiencies were associated with poor spatial structures, including limited number of samples are available for estimation.

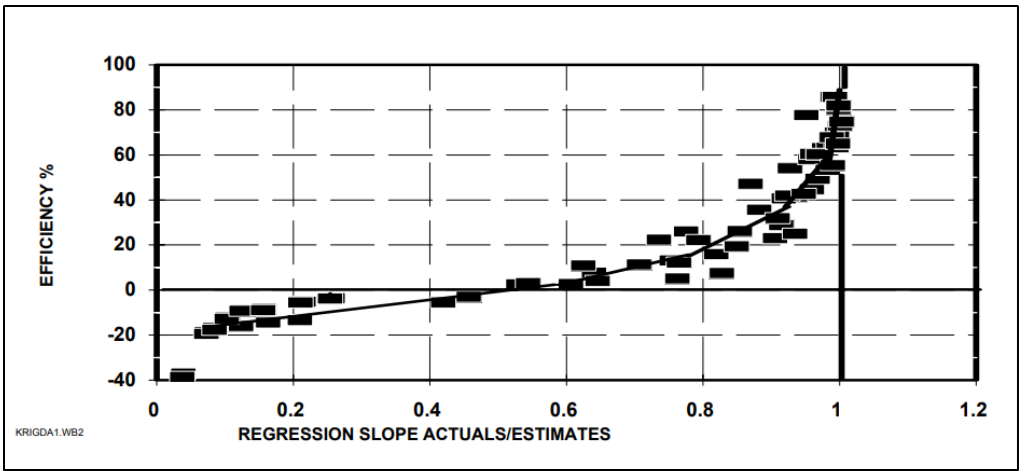


Figure 44: Correlation between efficiencies of block valuations and slopes of regression (Krige, 1996).

Glacken & Snowden (2001) mention that the Slope of regression and Kriging Efficiency can be used for Resource classification as a numerical approach as proposed by Krige (1996).

The Kriging Efficiency (KE) is measure that represent the robustness and effectiveness of the kriging estimates relating to the true block values. KE is directly related to the KV, and a perfect estimate will be associated with values of 1 (or 100%) and 0 for a poor estimate (De-Vitry, 2003). The slope of regression (SOR) is a measure of conditional bias with regards true values and estimated kriged values (Deutsch, et al., 2014). The slope of regression is an indication of how good a kriged estimation is, and a perfect estimate should have a value close to 1 (Mwasinga, 2001).

Deutsch, et al. (2014) explains the relationship between KE and KV:

> *"A high efficiency means that the kriging variance is low, and the variance of the block estimates is approximately equal to the variance of the true block values. A low efficiency implies a high kriging variance relative to the block variance. The kriging variance varies from block to block, so the kriging efficiency will vary as well".*

KV, KE and SOR can be used as measures asses the quality of an kriging estimate (Deutsch & Deutsch, 2012 and Amwaama, 2018), although slope of regression maps may be more useful (Vann, et al., 2003).

Clark (2015) highlights that Kriging efficiency can be negative, and refers to Krige (1996), and that in such cases the Mineral Resource should be classified as Inferred. Clark (2015), also states that

> *"… as a general rule, any block with negative kriging efficiency should never be included in a Measured Resource category".*

Mwasinga (2001) recommends using Kriging efficiency margins as ratios for Mineral resources classification (Table 16) and also mentions that based on personal communication with Krige, that the Indicated and Inferred categories can be relaxed, depending on observed geological continuity.

Table 16: Mineral Resource classification categories based on Kriging efficiency ratios (Mwasinga,2001) .

Krige's index	**Measured**	(Block variance - kriging variance)/Block Variance > 0.5
	Indicated	(Block variance - kriging variance)/Block Variance > 0.3
	Inferred	(Block variance - kriging variance)/Block Variance < 0.3

Mwasinga (2001) also presents other common criteria that are used for classification of coal resources in Table 17, these incorporate drillhole spacing; variogram range; KE ratio and SOR.

Table 17: Resource classification criteria commonly used for coal resources (Mwasinga,2001)

Tool	Drill Hole Spacing	Variogram range	Kriging efficiency Ratio	Slope of Regression
Measured	250m x 250m	Blocks within sampled area and using range of influence (66% of the variogram range)	0.5	0.95
Indicated	350m x 350m	Blocks within sampled area but beyond range of influence (34% of the variogram range)	0.3-0.5	0.80-0.95
Inferred	500m x 500m	Blocks within deposit but remote from data (extrapolated blocks)	<0.3	<0.80

The Kriging efficiencies and slope of regressions obtained from the OK_1 estimate were calibrated to resemble MCo's resource classification perimeters (Figure 45) based upon the criteria presented in Table 18. No manual adjustments were made to the classification, and geological complexities were also not considered.

Table 18: Resource classification using KE ratio and SOR that closely resemble MCo's resource classification perimeters.

Resource classification	Kriging efficiency ratio	Slope of Regression
MEASURED	> 0.4	> 0.8
INDICATED	0 - 0.4	0.5 - 0.8
INFFERED	< 0	< 0.5

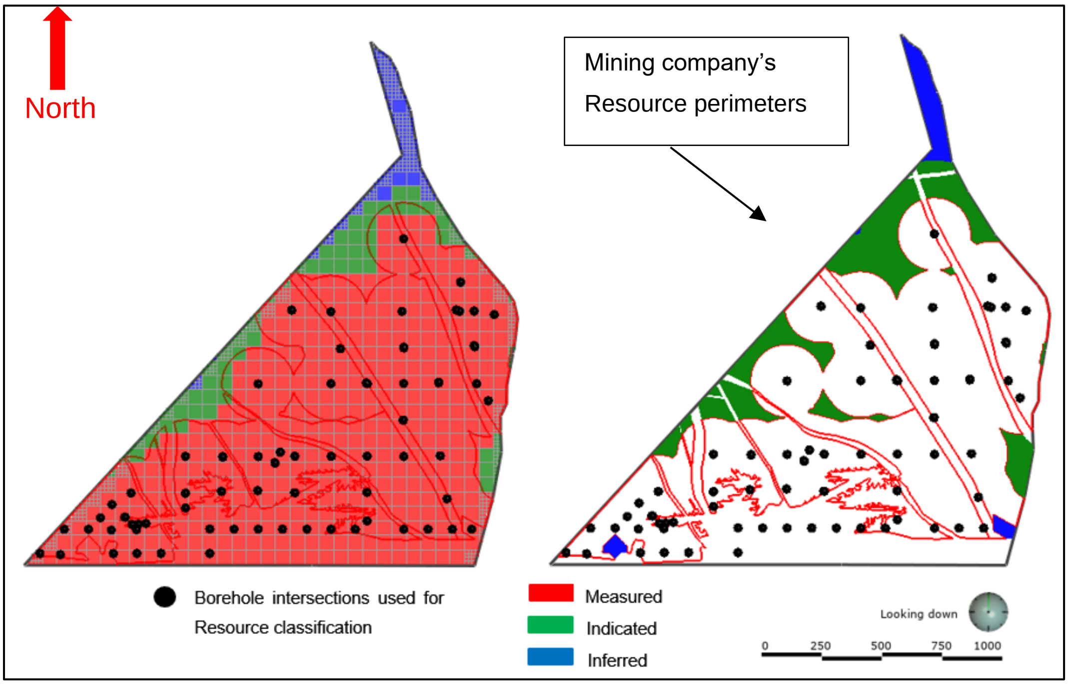


Figure 45 : Resource classification criteria specified in Table 18 compared to MCo's resource classification perimeters.

The visual observation of the comparison of using the criteria specified in Table 18, and MCo's approach, for resource classification are similar. However, due to MCo's radii approach, it is not surprising to observe slight differences. The geostatistical parameters are not bound by a fixed borehole intersection radii and represent the continuity between borehole intersections more realistically. The MCO classification reflect the "spotted dog" effect, especially where there is a decrease in sample data, however, should manual over-rides be conducted the MCo classification criteria could be considered appropriate when compared to criteria used in Table 18. It is also observed that MCo classification criteria (specified radii), is not as effective in classifying the Inferred category, as the KE and SOR criteria.

The classification criteria used in Table 18, is plotted on Krige's (1996), Kriging efficiency and slope of regression correlation graph (Figure 46), and although debatable, it does present an acceptable representation of confidence, based on the underlying spatial correlation of the sample configuration at hand.

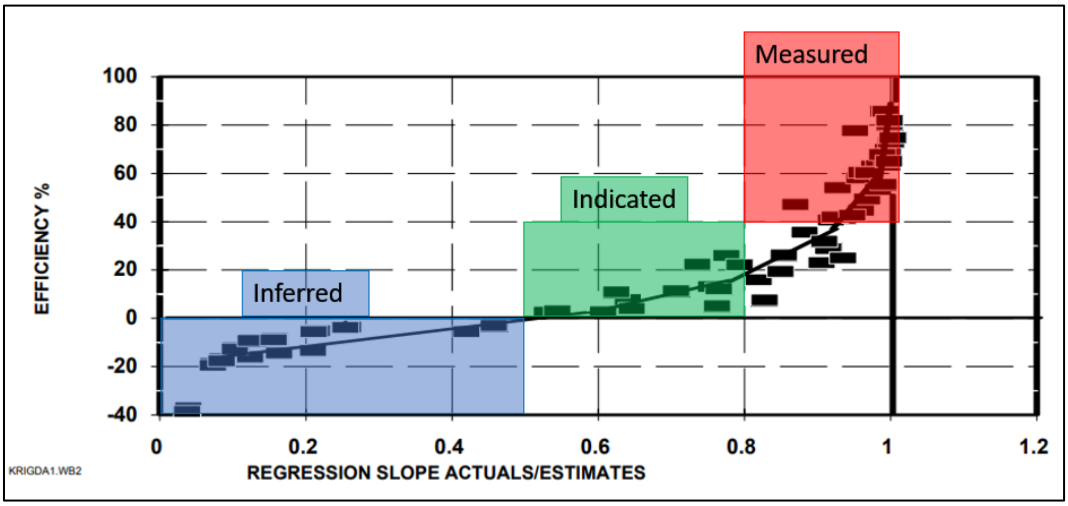


Figure 46 : Correlation between Kriging Efficiency and slope of regression, with calibrated resource classification criteria based on Table 18 (modified after Krige (1996)).

8.2.2 Resource Classification Comparison Results

The results of each comparative Mineral Resource classification method is presented in Figure 47, based upon a volume percentage of each classification category (Measured, Indicated & Inferred). The Inferred and Measured classification volumes were adjusted for the comparative classification methods to incorporate the manual interpretations of MCo.

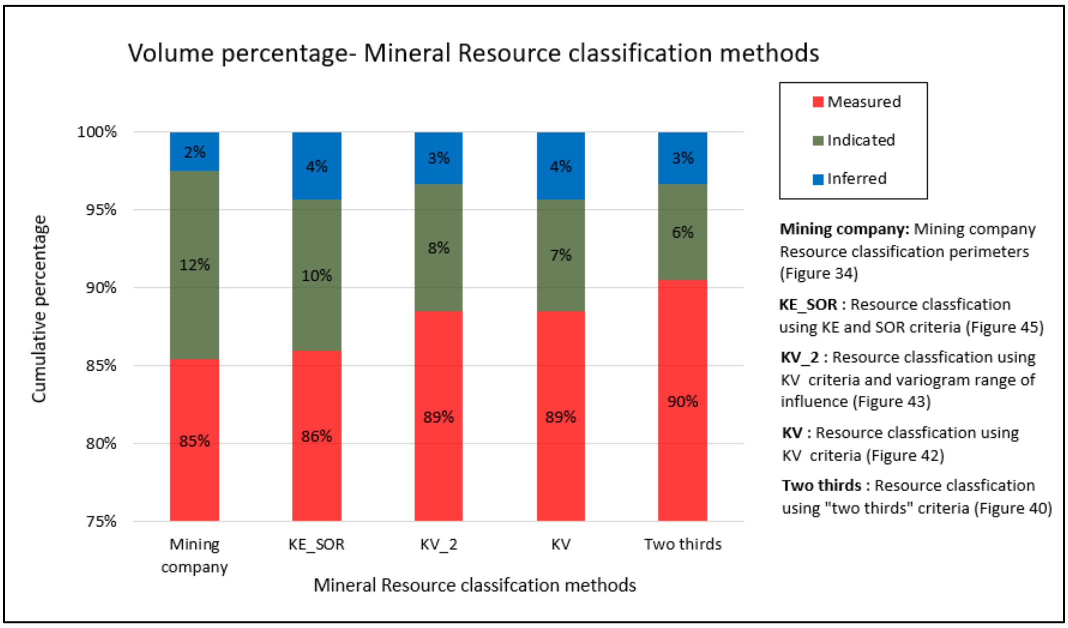


Figure 47: Comparative Mineral resource classification methods, compared to MCo's resource classification perimeters based on volume percentage.

It has been established that the "two thirds" classification method would not be applicable for the sampling configuration as the method does have a tendency to overstate the Measured category, when only relying on 66% of the spatial correlation of the Cr_2O_3% values. However, the two thirds method presents a more realistic approach towards the Inferred category, when criteria on the estimates being beyond the range of variogram are considered.

Although the KV and KV_2 classification methods do not differ much in terms of percentage volume of classification with regards to the "two thirds" method, the allocation of resource categories is spatially more realistic, especially when adding the component of the range of influence of the variogram. The KE_SOR method of Krige classification is closely related to MCo's percentage volume towards resource classification, however a slight increase is present for the Measured and Inferred categories, due to the fact that the criteria do not rely on a radii of borehole intersections. In fact, none of the alternative methods rely on specific dimension of borehole intersection radii, and the "gaps" that are created by the "spotted dog" effect is not present, which therefore will result in increases of the Measured category and decrease in the Indicated category. Resulting in more tonnage being allocated to the Measured category, and less tonnage towards the Indicated category, representing a more realistic approach recognising geological and grade continuity.

8.3 Principles of a Mineral Resource classification Scorecard-based Approach

MCo's current resource classification method is dependent on drill hole spacing and is associated with distance radii around validated chromitite borehole intersections with assayed Cr_2O_3% grades Measured (150m); Indicated(300m) and Inferred (600m) . The predetermined radii were designed to cater for geological and grade continuity with regards to confidence, in addition the CP or estimator can practice his/her own judgement for manual adjustments or reducing the drill spacing margin used for classification at own discretion.

However, it appears that MCo's classification method lacks in quantifying the confidence of geological influence in a formal procedure. This can be highlighted with regards to the example of the possible "pothole influence zones" indicated in **Section 7.1**, that could possibly have an effect on the Mineral Resource classification categories. Furthermore, criteria measuring the estimation confidence associated with the Growth technique estimates, are cannot bet considered in MCo's Mineral Resource classification procedure. Due to the fact that the Growth technique is devoid of estimation confidence statistics, analogous to those available in geostatistical methods, and discussed in **Section 8.2**. However, there could be other factors besides geostatistical measures of confidence, and geological complexities, that should be incorporated to define the Mineral Resource classification categories.

Mining companies have implemented scorecard approaches with regards to classifying Mineral Resources, as such an approach is transparent, defendable and robust methodology, it incorporates qualitative and quantitative attributes of various elements used to measure resource confidence. Examples of large mining companies that have adopted a Mineral Resource classification scorecard approach are Anglo American and De Beers, that are discussed in Mohanlal & Stevenson (2010) and Duggan , et al. (2017).

Mohanlal & Stevenson (2010) highlights that

> *"the scorecard approach to the classification of mineral resources ensures compliance and provides assurance that the CP has taken due consideration of all pertinent factors when assigning a resource classification".*

Parker & Dohm (2014) recommend key factors, that can be considered for the use of a classification scorecard approach, although not all factors could be applicable, depending on the deposit. The key factors are listed below:

- **Geometry of the orebody** : Geological confidence (structural interpretation, geological loss, structural complexities, etc.); drilling method; confidence in survey data (collar and down-hole); confidence in geological logging; drillhole spacing.
- **Data integrity**: sampling and analytical data ; QA/QC; data security.
- **Spatial correlation**: considering variography and quality of variogram models.
- **Estimation methodology**: estimation confidence (KE, SOR and KV); validation techniques.
- **Bulk density**: Method used for determination; estimation method applied.
- **Other factors**: mineralogy; geometallurgical.

The process of using a scorecard approach, based on the key factors above is explained consistent with Parker & Dohm (2014):

Factors are assigned non-linear scores, as specific weightings, according to importance that relates to the orebody. The scores for example can be low (1), medium (3) or high (5), and each factor is then multiplied by a rating of confidence no confidence (zero) to high confidence (five). The total weighted score for all factors, that were incorporated and the importance weighting factor, is then applied onto a block model. Perimeter strings can be used to constrain specific areas of confidence of each factor used. The weighted score can then be visualised and margins can be assigned to classify the Mineral Resource as Measured, Indicated or Inferred. Each classification category can be smoothed if required to produce the final Mineral Resource classification allocations.

MCo take cognisance and ensure validation of several factors listed by Parker & Dohm (2014), in accordance with the guidance of the SAMREC(2016) code. However the factors are not formally part of the classification procedure or quantified based on confidence. The main and only factor that is quantified to some extent is the drillhole spacing, based on MCo's radii approach. Other factors relating to the confidence of the geometry of the orebody; data integrity ; estimation methodology and bulk density is assumed to be accounted for through validation processes, standard compliant procedures, audits, inputs from geology department and the expert judgement of the CP. The Growth technique that is used by MCo for estimation, does not require variogram analysis, which contributes to a spatial correlation factor that can be used in a scorecard approach. The same accounts for Ordinary Kriging output perimeters such as KV, KE and SOR, which are not available for the Growth technique, that can form part of an estimation methodology confidence factor.

Other factors, such as geometallurgical factors, could possibly also have an influence on the resource classification, with regards to the confidence of Friability index of the MG1 chromitite resource that is fed to the plant. As mentioned, factors that can influence the confidence of the Mineral Resource, should be applicable to the orebody and adopted to the Mineral Resource practises currently in place.

It is evident, based upon the analysis and research in this report, that MCo can improve and optimize their current resource classification methodology. The researcher believes that a customized scorecard based approach would lead to a more structured, defendable, and transparent approach. Furthermore, a scorecard approach should normally contain a few non-negotiable factors, that would require inputs from geoscience experts (geologists), that should be formally drafted and confidence relating to various factors plotted for visible assessment.

9. CONCLUSIONS

It appears that the Growth technique performs similar (within comparable margin) to the alternative estimation techniques where there is an adequate amount of sample data. This can be attributed to the fact that the grade distribution of Cr_2O_3% is generally homogenous and close to a gaussian (normal) distribution and associated with a low nugget effect. However, in areas where the sample data spacing increase, the Growth technique tends to “smear” and inflate or exaggerate grade values, and alternative methods such as IDW2 and OK_1 performed better.

The Growth technique and IDW4 method estimates showed similar results , this can to some extent be attributed to the fact that an IDW4 method is similar to a nearest neighbourhood method. It is therefore be concluded that other variables (SG; Channel Width; SiO_2% and FeO%) estimated using the Growth technique will reveal similar tendencies, if compared to the alternative estimation methods. According to MCo’s standard, alternative estimation methods can be motivated for, however the nearest neighbour method cannot be used for Mineral Resource estimation.

Regarding MG1 resource estimation, the findings in this research report regarding the Growth technique do not conclude that the estimation method is inappropriate for the MG1 orebody, however, the CP and resource practitioners should be aware of the disadvantages of the technique when applied to specific sampling configurations. The major disadvantages of the Growth technique are listed below:

- If not mitigated, the Growth technique tends to “smear” or exaggerate grade values in areas that sample spacing increases. Subsequently, where the “smearing” effect is present, it can affect the reported grades of the Mineral Resource categories can be affected ad for example observed in the Inferred category of the MG1 orebody.

  This characteristic have also been observed when using the IDW4 method, that are almost similar to a nearest neighbour method and tends to mimic the Growth technique. The IDW2 and OK_1 estimation scenarios were able to mitigate this effect, by gradually smoothing grades estimates.

- Similar to IDW2 and IDW4 estimation method the Growth technique also fails to provide a measure for grade estimation errors or any quantification of the quality of estimation that OK provides. Kriging output parameters such as

KV, KE, and SOR can be used in this regard by providing measures of for Mineral Resource estimation confidence and thus resource classification.

- The Growth technique does not take into account spatial variability or correlation of variables that are estimated, compared to OK estimates that are based on a variogram model of this spatial variability. It is however accepted that the variograms produced in the research project might be considered as being subjective, due to a lack of closely spaced sampling data. Nonetheless the variograms were able to portray a good representation of the range of influence of spatial correlation. The same disadvantage is true for the IDW2 and IDW4 estimation methods.

The value in applying alternative estimation methods such as IDW and OK, is that they can serve as global and local validation tools for the Growth technique. This could result in more realistic estimates by adjustment of perimeters that are used for the Growth technique and mitigate the exaggeration of grade estimates as identified by IDW and OK estimates. Ordinary Kriging also has the ability to determine an appropriate search neighbourhood, and as mentioned can assist with assessment of the quality or error of estimates, that the Growth technique lacks.

Kriging, is however a more complex estimation method, and realistic or accurate estimates rely significantly on meaningful variogram models and an appropriate search neighbourhood. Although the Growth technique has drawbacks, similar to IDW methods, these are easier techniques to apply, and there is less room for error with regards to the estimation procedure.

It is difficult to reach a conclusion regarding whether the estimation results using IDW and OK methods are more realistic than the Growth technique, as the estimation methods performed fairly similar on a global scale. However, estimates of the Growth technique can be argued to be subjective, on a local scale, where sample spacing increases, or associated with outlying lower or higher values. Therefore, it is concluded that on a local scale and under certain sampling configuration conditions, the alternative estimation methods do appear to be a more realistic estimation approaches.

Despite the limited amount of closely spaced data for Cr_2O_3%, Channel width and SG variography, the semivariogram models, including deflection results, did reveal spatial variability that can be considered realistic in this depositional environment. The variogram models did also assist in providing ranges of influence for the spatial correlation of these variables. More data is however required, and the data base can be increased through the use of underground sampling programs or using additional data from MCo's surrounding adjacent mining sites; continuity is not affected by manmade lease boundaries; to further refine the variography and improve the estimation of a nugget effect.

By using geostatistical Mineral Resource classification methods, it was concluded that the underlying radii distances used for MCo's resource classification categories could be considered to be applicable.

However, the circular approach of borehole radii, results in a "spotted dog" effect where sample spacing increases, and the KV_2 approach, represented a more realistic and practical approach with regards to the classification categories.

Analysis of possible "pothole influence zones", revealed that a more detailed and rigorous geological approach be applied when allocating mineral resource categories, as the standard practice of MCo could result in overruling or ignoring the importance of the influence that geological factors can have on classification categories. The research report has shown that there is room for improvement and optimisation with regards to MCo's Mineral Resource classification procedure.

By comparing in principle, MCo's classification methodology to a scorecard approach, it is evident that an oversight of relevant factors can easily happen in allocating Mineral Resource classification categories. Therefore, the researcher is of the option that the development of scorecard approach would add significant benefits, that would result in a more realistic, defendable and transparent Mineral Resource classification methodology than the currently implemented method.

The only approach to come close to having an idea of how accurate or realistic MCo's or the alternative estimation methods are, would be to reconcile the Mineral Reserves, to the Run-of-mine tonnages and grade over at least a six month period of production. This process should also incorporate local grade control data and block models, and then derived back to the in-situ Mineral Resource estimation grades and tonnage. Currently MCo does not have an established grade control system in place, that contains validated sample assay data, and due to confidentially, run-of-mine data, was not made available for study in this research project.

10. RECOMMENDATIONS

- Implement a field QA/QC procedure for samples that are requested from analysis, additional to the current internal laboratory procedures. This will ensure more confidence and control of the quality of the sample data that is used in Mineral Resource estimation.

- Use parameters (if possible), that could mitigate the “smearing’’ effect of the Growth technique, especially where sample spacing increases or associated with high or low outlying values. The impact of using capping high outlying values could also be considered, to conform values to the general population of value distribution.

- Further analysis is required with regards to variography, to improve the understanding of the spatial variability associated with the relevant variables that are used for Mineral Resource estimation. Sampling information from underground and adjacent mine sites of MCo can assist with the expansion of the data base, and this is expected to improve variogram models.

- Mitigate the “spotted dog” effect where present by manual overrides to have a more realistic representation of the geological and grade continuity in terms of resource classification. Furthermore, this will also result in a more practical block model or gridded mesh, with regards to classification of Mineral Reserves and application in the mine value chain.

- Consider geostatistical criteria such as KV, KE, SOR and range of influence of the variogram, as guidelines to further refine the resource categories, when using a borehole radii approach as it is currently implemented. This will ensure that an statistical element of estimation confidence and spatial variability is accounted for with regards to Mineral Resource classification.

KV is also a useful tool to use to indicate requirements of infill drilling to increase confidence, as it incorporates both the drillhole sample spacing and the range of influence of the variogram.

- Geological influence zones should be analysed in more detail and more rigorously incorporated into the resource classification process.
- Developing and incorporating a Mineral Resource classification scorecard approach, that incorporates data integrity, geological, spatial correlation, statistical/geostatistical and other orebody specific confidence factors, will improve and optimise the current Mineral Resource classification methodology.

REFERENCES

African Rainbow Minerals (ARM), 2008. *Mineral Reserves and Resources.* [Online] Available at: https://www.arm.co.za/im/files/annual/2008/files/ARM_RR2008.pdf [Accessed 27 September 2019].

African Rainbow Minerals (ARM), 2016. *Mineral Resources and Mineral Reserves.* [Online] Available at: https://www.arm.co.za/im/files/annual/2016/ARM-RR16.pdf [Accessed 19 11 2019].

Anglo American, 2017. *Ore reserves and Mineral resources 2017.* [Online] Available at: https://www.angloamerican.com/~/media/Files/A/Anglo-American-PLC-V2/documents/annual-updates-2018/aa-ore-reserves-and-mineral-resources-2017.pdf [Accessed 30 12 2019].

Arik, A., 2002. *Comparison of resource classification methodologies with a new approach.* Phoenix,Arizona, In APCOM 2002: 30th International Symposium on the Application of Computers and Operations Research in the Mineral Industry, pp. 57-64.

Assibey-Bonsu, W., 2016. The basic tenets of evaluating the Mineral Resource assets of mining companies, as observed through Professor Danie Krige's pioneering work over half a century. *The Journal of the Southern Africa Institute of Mining and Metalurgy,* Volume 116, pp. 635-643.

Awaama, M. M., 2018. *Comparison of Kriging Neighbourhood Analysis (KNA) results from two different software packages – a case study,* Johannesburg: University of the Witwatersrand.

Babak, O. & Deutsch, C., 2008. Statistical approach to inverse distance interpolation. *Stochastic Environmental Research and Risk Assessment,* 23(5), pp. 543-553.

Batcha, J. B. & Reese, J. R., 1964. Surface determination and automatic contouring for mineral exploration extraction and processing. *Colorado School of Minex Quarterly,* Issue 59, pp. 1-14.

Bohling , G., 2005. *Introduction to geostatistics and variogram analysis.* [Online] Available at: https://www.coursehero.com/file/12867665/Variograms/ [Accessed 24 August 2019].

Canadian Aviation Electronics(CAE), 2013. *Resource Classfication Report for the Lesedi Project ,* Johannesburg : CAE.

Cawthorn, G., Latypov, R. & Vuthuza, A., 2018. Origin of discordant ultramafic pegmatites in the Bushveld Complex from externally-derived magmas. *South African Journal of Geology,* 15 February, 121(3), pp. 287-310.

Cawthorn, R. G., 2010. The Platinum Group Element Deposits of the Bushveld Complex in South Africa. *Platinum Metals Rev,* 54(4), pp. 205-215.

Chanderman , L., Dohm, C. & Minnitt, R., 2017. 3D geological modelling and resource estimation for a gold deposit in Mali. *The Journal of the Southern African Institute of Mining and Metallurgy,* Volume 117, pp. 189-197.

Chanderman, L., 2015. *3D geological modelling and mineral resource estimate for the fe2 gold deposit, Sadiola mine – Mali,* Johannesburg: University of the Witwatersrand.

Cheney, E. S. & Twist, D., 1991. The conformable emplacement of the Bushveld mafic rocks along a regional unconformity in the Transvaal succession of South-Africa. *Precambrian Research,* Volume 52, pp. 155-132.

Chilès, J.-P. & Delfiner, P., 2012. *Geostatistics Modeling Spatial Uncertainty.* 2nd ed. New Jersey: John Wiley & Sons,Inc..

Clark, I., 2001. *Practical Geostatistics.* Alloa: Geostokos Limited.

Clark, I., 2015. Regression revisited (again). *The Journal of The Southern African Institute of Mining and Metallurgy,* Volume 115, pp. 45-50.

Coombes, J., 1997. Handy Hints For Variography.. In: V. N. Misra & J. S. Dunlop, eds. Melbourne: The Australasian Institute of Mining and Metallurgy:, pp. 127-130.

Coombes, J., 2008. *The Art and Science of Resource Estimation.* First ed. Perth : Coombes Capability.

CRAIN, I. K., 1970. Computer interpolation and contouring of two dimensional data a review. *Geoexploration,* Issue 8, pp. 71-86.

Cressie, N. A., 1993. *Statistics for Spatial Data.* Revised Edition ed. Newyork: John Wiley & Sons, Inc.

Crowson, P., 2001. *Minerals Handbook 2000-01: Statistics and Analyses of the World's Minerals Industry.* Edenbridge,Kent: UK: Mining Journal Books Ltd.

Dassault Systèmes GEOVIA Inc., 2016. *Minex 650 usersguide.* s.l.:Dassault Systèmes GEOVIA Inc..

Dassault Systèmes, n.d. *Geovia Minex™.* [Online] Available at: https://www.3ds.com/products-services/geovia/products/minex/ [Accessed 29 Septemeber 2019].

Davey, S. R., 1992. Lateral variations within the Upper Critical Zone of the Bushveld Complex on the farm Rooikoppies 297 JQ, Marikana, South Africa. *South African Journal of Geology,* 95(3-4), pp. 141-149.

de Souza, L. E., Costa, J. F. & Koppe, J. C., 2010. Comparative analysis of the resource classification techniques: case study of the Conceic¸a˜o Mine, Brazil. *Applied Earth Science IMM Transactions section B,* 119(3), pp. 166-175.

Deutsch, C. V., Leuangthong, O. & Ortiz C, J., 2006. *A Case for Geometric Criteria in Resources and Reserves Classification,* Paper 301: Centre for Computational Geostatistics (CCG) - University of Alberta, annual report 08.

Deutsch, C. V., 2007. *The Slope of Regression for Kriging Estimators,* University of Alberta : Centre for Computational Geostatistics.

Deutsch, C. V. & Rossi, M. E., 2014. *Mineral Resource Estimation.* Dordrecht: Springer.

Deutsch, J. L. & Deutsch, C. V., 2012. *Kriging, Stationarity and Optimal Estimation: Measures and Suggestions,* CCG Annual Report 14: Paper 306.

Deutsch, J. L., Szymanski, J. & Deutsch, C. V., 2014. Checks and measures of performance for kriging estimates. *The Journal of The Southern African Institute of Mining and Metallurgy,* Volume 114, pp. 223-230.

De-Vitry, C., 2003. Resource classification – a case study from the Joffre-hosted iron ore of BHP Billiton's Mount Whaleback operations. *Mining Technology (Trans. Inst. Min. Metall. A),* Volume 112, pp. 185-196.

Dohm, C., 2004. Quantifiable Mineral resource classification: A logical approach. In: O. Leuangthong & C. V. Deutsch, eds. *Geostatistics Banff.* Dordrecht, The Netherlands: Springer, pp. 333-342.

Dohm, C. E., 2015. *Geostatical methods in Mineral Resource evaluation.* Johannesburg: University of the Witwatersrand, course notes,MINN7006.

Dominy, S. C., Noppé, M. A. & 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.

Dube, Z. A., 2010. *The Merensky Reef and UG2 layers at De Wildt, western limb of the Bushveld Complex,* Johannesburg: University of the Witwatersrand.

Duggan , S., Grills , A., Stiefenhofer, J. & Thurson, M., 2017. Development of a best-practice mineral resource classification system for the De Beers group of companies. *Journal of the Southern African Institute of Mining and Metallurgy,* 117(12), pp. 1127-1132.

Duggan, S., Grills, A., Stiefenhofer, J. & Thurston, M., 2017. Development of a best-practice mineral resource classification system for the De Beers group of companies. *The Journal of the Southern Africa Institute of Mining and Metalurgy,* Volume 117, pp. 1127-1132.

Emery, X., Ortiz, J. M. & Rodriguez, J. J., 2004. *Quantifying Uncertainty in Mineral Resources with Classification Schemes and Conditional Simulations,* s.l.: Department of Mining Engineering : University of Chile.

Exxaro, 2015. *Consolidated Mineral resources and ore reserves report (CMRR).* [Online] Available at: https://www.exxaro.com/assets/files/Consolidated_Mineral_Resources_Ore_Reserves_Report.pdf [Accessed 01 12 2019].

Gentile, M., Courbin, F. & Meylan, G., 2012. Interpolating point spread function anisotropy. *Astronomy & Astrophysics,* pp. 1-20.

Geostokos (Ecosse) Limited, n.d. *What is Kriging anyway?.* [Online] Available at: http://www.kriging.com/ [Accessed 05 November 2017].

GEOVIA, 2014. *The GEOVIA Blog.* [Online] Available at: https://blogs.3ds.com/geovia/using-borehole-distance-gridding-minex/ [Accessed 18 11 2019].

Glacken , I. M. & Snowden, D. V., 2001. Mineral Resource Estimation. In: A. C. Edwards, ed. *The AusIMM Guide to Good Practice (Monograph 23).* Melbourne: The Australasian Institute of Mining and Metallurgy, pp. 189-198.

Glacken, I. & Trueman, A., 2014. Overview – Mineral Resource Estimation. *The AusIMM Guide to Good Practice,* Monograph 30(2nd), pp. 263-275.

Google Maps , 2020. *Google Maps.* [Online] Available at: https://www.google.com/maps/@-25.6753781,27.4774792,55155m/data=!3m1!1e3 [Accessed 12 02 2020].

Gringarten , E. & Deutsch, C. V., 2001. Teacher's Aide Variogram Interpretation and Modeling. *International Association for Mathematical Geology,* 33(4), pp. 507-534.

Guidelines Review Commitee (JORC), 2014. *Australian guidelines for the estimation and classification of coal resources.* [Online] Available at: http://www.jorc.org/docs/Coal_Guidelines_2014_-_Final_Ratified_Document.pdf Accessed 18 11 2019].

Hancox, J. & Pinheiro, H., 2017. The new SANS 10320:2016 versus the 2014 Australian guidelines for the estimation and classification of coal resources—what are the implications for southern African coal resource estimators?. *The Journal of the Southern African Institute of Mining and Metallurgy,* Volume 117, pp. 1-8.

Hengl, T., 2007. *A Practicle Guide to Geostatistical Mapping of Enviromental Variables.* Luxembourg: European Communities.

Hoffman, D., 2010. Statistical size analysis of potholes: an attempt to estimate geological losses ahead of mining at Lonmin's Marikana mining district. *The Southern African Institute of Mining and Metallurgy,* Volume The 4th International Platinum Conference, Platinum in transition 'Boom or Bust', pp. 97-104.

Hunt, J. P., 2006. *Geological Characteristics of Iron Oxide-Copper-Gold (IOCG) Type Mineralisation in the Western Bushveld Complex,* Johannesburg: University of the Witwatersrand.

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

Jones, T. A., Hamilton, D. E. & Johnson, C. R., 1986. *Contouring Geologic Surfaces With The Computer (Van Nostrand Reinhold Catalysis Series).* 1987th ed. New York: Springer.

JORC code, 2012. *Australasian Code for Reporting Exploration Results, Mineral Resources and Ore Reserves,* prepared by: The Joint Ore Reserves Committee of The Australasian Institute of Mining and Metallurgy, Australian Institute of Geoscientists and Minerals Council of Australia : JORC.

Journel, A. G. & Huijbregts, C. J., 1978. *Mining Geostatistics.* London: Academic Press.

Kinnaird, J. A., Kruger, F. J. & Cawthron, R. G., 2004. Rb-Sr and Sm-Nd isotopes in fluorite related to the granites of the Bushveld Complex. *South African Journal of Geology,* Volume 107, pp. 413-430.

Kinnaird, J. A., Kruger, F. J., Nex, P. A. & Cawthorn, R. G., 2002. *Chromitites of the Bushveld Complex - process of formation and PGE enrichment.* Johannesburg: Economic Geology Research Institute (incorporating the Hugh Allsopp Laboratory).

Krige , D. G., 1996. *A practical analysis of the effects of spatial structure and of data available and accessed, on conditional biases in ordinary Kriging.* Wollongong-Australia, International Geostatistics Congress.

Krige, D. G., 1981. Lognormal-de Wijsian Geostatistics for Ore Evaluation. In: G. S. Baker & D. Phil, eds. *South African Institute of Mining and Metallurgy Monograph series.* 2nd ed. Johannesburg: The South African Institute of Mining and Metallurgy, pp. 1-50.

Leapfrog3d-Mining and Minerals team, 2019. *Understanding declustering in Leapfrog Edge.* [Online] Available at: https://blog.leapfrog3d.com/2019/03/07/understanding-declustering-in-leapfrog-edge/ [Accessed 06 11 2019].

Leapfrog, n.d. *Leapfrog Geo 4.5 Help.* [Online] Available at: http://help.leapfrog3d.com/Geo/4.5/en-GB/Content/interpolants/indicator-interpolant.htm [Accessed 17 11 2019].

Leuangthong, O. & Nowak, M., 2015. Dealing with high-grade data in resource estimation. *The Journal of The South African Institute of Mining and Metallurgy,* 115(1), pp. 27-36.

Lewis, W., 2018. *micon international limited - mineral industry consultants.* [Online]
Available at: https://www.micon-international.com/spotted-dog-still-issue-mineral-resource-classification/ [Accessed 18 11 2019].

Lipton, I. T. & Horton, J. A., 2014. Measurement of Bulk Density for Resource Estimation – Methods,Guidelines and Quality Control. *The AusIMM Guide to Good Practice,* Monograph 30(2nd), pp. 97-108.

Lonmin Platinum, 2013. *Regional Locality Plan Mining Rights.* North-West province South-Africa : Unpublished.

Maier, W. D. & Barnes, S. J., 1999. Platinum-Group Elements in Silicate Rocks of the Lower, Critical and Main Zones at Union Section, Western Bushveld Complex. *Journal of Petrology,* 40(11), pp. 1647-1671.

Makhuvha, M., Arellano, R. M. & Harney, D. M., 2014. Determination of bulk density, methods and impacts, with a case study from Los Bronces Mine, Chile. *Applied Earth Science ,* 123(3), pp. 196-205.

Manyeruke, T. D., 2006. *The petrography and geochemistry of the Platreef on the farm Townlands, near Potgietersrus, northern Bushveld Complex,* Pretoria: University of Pretoria.

Matheron , G., 1963. Principles of Geostatistics. *Reprinted from Economic Geology ,* Volume 58, pp. 1246-1266.

Merafe Resources, 2018. *Mineral resources and Mineral reserves report.* [Online]
Available at: http://www.meraferesources.co.za/reports/ir_2018/pdf/appendix-1.pdf [Accessed 19 11 2019].

Micon International , 2016. *Why Mines Fail.* [Online] Available at: https://www.micon-international.com/minex/ [Accessed 6 Novemeber 2017].

Mitra, N., 2017. *The GEOVIA Blog - Resource Classification in GEOVIA Minex.* [Online] Available at: https://blogs.3ds.com/geovia/resource-classification-geovia-minex/ [Accessed 18 11 2019].

Mohanlal, K. & Stevenson, P., 2010. *Anglo American Platinum's approach to resource classification case study—Boschkoppie/Styldrift minewide UG2 project.* The 4th International Platinum Conference, Platinum in transition 'Boom or Bust', The Southern African Institute of Mining and Metallurgy.

Morgan, C. J., 2005. *Analysing spatial data via geostatistical methods,* Johannesburg: University of the Witwatersrand.

Morgan, C. J., 2011. *Theoretical and practical aspects of variography: in particular, estimation and modelling of semi-variograms over areas of limited and clustered or widely spaced data in a two-dimensional South African gold mining context,* Johannesburg: University of the Witwatersrand.

Morrissey, C. J., 1988. Exploration for platinum. In: H. Prichard, ed. *Geo-Platinum 87.* London: Elsevier Applied Science, pp. 1-12.

Mpanza, M., 2015. *A comparison of ordinary and simple kriging on a PGE resource in the Eastern limb of the Bushveld Complex,* Johannesburg: The University of the Witwatersrand.

Mwasinga, P. P., 2001. Approaching resource classification: General practices and the integration of geostatistics. In: Xie, Wang & Jiang, eds. *Computer Applications in the Mineral Industries.* Tokyo: A.A.BALKEMA PUBLISHERS, pp. 97-104.

Myers, D. E., 1994. Spatial interpolation: an overview. *Geoderma,* Volume 62, pp. 17-28.

Nengovhela, A. C. N., 2018. *The application of geostatistics in coal estimation and classification,* Johannesburg: University of the Witwatersrand.

Njowa, G., 2008. Salient issues in the reporting of mineral resources and mineral reserves in the vein and reef mining. *The Southern African Institute of Mining and Metallurgy,* Volume Narrow Vein and Reef, pp. 1-15.

Noble , A. C., 1992. 5.6 Ore Reserve/Resource Estimation. In: H. L. Hartman, ed. *SME MINING ENGINEERING HANDBOOK.* Littleton: Society for Mining, Metallurgy, and Exploration, Inc., pp. 344-359.

Noppé, M., 2014. Communicating confidence in Mineral Resources and Mineral Reserves. *The Journal of The Southern African Institute of Mining and Metallurgy,* Volume 114, pp. 213-222.

Nowak, M. & Leuangthong, O., 2016. *Conditional Bias in Kriging - Let's Keep It ,* Vancouver & Toronto : SRK Consulting (Canada) Inc..

Oritz, J. M. & Emery, X., 2006. Geostatistical estimation of mineral resources with soft geological boundaries: a comparative study. *The Journal of The South African Institute of Mining and Metallurgy,* Volume 106, pp. 577-584.

Parker, H. M. & Dohm, C. E., 2014. *Evolution of Mineral Resource Classification from 1980 to 2014 and Current Best Practice.* [Online] Available at: http://www.crirsco.com/docs/H_Parker_Finex.pdf [Accessed 30 12 2019].

Revuelta , M. B., 2018. *Mineral Resources:From Exploration to Sustainability Assessment.* 1st ed. Madrid: Springer .

Rezaee, H., Asghari, O. & Yamamoto, J. K., 2011. On the reduction of the ordinary kriging smoothing effect. *Journal of Mining & Environment,* 2(2), pp. 25-40.

Saager, R., 2005. *The Bushveld Complex in the context of the Geology of South Africa's Kaapvaal Craton.* [Online] Available at: www.bacfund.ch/download/6thPD/Prof%20Saager%20Part.pdf [Accessed 12 10 2018].

SAMREC code, 2016. *The South African Code for the reporting of exploration results, Mineral resources and Mineral reserves,* Marshalltown: Prepared by: The South African Mineral Resource Committee (SAMREC) Working Group.

Scoon, R. N. & Teigler, B., 1994. Platinum-group element mineralization in the critical zone of the western Bushveld Complex; 1. Sulfide poor-chromitites below the UG-2. *Economic Geology,* 89(5), pp. 1094-1121.

Shepard, D., 1968. *A two-dimensional interpolation function for irregularly-spaced data.* New York, ACM Press,proceedings of the 1968 ACM National Conference, pp. 517-524.

Silva, D. S., 2015. *Mineral Resource Classification and Drill Hole Optimization Using Novel Geostatistical Algorithms with a Comparison to Traditional Techniques,* s.l.: Department of Civil and Environmental Engineering: University of Alberta.

Silva, D. S. & Boisvert, J. B., 2014. Mineral resource classification: a comparison of new and existing techniques. *The Journal of The Southern African Institute of Mining and Metallurgy,* Volume 114, pp. 265-273.

Sinclair, A. J. & Blackwell, G. H., 2002. *Applied Mineral Inventory Estimation.* Cambridge: Cambridge University Press.

Snowdengroup, 2017a. *4 key aspects to Variography.* [Online] Available at: https://snowdengroup.com/news/4-key-aspects-variography/ [Accessed 24 August 2019].

Snowdengroup, 2017b. *Supervisor 8.7 – Multi-block kriging neighbourhood analysis.* [Online] Available at: https://snowdengroup.com/news/supervisor-8-7-multi-block-kriging-neighbourhood-analysis/ [Accessed 28 September 2019].

Snowden, V., 1996. *Practical interpretation of resource classification guidelines.* West Perth, AusIMM 1996 Annual Conference.

Snowden, V., 2001. *Practical interpretation of mineral resource and ore reserve classification guidelines.* West Perth, The AusIMM Guide to Good Practice (Monograph 23), pp. 643-652.

Spragg, K., 2013. *Leapfrog3d.* [Online] Available at: https://blog.leapfrog3d.com/2013/05/08/leapfrog-interpolation-basics/ [Accessed 09 02 2020].

SRK Consulting , 2008. *An Independent Mine Feasibility Study for the Sky Chrome Project ,* North-West Province South- Africa: Report number 355663.

Stephenson, P. R. et al., 2006. Mineral Resource classification– it's time to shoot the 'spotted dog'!. *Australasian Institute of Mining and Metallurgy,* pp. 91-95.

Surpac Minex Group, 2005. *Klipstone.* [Online] Available at: http://www.klipstone.com.au/wp-content/uploads/MINEX_GROWTH_METHOD_GRIDDING.pdf [Accessed 02 10 2019].

Vann, J., Jackson, S. & Bertoli, O., 2003. *Quantitative Kriging Neighbourhood Analysis for the Mining Geologist — A Description of the Method With Worked Case Examples.* Bendigo, 5th International Mining Geology Conference.

Von Gruenewaldt, G., 1977. The mineral resources of the Bushveld Complex. *Minerals Science and Engineering,* 9(2), pp. 83-95.

Von Gruenewaldt, G., Sharpe, M. R. & Hatton, C. J., 1985. The Bushveld Complex; introduction and review. *Economic Geology,* Volume 80, pp. 803-812.

Wawruch, T. M. & Betzhold, J. F., 2005. Mineral resource classification through conditional simulation . In: *Geostatistics Banff 2004.* The Netherlands: Springer, pp. 479-489.

Weber, D. & Englund, E., 1992. Evaluation and Comparison of Spatial Interpolators. *Mathematical Geology,* Issue 24, pp. 381-391.

Webster, R., n.d. *AMC Consultants - Mineral Resource Validation.* [Online] Available at: https://amcconsultants.com/experience/mineral-resource-validation/ [Accessed 04 11 2019].

Webster, R., nd. *Mineral Resource Validation.* [Online] Available at: https://amcconsultants.com/experience/mineral-resource-validation/ [Accessed 6 July 2019].

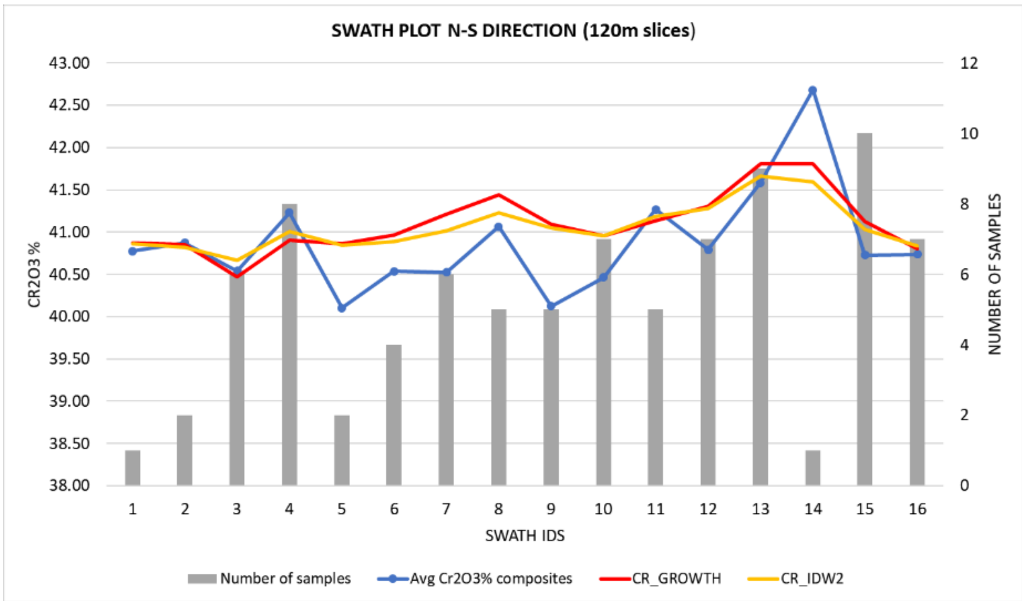
WSP, 2015. *Newfoundland and Labrador.* [Online] Available at: https://www.nr.gov.nl.ca/NR/mines/MRR2015-Lookback/WSP-Tricks_Block_Model_NL_CIM_2015_R1.pdf [Accessed 04 11 2019].

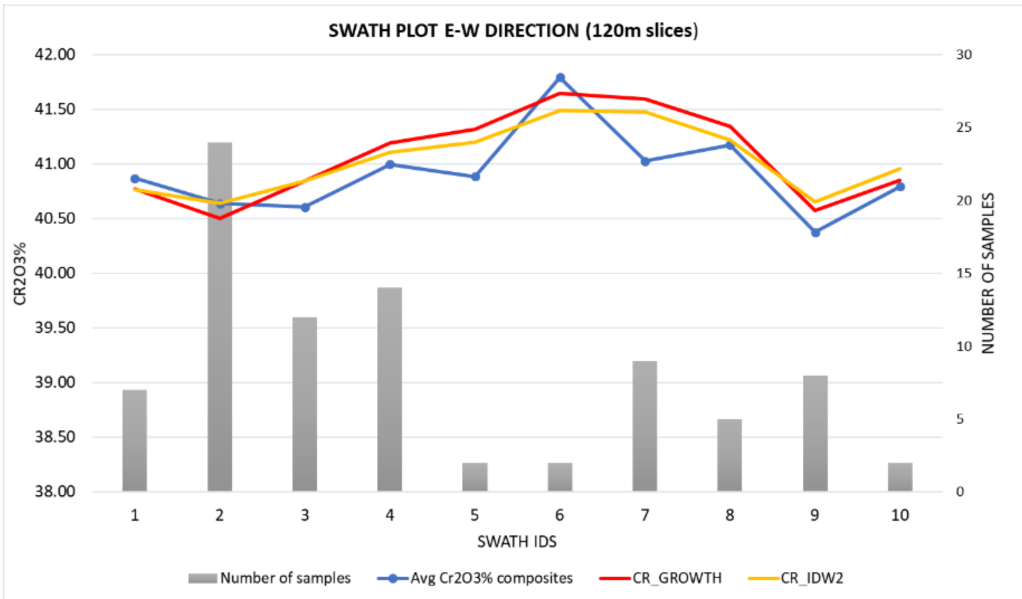
Yamamoto, J. K., 2005. Correcting the Smoothing Effect of Ordinary Kriging Estimates. *Journal of the International Association for Mathematical Geosciences,* 37(1), pp. 69-94.

APPENDIX

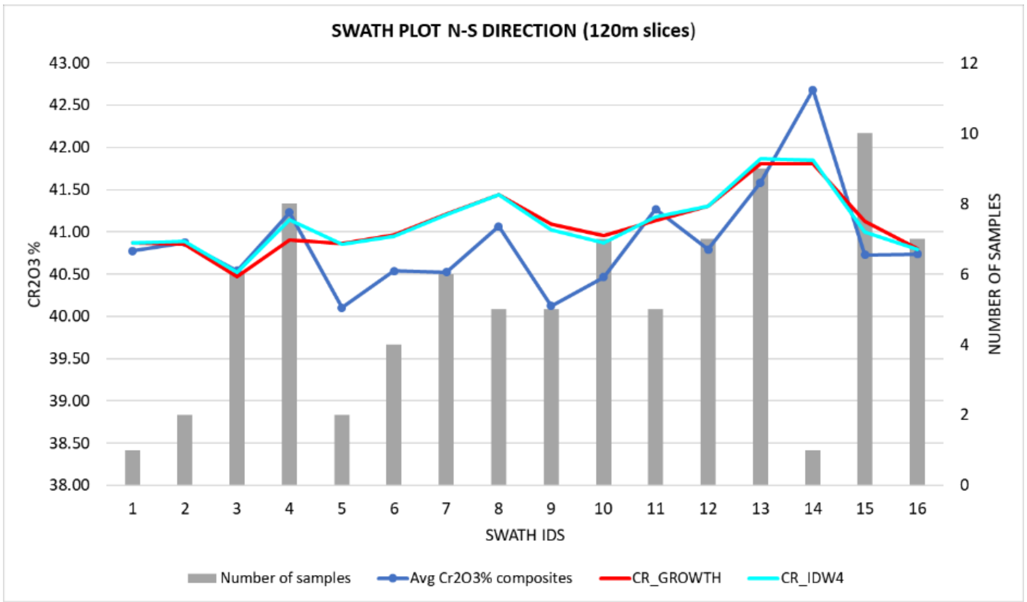
Appendix 1: North-South and West-East swath plot comparisons between the alternative estimation methods (IDW2;IDW4;OK_1;OK_2;OK_3) and MCo's Growth technique estimation for Cr_2O_3%.

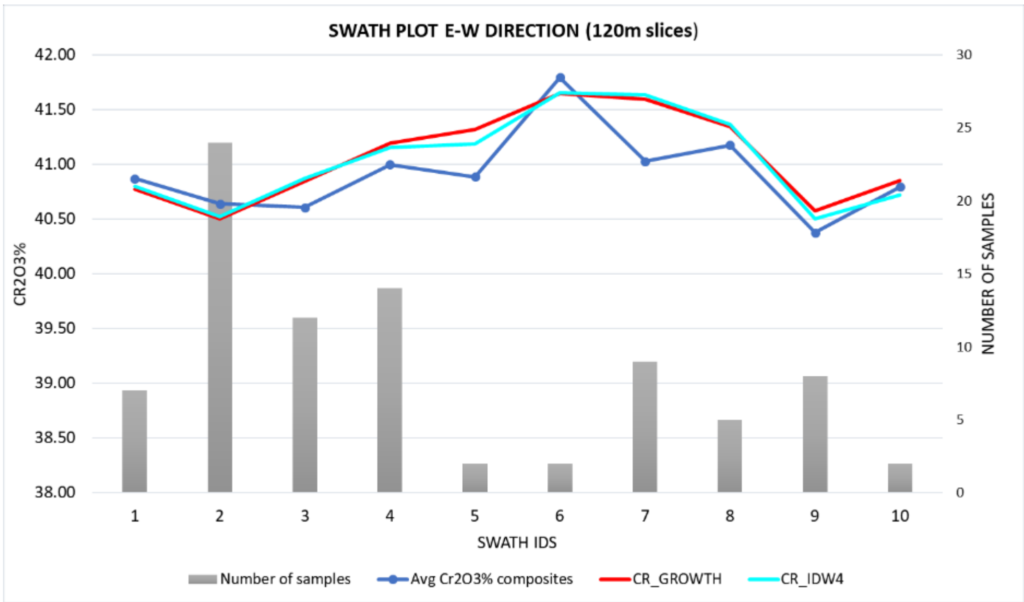
Swath plots - Growth technique compared to IWD2



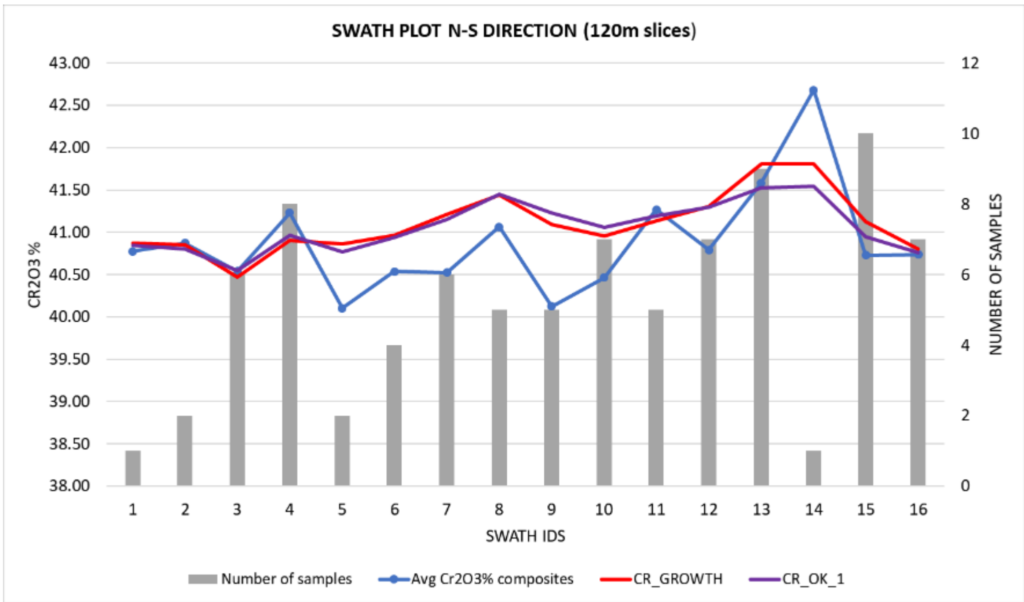


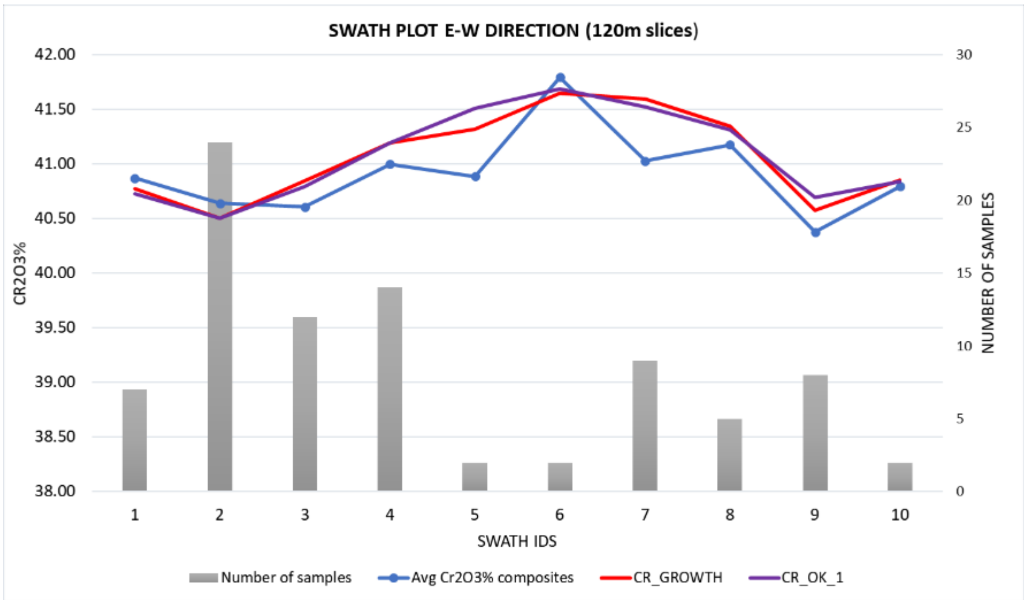
Swath plots - Growth technique compared to IWD4



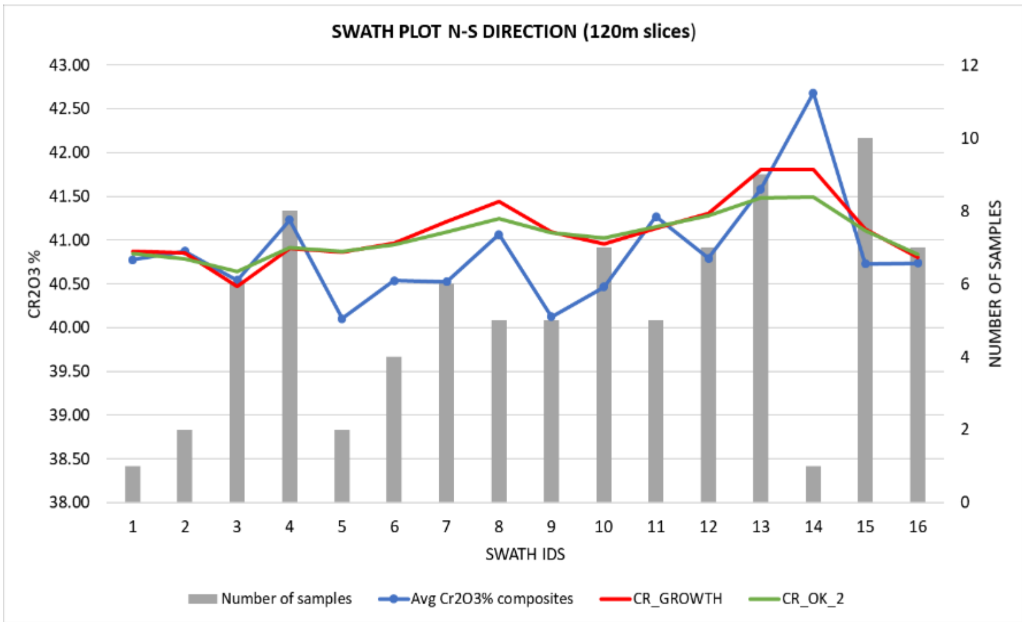


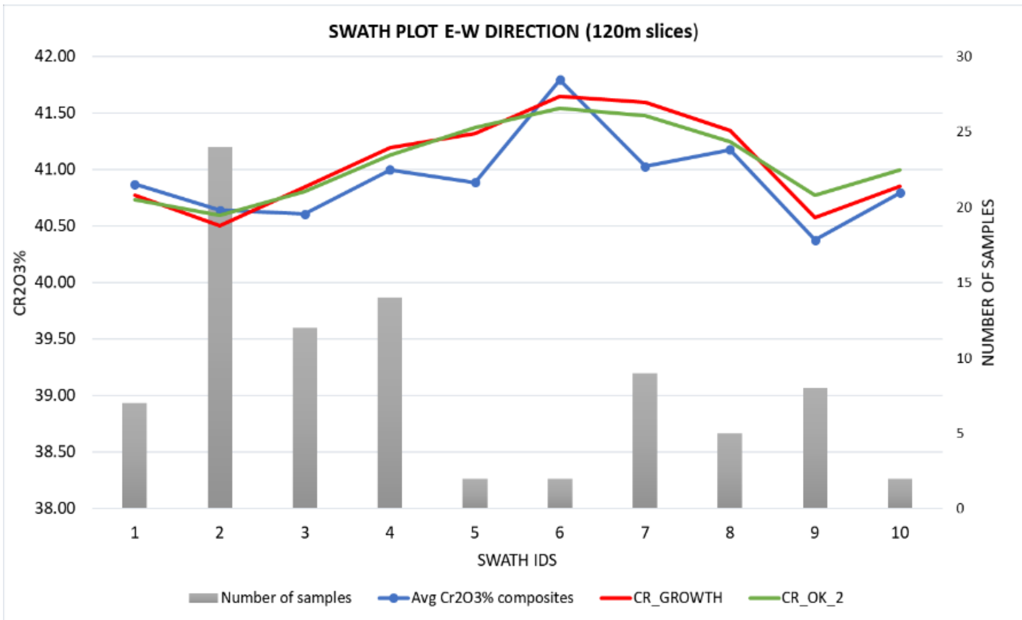
Swath plots - Growth technique compared to OK_1





Swath plots - Growth technique compared to OK_2





Swath plots - Growth technique compared to OK_3