RESOURCE CLASSIFICATION CRITERIA FOR HYDROTHERMALLY ENRICHED MANGANESE ORE BODIES

Student name: **Nokukhanya Zulu**

Student number: **0706376V**

School of Mining Engineering

University of the Witwatersrand

Johannesburg, South Africa

Supervisor: Prof. C. E. Dohm

A research report submitted to the Faculty of Engineering and the Built Environment, School of Mining Engineering, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of MSc (Eng).

Date of submission: August 2019

DECLARATION

I declare that this research 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.

The information used in this research was obtained from South32, Hotazel Manganese Mines (with permission). Information regarded as confidential has been excluded from this dissertation.

______________	29/08/2019
Signature	Date

ABSTRACT

Due to regulatory developments over the years, various international and local reporting codes have been consolidated to ensure clear and unambiguous reporting of Mineral Resources globally. The Committee for Mineral Reserves International Reporting Standards (CRIRSCO) incorporates in the International Reporting Template, the minimum standards for the Public Reporting of Exploration Results, Mineral Resources and Mineral Reserves, and also provides recommendations and interpretive guidelines for the countries represented on the CRIRSCO committee. This template is advisory only and in South Africa the South African Code for the Reporting of Exploration Results, Mineral Resources and Mineral Reserves (SAMREC); developed along the CRIRSCO guidelines; is relevant. SAMREC provides the definition for Mineral Resources and subdivides Mineral Resources in order of increasing confidence into Inferred, Measured and Indicated categories based on the confidence and quality of geoscientific evidence.

Whilst there are numerous publications on Mineral Resource classification, few publications exist on the application of Mineral Resource classification techniques applied specifically to manganese deposits. This has led to manganese resource geologists adopting classification methodologies applied to other commodities, and in some cases merging and adapting different methodologies, which might be inappropriate and not suited to the specific manganese ore bodies being investigated. This study set out to develop a defendable guideline for the Mineral Resource classification of hydrothermally enriched manganese ore bodies by considering confidence in both the geology and geostatistical estimation. Wessels mine was presented as a case study.

The literature review conducted, formed the foundation of this research report wherein various Mineral Resource classification techniques were investigated. Estimation parameters were identified to assess confidence in the estimate and to confirm the key geological considerations affecting confidence in the estimate. Statistical and geostatistical analyses of the geoscientific data were combined with geological knowledge to develop a guideline for the Mineral Resource classification of hydrothermally enriched manganese ore bodies.

The research report shows that using a purely mathematical approach to Mineral Resource classification is an over-simplification and not suited to the manganese ore body, particularly when applied to the skew and non-stationary data of the case study.

The absence of an assessment of geological risk in the current classification was found to be a gross oversight. A scorecard method for Mineral Resource classification is proposed, as an improvement over the current methodology. This proposed scorecard is designed to balance three crucial elements: confidence in data integrity, confidence in the geology, and confidence in the mathematical estimation technique. The fundamental research questions have been answered, thereby achieving the objectives of this research study. It is envisaged that this research will contribute to a published body of work that will lead to improved classification of hydrothermally enriched manganese ore bodies.

DEDICATION

This work is dedicated to my son.

ACKNOWLEDGEMENTS

My sincere gratitude to Hotazel Manganese Mines for their support throughout the duration of this project. In particular, I would like to thank Mr. F. T. Rambuda for his contribution towards my understanding of manganese geology and Mr. A. C. Nengovhela for challenging me during our debates and discussions.

A special thanks to my supervisor, Prof. C. E. Dohm for her guidance and valuable input. I would not have been able to complete this research without her.

I wish to express my heartfelt appreciation to my husband, without whose support, this research would not have been possible.

TABLE OF CONTENT

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

Aluminium oxide. .... Al_2O_3

Block variance .... BV

Calcium oxide. .... CaO

Canadian Institute of Mining. .... CIM

Change of support .... CoS

East .... E

Engineering Council of South Africa .... ECSA

Exploratory data analysis. .... EDA

Geological Society of South Africa. .... GSSA

Grams per cubic centimetre .... g/cm^3

Iron .... Fe

Information effect .... IE

Intitute of Mine Surveyors of South Africa .... IMSSA

Inverse distance weighted .... IDW

Joint Ore Reserves Commitee. .... JORC

Kilogram. .... kg

Kilometre. .... km

Kilowatt hour .... kWh

Kilowatt hour per tonne .... kWh/tonne

Kriging variance .... KV

Kriging efficiency .... KE

Latin phrase meaning "and others". .... et al.

Latin phrase meaning "and other things" .... etc.

Latin phrase meaning "in other words" .... i.e

Magnesium oxide. .... MgO

Mangenese .... Mn

Metres. .... m

Mineral Resource classification system .... MRCS

North .... N

Quality assurance and quality checks .... QAQC

Resource Classification Index .... RCI

Resource Reliability Rating. .... RRR

South. .... S

South African Code for the Reporting of Exploration Results, Mineral Resources and Mineral Reserves .... SAMREC

South African Council of Natural Scientific Proffessions. .... SACNASP

South African Geomatics Council. ....SAGC

South African Institute of Mining and Metallurgy ....SAIMM

South African Mineral for the Reporting of Mineral Asset Valuatios............ SAMVAL

South African National Standard .... SANS

Standard Operating Procedure .... SOP

Versus. ....vs.

West. .... W

LIST OF SYMBOLS

And ..... &

Approximately ..... ≈

Degrees ..... °

Equal ..... =

Greater than ..... >

Greater than or equal to ..... ≥

Less than ..... <

Less than or equal to ..... ≤

Percent ..... %

CHAPTER 1

INTRODUCTION

1.1 Background

Mineral Resource classification is intended to assist prospective investors and their advisors on the confidence that should be attached to resource estimates. The main elements that affect confidence in the Mineral Resource estimate are the reliability of the geological model, the continuity of mineralisation, the sampling grid configuration, the quantity and quality of sampling data, and the reliability of the evaluation method. Unfortunately, resource geologists tend to focus on the confidence associated with the grade estimate, often at the expense of considering the risk associated with the underlying geological model (Dohm, 2004).

The guidelines pertaining to Mineral Resource classification and reporting are provided by the South African Code for the Reporting of Exploration Results, Mineral Resources and Mineral Reserves (SAMREC, 2016). SAMREC defines Mineral Resources and subdivides the confidence associated with the Mineral Resources estimates in order of increasing knowledge and confidence in geoscientific evidence. The relationship between Inferred, Indicated and Measured Mineral Resources is shown in Figure 1.

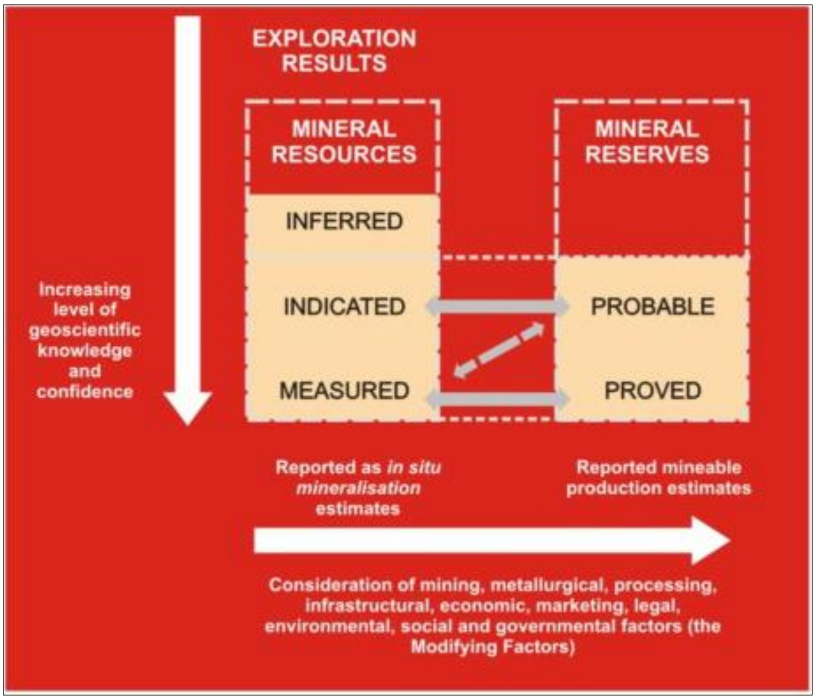


Figure 1: Relationship between Exploration Results, Mineral Resources and Mineral Reserves (SAMREC, 2016).

SAMREC defines a Mineral Resource as "a concentration or occurrence of solid material of economic interest in or on the Earth's crust in such form, grade or quality and quantity that there are reasonable prospects for eventual economic extraction. The location, quantity, grade, continuity and other geological characteristics of a Mineral Resource are known, estimated or interpreted from specific geological evidence and knowledge, including sampling" (SAMREC, 2016).

The SAMREC Code is deliberately not prescriptive as to how confidence in the estimate is assigned and relies on the experience and competence of the Competent Person to make the appropriate judgment. A Competent Person is defined as a minerals industry professional that is a member or fellow of the SAIMM, GSSA, IMSSA or any other Recognised Professional Organisation with a code of ethics, has a minimum 5 years relevant experience in the deposit or style of mineralisation and experience in estimation, assessment or evaluation. The Competent Person must be registered with SACNASP, ECSA or SAGC (SAMREC, 2016).

Whilst there exist many publications on Mineral Resource classification, few specifically address the application of Mineral Resource classification techniques to manganese deposits. This has led to the practice of manganese resource geologists adopting classification methodologies applied to other commodities, and in some cases merging and adapting different methodologies, that might be inappropriate and not suited to the ore bodies under investigation. Most of the manganese specific literature references are from individual mines that have developed their own method for Mineral Resource classification.

The advent of computers for geological modelling and the increased application of geostatistics in estimating Mineral Resources has seen many practitioners limiting the assignment of resource confidence to the suggestions made by software packages. This has seen a further reduced focus on the impact geology has on the confidence of an estimated block. As geostatistics software packages become more readily available, there is an emerging trend which threatens to ignore the role of classical geological interpretation. One of the reasons for this is that geological interpretation is more qualitative and as such difficult to analyse in a numeric sense using software (Stephenson *et al.*, 2006).

The impact of geology and classical geological interpretation in the estimation process cannot be underestimated, as the typical estimation process is dependent on both a geological model and the application of an appropriate estimation technique (Dohm, 2003). The geology influences the mineralisation, the determination of domain boundaries and the variability or continuity of the ore body.

Within this research report there are three terms referred to and related to the concept of confidence which require upfront clarification of both meaning and context . The term “confidence in the geology” refers to knowledge of mineralisation, the impact of geological structures on grade variability and continuity, the location and shape of geological boundaries and the understanding of the depositional environment. The term “confidence in the estimation” refers to assurance on the quality of the sampling data, the quantity of data, reliability of the variography, estimation domain boundaries, the type of estimate applied and the appropriateness of the spatial interpolation method. The term “confidence in the classification” refers to the confidence attached to the geological model and the grade estimate.

1.2 Purpose of study

A Competent Person must be able to face his/her peers regarding the resource estimation and classification methodology applied. The aim of this study has been to develop a defendable guideline for the Mineral Resource classification of hydrothermally enriched manganese ore bodies, through (1) a comprehensive literature review of existing Mineral Resource classification methods, (2) geostatistical study of the geoscientific data; and (3) a comparison of the existing and the new proposed Mineral Resource classification techniques for these orebody types.

The objective of this research has been to consolidate different Mineral Resource classification techniques that are relevant to manganese ore bodies, by considering confidence in both the geology and geostatistical estimation. The newly proposed method is compared with the current classification in terms of appropriateness and justification thereof. Confidence in the current classification criteria is reviewed. Wessels mine is presented as a case study, with consent.

Hotazel Manganese Mines are situated in the Northern Cape Province of South Africa. Wessels mine is situated approximately 80 km northwest of Kuruman. The mine is located on the northern part of the Kalahari Manganese Field, as shown in Figure 2.

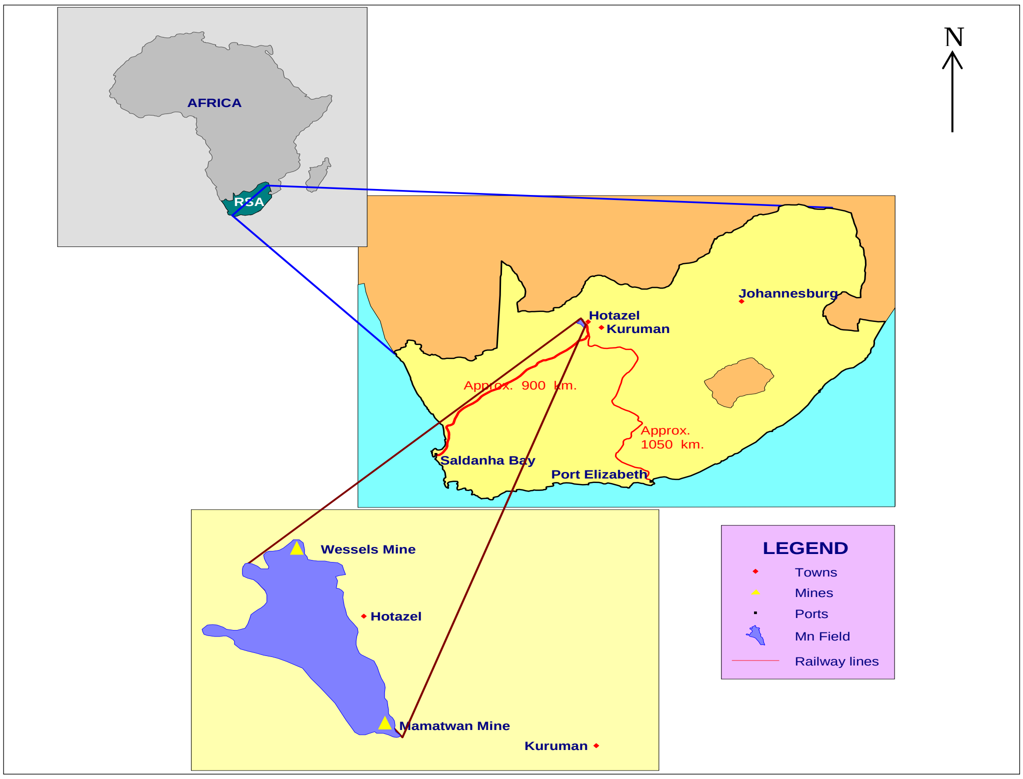


Figure 2: Schematic diagram showing the geographic location of Wessels mine (Hotazel Manganese Mines, 2001).

Wessels mine is an underground operation which opened in 1973 (South32, 2016) and is currently operated by South32. The ore body is preserved approximately 350 km below surface and is extracted using the Board and Pillar mining method. The mine produces approximately 0.8 million tonnes of manganese per annum, which is used primarily in the steel making process. Manganese content of less than 38% is considered waste. Two primary products are sold in both lumpy and fines form, W1 (high grade ore) and W4 (medium grade ore). Slimes is also sold as a production by-product, although it is not segregated by grade. Table 1 shows the simplified Wessels product grade specifications.

Table 1: Wessels mine simplified product grade specifications.

	Description	Mn	Fe	CaO
Waste	Waste	< 38%	< 18%	
W4	Medium grade ore	≥ 42%	≤ 16%	5-9%
W1	High grade ore	≥ 47%	≤ 12%	4-8%

Wessels mine is subdivided by dominant north-south trending faults into different blocks, the West Block, Graben Block, Central Block and East Block (shown in Figure 3). There are three manganese units, namely the Lower Body, the Middle Body and the Upper Body. Mining, however, occurs on the Lower Body due to the optimal Mn: Fe ratio and ore body thickness. The case study considered in this research report refers to the Mineral Resources of Wessels mine, Lower Body.

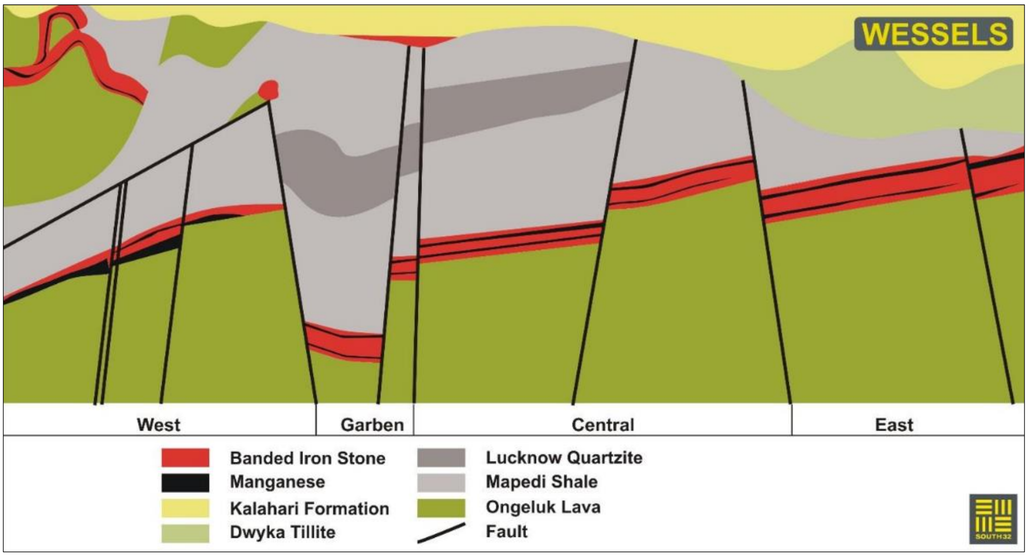


Figure 3: West-East cross-section through Wessels mine (Lautze & Lukhaimane, 2017).

1.3 Problem statement

A Competent Person must be able to defend decisions surrounding Mineral Resource classification classes, according to the guidelines laid out by the SAMREC Code. It is the responsibility of the Competent Person to "face their peers" regarding the Mineral Resource estimation and classification. The Mineral Resource classification problem addressed by this research report is the relevance of the inclusion of knowledge of mineralisation and geology in the Mineral Resource classification protocol.

Wessels mine has undergone several minor modifications in the Mineral Resource classification methodology employed over the years. The current Mineral Resource classification protocol at Wessels mine is as follows: Blocks estimated within the first range of the double structured spherical semi-variogram model are classified as being within the Measured category. This range of 30-40m represents approximately two thirds of the total variance. Mineral Resources estimated within the second structure of the double structured spherical model are classified as Indicated. Any Mineral Resources estimated beyond the second range are classified as Inferred (Nengovhela, 2013).

Practically, however, a rim of 30m around the sub-outcrop is classified as Inferred. Current practice is that any ground 30-40m ahead of a mining face is classified as Measured, whilst any estimates of the ground beyond that is classified as Indicated.

Research questions considered in this research report are: Firstly, is the current Mineral Resource classification method suitable for the ore body, and what are the pitfalls of the current methodology? Secondly, are there other, more relevant classification methods that can be recommended to replace or enhance the current Mineral Resource classification technique?

1.4 Assumptions

For the purpose of this study, it was assumed that the assay results as received from the mine are precise and accurate, that the samples are representative of the population, and finally that the samples were obtained randomly and independently, in terms of value and not location, (Dohm, 2016a). The estimation methodology is assumed to be ore body appropriate.

1.5 Limitations

Estimation process and the validation thereof are outside the scope of this research; however, the estimation parameters were considered to assess confidence in the estimate. Information regarded as confidential has been excluded from this dissertation.

1.6 Research methodology

The 2016 Global Resource model containing the Wessels mine annual Mineral Resource estimate, along with both uncomposited and composited data were received from Wessels mine. The Mineral Resource estimate presented in this research report was produced by Hotazel Manganese Mines. The exploratory data analysis, variography and validation were conducted by the researcher using the following software:

- MICROMINE: Exploration and Mine Design
- GEOVIA: Surpac, and
- MICROSOFT: Excel.

An extensive literature review, forming the foundation for the research and the investigations into various Mineral Resource classification techniques applied in the mining industry, was conducted. The researcher undertook statistical and geostatistical analyses of the data and from this developed the proposed Mineral Resource classification methodology for application on hydrothermally enriched manganese ore bodies. The proposed Mineral Resource classification was reviewed in terms of appropriateness with the technique currently applied at Wessels mine, for a comparative discussion on the advantages and disadvantages of both methodologies and their suitability for the ore body.

The proposed Mineral Resource classification criteria is intended as a guideline rather than a prescribed method, with the aim of assisting the Competent Person with his/her judgement on confidence. The guideline will allow for the inclusion of the Competent Person's knowledge and experience, while also providing a defendable approach.

1.7 Overview of the research report

The research report has been divided into seven chapters:

Chapter 1 Introduction: The chapter begins with an introductory context into the guidelines pertaining to Mineral Resource classification and the role of the Competent Person in the assignment of confidence. The background information about Wessels mine, product grades and mining methodology is presented. Additionally, the study objectives and the rationale behind the research study are discussed.

Chapter 2 Literature Review: An in depth literature review of different Mineral Resource classifications is presented. The literature review focuses on classifications applied elsewhere to similar deposits and, on what can be learnt and applied to the study area. The geology of the study area and different classification scorecards are reviewed.

Chapter 3 Exploratory Data Analysis: This chapter contains a classical statistical analysis of the data received from Wessels mine.

Chapter 4 Geostatistical Analysis: Spatial analysis, including spatial correlation and variography of the data is presented.

Chapter 5 Results: An alternative method of Mineral Resource classification is proposed and compared with the current method.

Chapter 6 Discussion: This chapter details the interpretation of the results presented in Chapters 3, 4 and 5.

Chapter 7 Conclusion and Recommendations: General research conclusions are presented in a manner that is focussed on answering the fundamental research questions. Included in this chapter are recommendations for future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Study Area Geology

The Kalahari Manganese Field is divided into two ore types based on the geochemical characteristics of the manganese ore. The low grade, sedimentary, Mamatwan–type ore is found in the south-east and the high grade, hydrothermally altered, Wessels-type ore in the north-west (Evans *et al*., 2001).

Approximately 3% of the total manganese resource is Wessels-type ore, while the remaining 97% is comprised of Mamatwan-type ore (Gutzmer & Cairncross, 2002). The two distinct geochemical zones are shown in Figure 4.

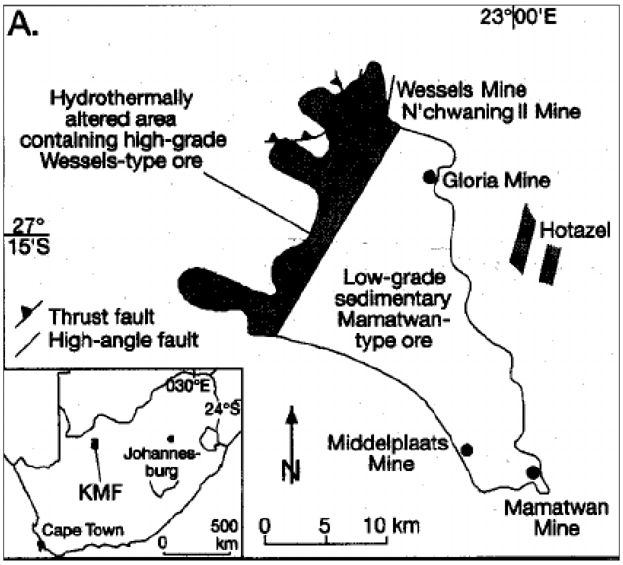


Figure 4: Zoning of the Kalahari Manganese Field (Evans *et al*., 2001).

2.1.1 Geological Setting

The Kalahari Manganese Field is hosted by the early Proterozoic Transvaal Supergroup, in the Griqualand West Basin, along the western margin of the Kaapvaal Craton. The manganese field is preserved in a structural basin which plunges regionally at an angle of 3° to 8° to the northwest (Hotazel Manganese Mines, 2001).

Rocks of the Transvaal Supergroup in the Griqualand West Basin are gently folded. These folds are truncated by the Olifantshoek unconformity at the base of the Olifantshoek Group. The Griqualand West is divided into two groups, the basal Ghaap Group and the unconformably overlying Postmasburg Group, as shown in Figure 5. Manganese mining is concentrated in the Hotazel Formation of the Postmasburg Group (Cairncross *et al*., 1997).

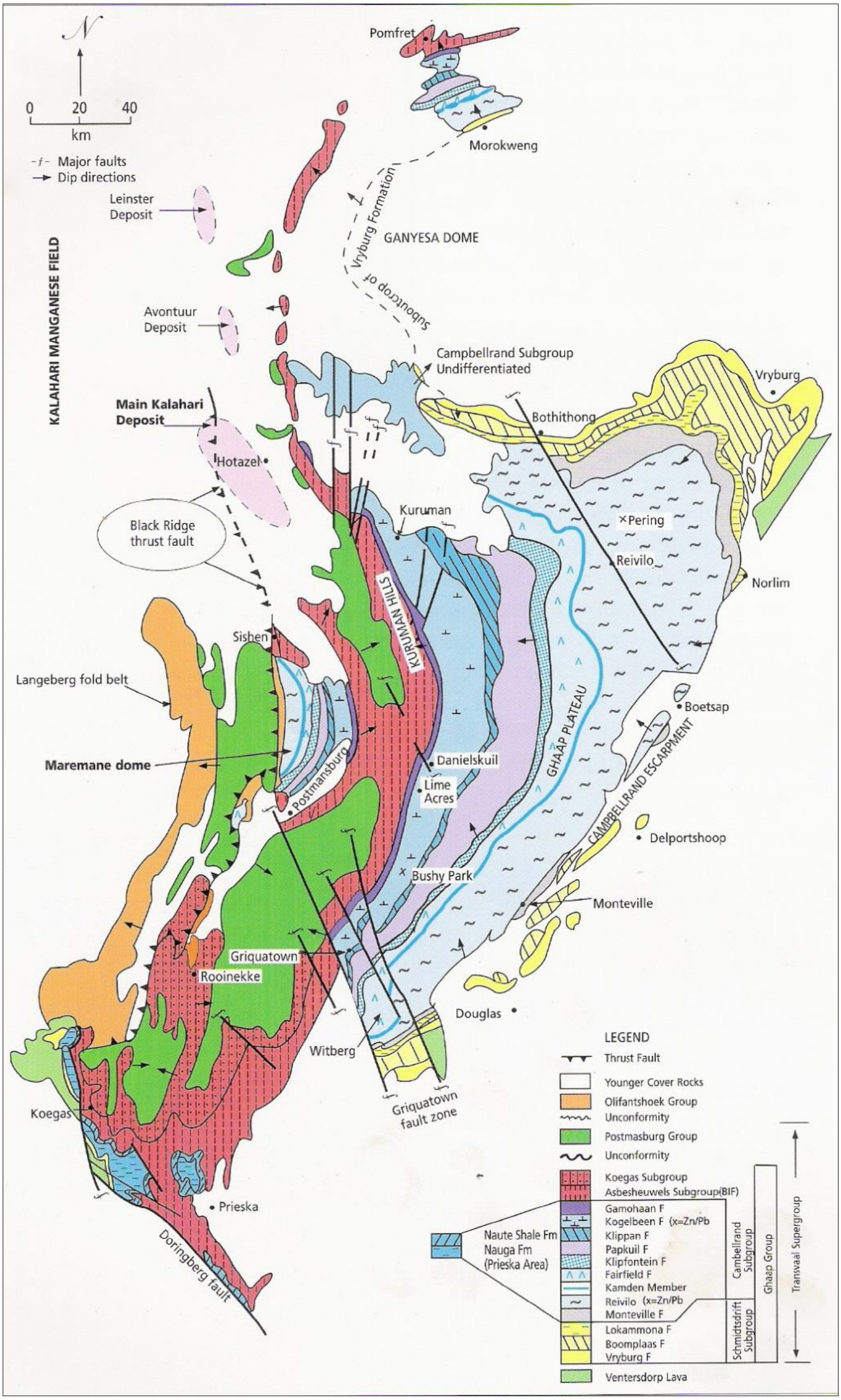


Figure 5: Geological map of the Transvaal Supergroup in Griqualand West, showing the distribution of major stratigraphic units and ore deposits (Hotazel Manganese Mines, 2001).

The detailed stratigraphy of Wessels mine is presented below. The economic zone of interest; the Hotazel Formation, comprises of ironstone (red in Figure 6) and manganese (black in Figure 6).

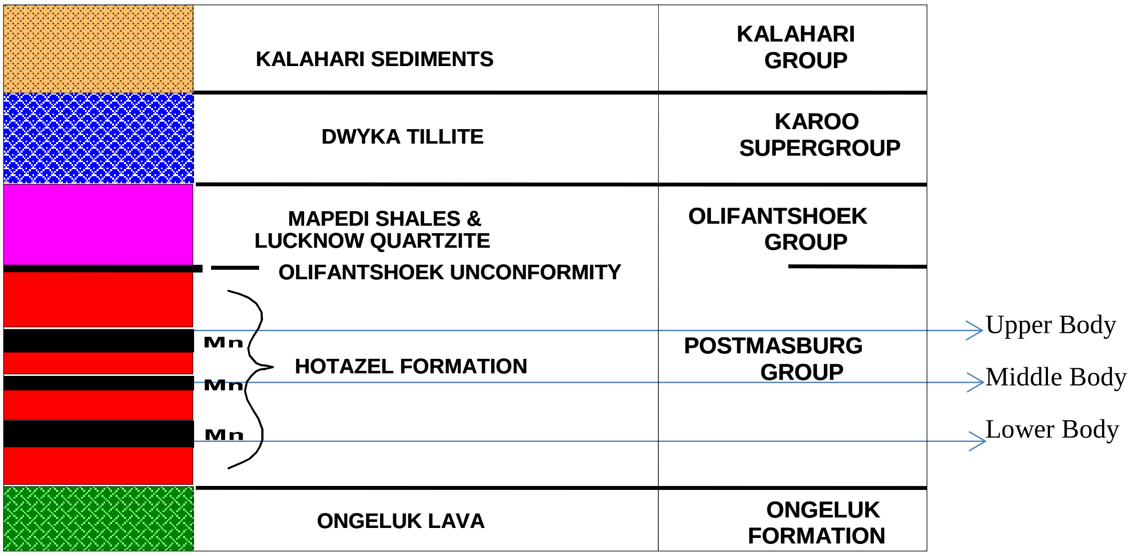


Figure 6: Stratigraphy of the study area (adapted from Hotazel Manganese Mines, 2001).

2.1.2 Depositional Environment

Manganese deposits can be divided into five basic types based on the depositional origin and the nature of secondary alterations: (1) sedimentary, (2) volcanic-sedimentary, (3) metamorphosed, (4) hydrothermal, and (5) supergene (Fan & Yang, 1999). Manganese ore in the study area has undergone hydrothermal alteration which resulted in manganese enrichment. The hydrothermal fluids infiltrated faults and joints (Evans *et al*., 2001). The effect of hydrothermal fluids on the ore body is most likely strongest around the faults and joints and dissipates away from the structures, introducing lateral inhomogeneity.

The origin of the Kalahari Manganese Field deposit is contentious. As summarised by Tsikos & Moore (1998), origin is described by: (1) the epigenetic replacement model (De Villiers, 1983 cited by Tsikos and Moore, 1998), (2) the volcanic-exhalative model (Cornell & Schütte, 1995; Beukes & Gutzmer, 1996) and (3) the volcanogenic sedimentary model (Beukes, 1983; Trendall & Morris, 1983). The uncertainty surrounding the origin of the Kalahari Manganese Field adds to the difficulty of confidently incorporating the geology during the Mineral Resource estimation and classification processes.

2.1.3 Magmatic Intrusions

Contact metamorphism in the Kalahari Manganese Field is associated with dykes which are basaltic in composition (Söderlund *et al*., 2010). Wessels mine employees describe the dykes as "Bostonite dykes".

Contact metamorphism effects on the ore body are strongest around the dykes and dissipate away from the structures, likely resulting in lateral ore body inhomogeneity. Thin section petrography indicates that contact metamorphism in the contact aureole of the dykes reached amphibolite facies metamorphism (Zulu, 2010).

2.1.4 Graphic Summary of the Geological Model

As mentioned previously, the origin of the Kalahari Manganese Field is a subject of debate. Tsikos and Moore (1998) summarised three of the more dominant theories within the geoscientific community. A summary of the most widely accepted model for the formation of Wessels-type ore and the controls on mineralisation are summarised by Gutzmer and Beukes (1998), as shown in Figure 7. Figure 7 was obtained from the Hotazel Manganese Mines Standard Operating Procedure (SOP). It is thus safe to assume, that this is the model endorsed by the mine.

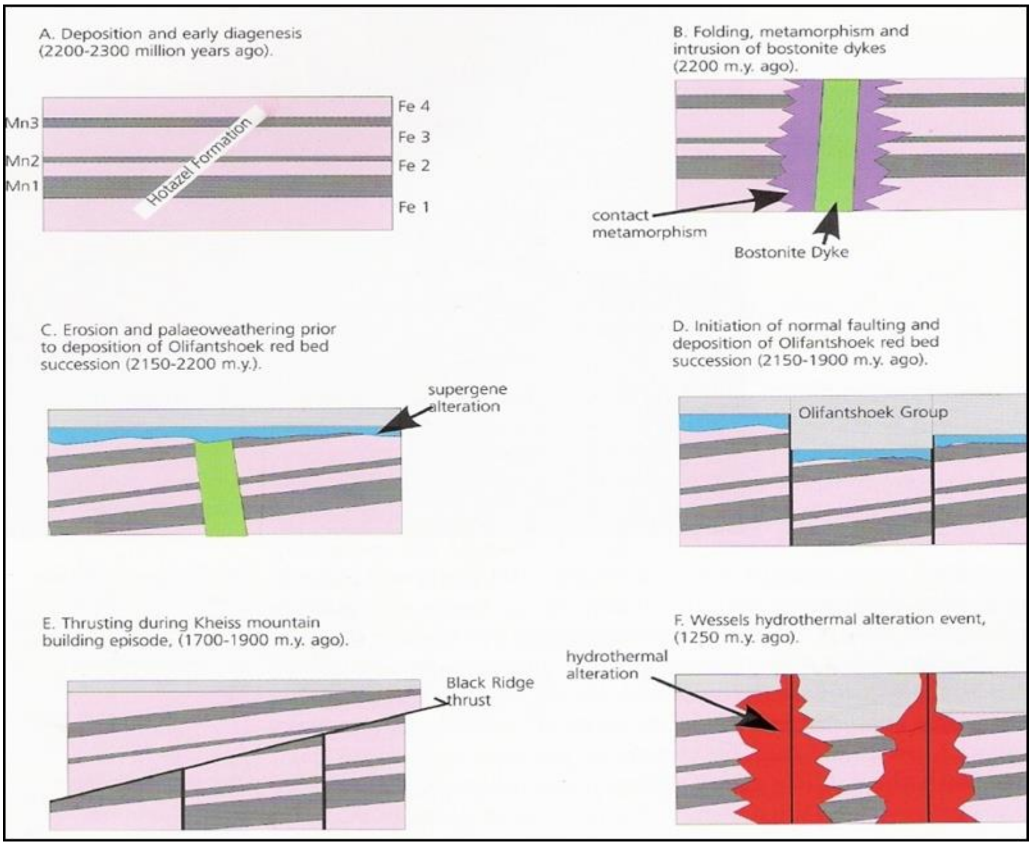


Figure 7: Formation of the Wessels-type (hydrothermally enriched) manganese ore (adapted from Gutzmer & Beukes, 1998).

2.2 Parameters Affecting Mineral Resource Classification

Due to the unique nature of each deposit, it is difficult to have a "one size fits all" approach to Mineral Resource classification. In response, geoscientists have merged and adapted methodologies to suit the deposits being investigated (Arik, 2002).

Classification must be transparent, objective, reproducible and auditable (Wawruch & Betzhold, 2005; Leuangthong & Deutsch, 2005). This is important as the category of Mineral Resource classification should reflect the credibility of the estimate and the confidence in continuity in both the geological structure and the deposit parameters (Mucha & Wasilewska-Blaszczyk, 2015).

Spatial distribution data of natural phenomena is often collected from point sources. The data is usually sparse and unevenly distributed. Spatial interpolation methods broadly fall into the following three categories: non-geostatistical interpolators, geostatistical interpolators and combined methods (Li & Heap, 2008).

2.2.1 Data Integrity

The quality of the data underlying the estimate is of crucial importance. Data must plot accurately in space and be representative of the population. Sampling, assaying, geological errors and other errors can be introduced during the interpretation, estimation and classification of Mineral Resources. Confidence limits are seldom quoted in Ore Reserve statements. When quoted, the selected confidence limits rarely take into consideration the various factors that could cause uncertainty in grade and tonnage estimates. It is important to note that some risk and uncertainty is always inherent in estimation (Dominy *et al*., 2002).

2.2.2 Slope of Regression

The regression effect has been recognised in Southern Africa for over 60 years. The concept was introduced by Krige (1951) to account for the discrepancy between stope and development estimates of Witwatersrand gold grades. Till (1974) expanded on Krige's 1951 work, by further developing the reduced major axis regression. The intention of the reduced major axis regression was to provide a better fit around the 45° line, by making use of the standard deviation of the actual value and the standard deviation of the estimate.

The regression effect is a function of both the information effect (having incomplete information at the time of estimation) and the change of support effect (attributable to the fact that block estimates are less than sample values). The regression effect is observed as the over estimation of the high values and the under estimation of the low values, resulting in a regression slope that is less than one. The impact of the regression effect is reduced when the slope is close to one, implying greater confidence in the estimate (Dohm, 2016b).

The slope of regression gives an indication of the degree of over and under estimation of the blocks evaluated. Corrections for the regression effect depend heavily on the sample values being normally distributed, as variance and covariance have little meaning when applied to skew data sets (Clark, 2015). The implication is that data should first be proven to follow a Gaussian distribution during the exploratory data analysis, before the slope of regression can be considered for Mineral Resource classification.

2.2.3 Distance to Nearest Sample

Geometric techniques involving inter-sample spacing are relatively common. Drill hole spacing as a means of Mineral Resource classification is based on the distance between boreholes in and around the estimated block. It is an easy technique when boreholes are vertical and evenly spaced (Silva & Boisvert, 2014).

Distance to nearest sample as a method of Mineral Resource classification has been applied by manganese mines at least since the 1970s (Beltrame *et al*., 1981). This method of resource classification, although somewhat outdated, is still prevalent in the South African and Australian manganese mining industry.

The method is based on the distance from the centre of the estimated block to the nearest known sample. In some cases, the distance to nearest sample is replaced by the average distance of all the samples. The highest estimated block confidence is assigned to the block closest to the known sample. Mineral Resource confidence attributed to the estimated block is usually based on the geology, drilling density and/or variogram ranges. It does however have some limitations, as using drill hole spacing assumes continuity of mineralisation (Arik, 2002).

It is only fully realised global and local continuity that characterises Measured Resources, while the Inferred Resources are based upon apparent global continuity. The application of borehole spacing as the sole criteria for resource classification assumes three-dimensional continuity, which may not always be the case (Dominy *et al*., 2002; Silva & Boisvert, 2014).

Arik (2002, p.58) stated "*Yet they (then existing resource classification methodologies) all have one common shortcoming. They fail to incorporate and use all the information or criteria available in the resource classification scheme. Distance to the nearest* *sample is important, but so are the minimum number of composites used and the kriging variance. How about local variability of the samples? Or quality of the data or drilling type considerations?"*

De Souza *et al*. (2004) documented classes of Mineral Resources based on coal sampling spacing defined by the JORC System. The classification guideline is shown in Table 2. The Mineral Resource classification guideline for coal has since been revised in the 2012 guideline, giving power of discretion to the Competent Person (Stoker, 2015).

Table 2: Coal Resource classification categories based on sample spacing (De Souza *et al*., 2004).

Confidence	Maximum extrapolation distance	Maximum spacing between points of observation	Degree of uncertainty
Measured	500 m	+1 km; <500 m	0-10 %
Indicated	1000 m	+2 km; <1 km	10-20 %
Inferred	2000 m	+4 km	> 20 %

2.2.4 Ore body Delineation and Volume

Beltrame *et al*. (1981) produced a report for the United States Bureau of Mines detailing revisions to both the computation procedures and Mineral Resource estimates of the manganese-bearing ores of the Cuyuna iron range. The estimation method was based on the surface area of the deposit to yield a volume of rock equivalent to the size of the deposit. The grade and tonnage estimates were divided into the following classification classes: 5-10%, 10-15% and greater than 15% to recognise the economic assessment of the areas. The resource confidence in the classification classes were categorised as Measured, Indicated and Inferred Resources based on drilling depths, Mn grades and grade cut-offs of the borehole logs. The Measured, Indicated and Inferred Resources are further subdivided into Economic, Marginally Economic and Sub-economic Reserves. It is worth noting that the references made to the confidence categories as stated by Beltrame *et al*. (1981) did not at the time, fully comply with the CRIRSCO definitions and guidelines.

Dominy *et al*. (2002) noted the effect of volume on tonnage estimation uncertainty. Geological boundaries may or may not be well defined. In some cases, gradational contacts exist. Drill hole deviation can have a serious impact on the accuracy of boundary delineation and therefore on volume modelling. To mitigate against incorrect boundary delineation and volume calculation, the authors stressed the importance of accurate measures at the location and orientation of drill hole intersections.

2.2.5 Resource Reliability Rating

This approach was first proposed by Annels (1995) and was later modified by Annels (1997) and Annels & Dominy (2002). The Resource Reliability Rating (RRR) system comprises questions which are posed and scored depending on the answer. The scores are weighted and combined to reflect the combined economic risk in a Mineral Resource estimate. The RRR rates the confidence in the estimate from 0% to 100%. The scorecard, shown in Table 3, was geared at providing a reflection of the combined risk associated with a Mineral Resource or Mineral Reserve estimate (cited by Dominy *et al*., 2002).

Table 3: Resource Reliability Rating (Dominy *et al*., 2002).

RRR Score	Confidence	Class
100-90	Very high	Measured
80-89	Good	Indicated
60-79	Moderate	Inferred
40-59	Poor	
<40	Unacceptable	

2.2.6 Kriging Efficiency

This scaled measure of confidence was first introduced by Krige (1996; Baafi & Schofield, 1996). 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 compared to the block variance. Krige showed that kriging efficiency can be negative if the kriging variance is greater than the true block variance (cited by Deutsch *et al*., 2014).

Kriging Efficiency (KE) is applied as a comparative assessment of the confidence in estimated block values in order to assign classification categories to the Mineral Resource estimates. It can be expressed as a percentage or proportion (Krige, 1996; Baafi & Schofield, 1996). The equation applied to calculate the kriging efficiency is shown by Equation 1.

$$\textbf{Kriging Efficiency(KE)\%} = \frac{\textbf{(Block Variance - Kriging Variance)}}{\textbf{Block Variance}} \times \textbf{100\%} \qquad \text{Equation 1}$$

Rezaee & Asghari (2012) applied kriging efficiency to classify Porphyry Copper Resources in Iran. KE is expressed as the kriging variance normalised by the variance of the true blocks as a percentage. The authors suggested that the Copper Resource blocks be categorised as Measured when the KE>0.5; Indicated if 0.3 <KE< 0.5 and Inferred when the KE<0.3

The application of kriging efficiency in Mineral Resource classification depends heavily on the sample values having an approximately normal distribution. As a general rule, negative kriging efficiencies should not be classified as Measured Mineral Resources (Clark, 2015). The implication is that in order to make sole use of kriging efficiency for Mineral Resource classification, data normality must be proved, followed by kriging neighbourhood analysis to verify the exclusion of negative kriging efficiencies in the estimate.

2.2.7 Kriging Variance

Early kriging estimates were developed by Matheron (1971 cited by Deutsch *et al*., 2014). The theory thereof is based on the work of Krige (1951) and Sichel (1973). The advantage of kriging was that not only were block estimates produced in the process, but also, a measure of the uncertainty of the estimate was generated in the form of the kriging variance (Matheron, 1971).

Glacken (1996 cited by Snowden 1996) warned that not all methods based on kriging variances are valid. The author cautioned against the tendency to consider the distribution of kriging variances set at an arbitrary distribution percentile, as mentioned in Arik (2002), for distinguishing Mineral Reserve categories.

Application of the kriging variance in Mineral Resource classification is a common geostatistical practice. Kriging variance represents the expected value of the squared error between the actual grade and the estimated grade. It depends on block size, internal block discretisation, sample numbers, sample layout and the semi-variogram. Kriging variance represents relative confidence from block to block and can be used to define Mineral Resource classification categories (Snowden, 2001).

For sparsely drilled deposits, using the distribution of the kriging variance can lead to some of the Mineral Resource being automatically and erroneously classified as Measured. Kriging variance should not be used without reference as to how well the drill hole spacing addresses the geometry and spatial continuity of the deposit and the overall integrity of the input data. Additional caution should be applied when taking into account the links between kriging variance, sample spacing, sample layout, the semi-variogram ranges of influence and Mineral Resource classification categories. Simply having a long range semi-variogram structure may not be sufficient to assume high confidence if small-scale nested structures are present. Complex nested structures may account for most of the variability and should be given most weight when assigning confidence. Confidence in the geological framework generally takes precedence over any mathematical indicator of confidence (Snowden, 2001).

Emery *et al*., (2004) found a way around the concerns mentioned by Snowden (2001) and Glacken (1996 cited by Snowden, 1996) by applying kriging variance as a Mineral Resource classification criterion for porphyry copper deposits. Emery *et al*., (2004) combined geometric and geological knowledge through geostatistical parameters by classifying each block according to its kriging variance.

Ordinary kriging is unable to recognise local data variability. An important shortfall when considering heterogeneous deposits of low and high grade domains (De Souza *et al*., 2004). It would be necessary to prove homogeneity before applying ordinary kriging variance as the sole method of Mineral Resource classification. The prevalence of contact metamorphism effects and faulting are known to have impacted the study area, introducing mineralogical heterogeneity.

The main disadvantage of kriging is its smoothing effect, particularly for non-Gaussian, highly skewed data. If kriging is applied to datasets with non-Gaussian distribution, spatial heterogeneity is not reproducible (Sadeghi *et al*., 2015). Shinozuka and Jan (1972) suggested Gaussian simulation as an alternative geostatistical interpolation method for skewed data.

2.2.8 Resource Classification Index

Arik (1999) proposed a classification technique, Resource Classification Index, based on a combination of the ordinary kriging variance and the weighted average of the squared difference between the estimated value of a block and the actual data values. The Resource Classification Index (RCI) takes into account the spatial data configuration around the estimated block and traditional distance measures. The method has several components, the most important being the combined variance. Combined variance is a combination of the kriging variance and the variance of the weighted average block value. RCI has the advantage of being both a function of the spatial configuration of points and the variability of samples used in the block estimation (cited by Arik, 2002).

Arik (2002) tested the Resource Classification Index on a gold deposit. He compared the results against those obtained from the distance to nearest sample and kriging variance. The author suggested making use of the cumulative probability or the histogram of the kriging variance to categorise Mineral Resources. The method includes some discretion in choosing classes from the cumulative probability or the histogram of the kriging variance. Industry norm is to consider obvious breaks in the cumulative probability curve or the median kriging variance and the 95th percentile as the cut-off values for Measured/Inferred resources and Indicated/Inferred categories. The kriging variance will already be available in an ordinary kriging estimate. It should be noted that kriging variance must be based on the original variogram parameters so that it would be in the same scale as the local variance. If the variogram parameters are normalised, or relative parameters are used, the necessary adjustments must be made.

2.2.9 Interpolation Variance

The inability of the ordinary kriging variance to recognise local data variability becomes an important shortfall when evaluating heterogeneous Mineral Deposits with high and low grade domains (De Souza *et al*., 2004). This draw back encouraged Yamamoto (2000) to introduce an alternative to the measure of reliability of ordinary kriging estimates, called Interpolation Variance (IV). IV is the weighted average of the squared difference between data values and the retained estimate. It depends on the data values, variogram and a measure of local accuracy.

Natural phenomena and geoscientific data are typically not homogeneous, thus requiring a correct assessment of uncertainty. As kriging variance is based on a global variogram averaged over the total estimation domain, it cannot properly measure local data dispersion. Additionally, IV is only valid if all the ordinary kriging weights are positive (Yamamoto, 2000).

2.2.10 Search Neighbourhood

Emery *et al*. (2004) applied the search neighbourhood as a means of classifying porphyry copper Mineral Resources. Blocks estimated within the first and most restrictive neighbourhood restriction were classified as Measured Resources. Blocks estimated by the second neighbourhood restriction were classified as Indicated. Blocks not estimated by the first two neighbourhood restrictions were classified as Inferred Resources. The authors state that the quantity of Measured Resource is likely to be inaccurate if it is calculated after the most restrictive search neighbourhood. Emery *et* *al*. (2004) found that in most cases, the first and most restrictive search had a small search radius and most likely contained few samples.

Applying the search neighbourhood consists of classifying blocks based on distance and constraints related to the number and configuration of the data within the search radius of the block to be classified. The most commonly considered constraints are the minimum number of data, minimum number of drill holes and the minimum number of informed octants. The method works by defining estimation passes with different search parameters. Blocks that are estimated by less restrictive passes are defined as Inferred. The most restrictive pass is defined as Measured and intermediate passes are classified as Indicated (Silva & Boisvert, 2014).

2.2.11 Conditional Simulation

Rather than producing a set of estimated block grades from kriging, conditional simulation is considered a better method for assessing the error in a Mineral Resource estimates. Conditional simulation is data dependent, which is considered an improvement over the kriging variance which does not take actual grades into account (Dominy *et al*., 2002).

Dohm (2003) introduced a method that makes use of the coefficient of variation of different volumes and the local small mining unit. This technique, combining conditional indicator simulations for geology and conditional sequential Gaussian simulations for grade, was demonstrated to assess the combined risk associated with both the geological interpretation and grade estimate. Although not tested on manganese deposits, conditional simulation takes into account change of support in order to account for the correlation between estimated blocks. The author generated 40 realisations for 100m by 100m coal blocks.

Conditional simulation is applied to simulate detailed sets of possible grades that can be re-blocked into meaningful mining block sizes and shapes to represent expected block grades. The success depends on carrying out a large number of realisations from the same dataset in order to obtain an estimated block grade from the average of all simulated block grades, as well as a distribution of likely block grades. The advantage of this method is that the results do not suffer from over smoothing. Therefore, the simulated grades have the same variability and continuity as the conditioning sample data. Also, because the volume-variance correction is achieved by re-blocking the simulated grades into the required block shapes and sizes, the grade-tonnage curve for small curves will be more reliable than those derived from direct block estimates using the available sample data (Dominy *et al*., 2002).

The increasing support seen for the use of conditional simulation as a Mineral Resource classification technique is due to the added advantage of objectivity, in that the degree of risk can be expressed quantitatively. Conditional simulation-based resource classification categories take into account grade variability in addition to the location of data (Snowden, 2001).

The main problem with the conditional simulation technique is the assumption of normality and the generalisation of the coefficient of variation. All distributions, including non-Gaussian distributions, can be assessed after the generation of sufficient number of realisations (Silva & Boisvert, 2014).

In the paper titled “Quantifiable Mineral Resources classification: A Logical approach”, the author concedes that the idea that a Mineral Resource classification be linked to a production period has been around since the 1990’s. Adding that the shorter the production period, the higher the confidence category. The objective of conditional simulation is to determine expected coefficient of variations for the estimated grade, tonnage and metal contents of the various production periods. The variability in realisations of the simulations are then interpreted to assess the uncertainty in the estimate. The result is a Mineral Resource model which is classified based on an objective, quantifiable classification that recognises the uncertainty related to subjective interpretations of the available information. The author further stressed the importance of conducting validations to establish the integrity of the simulations (Dohm, 2004).

Wawruch & Betzhold (2005) recorded the widely accepted rules for Mineral Resource classification of base metals. For Measured Resources, local variability was corrected to monthly or quarterly production units. Measured Resources were estimated within 15% error at a confidence of 90%. Following the correction of local estimate variability to yearly production units, Indicated Resources were estimated within 15% error at a 90% confidence limit. Anything outside of this was classified as Inferred (Wawruch & Betzhold, 2005; Leuangthong & Deutsch, 2005).

2.2.12 Mineral Resource Classification methods applied by manganese mines

Most South32 Limited mines classify Mineral Resources “*based on drill spacing considering data density, data quality, geological continuity or complexity and estimation quality*.” Cannington, a South32 mine in Australia, focuses solely on drill hole spacing as a classification criterion (South32 Limited, 2015).

African Rainbow Minerals (2016) and Assmang Proprietary Limited (2015) keep the classification criteria vague during reporting, stating that “*The classification into*

Measured, Indicated and Inferred Mineral Resources is done by consideration of geostatistical parameters, spacing of boreholes, geological structures and continuity of the mineralisation".

Gloria mine makes use of a similar, although more limited approach by classifying all material less than 50m away from the face as Measured, and everything else as Indicated. Gloria does not mention the separation of Inferred Resources from Indicated resources (African Rainbow Minerals, 2008).

The Mineral Resource and Reserve statements released by the above-mentioned manganese mines do not mention uncertainty in either the geological or Mineral Resource models. Although not referring to manganese deposits, Dohm (2004) highlighted the importance of considering uncertainty in both the geological and Mineral Resource models.

2.3 Scorecards documented in published literature

Snowden (1996) was one of the first authors to suggest the implementation of scorecards for Mineral Resource classification. By referring to the JORC code, the author developed the classification shown in Table 4 as an example of the various assessment criteria involved in determining the resource confidence for a given deposit. The checklist can be used for both qualitative and quantitative observations and be incorporated in the final decision of appropriate confidence.

The author suggested practical considerations which should be considered in the assignment of confidence. Drilling, sampling and assay integrity, drill hole spacing, geological control and continuity, grade continuity, estimation method and block size, potential mining method and reporting period should all be considered during Mineral Resource confidence classification (Snowden, 2001).

Table 4: Example of a classification log and assessment (Snowden, 1996).

ASSESSMENT CRITERIA	COMMENT	≅ Inf	≅ Ind	≅ Meas	Inf	Ind	Meas
GEOLOGICAL CONTROL							
Geological Information	*Availability/ quality/ detail of logging, geological interpretation*						
DATA INTEGRITY							
Co-ordinates	*Survey quality, downhole surveys*						
Drilling Technique	*% RAB, % RC, % DDH*						
Assay Quality	*Sample interval, selective assaying or not, detection limits applied to intervals not sampled, type of analysis*						
MINERALISATION CONTINUITY							
Domaining	*Basis for domaining (oxidation, geology, mineralisation envelope)*						
Drillhole Spacing	*With respect to continuity of mineralisation*						
Estimation Technique	*Manual or geostatistical, method (eg. median indicator kriging with high grade search restriction), top cuts applied, base of drilling, geological, end constraints (essentially summarises the assumptions and decisions made with regard to the model)*						
Variogram Continuity	*Ranges, anisotropy, sample pair confidence, type of variogram used and ranges used for classification (eg. range corresponding to <2/3 sill => measured, range corresponding to >2/3 sill and < range of continuity => indicated, > range corresponding to sill => inferred, nugget as a % of sIll*						
Sample Numbers	*eg. 5 => measured, 2=> indicated, 1=> inferred*						
ECONOMIC SENSITIVITY							
Cutoff Grades used	*With respect to mining method*						
Mining Scenario	*Open pit/ underground, bulk/ selective*						
RESOURCE	*Allow for entry of actual grades and state whether acceptable in terms of JORC code and date*						

At a presentation given by the SAMREC, SAMVAL & SANS Working Committee, Mathuray (2015) presented a Mineral Resource classification criteria for coal shown in Table 5 below. The author highlighted the relationships between inventory coal, coal resource and coal reserve and the public reporting codes. The addition of "Reconnaissance Inventory Coal" over and above the classical Inferred, Indicated and Measures confidence categories was put forward for "very low" confidence and "uncertain or unreliable" data integrity.

Table 5: Criteria for the Classification of Inventory Coal and Coal Resource (Mathuray, 2015).

CLASSIFICATION CATEGORY	CONFI-DENCE	DATA INTEGRITY	CONTINUITY REQUIREMENTS			
			Physical		Coal Quality	
			Seam Geometry	Structure	Raw Coal Quality	Washed Coal Quality
Reconnaissance Inventory Coal	very low	uncertain or unreliable	assumed at low level of confidence	assumed at very low level of confidence	limited raw data	limited or no washability data
Inferred	low	uncertain or limited	assumed at low level of confidence	assumed at a low level of confidence	assumed at low level of confidence	assumed at low level of confidence
Indicated	moderate	reliable	confirmed	assumed at a moderate level of confidence	assumed at moderate level of confidence	assumed at moderate level of confidence
Measured	high	reliable	confirmed	confirmed	confirmed	confirmed

The De Beers Group recognised the geologically complex environment in which diamonds occur and the significant variability in grade, size, colour, density and host rocks of diamonds. Having identified the need for an improved Mineral Resource classification, the company invested time in developing the Mineral Resource Classification System (MRCS). The MRCS prototype identified 5 key criteria: namely, geology, grade, volume, revenue and density, by posing a set of questions and scoring the answers. After exhaustive testing of the MRCS, the classification evolved into a set of representative and consistent classifications. De Beers takes considerable pride in the MRCS, considering it to be best practice in the diamond mining industry (Duggen *et al*., 2017). A flow chart of the MRCS process employed by De Beers is captured in Figure 8. Table 6 illustrates the 5 key criteria in De Beers' diamond classification and the maximum allowable scores for each group of questions.

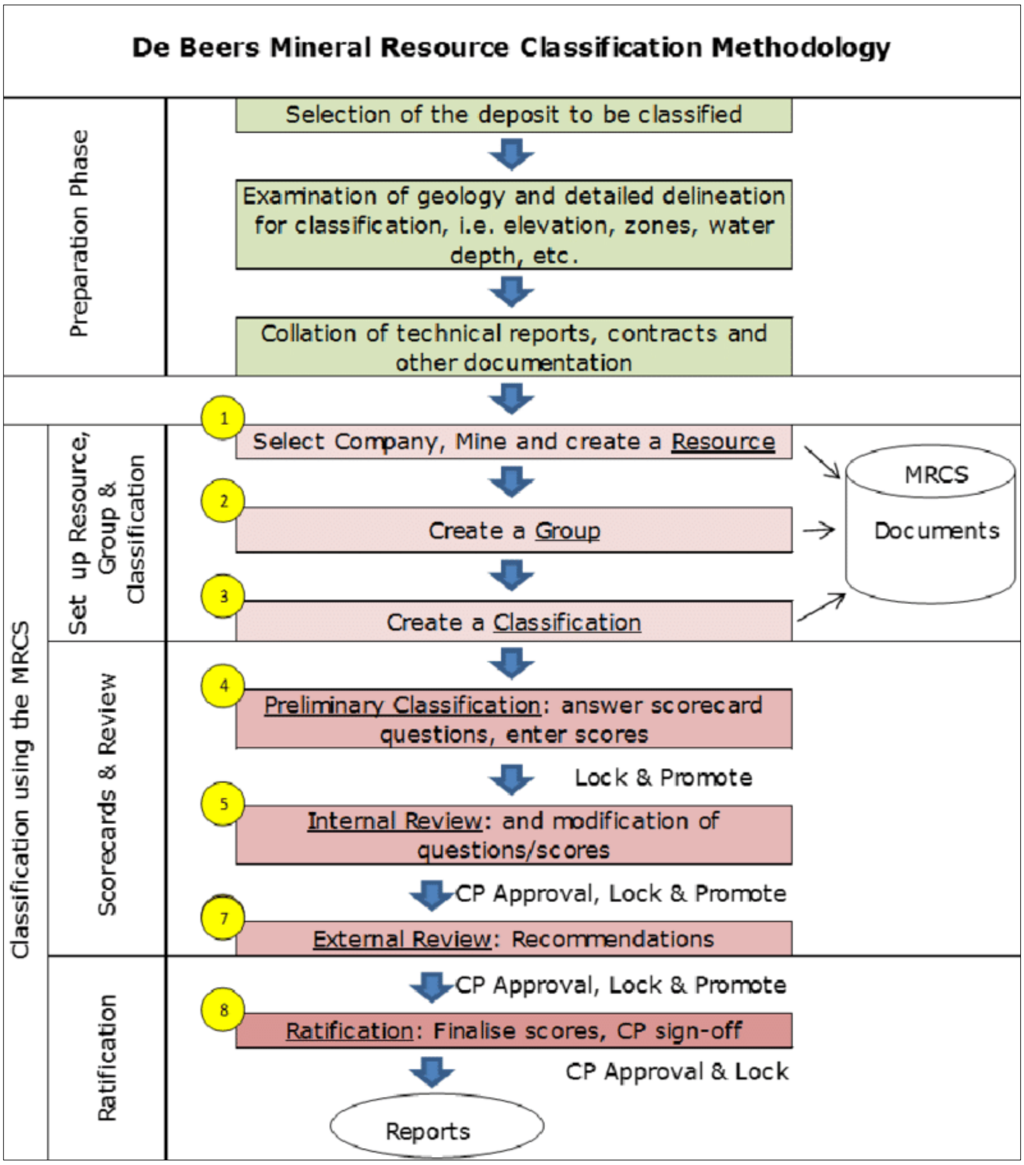


Figure 8: De Beers MRCS methodology (Duggan *et al.*, 2017).

Table 6: Five key criteria of the De Beers MRCS with groups of questions and maximum possible scores (Duggan *et al.*, 2017).

Illustration of the maximum possible score for groups of questions in each scorecard

Group	Geology	Grade	Volume	Revenue	Density
Knowledge techniques	20				
Sampling/data integrity	20	15	30	20	20
Sample representivity	20				
Sample accuracy		15			
Sampling programme		10	10	10	10
Estimation methodology		20	20	20	20
Definition of the geological model	40				
Other risk analysis techniques		40	50	50	50
Totals	100	100	110	100	100

Magnus (2017), in her masters research report investigated coal Mineral Resource classification methods applied elsewhere in the world, in light of the minimum requirements and guidelines set out by the 2012 JORC code and the 2004 South African National Standard (SANS) guide. With the objective to identify the most appropriate Coal Resource classification approach for the Witbank Coalfields in South Africa, three methods of uncertainty and probability were considered, Non-linear estimation approach, Conditional simulation and Global estimation variance.

This author found Global estimation variance to be most appropriate, conceding that the analysis did not result in robust Coal Resource classification of estimates but rather provided more insight into the variability of the deposit. The scorecard captured in Table 7 is linked to a coal map of mineralisation shown in Figure 9 below.

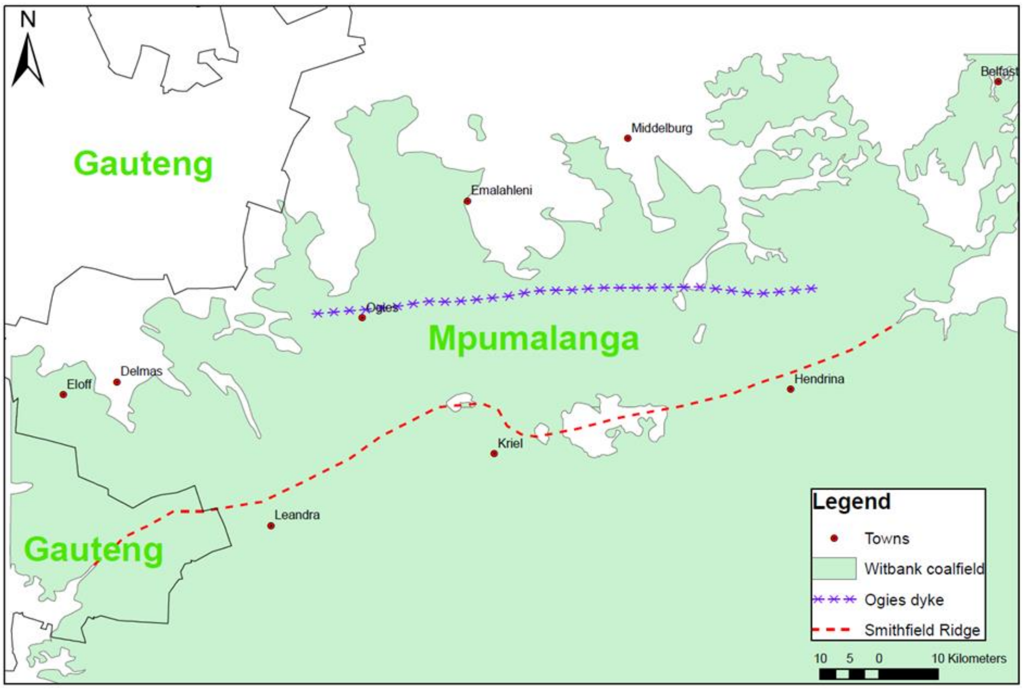


Figure 9: Proposed final geozones reflecting broad scale homogeneity and directions of continuity and linked to the scorecard Table 7 (Magnus, 2017).

Table 7: Proposed scorecard for Coal Resource Classification, incorporating geological factors, geostatistical analysis as well as drillhole spacing analysis (Magnus, 2017).

Geological Occurrences	Description			Confidence factor	Weighting	Additional comments
Faulting	Unaffected by tectonic deformation			5	10%	Only known faulting, based on exploration drilling or geophysics, can be evaluated
	Affected by some extent of tectonic faulting, folds are open with long wavelengths and faults are uncommon			3		
	Severely affected by tectonic activity, folds are tight and over turned			1		
Weathering	Coal seams not affected by weathering			5	10%	The influence of weathering as a result of the limit of weathering or in the vicinity of faults/dykes need to be evaluated
	Coal seams mildly affected by weathering			3		
	Coal seams severely affected by weathering			1		
Intrusions	Unaffected by magmatic intrusions			5	10%	The influence of intrusions in terms of effect on coal quality and size of intrusions need to be considered
	Affected by some intrusions, coal in the vicinity of intrusions are less burnt and affected area is less than 1x the thickness of the intrusion			3		
	Severely affected by intrusions, coal in vicinity of intrusions are burnt and affected area is more than 1x the thickness of intrusion			1		
Floor undulations	Moderate floor undulations of less than 10º expected			5	5%	Floor rolls are common in the Witbank coalfield and causes difficult mining conditions, especially for underground workings
	Moderate floor undulations of less than 15º expected			3		
	Moderate floor undulations of more than 15º expected			1		
Geological variability	**Level of assurance**				**Weighting**	
Drill spacing providing geological confidence	Zone 1	Zone 2	Zone 3			As delineated in Figure 17 of this research report
	High: Drillhole spacing less than 100m	High: Drillhole spacing less than 200m	High: Drillhole spacing but less than 200m	5	30%	Please see proposed geological zones in Figure 17
	Moderate: Drillhole spacing greater than 100m, but less than 150m	Moderate: Drillhole spacing greater than 150m, but less than 200m	Moderate: Drillhole spacing greater than 200m, but less than 250m	3		
	Low: Drillhole spacing greater than 150m	Low: Drillhole spacing greater than 200m	Low: Drillhole spacing greater than 250m	1		
Quality of data	**Level of confidence**					
Assay data	High level of confidence, relevant and appropriate QAQC applied to all data			5	15%	
	Moderate level of confidence, QAQC applied, but not to satisfactory levels/standards			3		
	Low level of confidence due to historic data/labs or little or no QAQC applied			1		
Logging data	High level of confidence, relevant and appropriate QAQC applied to all data			5	20%	
	Moderate level of confidence, QAQC applied, but not to satisfactory levels/standards			3		
	Low level of confidence due to historic data/labs or little or no QAQC applied			1		
TOTAL					**100%**	

CHAPTER 3

EXPLORATORY DATA ANALYSIS (EDA)

Statistics are concerned with the location, spread and shape of the statistical distribution of the data and Exploratory data analysis (EDA) is a crucial first step in understanding the data. It is assumed that the reader has a basic understanding of statistical principles and their application in the analysis of natural phenomenon. Whilst the theory is not presented in detail, the aspects relevant to this research are emphasised.

3.1 Graphical representation of data

Graphical representation of data assists in summarising the data in order for the important aspects to be identified. The histograms displayed in Figures 10 to 14 are generated from the composited borehole sampling and the composited underground face chip sampling data obtained from Wessels mine.

3.1.1 Histogram of the Mn %

Manganese ore bodies are comprised primarily of manganese, with the presence of iron and other trace elements. Figure 10 shows a histogram of all the Mn% values in the database. The raw data is negatively skewed due to the inclusion of waste hanging wall, foot wall and dyke samples.

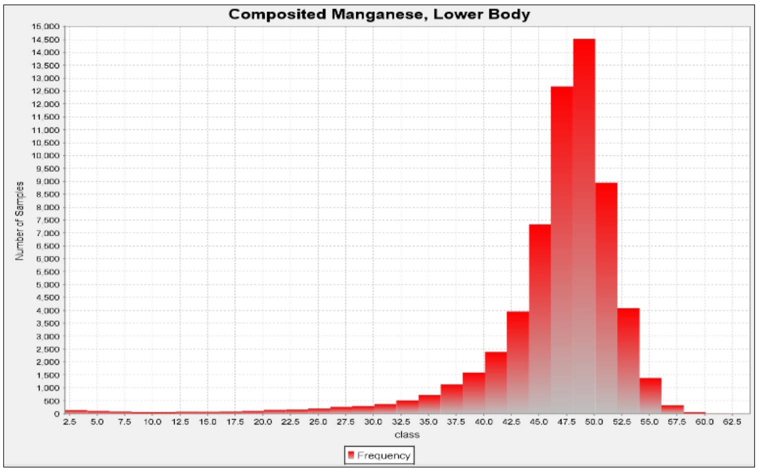


Figure 10: Histogram Mn % without cut-off.

Waste does not form part of the Mineral Resource and is separate from the manganese ore body. Bore hole samples include 1m of hanging wall and 1m of foot wall to verify, by assay results, that the logging geologist has accurately placed the boundary contacts between manganese and ironstone. This is especially important for the Lower Body basal contact which is gradational in nature. Additionally, underground face chip samples incorporate the entire face as exposed by mining, including waste ironstone or dyke material. The hanging wall and foot wall exposures do not form part of the Mineral Resource and are excluded from the statistical and geostatistical analyses.

From a total metal content summation study and considering the split where the Mn concentration exceeds that of Fe, a bottom cut-off of 30% Mn was introduced by the researcher. The introduction of a bottom cut will prevent the underestimation of manganese grade due to the inclusion of a disproportionate number of waste samples. From the probability distribution shown in Figure 11, Lower Body manganese grade has a slightly negatively skewed distribution.

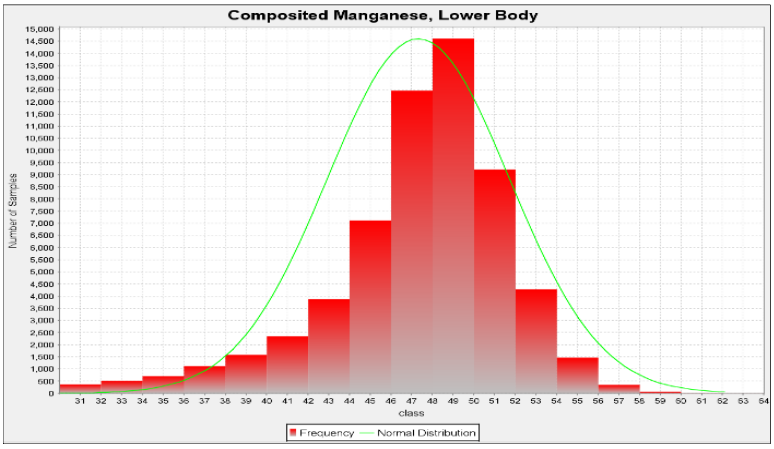


Figure 11: Histogram Mn % ≥ 30% with fitted normal distribution.

3.1.2 Histogram of the Fe %

Manganese removes oxygen and sulphur when iron ore is converted to steel. The incorporation of manganese with iron, creates an important alloy (steel), which has reduced brittleness as compared to pure iron (United States Geological Survey, 2014). Due to the economic importance of steel, the concentration of iron is just as important as the concentration of manganese. The Global model incorporates a Fe estimate for accurate prediction, reliable classification and meaningful reconciliation.

Figure 12 shows a histogram of all the Fe % values in the database. The raw data is strongly positively skewed due to the inclusion of ore samples along with waste hanging wall and foot wall samples.

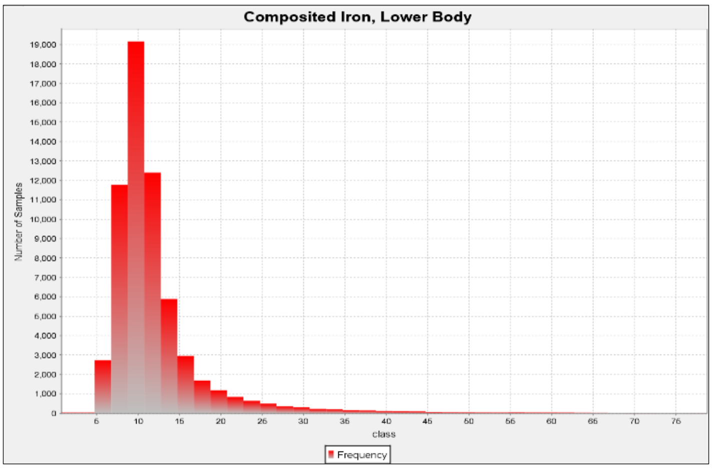


Figure 12: Histogram Fe % without cut-off.

Due to the nature of the chip and the bore hole sampling as previously explained, the hanging wall and foot wall exposures were excluded from the statistical and geostatistical analysis. From a total metal content summation study and looking at the split where the Fe% exceeds the Mn%, a top cut-off of 35% Fe was introduced. The introduction of a top cut is to prevent the overestimation of Lower Body iron content as a result of the inclusion of a disproportionate number of waste (ironstone) samples in the data.

The distribution of the % Fe within the Lower Body manganese seam appears in Figure 13. The distribution is positively skewed and deviates from a normal distribution. The composited Fe data reflects the same data records as those used for the Mn and CaO distributions.

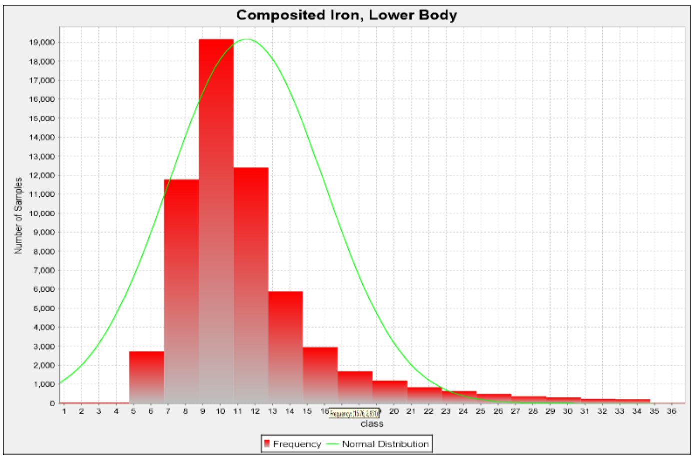


Figure 13: Histogram Fe % ≤ 35% with fitted normal distribution.

3.1.3 Histogram of CaO %

In the generation of silicomanganese, slag is produced as a by-product. An increase in the amount of slag at the expense of Mn ore will lead to a larger slag/metal ratio and an increased consumption of energy. CaO, along with MgO and Al_2O_3, is one of the more stable oxides which go entirely to the slag phase. Although CaO does not take part in the reduction process, it is of great importance to the thermodynamic and physical properties of the slag phase. The specific power consumption for production of standard silicomanganese from a mixture of manganese ore can be typically 3500-4500 kWh/tonne metal. This is dependent on the amount of metallics added to the feed. The power consumption can increase by 50 kWh for each 100 kg of slag produced (Olsen & Tangstad, 2004).

Control over the energy costs involved in the smelting processes is of particular importance to alloy producers due the high input electricity cost. The financial implications associated with the cost of electricity require that alloy producers also pay attention to the CaO content. Wessels mine thus bears the responsibility of accurately estimating and predicting CaO content, as well as the responsibility for classification. The Global model incorporates a CaO estimate for accurate prediction, classification and reconciliation.

From the probability distribution in Figure 14, CaO grade appears to be approximately normal. No cut-offs were applied to the CaO dataset. The composited CaO data reflects the same records as those used for the Mn and Fe distributions.

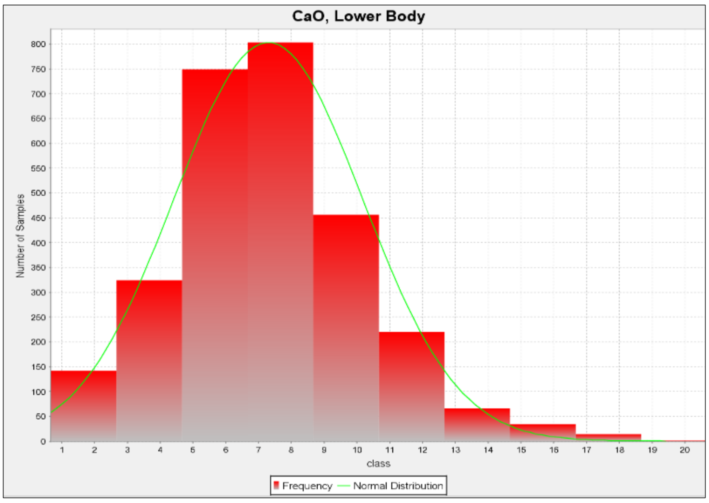


Figure 14: Histogram CaO % with fitted normal distribution.

3.2 Summary statistics

A requirement for reliable statistical and geostatistical analysis is a clean data set. The cleaned and composited data was received from Wessels mine. Table 8 shows the cleaned and composited data which was analysed statistically and geostatistically. Details on the compositing method are captured under Section 4.5 of this report.

Table 8: Statistical summary of composited variables in the Lower Body.

	Mn (%)	Fe (%)	CaO (%)
n	60043	60919	2809
Minimum	30.0 (lower cut)	0.8	0
Maximum	62.1	35.0 (upper cut)	19.4
Range	32.1	34.2	19.4
Standard deviation	4.4	4.5	2.9
Variance	19.3	20	8.3
Mean	47.3	11.5	7.3
Mode	49.2	9.8	7.5
Median	48.0	10.4	7.1
Coefficient of variation	0.1	0.4	0.4
Skewness	-1	+2.1	+0.5
Kurtosis	4.6	8.7	3.6

3.3 Measures of Central Tendency

The central location of data is often described by the mean, mode and median. The relationship between the three descriptors is used to indicate the shape of the distribution or the degree of symmetry of the data (Dohm, 2016a).

Measures of central tendency indicate that the distribution of manganese (Mn %) grade is moderately negatively skewed (Average ≈ Median ≈ Mode), approaching a normal distribution. The arithmetic mean is 47.3% and the median is 48.0%. The difference between the mean and median is less than 1%, which is insignificant. This implies that the mean manganese grade can be used as an acceptable estimator for the population.

The central location of the iron data shows the Fe distribution to be moderately positively skewed (Average > Median > Mode). The arithmetic mean is 11.5% while the median is 10.4%. The difference between the mean and median is approximately 1%, which may be significant. The mean might not be an acceptable estimator for the population. A log normal 3 parameter estimate may be more appropriate.

Calcium oxide (CaO) is slightly negatively skewed (Average ≈ Median ≈ Mode), approaching a normal distribution. The arithmetic mean is 7.3%, the median is 7.1%. The difference between the mean and median is less than 0.5%, which is insignificant. This means that the mean can be used as an acceptable estimator for the CaO grade of the ore body.

3.4 Variability of the data

The variance and standard deviation are measures of the spread of the data around the mean. Parameters such as range, variance, standard deviation and coefficient of variation describe how similar or dissimilar the observed values are for a particular variable. (Dohm, 2016a).

Ore bodies that have been affected by significant strato-tectonic activity are expected to show greater spread in grade. The most important geological features affecting Lower Body grade are faults and hydrothermal alteration; magmatic intrusion and contact metamorphism; and the sub-outcrop erosional unconformity.

<u>Faults and hydrothermal alteration</u>

Hydrothermal enrichment took place when hot fluids percolated through faults during the Namaqua orogeny approximately 1.1 Billion years ago. The hydrothermal fluids leached calcium, magnesium, carbon dioxide and silicon dioxide from the low-grade Mamatwan-type ore, leaving behind recrystallized, coarse-grained, high grade, Wessels-type ore (Gutzmer & Cairncross, 2002).

<u>Magmatic intrusion and contact metamorphism</u>

The intrusion of the predominantly NE-SW trending dykes had two different effects on the surrounding host rock. Most of the dykes are associated with reduced Mn grade and increased Fe content, while other dykes are associated with increased Mn content and reduced Fe content. Gutzmer and Beukes (1998) concluded that the 'bostonite' dykes have been affected by at least two distinct styles of alteration, magmatic intrusion and contact metamorphism. The most dominant is pervasive hydrothermal alteration that is expressed by extensive sericitisation and increased hematite content. The second alteration style is defined by metasomatic transformation of the contact zone of the dykes to the surrounding manganese ore into calcium-bearing and manganese-bearing silicates.

<u>Sub-outcrop erosional unconformity</u>

The Olifantshoek unconformity allowed for the movement of fluids which resulted in the leaching of manganese, the increase of iron and calcium, and the increase of aluminium, magnesium and silicon. The latter are elements which are associated with the overlying sedimentary assemblages.

3.5 Shape of the Distribution

Skewness is a measure of symmetry of the data. A distribution is said to be symmetric when it looks the same to the left and to the right of the centre point. If skewness is negative, the distribution is said to be negatively skewed. If skewness is positive, the distribution is described as positively skewed. If skewness is zero, then the distribution is symmetrical (Isaaks & Srivastava, 1989).

Kurtosis is a measure of whether the data distribution is peaked or flat relative to a normal distribution. Data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Distributions of data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. The kurtosis statistic measures the concentration of the values in the centre as opposed to the thickness of the tails (Dohm, 2016a).

The Mn% grade skewness is -1.0, confirming that the data is moderately negatively skewed. The kurtosis (4.6) is slightly leptokurtic, and is comparable to the kurtosis of 3, which is typical for normal distributions. The coefficient of variation (0.1) reinforces the low variability of the Mn dataset.

Fe grade skewness is +3.6, confirming that the data is positively skewed. The kurtosis (21.1) is leptokurtic, with a high peak on the left and a long, thin tail to the right. As shown by Figure 13, the skewed distribution of iron means that the average may be a poor estimator of the ore body mean.

The central limit theorem states that as the number of samples increases, given any population with a mean and variance, the sampling distribution of the sample mean will approach a normal distribution with mean and standard deviation. Furthermore, the sample size will be large enough for the arithmetic average to be an unbiased estimator of the expected value when the difference between the expected value of the assumed probability density model of the data and the average of the data becomes negligible (Dohm, 2016a).

To improve the global estimate for the Fe%, a cumulative log probability plot of the composited data is generated to see whether that would give a distribution closer to normality. The data is transformed using the following equation:

$$\mathbf{Y = \ln (Fe\%)} \qquad \text{Equation 2}$$

The observed cumulative log-probability plot for Fe chip data (Figure 15) deviates from a normal distribution at the lower end. The cumulative probability plot bends downwards, implying that the additive constant might be used to transform to a log normal distribution.

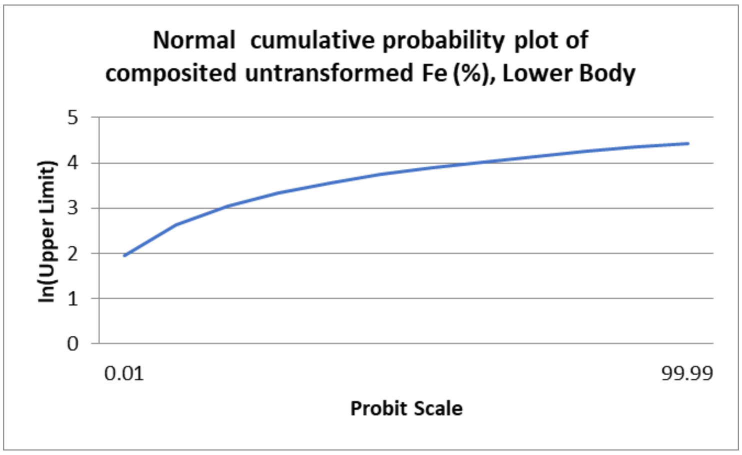


Figure 15: Normal cumulative probability plot of composited Fe data.

A 3-parameter lognormal LN(3) estimate using the following formula is applied:

$$\mu^* = e^{(\xi_\beta - \sigma_\beta^2)} - \beta \qquad \text{Equation 3}$$

Where

μ^* = the estimate of the population mean

e = the exponential function

β = the additive constant is introduced in order to achieve normality

ξ_β = the average of the ln (grade% + β) values

σ_β^2 = the variance of the ln (grade% + β) values

The LN(3) estimator of the mean is calculated to be 9.78 % Fe from the composited iron data. The arithmetic mean (average) is 11.5% Fe and the LN(3) estimate for the mean is (≈ 9.8% Fe), a difference of 1.7% Fe is observed, highlighting the influence of the high grade values with a low probability on the calculation of the arithmetic mean even when more than 60000 samples are considered. It is concluded that the average is an unacceptable estimator for Fe%, and the 3-parameter lognormal estimator is more appropriate.

The CaO skewness is +0.5, confirming that the data is approximately symmetric. The kurtosis (3.6) is approximately mesokurtic, with a balanced centre and tails. The skewness and kurtosis are comparable to those of a Gaussian distribution, which has a typical skewness of 0 and a typical kurtosis of 3. Because the coefficient of variation

(0.4) is less than 1, it indicates moderate variability around the mean, which is typical of normal distributions.

3.6 Distribution of the Ore body Thickness

The Lower Body average mining thickness is 5.5m. Manganese ore that has been affected by significant strato-tectonic activity, is expected show a greater spread in thickness and grade due to the influence of thrust faults and the erosional unconformity. Figure 16 shows the “full reef” Lower Body ore composites created from both borehole samples and underground chip samples.

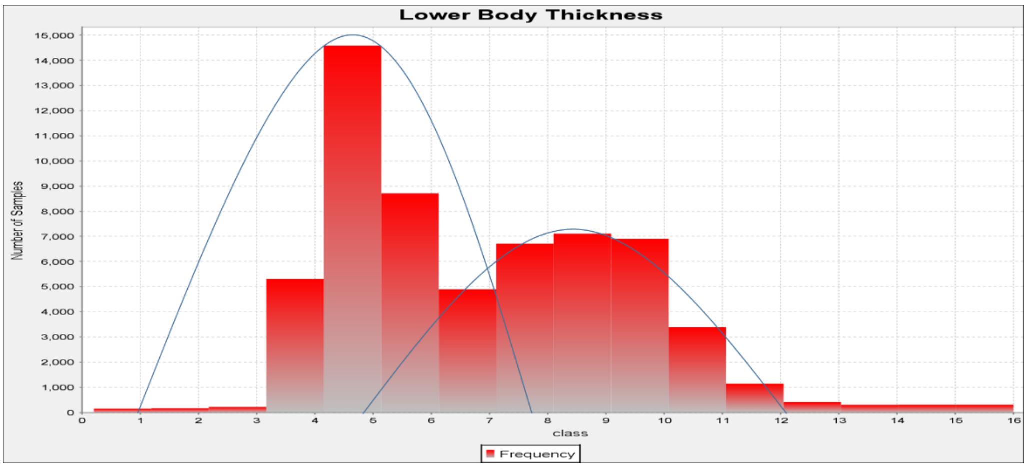


Figure 16: Lower Body thickness histogram, generated from composited data.

The outliers on the lower end of the histogram are most likely in proximity to the Olifantshoek unconformity where the Lower Body manganese unit has been eroded away. The Olifantshoek erosional unconformity at the base of the Olifantshoek group and at the top of the Postmasburg Group, see Figure 5, resulted in ore body thinning and, in some areas, complete erosion of the Lower Body. The outliers on the upper end of Figure 16 most likely represent the nappe structures, where there is known and mapped Lower Body duplication due to the prevalence of thrust faults. Thrust faults are almost entirely restricted to the West Block.

From the thickness histogram of Figure 16, it appears as though there may be a bimodal distribution, with the intersection of the two distributions around 6.7m. The first distribution has a mode of approximately 5.5m and the second a mode of approximately 8.5m. The two distributions are suspected to be due to the inclusion of two types of data, chip samples and borehole samples. The first distribution with a mode of 5.5m mostly represents the Chip data, where only a portion of the Lower Body is mined. The mining height is 5.5m on average, in line with the mode. The second distribution with a mode of 8.5, mostly represents the borehole data, where the entire Lower Body is sampled.

The borehole data comprises approximately 1% of the total data, while the chip data represents the remaining 99% of the data. This is reflected in the frequencies of the two modes.

To test for bimodality in thickness distribution, additional geostatistical analysis will be conducted in Section 4.4, by looking into the spatial distribution of the thicker and thinner areas, to assess confidence in the estimation of thickness.

3.7 Relationship between manganese, iron and calcium oxide

Scatter plots are a useful method of displaying relationships between two continuous attributes, known as a bivariate description (Goovaerts, 1997). The raw uncomposited data for both manganese and iron is displayed in Figure 17, with no cut-offs applied.

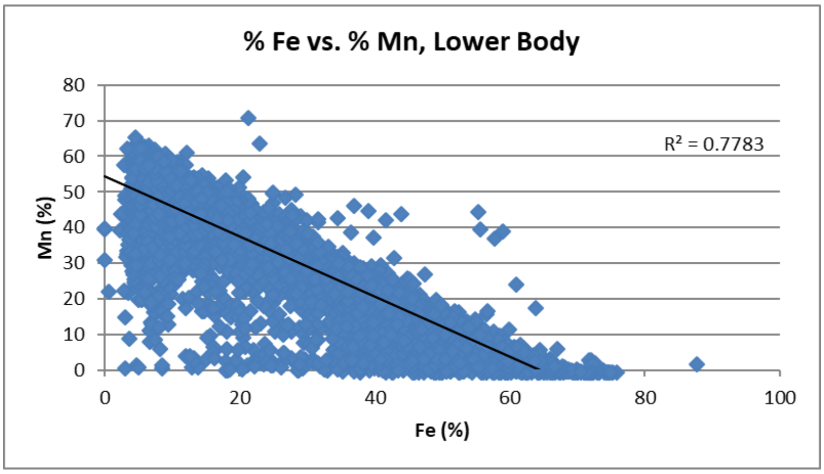


Figure 17: Scatterplot showing uncomposited and uncapped data, Fe (%) vs. Mn (%).

The correlation coefficient tells us about the intensity of the linear relationship between two variables. The correlation coefficient (r = -0.83) indicates a strong negative relationship between Fe and Mn. The inverse relationship between manganese and iron is well known at Wessels mine and reflects the general trend that high Fe grades indicate low Mn grades, and vice versa.

The regression coefficients displayed in Figures 18 and 19 imply virtually no relationship between CaO and Mn and CaO and Fe, respectively. The correlation coefficients calculated for the uncomposited data are in agreement with the previous statement. From the low correlation between Mn and CaO (0.08) and Fe and CaO (0.16) and the scatter plots (Figure18 and Figure 19), it appears that CaO mineralisation may have different geological controls than those of Fe and Mn.

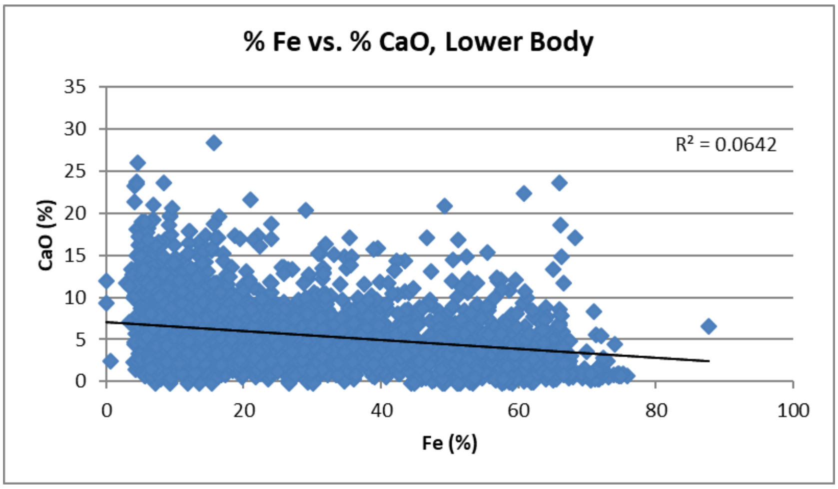


Figure 18: Scatter plot showing uncomposited and uncapped data, CaO (%) vs. Mn (%).

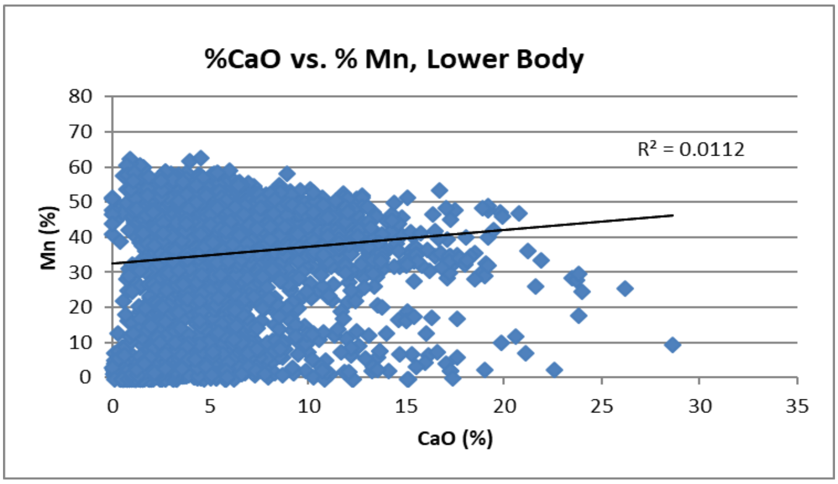


Figure 19: Scatter plot showing uncomposited and uncapped data, CaO (%) vs. Fe (%).

CHAPTER 4

GEOSTATISTICAL ANALYSIS

4.1 Manganese

Geostatistics is a crucial tool that can give a quantitative measure of spatial uncertainty. Geostatistical analysis should be carried out, prior to making statements regarding geological confidence (Olea *et al*., 2011).

The best Mineral Resource classification approaches integrate both practical geological knowledge and geostatistics. Assuming that the underlying data is of sound scientific integrity, the geostatistics should confirm the geological interpretation and vice versa (Dohm, 2016b).

It is assumed that the reader has a basic understanding of random functions, variography and geostatistical principles. The theory will not be presented in detail, although some of the important aspects are emphasized for the completeness of the chapter.

4.1.1 Spatial variability

Spatial analysis is the foundation of geostatistical evaluation of Mineral Resources. Depending on how you look at it, it is a measure of uncertainty or of confidence. A low spatial variability means that the spatial correlation and spatial continuity is high, resulting in gradual changes over distance (Magnus, 2017).

The information available at the time of estimation represents only a fraction of the ore body. As a result, grade estimates are generated from partial information. The decision about whether a block is waste, or ore is made from estimates rather than the true block value. The information effect results in a reduction in mining selectivity. Therefore, mining cannot occur at the sample level and the observed grades are often lower than expected. Additional drilling and sampling can help to reduce the impact of the information effect.

To quantify the information effect (IE), we need the block variance (BV) and the kriging variance (KV). The information effect is calculated by subtracting the kriging variance from the block variance (Dohm, 2016b).

$$\boldsymbol{Information\,Effect} = \boldsymbol{IE} = \frac{\boldsymbol{BV - KV}}{\boldsymbol{BV}} \qquad \text{Equation 4}$$

Wessels mine's Inverse distance weighting (IDW) estimate does not have the variance parameters which are included in Equation 4. Considering the known existence of the information effect, it would be premature to simply assume that there are no significant trends in manganese grade. Due to the influence of the geology of the area, it is expected that the ore body will exhibit some spatial variability. Variography is performed as a way of analysing the spatial continuity of the mineralisation of the ore body.

4.1.2 Variography

A variogram is a graphical representation used to understand spatial variation. A typical variogram with its various components is shown by Figure 20. Information that can be extracted from a variogram includes the inherent variability of a sample (nugget effect), the pattern of mineralisation, the extent to which samples are related, as well as the maximum variability within all selected samples (Nengovhela, 2018).

Variation, defined as the square difference between points of data, is displayed as a function of distance. The pairs of data points are grouped into distance classes, also known as lags. The variogram relates the degree of similarity between sample grades to the distance between them, along a given orientation (Snowden, 2001).

The experimental semi-variogram is calculated from the equation:

$$\hat{\gamma}(h) = \frac{1}{2N_h}\sum_{i=1}^{N_h}[\{Z(x) - Z(x+h)\}]^2 \qquad \text{Equation 5}$$

Where $\gamma(h)$ is the experimental variogram value at distance h, Z(x) is the sample value at location (x), Z(x + h) is the sample value at location (x + h) and the lag (h) between (x + h) is the sample value at location (x + h) and the lag (h) between samples is a vector determining the distance and direction between the samples. N(h) is the number of pairs in that direction and that distance between the samples (du Toit, 2018).

The nugget effect (C_0) is used to describe how well sample results can be reproduced by repeated sampling at the same location. A more homogeneous mineralisation will exhibit a low nugget effect. On the semi-variogram, the nugget effect is represented by the intersection of the semi-variogram on the y-axis (Snowden, 2001).

Where the separation distance tends to zero the semi-variogram, represents the random variation in the sample values. The Nugget effect may be due to sampling and assaying error, smaller microstructures or nested variogram at the shorter distance where there is no borehole. The semi-variogram flattens at the sill ($C_1 + C_0$). The total sill represents a value equal to the sample variance (Haldar, 2013).

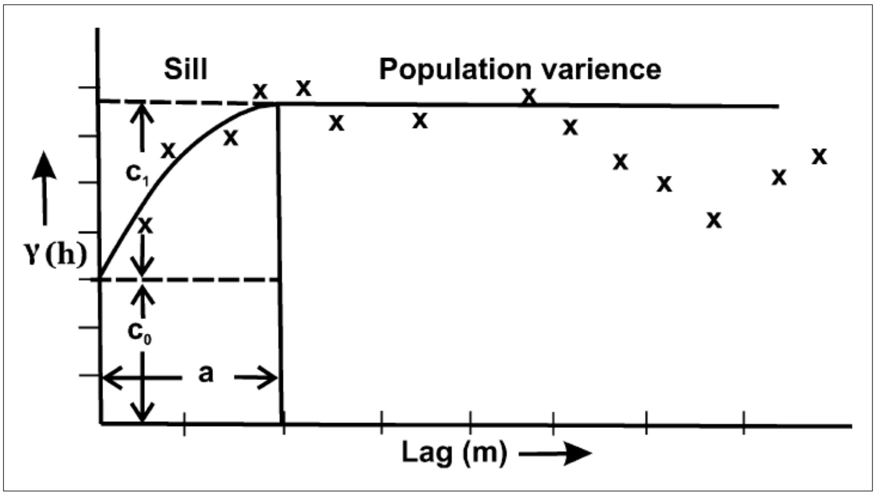


Figure 20: Typical semi-variogram plot, with the model fitted (Haldar, 2013).

The range of influence (a) represents the distance within which samples are correlated. It allows the anisotropy of the mineralisation to be measured mathematically. The distance at which the semi-variogram levels off is the range of influence (Snowden, 2001).

The zone of influence (C_1) is that neighbourhood beyond which samples become uncorrelated, where samples become independent of each other in space. The structured component of the semi-variogram is represented by the area between the nugget and the sill. The structured component represents samples which are spatially related according to distance and direction. A steady and smooth increase is indicative of high continuity of mineralisation, until it plateaus at some distance (Haldar, 2013).

4.1.3 Stationarity

The theory of geostatistics is often divided into two categories, linear and non-linear geostatistics. Linear geostatistics is most commonly applied in the South African mining industry. The application of linear geostatistics implies the assumption of a stationary random function. A random function is a set of spatial variables (Morgan, 2011). In this case, the random function is grade in three dimensional space.

Stationarity is a property of the random function and not of the data. This means that the mean and variance are the same in the whole space. First order stationarity is required for the application of non-linear techniques such as disjunctive kriging, indicator and probability kriging. The definition of strict stationarity requires that the joint distribution of any number of points be invariant under translation, if the moment exists (Myers, 1989).

Conventional geostatistics defines second order stationarity of the random function as constant local means and constant local variances of the random variables in the estimation domain. Determining the influence of the local mean and variance requires representative sampling of the domain. Where large unsampled regions exist in the domain, results can be misinterpreted. Additionally, the scale of observation can lead to the appearance of apparent trend. Without knowledge of the features of the dataset, it may not always be possible to determine whether the trend is apparent or representative. It is therefore recommended to remove the presence of mean and variance trend before estimation (Cuba *et al*., 2011).

Nine experimental semi-variograms were generated in 20 degree (azimuth) increments. All of the semi-variograms were generated at a plunge of 6 degrees, in line with the average dip of the ore body. A lag distance of 50m was calculated as half of the average inter-borehole spacing (100m/2=50m). The maximum distance chosen is 500m, so as to stay within domain boundaries.

The experimental semi-variograms displayed in Figure 21 show a continuous increase, although the rate of increase is different in the different directions. Up to a range of approximately 200m, the variability is the same in all directions, implying that the Lower Body Mn grade is stationary up to 200m.

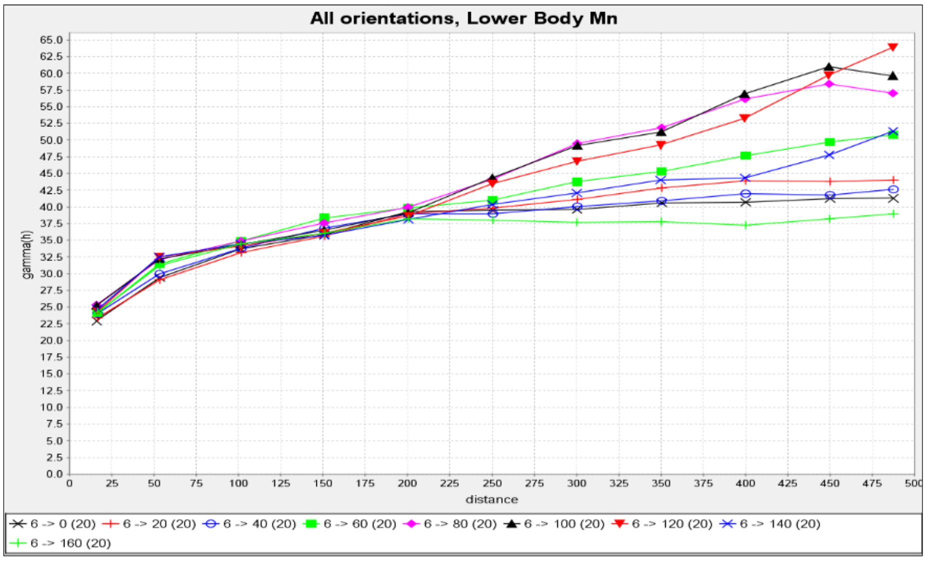


Figure 21: Experimental semi-variograms of the Lower Body manganese grade.

Figure 22 shows that the-semi-variograms of the 0°, 20°, 40°, and 160° directions exhibit stationarity by plateauing off at the sill. From 200m to 500m, the experimental semi-variograms of the 60°, 80°, 100°, 120° and 140° directions exhibit trend in the geozones. Trend is identified by the semi-variograms continuing to increase above the sill. The experimental semi-variograms from Figure 21 are displayed below individually, with the sills visible.

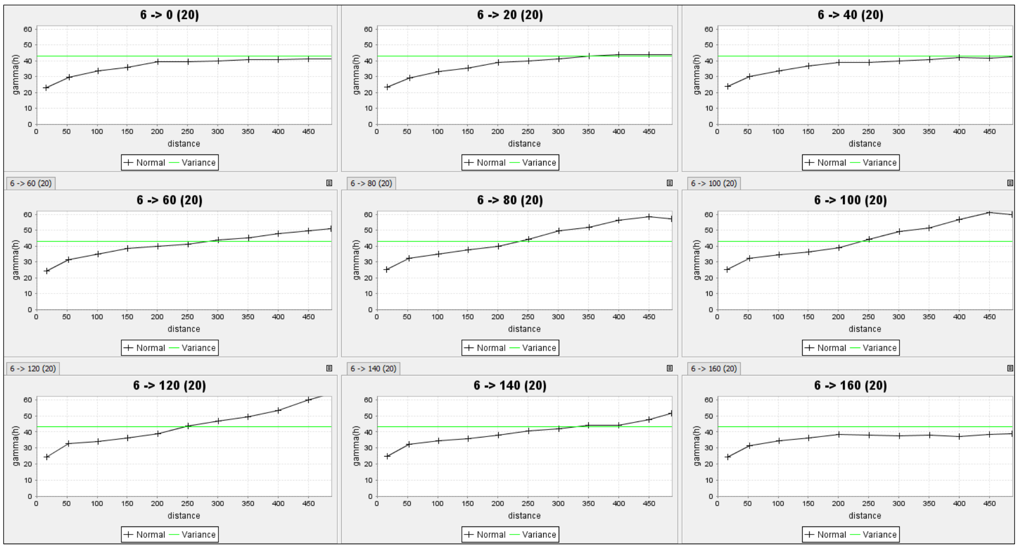


Figure 22: Individual experimental semi-variograms of Lower Body manganese grade.

4.1.4 Anisotropy

Anisotropy refers to a case where the range is longer in one specific direction than in the other, usually perpendicular direction. Anisotropy describes the existence of a preferred direction of spatial continuity (Du Toit, 2018).

Anisotropy is easily depicted by computing semi-variograms in different directions. If the semi-variograms show the same features in different directions, then the underlying structure is defined as 'isotropic'. If the semi-variograms display different features in various directions, then the structure is 'anisotropic' and an average semi-variogram can be considered (Haldar, 2013).

From the individual semi-variograms depicted by Figure 22, the ranges are different in different directions, showing anisotropy. The sills are the same in different directions and the semi-variogram reaches the sill within different distances, indicating zonal anisotropy. In the approximately N-S directions the semi-variograms plateau at the sill, while in other directions they continue to increase above the sill.

4.1.5 Semi-variogram modelling

How to fit the best variogram model is a topic of debate, with automated methods becoming increasingly popular. Questions about the degree of complexity that is justified in fitting the model and the practice of forcing the modelled sill parameter to equal the sample variance do not have standard answers (Cressie, 1993).

Armstrong (1998) emphasised the importance of the behaviour of the semi-variogram at and near the origin on the kriging results and their stability. Morgan (2011) also concluded that the most important aspect of the variogram model is the nugget effect and the slope near the origin. As relates to the practice of forcing the modelled sill parameter to equal the sample variance, Goovaerts (1997) found it an unreliable practice, stating that the core objective of the variogram model is to capture the major spatial structure of the attribute.

Morgan (2005) confirmed that theoretically, the semi-variogram sill is equal to the variance of the attribute being modelled. The author suggested fitting the modelled semi-variogram sill to the experimental semi-variogram, rather than to the sample variance, stating that the sample variance was calculated by assuming random, independent samples, which were generally not the case as samples were usually correlated. This is especially true for skewed distributions, where the estimate of the classical sample variance was frequently poor and unreliable. It is important to remember that the variogram model is an estimate, which carries some degree of error. It follows then that fitting a semi-variogram model as closely as possible to the experimental semi-variogram is not always reasonable.

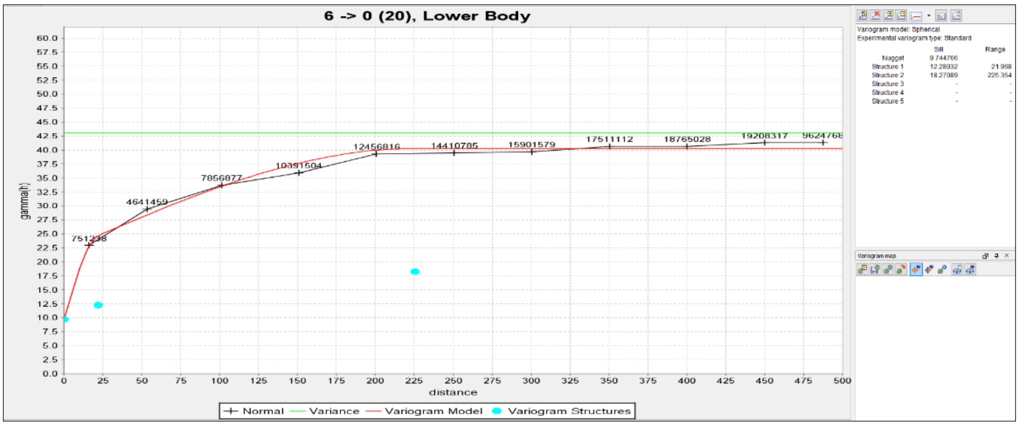


Figure 23: The direction of highest Mn continuity is in the 0° direction.

Figure 23 shows the direction of highest continuity to be in the N-S direction. The continuity is consistent with the strike of the faults and is approximately perpendicular to local orebody dip. Figure 24 shows the direction of least continuity to be in the E-W direction. This direction is perpendicular the dominant N-S trending faults but is parallel to local ore body dip.

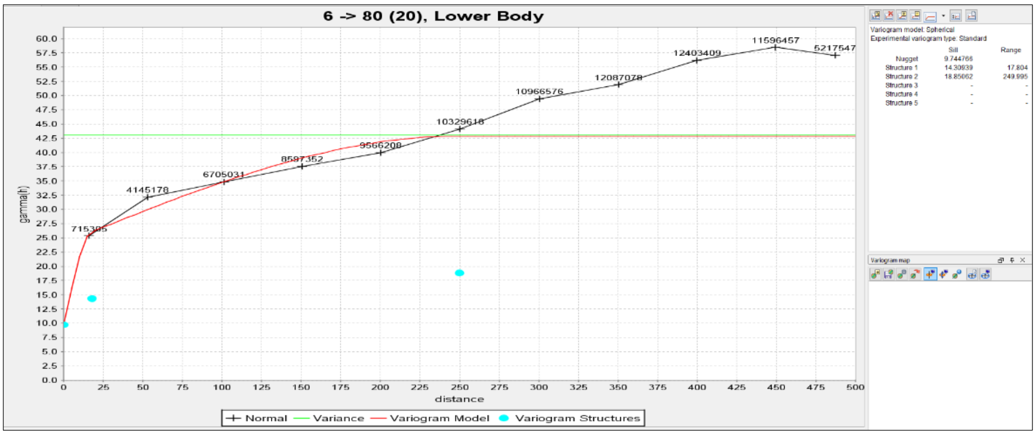


Figure 24: The direction of lowest Mn continuity is in the 80° direction.

A double-structured spherical model was fitted, with a sill of 43 and a nugget of 9.7. This is in agreement with the work of Nengovhela (2013), the Competent Person, who also modelled a double-structured spherical model but with a nugget of approximately 7. The Appendix shows the standardised (normalised) semi-variogram of the 80° direction of lowest continuity. From the standardised Mn semi-variogram, the direction of least continuity exhibits significant tend, with approximately a third of the semi-variogram above the sill.

The large-scale negative correlation indicative of geologic trend shows up as a variogram that increases beyond the sill variance σ^2. Trends are undesirable as they cause the variogram to show a negative correlation at large distances (Gringarten & Deutsch, 2001). IDW will solve the problem of negative weights, because the estimation method weights the samples closest to the estimated blocks the most. This may be one of the reasons why IDW is preferred over ordinary kriging at Wessels mine.

The choice of a double or triple structured variogram model is supported by geological knowledge. Gutzmer and Beukes (1998) confirmed the existence of at least two hydrothermal overprints in the study area. Additionally, it is known that dyke emplacement with associated contact metamorphism and the major faulting with associated hydrothermal alteration of the Kalahari manganese field post-date depositional mineralisation.

Nengovhela (2015) produced a planar variogram for Lower Body manganese. The variance was comparable to that of the researcher at approximately 43. There was significant trend in the variogram, although the author forced the model to plateau at the sill. Nengovhela (2015) showed a higher nugget of approximately 14, as compared to the researchers 9.7. The difference in nugget may be attributed to the difference in the method of nugget determination. Nengovhela (2015) only made use of 394 drill holes to produce a downhole variogram to determine the nugget, while the researcher made use of both chip and borehole data. In this way, Nengovhela (2015) ignored >500000 chip samples in the determination of the nugget. Nengovhela (2015) did, however, generate the planar variogram by incorporating both drill hole and chip data. The modelled ranges were 50m and 300m for the double- structured spherical model.

Lautze and Lukhaimane (2017) modelled a triple structured spherical variogram model with a nugget of 8.9. The ranges were 30m, 155m and 109m for the first, second and third structures respectively. Their Lower Body manganese variogram had a sill of approximately 71. The authors, however, do not mention anything on ore selection or grade capping. It is possible that the high variance is due to the inclusion of ore as well as waste samples in the variography. Additionally, a triple-structured model may be too complex for the tabular ore body. Goovaerts (1997) stated that "*One should avoid overfitting experimental semi-variograms. The objective is to capture the major spatial features of the attribute, not to model any (possibly spurious) details of the sample semi-variograms. When different nested models provide similar fits, one should select the simplest one. Where a spherical model suffices, there is no need to sum two exponential models …. The more complicated model usually does not lead to more accurate estimates.*" (Goovaerts, 1997, p.98). This was further emphasised by the work of Morgan (2005) and Morgan (2011).

4.2 Iron

4.2.1 Fe Stationarity

Stationarity requires that the mean and variance not vary significantly in space. A stationary variable is homogeneous and self-repeating in space. The parameters commonly used to summarise the bivariate behaviour of a stationary random function are the Covariance Function, the Correlogram Function and the Variogram Function.

To investigate stationarity, we can measure the difference between the values of all samples in a given direction (θ) and for a given distance (h) apart. If there is no trend in the data, the sum of the differences between the values of the samples will be approximately zero. The identification of geologically homogeneous zones, commonly called "domains", are crucial in ensuring stationarity (Dohm, 2016b).

Most geostatistical methods rely on the assumption of stationarity. Making proper decisions about stationarity is important for the representativeness and reliability of the geostatistical tools applied (Deutsch & Journel, 1998 cited by Mandava, 2016).

The experimental semi-variograms of Figure 25 show a continuous increase, although the rate of increase is different in the different directions. Up to a range of approximately 200m, the variability is the same in all directions, implying that the Lower Body Fe grade is stationary up to 200m.

Figure 26 shows that the approximately N-S trending semi-variograms of the 0°, 20°, 40°, and 160° directions exhibit stationarity by plateauing off at the sill. From 200m to 500m, the experimental semi-variograms of the approximately E-W directions (60°, 80°, 100°, 120° and 140°) exhibit trend in the geozones. The pattern of stationarity observed from the iron data is virtually identical to that observed in the manganese dataset. This speaks to the close relationship between Mn and Fe already highlighted during the statistical analysis of the two variables.

4.2.2 Fe Anisotropy

Nine experimental variograms were generated in 20 degree (azimuth) increments. The semi-variograms were generated at a plunge of 6 degrees, in line with the average dip of the ore body. The 50m lag was calculated as half of the average inter-borehole spacing (100m/2=50m). The maximum distance chosen represents 500m, so as to remain within domain boundaries.

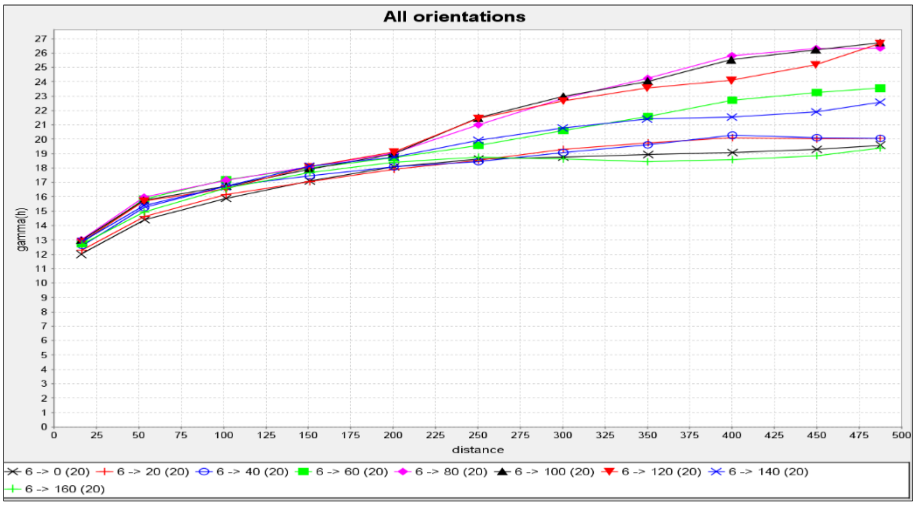


Figure 25: Experimental semi-variograms of the Lower Body iron grade.

The experimental semi-variograms from Figure 25 are individually displayed below, with the sills visible. From the individual semi-variograms depicted by Figure 26, the ranges are different in different directions, showing anisotropy. The sills are equal in the different directions and the semi-variogram reaches the sill within different distances, indicating zonal anisotropy. In the approximately N-S directions the semi-variograms plateau at the sill, while in other directions they continue to increase above the sill. It is important to note the striking similarity between the Mn and the Fe semi-variograms.

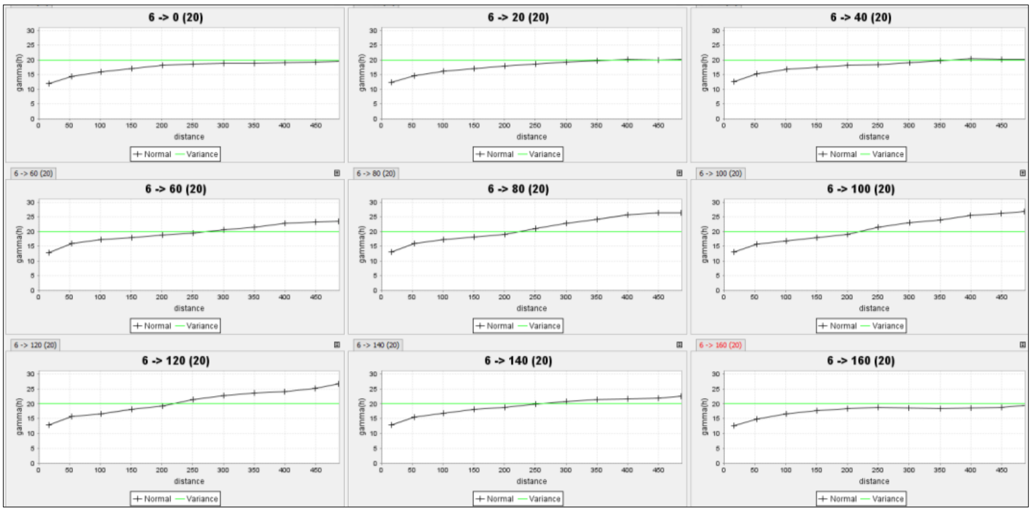


Figure 26: Individual experimental semi-variograms of the Lower Body iron grade.

4.2.3 Fe semi-variogram modelling

The variogram model is chosen from a set of mathematical functions that best describe spatial relationships. The appropriate model is chosen by matching the shape of the curve of the experimental variogram to the shape of the curve of the mathematical function (Barnes, 2003).

The purpose of fitting a model is to produce an algebraic formula for the relationship between values at specified distances (Clark & Harper, 2000). Figure 27 shows the direction of highest continuity to be in the N-S direction. The continuity is consistent with the strike of the faults and is approximately perpendicular to ore body dip. Figure 28 shows the direction of least continuity to be in the E-W direction. This direction is perpendicular the dominant N-S trending faults but is parallel to local ore body dip.

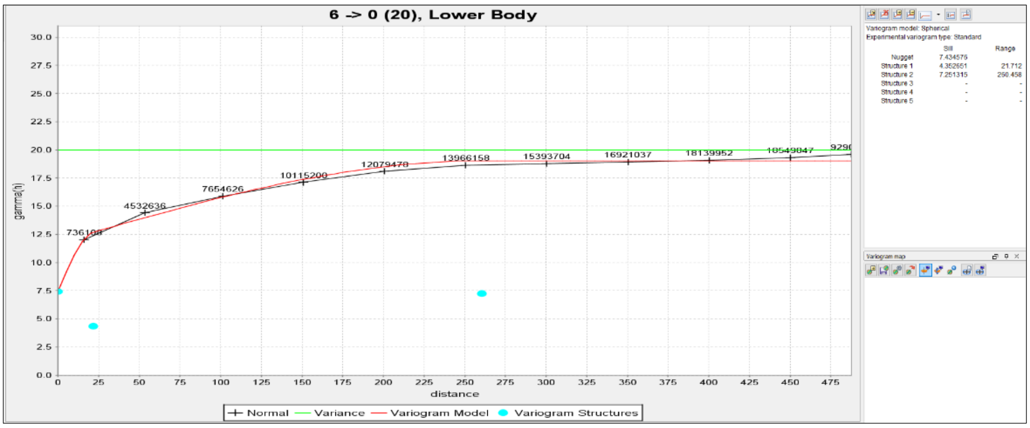


Figure 27: The direction of highest Fe continuity is in the 0° direction.

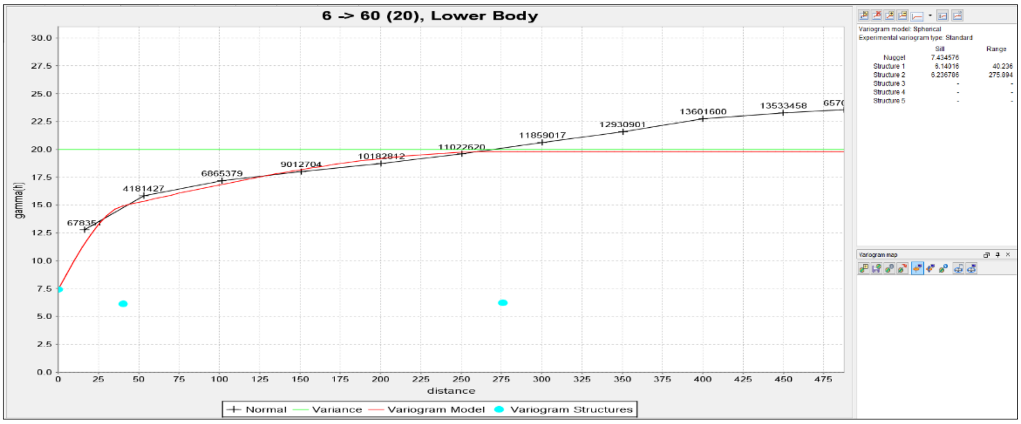


Figure 28: The direction of lowest Fe continuity is in the 60° direction.

A double-structured spherical model was fitted, with a sill of 40 and a nugget of 7.4. This is in agreement with the work of Nengovhela (2013) who chose a double-structured spherical model with a nugget of approximately 7.9. Nengovhela (2015) did not produce any variography for iron. The appendix shows the standardised (normalised) semi-variogram of the 60° direction of lowest continuity. From the standardised semi-variogram, the direction of least continuity exhibits tend, with approximately a fifth of the semi-variogram above the sill.

Lautze and Lukhaimane (2017) also fitted a double-structured spherical model with a nugget of 7.6 and a sill of 175. It is important however to note that the authors produced an omni-directional variogram for Lower Body iron with modelled ranges of 22m and 760m. The work of Lautze and Lukhaimane (2017) yielded a significantly high variance, which is contrary to the desired input of a Mineral Resource estimate. There was also significant trend in the variogram, although the authors forced the model to plateau at the sill.

The similarity between the shapes of the Mn and the Fe experimental semi-variograms is striking. The directions of least (E-W) and highest (N-S) continuity are identical, as well as the range of up to 200m where the variability is the same in all directions. Furthermore, the variogram models for both Mn and Fe are double-structured spherical models.

4.3 Calcium oxide

4.3.1 CaO Stationarity

The experimental semi-variograms of Figure 29 show a continuous increase, although the rate of increase is different in the different directions. Up to a range of about 60m the variability is the same in all directions, implying that the Lower Body CaO grade is stationary only up to 60m. CaO has a short range of approximately 60m and a long range of approximately 100m. After 60m, mild troughs and peaks as well as sharp spikes are visible in the vast majority of the experimental semi-variograms.

4.3.2 CaO Anisotropy

Again nine experimental variograms were generated in 20 degree (azimuth) increments. All of the semi-variograms were generated at a plunge of 6 degrees, in line with the average dip of the ore body. The spread is 20 degrees and the lag (50m) was calculated as half of the average inter-borehole spacing (100m/2=50m). The maximum distance chosen represents 500m, to ensure that the semi-variograms remain within current domain boundaries.

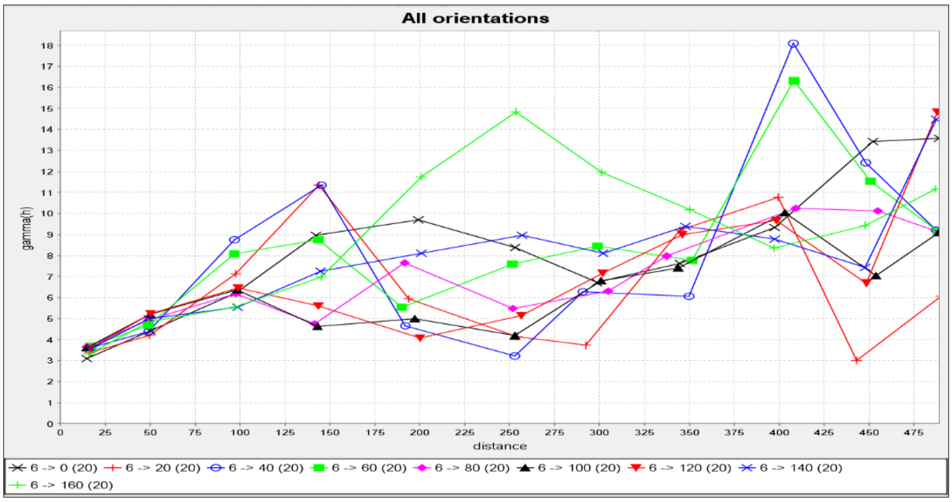


Figure 29: Experimental semi-variograms of the Lower Body calcium oxide grade.

From Figure 30, it is evident that an event around 60m, is common in all directions. The experimental semi-variograms from Figure 29 are displayed below individually, with the sills visible. The calcium oxide experimental semi-variograms are characterised by a marked component of peaks and troughs, implying little spatial continuity within domain boundaries.

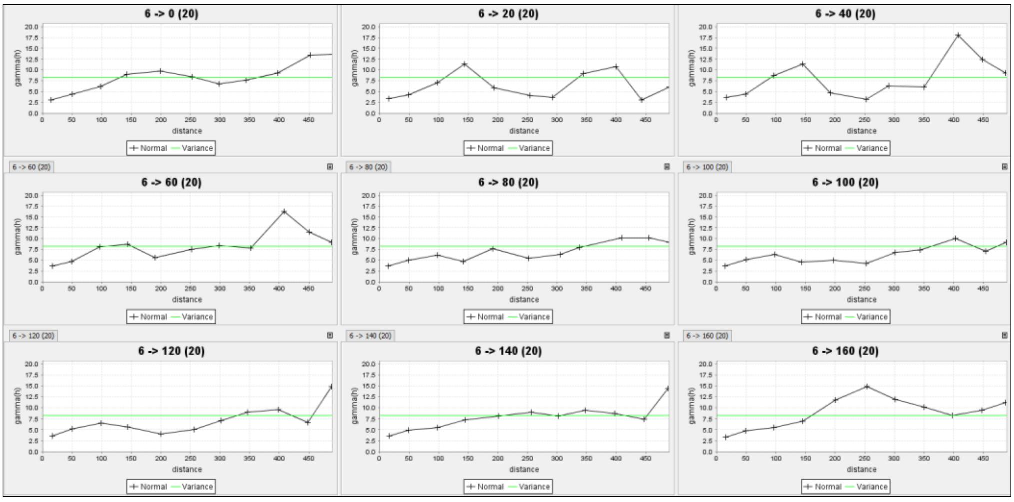


Figure 30: Individual semi-variograms of the Lower Body calcium oxide grade.

4.3.3 CaO Semi-variogram modelling

It is desirable when fitting semi-variogram models that the semi-variogram plots be isotropic and for the semi-variogram values to remain basically constant or increase smoothly to a plateau (sill) (Gunst & Hartfield, 1996; Gregoire *et al*., 1996). Unfortunately, calcium oxide grade does not follow that pattern, with the exception of the 140° direction, which shows trend only after a distance of 450m.

No variography of CaO grades has been undertaken to date at Wessels mine. As such, the researcher cannot compare with the work of other resource geologists. Nengovhela (2013), Nengovhela (2015) and Lautze and Lukhaimane (2017) variography did not include calcium oxide.

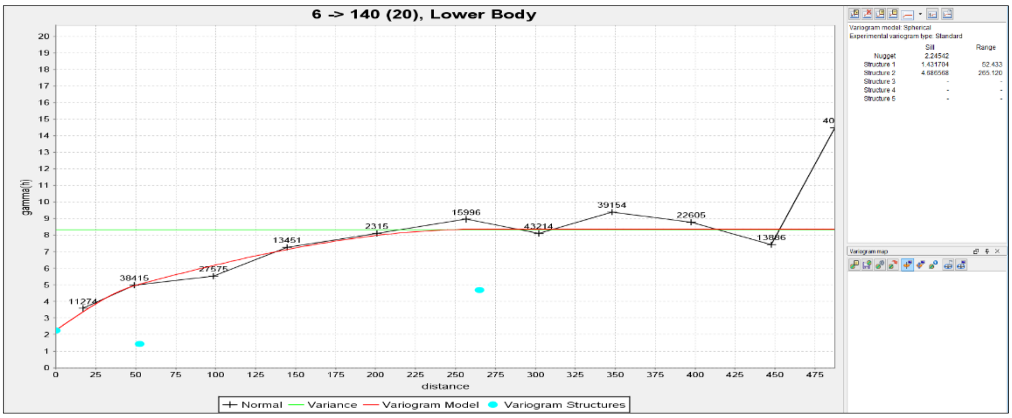


Figure 31: 140° direction CaO experimental semi-variogram with the sill and number of pairs.

A double-structured spherical model was fitted to the experimental semi-variogram of the 140° direction, with a sill of 15.5 and a nugget of 7.1. Evidence of trend is observed beyond 450m, identified by the sharp and continual increase of the semi-variogram beyond the sill. In cases where trend does not interfere with the variogram until after the range of influence has been passed, Clark (1979) modelled the variogram only to the distance where the trend begins. The author further stated that less attention can be paid to the trend in cases where the parabolic behaviour of the semi-variogram is further from the origin. The appendix shows the standardised (normalised) semi-variogram of the 140° direction of greatest continuity. From the standardised semi-variogram, the trend is visible only towards the last 50m, which is one tenth of the total semi-variogram range. A decision was made not to model beyond 450m due to the trend present.

From Figure 31, the direction of greatest continuity is in the 140° direction. Interestingly, the NW (320°) – SE (140°) trend corresponds to the regional ore body dip as shown in Figure 32. As mentioned previously in Section 2.1.1, the manganese field is preserved in a structural basin which plunges shallowly to the northwest. CaO mineralisation is possibly related to ore body dip. Further, the trend of CaO greatest continuity is perpendicular to the dominant NE-SW trend of the dykes.

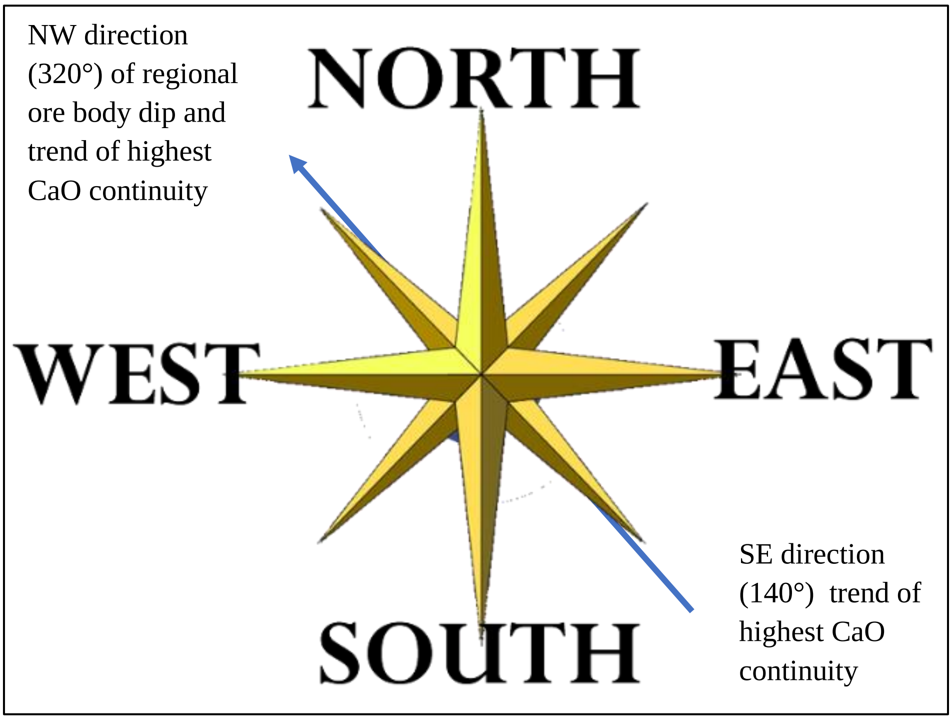


Figure 32: The direction of highest CaO continuity placed in a georeferenced perspective (adapted from Compass English, n.d.).

The experimental semi-variograms in the other directions (0°, 20°, 40°, 60°, 80°, 100°, 120°, 160°) exhibit more erratic behaviour. A sample semi-variogram of the 20° direction is depicted below (Figure 33) to illustrate the difficulty in variogram modelling.

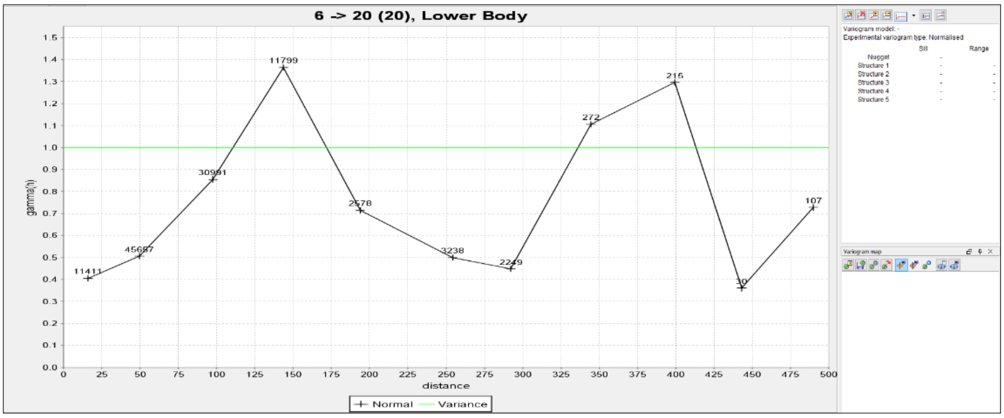


Figure 33: Standardised 20° direction CaO experimental semi-variogram with the sill and number of pairs.

There are several suggestions for dealing with an experimental semi-variograms which have sills above the calculated sample variance. Morgan (2011) suggested re-examining the stationarity of the area being studied. Adding that it is possible that the area concerned does not meet the requirements of a second-order or intrinsically stationary random function. In some circumstances, another option is to consider a different kind of semi-variogram model (such as the hole effect semi-variogram model).

The most commonly applied variogram models increase monotonically with increasing lag. Examples of common models are the spherical and exponential variogram model structures. Non-monotonic variograms that show cyclic patterns are called “hole effect” variograms. Hole effect variograms vary cyclically as a function of distance. The cyclicity must be geologically legitimate, often representing clustered lenses or layered units (Pyrcz & Deutsch, 2017).

A hole effect variogram model was considered and then rejected. Although there appears to be peaks and troughs in the data, the peaks and troughs are not cyclic. Ma and Jones (2001) stressed the importance of matching at least the first few peaks and troughs to the hole effect model, in order to adequately convey the periodicity of the geological attribute. The experimental semi-variograms (Figure 29) do not show any predictable pattern of periodicity.

‘*The most important consideration when electing any particular semi-variogram fitting method is that care be taken to ensure that the parametric assumptions [of the method] are reasonable’* (Cressie, 1993, p.91). In this case study, there is currently no proven geological premise to assume that calcium oxide occurs in clustered lenses or layered units.

The number of samples used to calculate the sample variance and the number of data pairs used in calculating the experimental semi-variogram lags need to be considered when fitting the variogram model. A closer look at the number of pairs associated with the anomalous peaks (as seen in Figure 33) indicates that the number of pairs in the peaks form a significant portion of the semi-variograms. This implies that the peaks are a true function of the spatial characteristics of CaO mineralisation. Basu *et al*. (1997, p.490) showed that "*individual observations can have a dramatic effect on sample semi-variograms because each observation is used many times in the calculation of the semi-variogram values. Anomalous observations may induce spikes, give rise to sharp peaks, shift the entire semi-variogram upwards, or induce a linear trend in the sample semi-variogram plot*".

The danger of modelling the experimental semi-variograms with the peaks and troughs as they are, is that the assumption will be one of spatial correlation across potentially inhomogeneous zones. The total effect thereof will be the screening out of the closest pairs by the pairs further away, decreasing the confidence associated with the CaO estimate. Where semi-variograms show erratic behaviour, Gringarten and Deutsch (2001) suggest transforming the data to normal space before variogram calculation. This is to dampen the difference between extreme high and low values. Additionally, robust alternatives to traditional variograms include madograms, rodograms, general and pairwise relative variograms which may be used to determine ranges and anisotropy, although they cannot be modelled.

The dominance of fluctuating semi-variograms implies the prevalence of abrupt changes in grade when moving across boundaries (Ortiz & Emery, 2006). It is important to note that the delineation of domains at Wessels mine is done by analysis of Fe and Mn grades. The analysis of CaO is excluded in domain analysis. It is likely that the controls on CaO mineralisation are different to those of Mn and Fe. The high correlation between Mn and Fe is already documented in this research. The lack of correlation between Mn and CaO, as well as Fe and CaO is already captured in Figure 18 and Figure 19, respectively.

The CaO experimental-semi-variograms imply the existence of more than one zone within the traditional West Block, Graben block, Central Block and East Block domains. The semi-variograms are indicative of non-homogenous zones which could be remedied by sub-domaining to split the geology further. A good starting point is to sub-domain within the major fault and dyke boundaries of the traditional domains.

Geological controls may or may not be related to mineralisation continuity. It is thus important to establish the relevant geological controls which affect calcium oxide mineralisation in order to quantify spatial continuity within meaningful geological domains (Snowden, 1996).

As a word of caution, geostatisticians have tried to correct for the lack of stationarity by defining even smaller ‘homogenous’ zones. This has often lead geostatisticians into the trap of identifying zones which contain too little data from which useful statistics of any kind may be derived (Henley, 2001 cited by Nengovhela, 2018).

There remains room for further considered sub-domaining analysis of calcium oxide based on the results of the experimental semi-variograms generated across the traditional Wessels mine domains. Estimation validation is outside the scope of this research; however, the estimation parameters are considered to assess confidence in the estimate (Section 4.5 of this report). Additional work is required to fully understand the controls on CaO mineralisation and how the geological interpretation ties in with the spatial analysis of calcium oxide grade.

4.4 Lower Body Thickness

Figure 16 implied the existence of two Lower Body thickness populations, which intersect around 6.7m. The Cumulative frequency plot (Figure 34) shows a dip around 6.7m from the red arrow. From the information gathered from Figures 16 and 34, a colour plot was generated to assess if the Lower Body has thicker and thinner areas. The colour plot is to visually display the spatial character of ore body thickness and evaluate confidence in the estimate for Lower Body thickness.

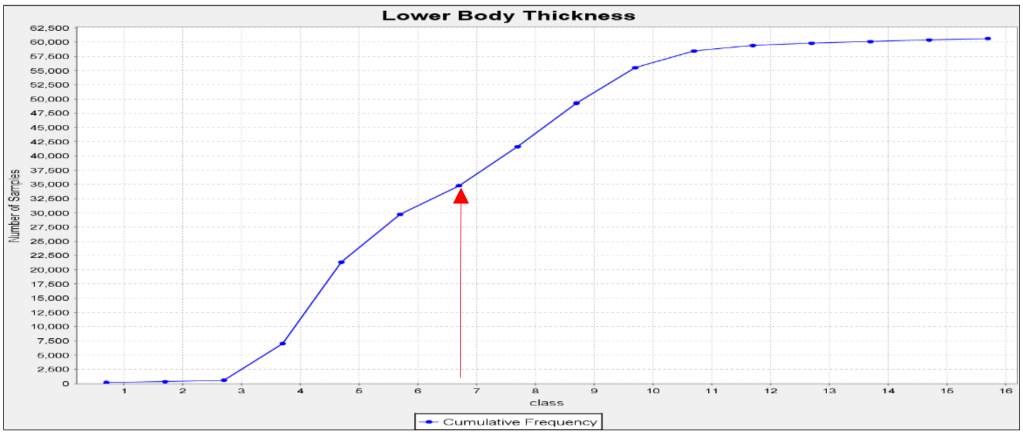


Figure 34: Lower Body thickness Cumulative frequency plot.

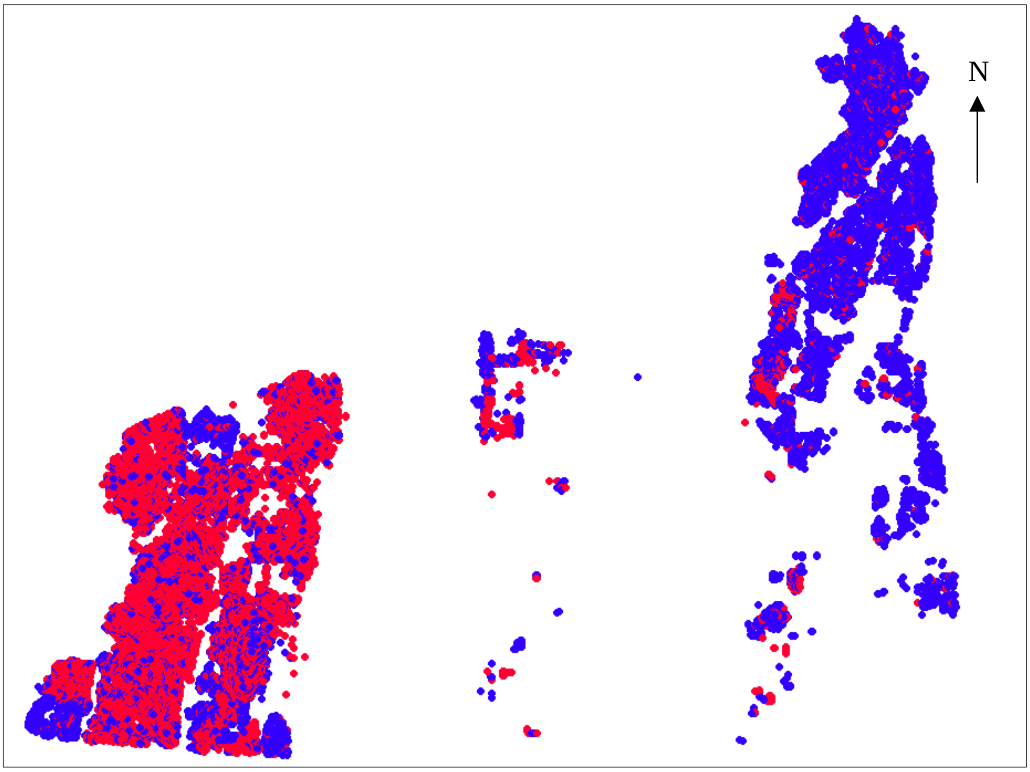


Figure 35: Colour plot of Lower Body thickness ≥ 6.7m (red) and ≤ 6.7m (blue).

Samples with thickness greater than 6.7m are displayed in red and thinner than 6.7m are displayed in blue. From Figure 35, the thinner areas (blue) are more prevalent towards the East Block, while the thicker (red) areas are more prevalent towards the West Block.

The thinner areas are most likely in proximity to the Olifantshoek unconformity where the Lower Body manganese unit has been eroded away. The thicker areas of the West Block most likely represent the nappe structures, where there is known and mapped Lower Body duplication due to the prevalence of thrust faults. Thrust faults are almost entirely restricted to the West Block.

Nine experimental semi-variograms were generated in 20 degree (azimuth) increments. All of the semi-variograms were generated at a plunge of 6 degrees, in line with the average dip of the ore body. A lag distance of 50m was calculated as half of the average inter-borehole spacing (100m/2=50m). The maximum distance chosen is 500m, so as to remain within domain boundaries.

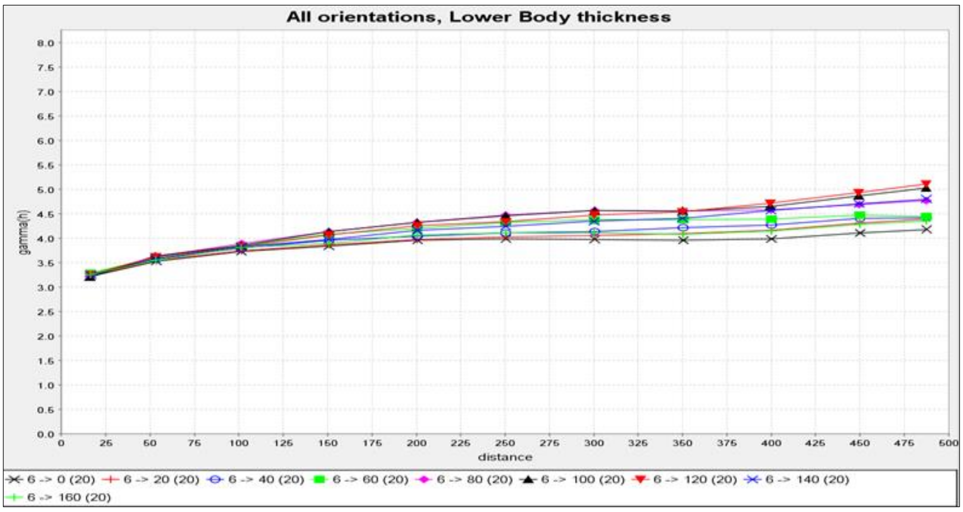


Figure 36: Experimental semi-variograms of Lower Body thickness.

The expiremental semi-variograms presented in Figure 36 are individually displayed in Figure 37, highlighting that thickness has a similar spatial continuity in the nine directions. There is no evidence of trend in the structure of the nine semi-variograms. Further, the anisotropy is weak, implying that an omni-directional variogram can be applied such as in Figure 38.

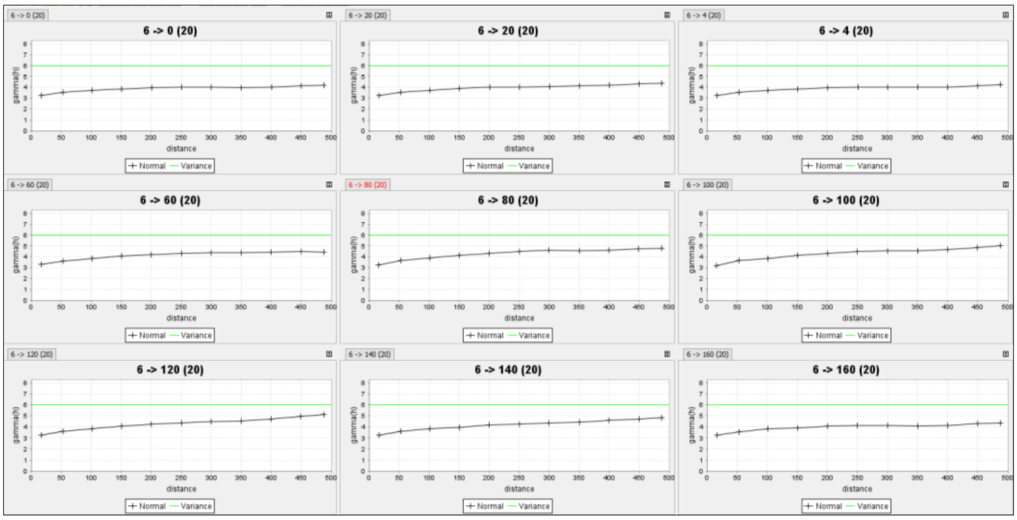


Figure 37: Individual experimental semi-variograms of Lower Body thickness.

From Figure 37, the variance between pairs Z(x) and Z(x + h), shown in Equation 5, is stabilising below sample variance. The absence of trend established by the stable semi-variogram sill results in a more reliable variogram model and consequently also a more robust thickness estimate.

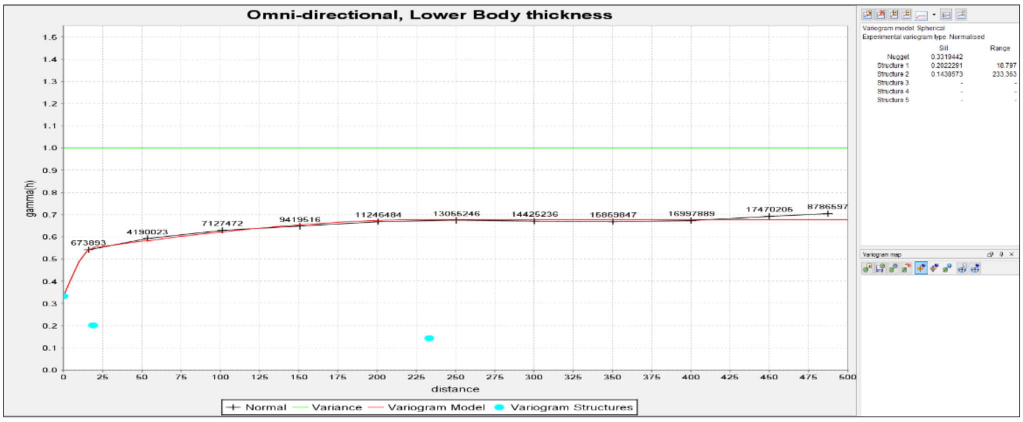


Figure 38: Standardised omni-directional thickness semi-variogram, with model.

A double-spherical exponential model was fitted to the thickness variogram (Figure 38). The standardised nugget of 0.3 is slightly higher than the 0.1 of Nengovhela's (2015) standardises omni-directional variogram model. Both the researcher and the Competent Person fitted double-structured spherical models, with Nengovhela's (2015) ranges being 62m and 300m. The Appendix shows the ordinary omni-directional semi-variogram of Lower Body thickness, with a non-standardised nugget of approximately 2 and ranges of 18m and 233m.

4.5 Resource Estimation

This section does not aim to investigate the most appropriate modelling techniques or functions. The aim is to discuss the current estimation methodology as it affects the reliability of the Mineral Resource classification. The Mineral Resource estimate was not generated by the researcher but was obtained from Wessels mine. This section details the methodology employed by the mine geologists and geostatisticians in the generation of the estimate.

Sections are created with the aim of intersecting as many drill holes as possible. Strings are digitised along each section to define the top and bottom contact of both the Lower Body and Upper Body, taking into account structural discontinuities within each block. The sectional strings are then linked to generate Lower Body and Upper Body wireframes (Lautze and Lukhaimane, 2017). The area in between the Upper Body and Lower Body wireframes is converted into a single closed polygon named "Interburden".

Wessels mine does not have a comprehensive geological model of the entire geology sequence from surface to below the Hotazel Formation. The geological model, as shown by Figure 39, comprises the Upper Body and Lower Body, because of their economic significance, and the interburden between the two units. Wessels mine has wireframes of the two manganese units, the Upper Body and the Lower Body, and the Interburden (waste).

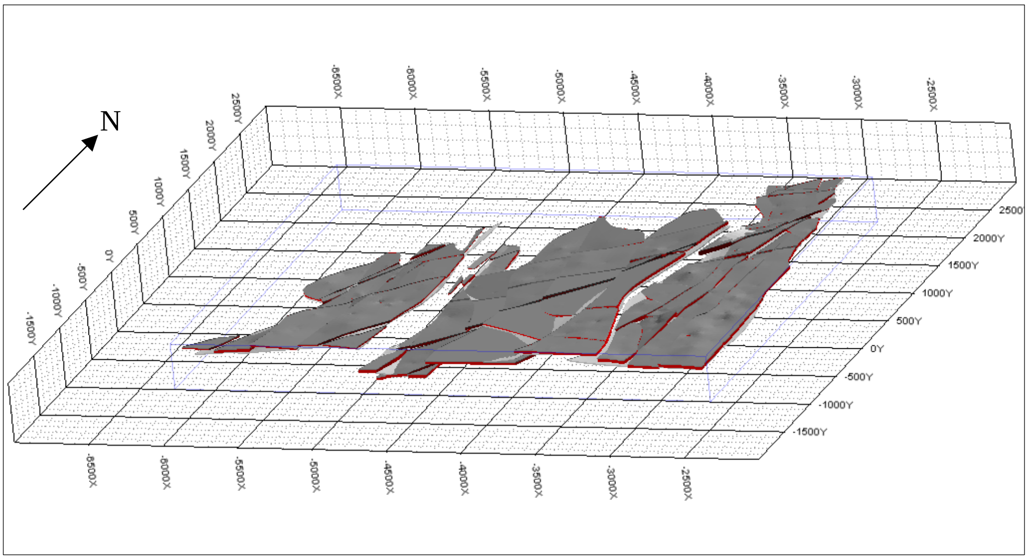


Figure 39: Final solids representative of the Lower Body (light grey), Upper Body (dark grey) and the Interburden (red).

The project area is divided into estimation domains for both the Lower Body and Upper Body horizons. One of the primary reasons informing the domaining process is related to the density of information within the different fault blocks of the West, Graben, Central and East blocks. Additionally, domaining is also based on the structural controls on the ore body (Nengovhela, 2013).

The domain boundaries are defined by the major fault blocks (Figure 40 and Figure 41) identified in the Lower Body. Figure 40 shows the dominantly NE-SW trending dykes in green and the dominantly N-S trending faults in blue. The mineralisation boundary applied to the estimate is the Olifantshoek unconformity (erosional sub-outcrop). The unconformity is represented by the thick red dotted line. There is no Lower Body manganese mineralisation to the north of the Olifantshoek unconformity, due to the erosion of the Hotazel Formation. The domains (West Block, Graben Block, Central Block and East Block), which are bounded by the dominant N-S trending faults, are indicated towards the bottom of Figure 41.

Figure 40: Wessels geology mine plan, Lower Body.

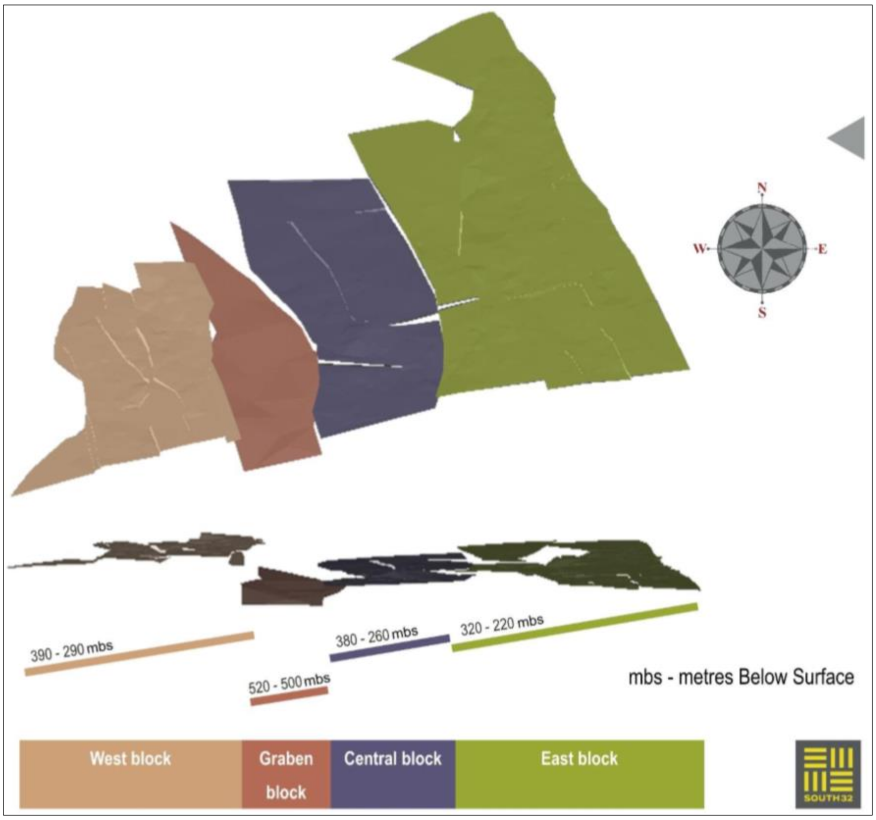


Figure 41: Wessels mine estimate domains based on fault blocks (Lautze & Lukhaimane, 2017).

The chip data is composited on 20m x 20m x total ore body thickness. The area within the mining rights boundary is 10.7 km^2, whilst the mineralised area is 6.6 km^2. A blank block model is constructed by filling the modelled Lower Body and Upper Body wireframes with 20m x 20m x 1m blocks. The cell declustering method is applied to decluster the data on a 20m x 20m x 1m pseudo grid. An average global in-situ dry bulk density of 4.23 g/cm^3 is applied (Nengovhela, 2013).

Wessels mine currently applies Inverse distance weighted (IDW) to generate the manganese, iron and calcium dioxide grade estimates. IDW works by assigning more weight to the known values closer to the unknown point. It does not require additional information such as a variogram model. The application of IDW as the Wessels mine estimation technique remains the estimation methodology at the time of publication of this research.

Kriging neighbourhood analysis helps with the determination of the number of samples required for a representative mean of a regularized block. Kriging neighbourhood analysis is conducted with the intention of generating a more accurate estimate. The exercise ensures that an optimal number of samples are incorporated in the data search ellipsoid, leading to a more representative localised mean of the area and a good percent overlap between the estimated block histogram and the histogram of the true block grades. The procedure for determining the appropriate number of samples is heavily dependent on the sample density of the mineralised area. The IDW estimate is generated on a minimum number of 4 samples per block (Nengovhela, 2013).

The kriging neighbourhood analysis yielded a significant percentage of negative weights and zero kriging efficiencies when ordinary kriging was applied to the Wessels data. For this and other reasons, inverse distance weighting still remains the preferred method of estimation (Nengovhela, 2013).

Figure 42 shows a two-dimensional view of the 2016 Wessels IDW manganese grade estimate. The estimate is displayed using the standard mine legend. The dykes are visible in blue.

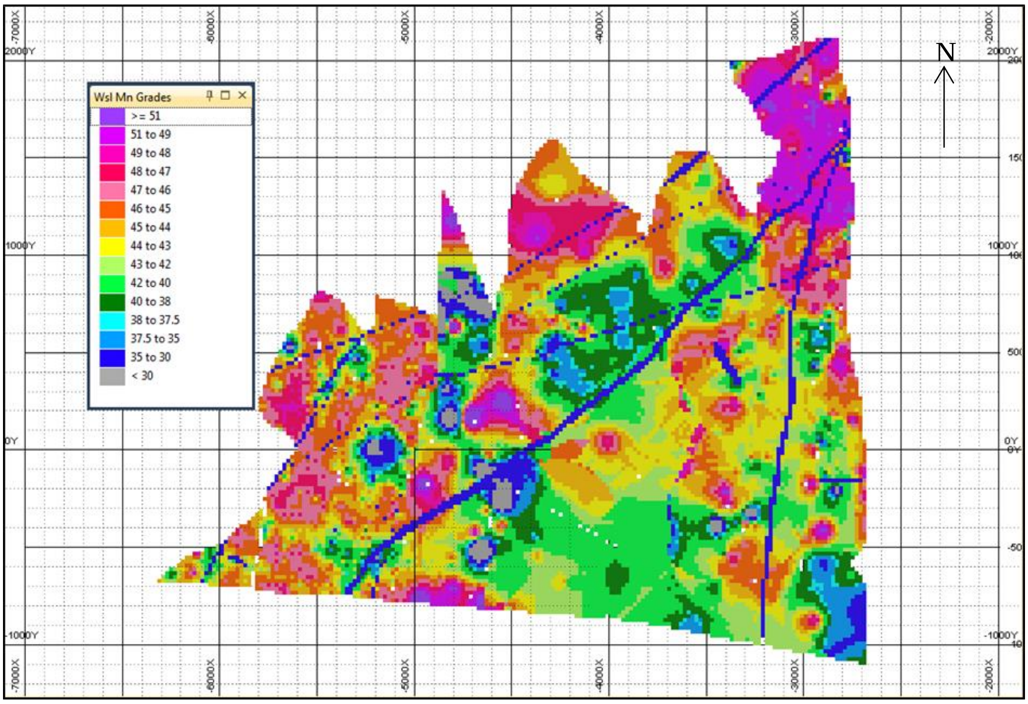


Figure 42: Wessels mine Lower Body Mn IDW estimate i.e. 2016 Global Mineral Resource Model.

In 2017, Lautze and Lukhaimane (2017) changed the global resource estimation methodology. The 2016 estimate incorporated full width composites, while the 2017 estimate incorporated 1m composites. The 2017 methodology change was effected to ensure that estimation was performed using equal composite lengths and that vertical grade changes within the ore body were preserved. The 2016 estimate was generated based on 4 domains, while the 2017 estimate was generated based on 5 domains. The 2017 domains were primarily driven by grade distribution as opposed to data density. A last but important difference between the two estimates is that the 2016 estimate incorporated both chip and borehole data, while the 2017 estimate completely excluded the chip data. Keep in mind that approximately 99% of the sampling data is from underground face chip sampling.

Following the MPOR audit, Finding #2 spoke to the inappropriate Mineral Resource classification of Wessels mine. The finding stated that the classification based on the variogram ranges from the spherical model did not provide enough information to make an informed decision about resource uncertainty, creating a risk of Mineral Resources and Ore Reserves misclassification and incorrect public reporting. To close out this audit finding, a new classification was proposed to include the number of samples, regression slope, search range, geological considerations and consideration of production volumes instead of individual estimation blocks. The 2015 classification is shown by Table 9. This classification has not yet been adopted, it is however, under review. The review panel met in February 2019, and was comprised of South32 subject matter experts, Competent Persons and external Consultants.

Table 9: Mineral Resource classification under debate (Nengovhela, 2015).

	Measured	Indicated	Inferred
Variogram Range	<300	<300	>300
Geological Risk	No problem areas	Some problem areas	Areas that are 30m within the sub-outcrop line have now been reduced to Inferred
Minimum number of Samples	8	4	<4
Regression slope	0.9	0.5-0.9	<0.5
Suboutcrop	30 inside the sub outcrop line was classified as inferred		
Dykes	The area occupied by dykes have had the Mn reduced to 30%. This allows for proper mine planning without compromising the volumes		

The Competent Person went on further to state that "*To augment the classification process, consideration will be given to defining a clear risk matrix which would incorporate the different layers of uncertainty. Such layers should include structural maps (faults and dykes), extent of ferruginisation and the uncertainly attached to the sub outcrop line amongst others*."(Nengovhela, 2015;p.15). It is the researcher's hope that the proposed Mineral Resource classification will assist to address the need for "a clear matrix" that incorporates geological risk.

CHAPTER 5

RESULTS

5.1 Alternative method of Mineral Resource classification

Purely geostatistical methods of Mineral Resource classification are optimal when the data is normally distributed and stationery. Significant deviations from normality and stationarity do not support a purely statistical Mineral Resource classification technique. (Bohling, 2005).

From the EDA and geostatistical evaluation, it was established that the data is non-stationarity. Due to the non-stationarity of the data and the slightly skewed distribution, a purely geostatistical Mineral Resource Classification technique is not recommended.

A scorecard method is proposed for the Mineral Resource Classification of hydrothermally altered manganese ore bodies, as an improvement over the current methodology, see Table 10. The proposed scorecard method is designed to balance three crucial elements: confidence in data integrity, confidence in the geology, and confidence in the estimation technique. Associated weights are suggested for the factors considered to be of significance to the Mineral Resource evaluation.

The weighting of these factors included in the scorecard can be modified by the Competent Person, based on his/her experience and judgement. The confidence limits are based on what the researcher considers to be defendable and realistic degrees of certainty. It is suggested that the confidence limits be divided as follows, in accordance to the proposed scorecard:

- Measured: >70%
- Indicated: 70% - 30%
- Inferred: <30%

Chapter 2 contains various Mineral Resource classification scorecards, based on the JORC and SAMREC guidelines that were encountered in the literature research. Included in the chapter are examples of the various assessment criteria involved in determining the Mineral Resource confidence for a given deposit.

There is often a Lead Competent Person who relies on the input and knowledge of technical specialists who in their own right might be Competent Persons contributing to the Mineral Resource classification. This is also the case at Wessels mine, where the Hotazel Manganese Mines 'Competent Persons Team' comprises of two Mineral

Resource (a geologist and a geostatistician) and two Mineral Reserve (the Production Planning Manager and the Asset Planning Manager) Competent Persons under the leadership of the Lead Competent Person who finally signs off on the Mineral Resources and Mineral Reserves.

Since the subject of resource and ore reserve estimation addresses many disciplines including geology, geostatistics and mining, various decision makers need to understand and acknowledge that all estimates have an associated risk and they deserve to be given a measure of uncertainty (Snowden, 2001). Factor elements contributing to geoscientific confidence are related to geological confidence in domaining, the block model grid in light of the inter-sample spacing, density, the estimation method and confidence in thickness estimate.

Table 10: Proposed Mineral Resource classification criteria for hydrothermally enriched manganese ore bodies.

Confidence in the data Integrity					
Confidence Factor	*High (5)*	*Moderate (3)*	*Low (1)*	*Weight (%)*	*Comment*
Sample spacing	Inter-sample spacing ≤100m	Inter-sample spacing 100m - 200m	Inter-sample spacing >200m	10	Important for the determination of spatial continuity of mineralisation.
Quality Assurance and Quality Checks	Relevant and appropriate QAQC applied to all data. Lab audits conducted as per mine schedule by the Competent Person.	QAQC applied, but not to satisfactory standards. Limited Lab audits conducted by the Competent Person.	Historic data has little or no evidence of QAQC applied. No lab audits conducted by the Competent Person.	10	Surety in data quality results in increased estimation confidence, provided the interpretations are legitimate.
Data Capturing and validation	Data electronically imported and validated.	Data imported and not validated, OR data manually captured and validated.	Data manually captured and not validated.	5	Verification to reduce the effects of human error in data capturing as far as possible.
Georeferencing	Complete XYZ survey data exists and is validated.	Complete XYZ survey data exists but is not validated.	Incomplete XYZ survey data.	5	To ensure that data plots accurately in space. Important for reliable geostatistical evaluation.
Density	Local density of individual drill holes.	Application of a domain average.	Use of global average.	10	Important for better estimation of grade and tonnages.

Confidence in the geology					
Confidence Factor	*High (5)*	*Moderate (3)*	*Low (1)*	*Weight (%)*	*Comment*
Domaining	Highly confident. Domain analysis is satisfactory.	Confident. Domain analysis is conducted.	Domain analysis not conducted.	10	Basis for domaining must be evaluated due to stationarity requirement.
Faulting	Unaffected	Affected	Severely affected	10	Must be evaluated due to the resultant mineralisation anisotropy.
Magmatic intrusions	Unaffected	Affected	Severely affected	10	Must be evaluated due to the resultant mineralisation anisotropy.
Unconformity sub-outcrop	Unaffected	Affected	Severely affected	10	Boundary delineation affecting tonnes and volumes. Geometry of the orebody and volume determination.
Confidence in the estimation methodology					
Confidence Factor	*High (5)*	*Moderate (3)*	*Low (1)*	*Weight (%)*	*Comment*
Estimation methodology	Highly confident. Model validation is satisfactory.	Confident. Model validation is conducted.	Model validation is not conducted.	20	Assessment of the estimates representativity of the data and geostatistical parameters.
Total				**100%**	

5.2 Comparison between current and proposed methodology

A comparison of the Measured, Inferred and Indicated Mineral Resource estimates between the current and the proposed Mineral Resource classification criteria is not included in this research, due to the sensitivity of the information and any potential investor confidence repercussions that may result. The current and proposed classification methodologies are however compared in Table 11.

Table 11: Comparison of the current and proposed Mineral Resource classifications.

Classification parameter	Current	Proposed
Sample spacing	Yes	Yes
Georeferencing	No	Yes
Data capturing and validation	No	Yes
Quality assurance and quality checks	No	Yes
Conditional simulation	No	No
Data capturing and validation	No	Yes
Density	No	Yes
Faulting	No	Yes
Magmatic intrusions	No	Yes
Unconformity sub-outcrop	No	Yes
Domaining	No	Yes
Estimation methodology	No	Yes

The current Mineral Resource classification protocol applied at Wessels mine is as follows: Blocks estimated within the first variogram range of the double structured spherical semi-variogram model are classified as being within the Measured category. This range of 30-40m represents approximately two thirds of the total variance. Mineral Resources estimated within the second structure of the double structured spherical model are classified as Indicated. Any Mineral Resources estimated beyond the second range are classified as Inferred. Practically, however, a 30m rim around the sub-outcrop is classified as Inferred. Current practice is that any ground 30-40m ahead of a mining face is classified as Measured, whilst any estimates of the ground beyond that is classified as Indicated (Nengovhela, 2013).

The practice of applying the semi-variogram ranges for classification confidence most likely found its origin and justification in the paper by Snowden (1996), wherein the author suggested determining the appropriate drill hole patterns to achieve various resource confidence categories, in terms of the variogram range. When applying variography to Mineral Resource classification Snowden (1996) proposed as a guiding principle, that two-thirds of the semi-variogram sill (usually represented by the first structure of a double structured semi-variogram) as Measured and the material between the second structure and the sill (one third of the semi-variogram sill) as Indicated. Anything beyond the range should be considered Inferred.

Snowden (2001) later cautioned that simply having a long range semi-variogram structure may not be sufficient to assume high confidence if small scale nested structures are present. The author went on further to state that confidence in the geological framework should take precedence over any mathematical indicator of confidence.

The best Mineral Resource classification approaches integrate both practical geological knowledge and geostatistics. Assuming that the underlying data is of sound integrity, the geostatistics should confirm the geology. Comprehensive geological understanding and reliable sample information remain the foundation of Mineral Resource evaluation. A sound understanding of the relationship between the mineralisation and the geological processes that govern its geometry is essential for improving the quality of the resource estimation model (Dohm, 2016b).

Confidence in the geological framework is absent from the current Mineral Resource classification, making the appropriateness of the current classification limited. Although the geology is incorporated in the generation of the Mineral Resource estimate, it is it's exclusion in the classification criteria which is problematic.

The proposed Mineral Resource classification check list can be used for both qualitative and quantitative observations, all of which are incorporated in the final decision about the assigned levels of confidence. It allows for informed decisions to be made based on spatial continuity and probability as well as interpreted geology, making it more justifiable (Snowden, 2001).

CHAPTER 6

DISCUSSION

Section 6.1 articulates why a scorecard method of Mineral Resource classification; provided in Table 10; is proposed by the researcher. Section 6.2 details the development of the proposed scorecard. Finally section 6.3 considers the inclusion of geology in the estimation methodology, by focusing on detailed results of the statistical and geostatistical analysis.

6.1 Rationale behind the proposal of the scorecard method

Industry best practice in the field of Mineral Resource classification has evolved over time. The Geological Survey Circular 831, published by the United States Bureau of Mines and the United States Geological Survey, highlighted geological confidence as one of the cornerstones of Mineral Resource and Reserve classification. The development of the JORC Code added a requirement for reasonable expectations for eventual economic extraction in the definition of a Mineral Resource. In August of 2000, the Canadian Institute of Mining (CIM) approved the CIM Standard on Mineral Resources and Reserves- Definitions and Guidelines, wherein the concept that Indicated and Measured Mineral Resources had to support mine planning was introduced. In 2012 to 2013, the Committee for Mineral Reserves International Reporting Standards further broadened the definition of Indicated and Measured Mineral Resources by stipulating that the grade, density and shape of the ore body must be estimated with sufficient confidence to allow for the application of Modifying Factors in sufficient detail to support both mine planning and the economic viability of the deposit (Parker & Dohm, 2014).

There is a growing movement towards the implementation of scorecard based Mineral Resource classifications across the mining industry. Several companies have moved towards scorecard/checklist methods. These include Anglo American Platinum (Mohanlal & Stevenson, 2010), Kumba Iron Ore (Kumba Iron Ore, 2012) and De Beers (Duggan *et al*., 2017).

Current best practice in the field of Mineral Resource classification takes cognisance of geological continuity of both ore body grade and shape, deleterious elements, quantification of the accuracy of estimates at local scales, the impact of uncertainty on financial performance, and implicit levels of mining selectivity (Parker & Dohm, 2014).

A scorecard based Mineral Resource classification allows for the holistic consideration of pertinent aspects such as the degree of geological understanding of the deposit, the integrity of the input data, and the degree of confidence in the data that supports the Mineral Resource estimate. Scorecards thus deliver a more comprehensive and balanced classification (Harney & Dohm, n.d.). In keeping with current best practice, the researcher proposed a scorecard method for the Mineral Resource classification of hydrothermally enriched manganese ore bodies. It is envisaged that the proposed scorecard will lead to improved classification of Mineral Resources.

The idea that the scores be weighted and combined to reflect the combined risk was gained from the work of Annels (1995), Harney & Dohm (n.d) and Magnus (2017) where the authors rated the combined confidence in the estimate from 0% to 100%.

6.2 Rationale behind the aspects incorporated in the proposed Mineral Resource classification

The literature review and geostatistical analysis, along with the researchers understanding of the geology, formed the basis for the aspects incorporated in the proposed Mineral Resource classification. Some aspects were found to be relevant to manganese ore bodies, while others were rejected by the researcher. This portion of the discussion follows the SAMREC Codes “If not, why not” logic to discuss why some aspects from the literature review were adopted while others were omitted from the proposed classification.

The largest criticism of the current Wessels mine Mineral Resource classification was the lack of incorporation of geological risk. The lack of published literature on Mineral Resource classification of manganese ore bodies has led to the practice of manganese resource geologists adopting classification methodologies applied to other commodities, and in some cases merging and adapting different methodologies to suit the ore bodies under investigation. The purpose of this research was to bridge the identified gaps in the current resource classification by reviewing methodologies adopted for similar bulk commodities, with the aim of developing a defendable Mineral Resource classification criteria for hydrothermally altered manganese ore bodies. It is important that a Competent Person be able to defend the classification methodology applied to peers.

Although the EDA proved the approximately Gaussian nature of the manganese and calcium oxide data, the slope of regression, was excluded from the proposed Mineral Resource classification. The slope of regression is not relevant to an IDW estimate, where the parameter cannot be calculated. Should the estimation methodology be changed to ordinary kriging, it is proposed that the slope of regression be included in the score to assess confidence in the estimation methodology.

It is only fully realised global and local continuity that characterises Measured Mineral Resources, while the Inferred Resource is based upon apparent global continuity. Making use of borehole spacing as the sole criteria for resource classification assumes three-dimensional continuity, which may not always be the case (Dominy *et al*., 2002; Silva & Boisvert, 2014). Inter-sample spacing was incorporated as one of the criteria for Mineral Resource classification, and not the sole criteria due to the proven lack of three-dimensional continuity in the directions other than N-S. Sample density is an indicator of the quantity of data, although not necessarily of the quality of data. In an effort to bridge the gap between data quality and quantity, the researcher felt it important to incorporate measures of data integrity in the proposed Mineral Resource classification.

Dominy *et al*. (2002) noted the effect of volume on tonnage estimation uncertainty when referring to the Beltrame *et al*. (1981) "ore body delineation and volume" method of Mineral Resource classification. Geological boundaries may or may not be well defined. In some cases, gradational contacts exist. Drill hole deviation can have a serious impact on the accuracy of ore body boundary delineation and therefore on volume modelling.

The most important mitigation against incorrect boundary delineation and volume calculation is to ensure that data plots accurately in space. This provision is met by the inclusion of "Survey data" in the proposed Mineral Resource classification. Additionally, confidence in the accuracy of georeferencing is also important for reliable geostatistical analysis.

Resource Reliability Rating includes a series of questions about QAQC (Annels & Dominy, 2002). Variations of these questions were incorporated in the proposed Mineral Resource classification under the sub-heading "Confidence in the data integrity".

Due to the generation of an IDW estimate and not an OK estimate for the Wessels mine grade estimate, the kriging efficiency, kriging variance, interpolation variance and combined variance were excluded from the proposed Mineral Resource classification. Should the estimation methodology change some time in the future, the inclusion of these parameters in the classification can be re-evaluated.

The application of the search neighbourhood consists of classifying blocks based on distance and constraints related to the number and configuration of the data within the search radius from the block to be classified. The most commonly considered constraints are the minimum number of data, minimum number of drill holes and the minimum number of informed octants. The method works by defining kriging estimation passes with different search parameters (Silva & Boisvert, 2014). Wessels mine generates an IDW Mineral Resource estimate instead of kriging, as such, the application of the search neighbourhood was also not incorporated in the proposed classification.

Conditional simulation has been proposed as a possible solution to overcoming some of the problems associated with kriging (Dominy *et al*., 2002). There are a few specialised software packages that are designed for conditional simulation. This methodology has also been considered as being too mathematically complex and time consuming (Magnus, 2017). In consideration of the degree of geoscientific knowledge and training of the current group of mine geologists, conditional simulation is not included in the proposed Mineral Resource classification. It is the researcher's opinion that a simpler Mineral Resource classification is preferable.

6.3 Current Estimation Methodology

6.3.1 Inverse distance weighting

Linear geostatistical methods such as IDW are widely used within the manganese industry due to their relative simplicity and the stratified nature of manganese ore bodies. Magnus (2017) highlights as a drawback that these linear geostatistical estimation methods do not provide a measure of variability or of confidence in the estimate.

IDW fails to provide useful additional information such as kriging efficiency, slope of regression, estimation error and precision. On the other hand, one of the fundamental requirements before ordinary kriging can be applied is that the regionalised variable be stationary (Nengovhela, 2018), which is not the case at Wessels mine. From the variography displayed in Chapter 3, Mn and Fe are stationary up to 200m, while CaO is stationary only up to 60m. This is in spite of domain boundaries extending beyond 200m.

A disadvantage of applying IDW for estimation is that the method does not take cognisance of direction, making it ideally suited to an omni-directional ore body. Additionally, change of support is not considered, meaning that the difference in size of the samples and the size of the blocks to be estimated are not considered (Dohm, 2016b).

Ordinary kriging was trialled with chip and borehole data, however, the percentages of negative weights reached levels above 30%, which was deemed unacceptable. Additionally, the kriging efficiencies were zero. Without the chip sampling data, ordinary kriging did not produce the negative weights. It was the addition of the chip data that lead to considerable problems with the kriging matrix. To retain variability within the resource model and to incorporate the chip sampling data into the global estimation model, a decision was made to retain the use of inverse distance weighting for the Lower Body. Drill holes were considered an incomplete representation of the areas that have been sampled. This is because, the chip data makes up approximately 99% of all available data, and thus could not be ignored. For these reasons, IDW is still applied at Wessels mine (Nengovhela, 2015).

The Fe and Mn variography showed significant trend in all directions except the N-S direction, and for the CaO semi- variograms a visible trend was observed in all directions. A semi-variogram which trends above the sill will result in a negative correlation between sampled pairs, yielding negative weights. IDW, will of course solve this problem, as it assigns the highest weights to the closest samples. It is possible that Ordinary Kriging may outperform IDW for the Wessels estimate, provided that the appropriate kriging parameters and variography are applied.

A key aspect of selective mining is to separate the economic portion of the ore body from the non-economic waste. To obtain realistic estimates of tonnage, metal content and mean grade of the recoverable Mineral Resources, the difference in support between the available data (drill hole samples, blast holes, channel samples, etc., regarded as quasi-point supports) and the proposed selective mining units must be taken into account (Emery, 2008). Spatial estimation, however, is often required at a larger support than mining, prompting the need for some form of change of support. The Support Volume relationship should be considered to avoid over or underestimation of Mineral Resources and Reserves, to effectively optimize mine development plan and improve the Net Present Value (Zagayevskiy & Deutsch, 2011).

Questions which the practitioner must adequately answer before applying IDW are (Dohm, 2016b):

- How to determine the optimal weighting function?
- How many samples are optimal?
- How far away from the block to be estimated should samples be included in the search radius/ellipse?

- How to deal with a clustered sampling grid or a random grid?
- How to cope with anisotropy?
- How to cope with the regression effect?

6.3.2 Declustering

Regular sampling grids are usually applied in preliminary Mineral Resource investigations. The exploration phase is usually done by borehole drilling and sampling. As mining begins, infill drilling (such as forward prospecting drilling) and production sampling (such as underground face chip sampling) occurs. Due to the common practice of targeting high grade areas for mining, it is common for there to be more samples taken in the high grade portions of the Mineral Resource. Preferential sampling introduces spatially biased samples which are contrary to the fundamental principle of sample representivity. Representative sampling is when each unit of the population has the same probability of being sampled (Pyrcz & Deutsch, 2003).

When data are not on a regular grid, using the full data set will give a biased estimate of the mean and variance. Declustering is the process of adjusting the full data set to give a more representative set of samples. It involves placing a regular three dimensional grid over the sample data and assigning a single value to each grid cell. In the cell declustering approach, the entire area is divided into rectangular regions called cells. Each sample receives a weight inversely proportional to the number of samples that fall within the same cell. This allows for clustered cells to receive lower weights because the cells in which they are located will also contain several other samples (Isaaks and Srivastava, 1989).

Cell declustering of the Wessels data was employed to reduce the number of samples and make the data file more manageable (Nengovhela, 2013). Cell declustering is one method of calculating declustering weights. It is insensitive to boundary locations. The method relies on the weighting of sample data in order to account for spatial representivity. The assigned weights are sensitive to the chosen cell size and grid origin. The practitioner must decide on a cell size which identifies the best weights (Pyrcz & Deutsch, 2003).

From the location plot shown in Figure 43, it is evident that the borehole data (shown in red) is relatively evenly spread. The boreholes become sparser towards the centre of the plot, due to the surface infrastructure which is not displayed in Figure 43. The inter-borehole spacing is between 80m to 120m. The chip sampling data (shown in blue) is clustered around the production areas. That is, the areas which have been mined and sampled in the past. The extent of the Wessels mining rights boundary is represented by the green line.

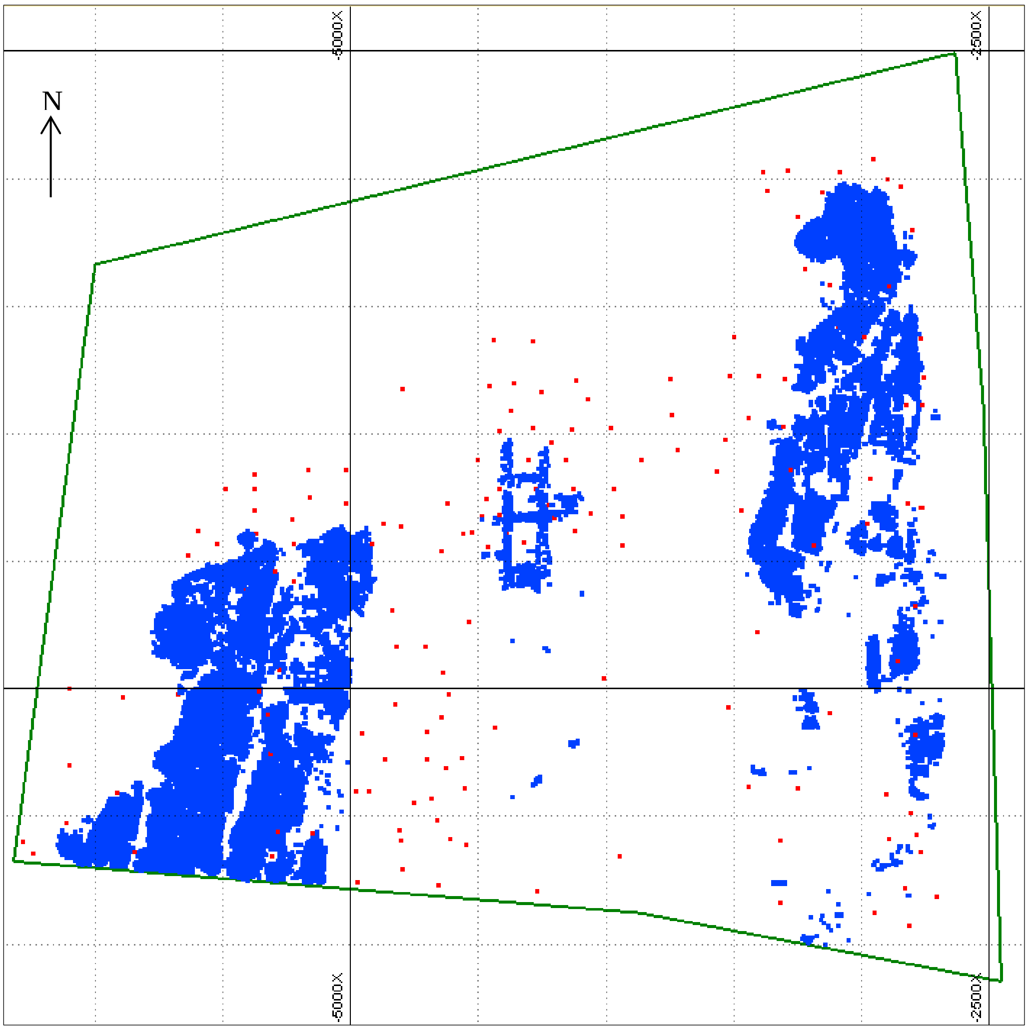


Figure 43: Location plot showing the spread of chip data (blue) and borehole data (red) within the Wessels mining rights boundary.

Pyrcz and Deutsch (2003) suggested selecting the coarsest sample spacing, where there was a coarse grid with additional infill sampling. This scenario fits in well with Wessels mine where there is a coarse drilling inter-bore hole spacing of approximately 100m and underground face chip sampling (infill samples) at approximately 2.5m inter-sample spacing in the mined out areas. The authors further stated that in the absence of a coarse sampling configuration, common practice is to assign the cell size which maximises or minimises the declustered mean. And, to remove the sensitivity relating to the grid origin, Pyrcz and Deutsch (2003) suggested repeating the cell declustering technique with a specified number of origin offsets and the results averaged.

The Olifantshoek unconformity is the boundary between the mineralised zone and the unmineralised zone within the Mining Rights Boundary. Following the 2016 Mineral Resource and Reserve statement, the area surrounding the sub-outcrop was downgraded from Indicated to Inferred Mineral Resource (South32, 2016). The exact position of the Olifantshoek unconformity was not known in some areas, creating a risk of inaccurate ore body boundary delineation and associated volume and tonnage discrepancies. In light of the uncertainty surrounding the exact position of the Olifantshoek unconformity, the application of cell declustering is ideally suited to Wessels mine due to the insensitivity of the method to boundary locations.

6.3.3 Density

Wessels mine began the work of performing density analysis on all historical boreholes several years ago. Density analysis was historically given to vacation work students who came to the mine to complete their vacation work projects over the December and January months. The vacation work reports were saved as word, excel and pdf documents. An ongoing project is underway to manually compile the work on Microsoft Excel and import into Geobank (Wessels mine geological database). It is important to note that the manual capture will result in some human error. On average, the various density analysis projects have yielded an average global density of 4.23g/cm^3. This is the global density factor still applied to the entire Wessels estimate, irrespective of the different domains.

Grades are usually reported as a ratio of the economically viable components, metals or minerals, to weight units (e.g. gram/tonne). This makes bulk density a critical component of the Mineral Resource estimate. In some instances, such as in the case of manganese, and iron resources, grades are reported as percentages. An overly simplistic estimate of bulk density can cause serious errors in tonnage estimates and an over or underestimate of metal content, with significant financial implications.

For mineral deposits with low metal content and simple mineralogy, the practitioner may be able to get away with calculating an average of all bulk density measurements, with sufficient data. It is important to note however, that each geological domain must be examined individually with a separate bulk density value calculated for each. For deposits with more complex mineralogy, where a relationship exists between density and grade, simply averaging bulk density for each geological domain will produce errors in local estimates and errors in tonnage determination. For deposits with high grade and density variability, weighting mineral grades by density and estimating by multiplying grade and bulk density together can produce a more accurate resource estimate (Abzalov, 2013).

In the generation of the Wessels estimate, a global density of 4.23g/cm^3 was applied to each block in order to convert volume into tonnes, based on historical samples. The Competent Person acknowledged the need to model density information simultaneously with the grade to introduce the necessary variability in the different sections of the mine (Nengovhela, 2013).

6.3.4 Incorporation of geology in the estimation process

South32 resource geologists incorporate the geology during the Wessels estimation process in the following three ways:

(1) The areas with known and mapped dykes have the grade excluded. This is because dykes represent waste which is below cut-off grade and certainly not part of the Mineral Resource. By excluding the dyke areas, those tonnes are not reported as being part of the Mineral Resource, allowing for proper mine planning, without compromising volumes and tonnes.

(2) The Olifantshoek unconformity forms the ore body boundary. The unconformity represents the delineation between the mineralised and unmineralised portions within the mining rights boundary. The unconformity forms the circumference around the geometry of the ore body, affecting volume and tonnes.

(3) In the generation of the Global Resource Model, wireframes are generated to define volumes. Practically, geological domains are defined by the major north-south trending faults. The faults formed the conduits through which the hydrothermal fluids infiltrated the ore body. Contact metamorphism effects are strongest in proximity of the faults and dissipate further away from the faults. The resultant hydrothermal alteration thus introduced some degree of heterogeneity and anisotropy. The experimental semi-variograms stressed the north-south direction as the direction of highest continuity of manganese and iron grade. The north-south direction correlates to the dominant fault direction and the traditional premise for ore body domaining. The variography undertaken by the researcher supported the theory that the hydrothermal alteration event was indeed the dominant ore body alteration event, over the contact metamorphism associated with dyke intrusion. This is emphasised by the N-S direction of highest

continuity, corresponding to the fault trend, and not the NE-SW direction which corresponds to the dyke trend.

The practices of domaining, dyke exclusion and ore body delineation represent a crucial understanding of three of the key geological considerations during estimation. Their incorporation into the generation of the estimate should extend further into the assignment of confidence in the Mineral Resource classification.

The calcium oxide variography implied the existence of more than one zone within the traditional West Block, Graben Block, Central Block and East Block domains. The semi-variograms were indicative of non-homogenous zones which could be remedied by sub-domaining to split the geology further. It is thus important to establish the relevant controls which affect calcium oxide mineralisation in order to quantify spatial continuity within meaningful geological domains.

The existence of mean trend causes the geostatistical model to exaggerate spatial continuity and to inflate conditional variances. The existence of variance trends causes conditional variances to be overestimated in some regions of the domain and underestimated in others. The result is an inappropriate assessment of the uncertainty associated with the estimate (Cuba *et al*., 2012). The lack of stationarity of the CaO dataset, the Mn data in the E-W directions and the Fe data in the E-W directions, resulted in differences in the local mean and the local variance of random variables, referred to as trends. This was evident where certain experimental semi-variograms extended above the sill.

Cuba *et al*. (2012) cautioned that even after the mean and variance trends are removed from the dataset, the data should not yet be assumed to be stationary. The stationarity of the spatial covariance is required before the condition of total stationarity can be met. As the semi-variogram is a two-point statistic, it may not adequately capture complex trend features in the random function. Chilès and Delfiner (1999) suggest the application of generalised covariances for verification of spatial variability by taking configurations with more than two points (cited by Cuba *et al*., 2012).

CHAPTER 7

CONCLUSION AND RECOMMENDATIONS

7.1 Conclusion

The problem statement set out at the beginning of this research report questioned the relevance of the Mineral Resource classification method currently applied by Wessels mine on its hydrothermally altered manganese ore body. The objective of this study was to review the Mineral Resource classification methodologies applied to similar bulk mining commodities, and based on a statistical and geostatistical analysis, to develop a defendable Mineral Resource classification criterion for hydrothermally enriched manganese ore bodies. This chapter provides answers to the two fundamental research questions outlined in Chapter 1.

Research question 1: Is the current Mineral Resource classification method suitable for the ore body?

The answer is “No”. The current Mineral Resource classification applied at Wessels mine is based on a purely mathematical indicator of confidence, namely, the semi-variogram range. This study has shown that Fe data is positively skewed. As emphasised by Clark (2015), variance and covariance have little meaning when applied to skewed datasets. Additionally, the non-stationarity of the data means that there are considerable limitations to the application of a purely geostatistical classification method.

Purely geostatistical methods of Mineral Resource classification are optimal when the data is normally distributed and stationery. Significant deviations from normality and stationarity do not support a purely statistical Mineral Resource classification technique. (Bohling, 2005).

Even if the manganese, iron and calcium oxide distributions were both Gaussian and stationary, there are still sources of errors that can have a large effect on the reliability of the estimate. These sources include understanding of elements such as connectivity of the mineralisation, information effect, support effect and the regression effect. The Competent Person and investors need to be aware of these effects and their influence on the reliability of the estimate and therefore on the confidence associated with the estimate (Magnus, 2017).

The value of onsite practical geological knowledge and information should not be underestimated and the geostatistics should always confirm the geology. For this reason, a purely mathematical approach to Mineral Resource classification would be a gross oversight. A combination of geological factors should be used (Magnus, 2017) for reliable classification criteria for hydrothermally enriched manganese ore bodies.

The complete absence of the consideration of geological risk in the current Mineral Resource classification, the exclusion of the risk associated with data integrity and the limited assessment of the risk associated with the estimate lead the researcher to conclude that the current Mineral Resource classification is an over-simplification and thus not suitable for the ore body.

Research question 2: Are there better classification methods that can be recommended to replace or improve the current Mineral Resource classification technique?

Mineral Resource classification methods used elsewhere in the world for similar bulk commodities were investigated as part of this study, to establish what other methods of classification were available. Whilst there are many publications on Mineral Resource classification, few publications exist on the application of Mineral Resource classification techniques applied to manganese deposits. Most of the manganese specific literature references are from individual manganese mines that have each developed sight specific Mineral Resource classification methods. The literature review showed that most South African and Australian manganese mines still employ a variation of drill spacing, as the preferred classification methodology, with Wessels mine being an exception by applying the "Search Neighbourhood" technique.

The basis of the Mineral Resource classification criteria investigated relied on levels of increasing geological confidence as highlighted by the SAMREC Code. From the literature review, several methods of Mineral Resource classification were considered. Several pertinent aspects were incorporated in the proposed Mineral Resource classification scorecard. Pertinent aspects were sorted into three broad categories according to confidence in data integrity, confidence in the geology and confidence in the estimation methodology. The proposed scorecard method was designed to balance these three crucial elements.

The results of the literature review also revealed that the mining industry is increasingly moving towards the implementation of scorecard based classifications. In keeping with this trend, the researcher developed a scorecard classification criteria for hydrothermally enriched manganese ore bodies, envisaged as an improvement over the current methodology. The proposed Mineral Resource classification criteria is intended as a guideline rather than a prescribed method, with the aim of assisting the Competent

Person with his/her judgement on confidence. The guideline will allow for the inclusion of the Competent Person's knowledge and experience, while still providing a defendable approach.

In conclusion, the researcher has answered the fundamental research questions, thereby achieving the objectives of the study. It is envisaged that this research will contribute to a published body of work that will eventually lead to improved classification of hydrothermally enriched manganese ore bodies.

7.2 Recommendations

The trialling of software that is designed for Conditional Simulation to generate equiprobable geostatistical models is recommended for Wessels mine. A benefit of this approach is that the realisations collectively constitute a versatile model of uncertainty which can be investigated at a variety of scales, from yearly down to weekly (Magnus, 2017). A comparison of the results of the current Mineral Resource classification, the newly proposed Mineral Resource classification and Conditional Simulation classification results is required. This will greatly assist the Competent Person in determining which criteria he/she feels is best suited for the deposit. The undertaking of this study on Wessels mines most recent data will aid in the ability to justify the selected Mineral Resource classification to peers and auditors.

There remains room for further sub-domaining analysis of calcium oxide based on the results of the experimental semi-variograms generated across the traditional Wessels mine domains. Additional work is required to fully understand the controls on CaO mineralisation and how the geological interpretation ties in with the spatial analysis of calcium oxide grade. The researcher suggests that this area of research be encouraged and funded by South32. This can be done most cost effectively by suggesting this research topic to post-graduate students who are already on the company bursary scheme and are in need of a research topic.

The use of the global density average of 4.23 g/cm^3 still persists to this day. The Density Re-logging Project should continue until density is stored for each available borehole, corresponding to the sampled units. Having comprehensive density data readily available in Geobank will likely have significant financial implications and lead to increased estimation confidence. At the very least, domain averages can be calculated and applied during estimation. The lack of comprehensive density data can cause serious errors in tonnage estimates and an over or under estimate of metal content. The financial implication of using the global density average is likely significant.

The Borehole Re-survey Project should be continued, focusing only on reducing the number of boreholes which have incomplete geo-referencing (X, Y, Z) data. The incomplete geo-referencing data results in the Global model having less data than what is actually available, rendering those boreholes virtually useless. The completion of the re-survey project will mean that the money spent to drill the holes with incomplete survey and collar data will finally realise its full value.

The degree of skewness of the Fe data requires additional work to compare the estimate mean with the estimator for the mean of the population. To improve the global estimate for the Fe%, a cumulative log probability plot of the composited data can be generated to see whether that would give a distribution closer to normality. Any deviation from a straight-line suggest would that a 3-parameter lognormal estimate might be more appropriate. A significance test can be conducted to determine if the difference between the two means is significant. The discrepancy may be one of the contributing factors to the reoccurring iron content complaints of the Wessels product, along with the inherent, mineralogical Fe of the ore, ferruginisation associated with structures and mining discipline.

Issues which were not elaborated upon in the estimation methodology of Nengovhela (2013), Nengovhela (2015) and Lautze & Lukhaimane (2017) include the application of grade capping to remove waste outliers and a distinction on whether hard or soft boundaries were applied during the domaining process. Although the researcher found no evidence to discourage the use of IDW as the estimation technique, it is possible that with the application of adequate kriging parameters and variography, a case could be made for the application of ordinary kriging over inverse distance weighting. Extensive estimate validation was outside the scope of this research, with the research focus being on Mineral Resource classification and the confidence assigned to the estimate. Wessels mine may benefit significantly from further, robust estimate validation, perhaps as a post-graduate research topic for the future.

REFERENCES

Abzalov, M. Z. (2013) Measuring and modelling of dry bulk rock density for mineral resource estimation. *Applied Earth Science*. 122 (1). p. 16-29.

African Rainbow Minerals. (2008) *Mineral Reserves and Resources*. [Online] Available from http://www.arm.co.za/im/files/annual/2008/files/ARM_RR2008.pdf. [Accessed: 30 June 2017].

African Rainbow Minerals. (2016) *Mineral Reserves and Mineral Resources*. [Online] Available from http://www.arm.co.za/im/files/annual/2016/ARM-RR16.pdf. [Accessed: 30 June 2017].

Annels, A. E. (1995) The development of a Resource Reliability Rating (RRR) system for the evaluation of mineral deposits. In *Proceedings, Mineral Resource Evaluation Conference.* University of Leeds. Yorkshire, England. p. 16.

Annels, A.E. (1997) Errors and classification in Ore Reserve estimation: The Resource Reliability Rating (RRR). In *Proceedings, Assaying and Reporting Standards Conference*. AIC Conferences, Paper no.5. p. 29.

Annels, A.E. & Dominy, S. C. (2002) The development of a Resource Reliability Rating (RRR) system for Mineral Resource estimation. In: *Proceedings, Value Tracking Symposium*. Australian Institute of Mining and Metallurgy. p. 27-32.

Arik, A. (1999) Uncertainty, Confidence Intervals and Resource Categorization: A Combined Variance
Approach. *ISGSM Symposium Proceedings*. 1999. Perth, Australia. ISGSM.

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

Armstrong, M. (1998) *Basic Linear Geostatistics*. New York: Oxford University Press.

Assmang Proprietary Limited. (2015) *Assore Mineral Resources and Reserves Report*. [Online] Available from http://www.assore.com/wp-content/uploads/2015/10/Assore-mineral_resources_and_reserves.pdf. [Accessed: 30 June 2017].

Baafi, E. Y. & Schofield, N. A. (1997) *Geostatistics Wollongong*, 1996. Dordrecht, the Netherlands: Kluwer Academic Publishers. p. 799-821.

Barnes, R. (2003) Variogram tutorial. Golden Software incorporated. [Online] Available from http://gis.fns.uniba.sk/vyuka/DTM_ako_sucast_GIS/Kriging/2/Variogram_Tutorial.pdf. [Accessed: 15 October 2018].

Basu S., Gunst, R. F., Guertal, E. A. & Hartfield, M. I. (1997) The Effects of Influential Observations on Sample Semivariograms. *Journal of Agricultural, Biological and Environmental Statistics*. 2(4). p. 490-512.

Beltrame, R. J., Holtzman, R. C. & Wahl, T. E. (1981) *Manganese Resources of the Cuyuna Range, East-Central Minnesota*. Minnesota: University of Minnesota.

Beukes, N. J. (1983) Palaeoenvironmental setting of iron formations in the depositional basin of the Transvaal Supergroup, South Africa. In: Trendall, A. F. & Morris, R. C. (eds.) (1983) *Iron-formations: facts and problems*. Amsterdam: Elsevier. p. 131-209.

Bohling, G. (2005) *Introduction to Geostatistics and Variogram Analysis*. Kansas Geological Survey. p. 1-20.

Cairncross, B., Beukes, N. J. & Gutzmer, J. (1997) *The manganese adventure: the South African manganese fields*, Johannesburg: Associated Ore & Metal Corporation Limited. p. 48-74

Chilès, J. & Delfiner, P. (1999) *Geostatistics: Modelling Spatial Uncertainty*. New York: John Wiley and Sons. p. 52.

Clark, I. (1979) *Practical Geostatistics*. Alloa: Geostokos Limited.

Clark, I. (2015) *Regression Revisited (again)*. Journal of the Southern African Institute of Mining and Metallurgy, 115 (1).

Clark, I. & Harper, W. V. (2000) *Practical Geostatistics*. Columbus, Ohio: Ecosse Northern America LLC. p. 216.

Committee for Mineral Reserves International Reporting Standards. (2013) International Reporting Template for the Public Reporting of Exploration Results, Mineral Resources and Mineral Reserves. [Online] Available from http://www.crirsco.com/templates/international_reporting_template_november_2013.pdf [Accessed: 26 February 2019].

Compass English. (n.d.) Image gallery. [Online] Available from http://filmi-onlain.info/jpgcpng-compass-english.shtml. [Accessed: 17 January 2019].

Cornell, D. H. & Schütte, S. S. (1995) A volcanic-exhalative origin for the world's largest (Kalahari) Manganese field. In: Beukes, N. J. & Gutzmer, J. (eds.) (1996). *Mineralium Deposita*, 30, p. 146-151.

Cressie, N. A. C (1993) *Statistics for spatial data*. Berlin: Springer-Verlag.

Cuba, M. A., Leuangthong, O. & Ortiz, J. M. (2012) Detecting and quantifying sources of non – stationarity via experimental semivariogram modelling. *Stochastic Environmental Research and Risk Assessment.* 26. p. 247-260.

De Souza, L. E., Costa, J. F. C. L. & Koppe, J. C. (2004) Uncertainty estimate in resource assessment: A geostatistical contribution. *Natural Resources Research*. 13 (1). pp. 1-2.

Deutsch, C. V. & Journel, A. G. (1998) *Geostatistical Software Library and User's Guide, Second Edition*. Oxford University Press, Applied Geostatistics Series, Deutsch

J. L., Szymanski, J. & Deutsch, C. V. (2014) Checks and measures of performance for kriging estimates. *Journal of the Southern African Institute of Mining and Metallurgy*. 114 (3). p. 223-223.

De Villiers, J. E. (1983) The manganese deposits of Griqualand West, South Africa: some mineralogical aspects. *Economic Geology*, 78. pp. 1108-1118.

Dohm, C. E. (2003) Application of simulation techniques for combined risk assessment of both geological and grade model- an example. *Journal of the Southern African Institute of Mining and Metallurgy*. 155. pp. 351-354.

Dohm, C. E. (2004) Quantifiable Mineral Resources classification: A Logical approach. *Quantitative Geology and Geostatistics*. 14 (1). pp. 333-342.

Dohm, C. E. (2016a) *MINN7007: Statistical Evaluation of Mineral Resources*. [Class notes 01-04]. Johannesburg: University of the Witwatersrand.

Dohm, C. E. (2016b) *MINN7006: Geostatistical Methods in Mineral Resource Evaluation*. [Class notes 05-07]. Johannesburg: University of the Witwatersrand.

Dominy, S. C., Noppé, M. A. & Annels, A. E. (2002) Errors and uncertainty in Mineral Resources and Ore Reserve Estimation: The importance of getting it right. *Exploration Mining Geology.* 11 (1-4). pp. 77-98.

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 African Institute of Mining and Metallurgy. 117. pp. 1127-1132.

Du Toit, R (2018) *A Refined Resource Model for Tshepong Mine*. A Thesis Submitted in partial fulfilment of the Requirements of University of the Witwatersrand for the Degree of Master of Science. Johannesburg: University of the Witwatersrand.

Emery, X., Ortiz, J. M. & Rodriguez, J. J. (2004) *Quantifying uncertainty in Mineral Resources with classification schemes and conditional simulations*. Chile: University of Chile.

Emery, X., (2008) Change of Support for Estimating Local Block Grade Distributions. *Mathematical Geosciences*, 40 (6), pp. 671-688.

Evans, D. A. D., Gutzmer, J., Beukes, N. J. & Kirschvink, J. L. (2001) Paleomagnetic constraints on ages of mineralization in the Kalahari manganese field, South Africa. *Economic Geology*. 96 (3). pp. 621-631.

Fan, D. & Yang, P. (1999) Introduction to and classification of manganese deposits of China, *Geological Review*. 15. pp. 1-13.

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

Glacken, I. M. (1996) Resource classification: use and abuse of the kriging variance. *Datamine Annual Conference Proceedings.* 1996. Datamine.

Goovaerts, P. (1997) *Geostatistics for Natural Resources Evaluation*. New York: Oxford University Press. pp. 19, 100-105.

Gunst, R. F. & Hartfield, M. I. (1996) Robust Semivariogram Estimation in the Presence of Influential Spatial Data Values. In: Gregoire, T. G., Brillinger, D. R., Diggle, P. J., Russel-Cohen, E., Warren, W.E. & Wolfinger, R. D. (eds.). *Robust Semivariogram Estimation in the Presence of Influential Spatial Data Values*. Lecture notes in Statistics volume 112 . Netherlands: Springer. pp. 265-274.

Gutzmer, J. & Beukes, N. J. (1998) *High-grade manganese ores in the Kalahari Manganese Field: characterisation and dating of ore-forming events*. Hotazel: Johannesburg. Unpublished. p. 78.

Gutzmer, J. & Cairncross, G. (2002) Spectacular Minerals from the Kalahari Manganese Field, South Africa. *Rocks & Minerals*. 77 (2). pp. 94-107.

Haldar, S.K. (2013) Statistical and geostatistical applications in geology. In Halder, S.K. (ed). *Mineral Exploration.* India: Elsevier. pp. 174-177.

Harney, D. & Dohm, C. (n.d.) *Balanced Score Card for Resource Classification 01*. Mining Geology Best Practices. Unpublished.

Henley, S. (2001) The importance of being stationary. *Earth Science Computer Applications*. 16 (12) pp. 1-3.

Hotazel Manganese Mines. (2001) *Basic Training Programme for Geology*. Document no. HRR-SOP- 00. pp. 5-11.

Isaaks, E. H and Srivastava, R. M. (1989) *An introduction to Applied Geostatistics* . New York: Oxford University Press. pp. 241-247.

Krige, D. G. (1951) *A statistical approach to some mine evaluation and allied problems on the Witwatersrand*. A Thesis Submitted in partial fulfilment of the Requirements of University of the Witwatersrand for the Degree of Master of Science. Johannesburg: University of the Witwatersrand.

Krige, D. G. (1996) A practical analysis of the effects of spatial structure and of data available and accesses, on conditional biases in ordinary kriging. In: Baafi, E. Y. & Schofield, N. A. (eds.). *Geostatistics Wollongong. Fifth International Geostatistics Congress*. Wollongong, Australia, September 1996. Kluwer Press. p. 799-810.

Kumba Iron Ore. (2012) *Estimation Methodology Summary: Mineral Resources*. [Online] Available from www.overendstudio.co.za/online_reports/kumba_ar2011/reserves/rr_summ_min.php. [Accessed: 19 July 2018].

Lautze, L & Lukhaimane, T. (2017) *Wessels Geology and Resource Estimation Methodology Report*. Johannesburg: South32. Unpublished.

Li, J.& Heap, A. D. (2008) *A review of spatial interpolation methods for environmental scientists: applying geoscience to Australia's most important challenges*. Commonwealth of Australia: Canberra-Australia.

Ma, Y. Z. & Jones, T. A. (2001) Teacher's Aide: Geologic Characteristics of Hole-Effect Variograms Calculated from Lithology-Indicator Variables. *Mathematical Geology.* 33 (5). p. 615-629.

Magnus, E. (2017) *Alternative Methods for Coal Resource Classification of the geologically complex Witbank Coalfield*. A Thesis submitted in partial fulfilment of the Requirements of the University of the Witwatersrand for the degree of Master of Science in engineering. Johannesburg: University of the Witwatersrand.

Mandava, S. M. (2016) *Finding the Optimal Dynamic Anisotropy Resolution for Grade Estimation Improvement At Driefontein Gold Mine, South Africa*. A Thesis submitted in partial fulfilment of the Requirements of the University of the Witwatersrand for the degree of Master of Science in engineering. Johannesburg: University of the Witwatersrand.

Matheron, G. (1971) *The theory of regionalized variables and its applications*. Paris: Ecole Nationale Supérieure des Mines de Paris.

Mathuray, S. (2015) *Criteria for the Classification of Inventory Coal and Coal Resources*. [Online] Available from file:///C:/Users/0706376V/Downloads/SANS%20Code%20Update%20Mar2015%20KM%20DRWD%20final.pdf. [Accessed: 24 October 2018].

Mohanlal, K. & Stevenson, P. (2010) Anglo American Platinum's approach to resource classification case study- Boschkoppie/Styldrift minewide UG2 project. *Journal of the Southern African Institute of Mining and Metallurgy*. pp. 105-112.

Morgan, C. J. (2005) *Analysing spatial data via geostatistical methods*. A Thesis submitted in partial fulfilment of the Requirements of the University of the Witwatersrand for the degree of Master of Science in engineering. 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*. A Thesis submitted in partial fulfilment of the Requirements of the University of the Witwatersrand for the degree of Doctor of Philosophy. Johannesburg: University of the Witwatersrand.

Mucha, J. & Wasilewska-Blaszczyk, M. (2015) Geostatistical support for categorization of metal ore resources in Poland. *Mineral Resources Management*. 31 (4). pp. 21-34.

Myers, D.E. (1989) To Be or Not to Be... Stationary? That Is the Question. *Mathematical Geology*. 21 (3). pp. 347-362.

Nengovhela, C. (2013) *Wessels Mine Global Mineral Resource Model Methodology Report*. Johannesburg: BHP Billiton. Unpublished.

Nengovhela, C. (2015) *Mineral Resource Estimation Wessels Mine*. Johannesburg: South32. Unpublished.

Nengovhela, A. C (2018) *The Application Of Geostatistics in Coal Estimation and Classification*. A Thesis submitted in partial fulfilment of the Requirements of the University of the Witwatersrand for the degree of Master of Science in engineering. Johannesburg: University of the Witwatersrand.

Olea, R., Luppens, J. & Tewalt, S. (2011) Methodology for quantifying uncertainty in coal assessment with an application to a Texas Lignite deposit. International Journal of Coal Geology. 85 (1). pp. 78-90.

Olsen, S. E. & Tangstad, M. (2004) Silicomanganese production- process understanding. *Tenth International Ferroalloys Congress Proceedings*. 2004. Cape Town, South Africa. Document Transformation Technologies.

Ortiz, 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*. 106. pp. 577-584.

Parker, H. M. & Dohm, C. E. D. (2014) *Evolution of Mineral Resource Classification from 1980 to 2014 and Current Best Practice*. [Lecture]. Finex 2014 Julius Wernher Lecture. Amec & Anglo American.

Pyrcz, M. J. & Deutsch, C. V. (2003) *The whole story on the hole effect*. [Online] Available from https://www.researchgate.net/publication/228596880_The_whole_story_on_the_hole_effect. [Accessed: 9 October 2018].

Pyrcz, M. J. & Deutsch, C. V. (2017) *Declustering and Debiasing*. [Online] Available from https://www.researchgate.net/publication/228427948_Declustering_and_debiasing. [Accessed: 19 July 2018].

Rezaee, H. & Asghari, O. (2012) Accounting for secondary variable for the classification of Mineral Resources using cokriging technique; a case study of Sarcheshmeh porphory copper deposit. *International Journal of Mining and Geo-Engineering*. 46 (1). pp. 617-80.

Sadeghi, B., Madani, N. & Carranza, E. J. M. (2015) Combination of geostatistical simulation and fractal modelling for Mineral Resource classification. *Journal of Geochemical Exploration*. 149. pp. 59-73.

SAMREC (2016). *The South African Code for the Reporting Of Exploration Results, Mineral Resources and Mineral Reserves*. 2016 Edition. [Online] Available from www.samcode.co.za. [Accessed: 31 October 2017].

Shinozuka, M. & Jan, C. M. (1972) Digital simulation of random processes and its applications. *Journal of Sound and Vibration*. 25. pp. 111–128.

Sichel, H. S. (1973) Statistical valuation of diamondiferous deposits. *Journal of South African Institute of Mining and Metallurgy*. pp. 235-243.

Silva, D. S. F. & Boisvert, J. B. (2014) Mineral Resource classification: a comparison of new and existing techniques. *Journal of the Southern African Institute of mining and Metallurgy*. 11. pp. 265-273.

Snowden, D. V. (1996) Practical interpretation of resource classification guidelines. In *AusIMM Annual Conference "Diversity, the key to Prosperity"*. Perth, 1996.

Snowden, D. V. (2001) Practical interpretation of Mineral Resource and Ore Reserve classification guidelines. *Mineral Resource and Ore Reserve Estimation-the AusIMM Guide to Good Practice*. Australian Institute of Mining and Metallurgy, Melbourne. pp. 643-652.

Söderlund, U., Hofmann, A.,Klausen, M. B., Olssona, J. R., Ernst, R. E. & Perssone, P. (2010) Towards a complete magmatic barcode for the Zimbabwe craton: Baddeleyite U–Pb dating of regional dolerite dyke swarms and sill complexes. *Precambrian Research*. 183 (3). pp. 388-398.

South32 Limited. (2015) *Mineral Resources and Ore Reserves Update*. [Online] Available from https://www.south32.net/docs/default-source/exchange-releases/resources-and-reserves-market-announcement-2015.pdf?sfvrsn=afb0c9c0_6. [Accessed: 30 June 2017].

South32 Limited. (2016) *Annual Report 2016*. [Online] Available from https://www.south32.net/investors-media/annual-report-suite [Accessed 19 July 2018].

Stephenson, P. R., Allman, A., Carville, D. P., Stoker, P. T., Mokos, P., Tyrrell, J. & Burrows, T. (2006) Mineral Resource Classification - It's Time to Shoot the 'Spotted

Dog'! In *Sixth International Mining Geology Conference*. Darwin, Australia, August 2006. Australian Institute of Mining and Metallurgy. pp. 91-96.

Stoker, P. (2015) The JORC Code and the coal guidelines. *JORC code guidelines seminar*. 25 June 2015. Australia. AusIMM Hunter Region Branch.

Till, R. (1974) *Statistical methods for the Earth Scientist*. Palgrave: MacMillan. p. 168.

Tsikos, H. & Moore, J. M. (1998). The Kalahari manganese field: an enigmatic association of iron and manganese. *South African Journal of Geology*. 101, p. 287.

United States Geological Survey. (2014) *Manganese -It Turns Iron Into Steel (and Does So Much More)*. USGS Mineral Resources Program. [Online] Available from https://pubs.usgs.gov>pdf. [Accessed: 2 October 2018].

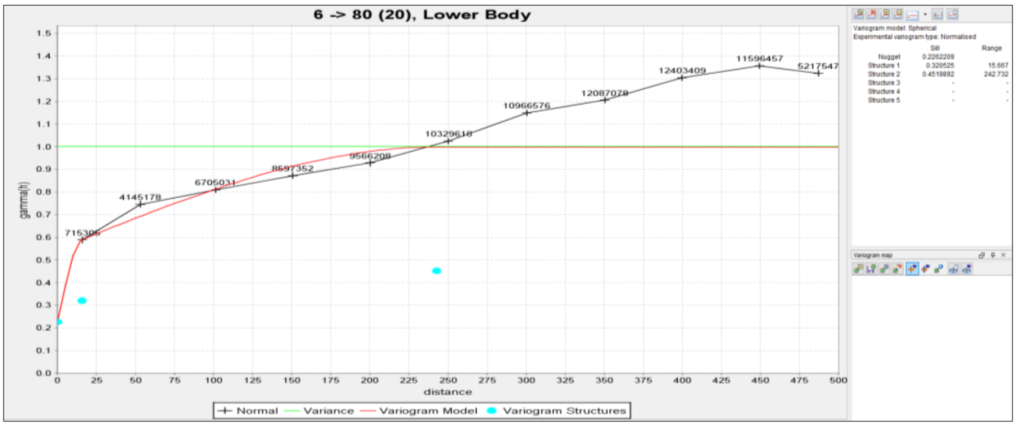
Wawruch, T. M. & Betzhold, J. F. (2005) Mineral Resource classification through conditional simulation. In: Leuangthong, O. & Deutsch, C. V. (eds.). *Quantifiable Mineral Resource classification: a logical approach.* Quantitative Geology and Geostatistics volume 14 .Netherlands: Springer.

Yamamoto, J. K. (2000) An alternative measure of the reliability of ordinary kriging estimates. *Mathematical Geology*. 32 (4). pp. 489-509.

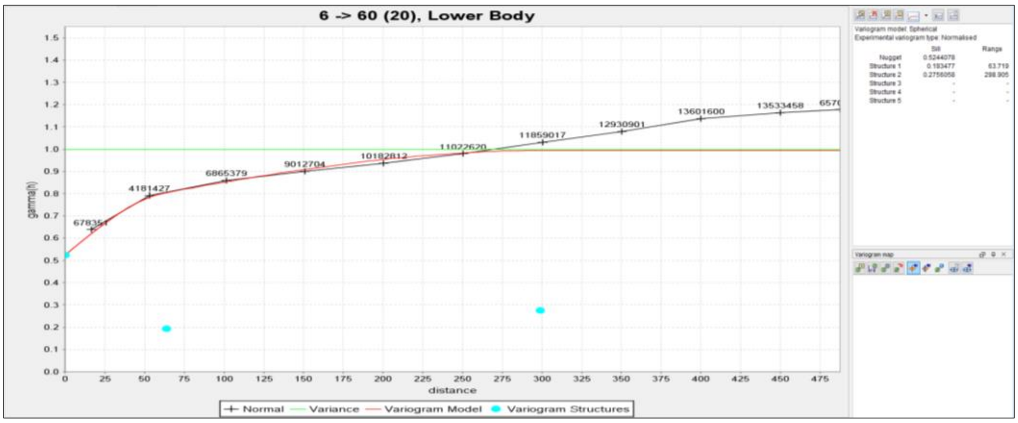
Zagayevskiy, Y. V. & Deutsch, C. V. (2011) *A Short Note on an Update to the Change of Support Program*. Paper 313, CCG Annual Report 13. p. 313.

Zulu, N. (2010) *The geology of the Kalahari manganese field between Hotazel Mine and Ga-Letola, Northern Cape, South Africa*. A Thesis submitted in partial fulfilment of the Requirements of the University of the Witwatersrand for the degree of Honours. Johannesburg: University of the Witwatersrand.

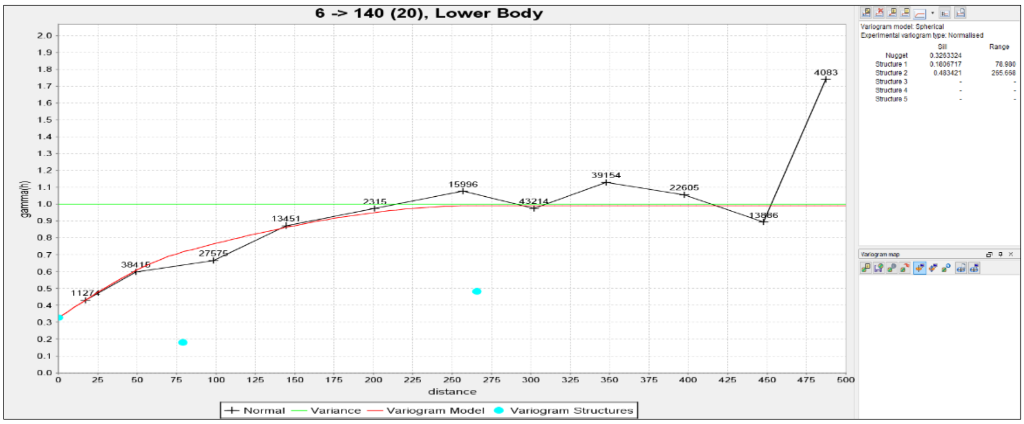
APPENDIX



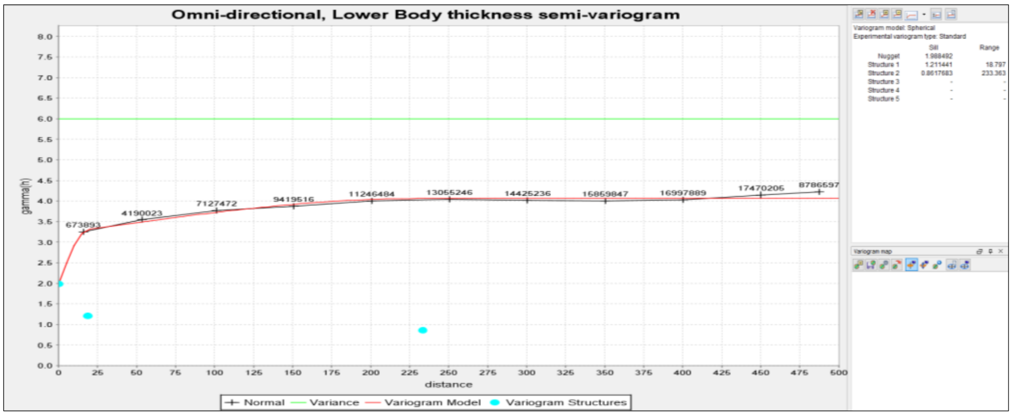
Mn standardised semi-variogram in the 80°direction of least continuity.



Fe standardised semi-variogram in the 60° direction of least continuity.



CaO standardised semi-variogram in the 140°direction of greatest continuity.



Normal (ordinary) Lower Body thickness semi-variogram.