IMPROVING RECONCILIATIONS THROUGH GEOSTATISTICAL RESOURCE MODEL UPDATES OF PHOENIX DEPOSITS, TATI NICKEL MINE

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

Declaration

I declare that this Research report is my own, unaided work. It is being submitted for the Degree of Master of science at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.

Mothusi Ntshole

(Signature of candidate)

27 day of September 2019 in Orapa, Botswana.

Abstract

Periodic resource model updates are necessary to bridge the reconciliation variances between the resource model estimates and actual ore mined. As a tool, Mineral Resources reconciliation focuses on identifying, analysing and managing variance between estimated Mineral Resources and actual ore mined. The aim is to minimize the business risk associated with poor resource model estimate performance against actual ore mined at Phoenix Mine.

The Phoenix Mine Mineral Resource model update research project incorporates historical and recently acquired drillhole data, other relevant geological information in the form of geological pit floor and face maps to update the Phoenix Mineral Resource model. Employing appropriate geostatistical estimation methods and improved modelling procedures can highlight and overcome some of the causes of observed reconciliation variances. Each of the five domains of the Phoenix resource was estimated through ordinary kriging and indicator kriging as principal methods. Nearest neighbour (NN) and inverse power of distance (IPD) methods were used as a check and where the above geostatistical methods proved inappropriate.

The comparison between model estimates from these various estimation techniques and raw drill hole data was undertaken. The results indicate areas of both good and poor correlation across the different methods and sections of the resource. Areas where there is good correlation coincides with good sampling coverage where as poor correlation coincides mostly with portions of the resource where there is paucity of sampling data. Subjecting the individual domains' resource estimates from the various estimation methods to a validation check against the sampling data assisted in selecting the estimate that honours the sampling data the most. Such Estimate was selected as the most suitable and reported as the Estimated Resources. Indicator Kriging produced better results compared to the rest of the techniques. In domain four geostatistical methods were unsuccessful thus Inverse power of distance method was used.

Dedication

This work is dedicated to my wife; she has been a pillar of support and motivation over the years during my studies. I thank you Mrs. Rachel Ntshole.

Acknowledgements

The data used in this research work and the software for geostatistical evaluations were provided by Tati Nickel mine. I am also grateful to Tati Nickel Mine for allowing me to undertake this project and present the results as a business case for process improvement. I must single out Mr. K Botepe (Mineral Resources Manager, Tati Nickel Mine) who supported the project proposal at management level.

I would also like to show appreciation to Datamine especially Dr. B Chisonga who provided mentorship, software and technical support in areas of variography and grade estimation. My supervisor, Professor R.C.A Minnitt guided me through this research investigation, providing mentorship to see the project to completion. Lastly special thanks to my family who allowed me to undertake the studies and often accompanied me on many trips to the university.

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List of symbols and abbreviations

a	Variogram range
C(h)	Covariance
C	Total sample variance
CIM	CIM Definition Standards for Mineral Resources and Mineral Reserves
C_1	First sill of the semi variagram
Co	Nugget effect
COV	Coefficient of variation
CP	Competent person
CRM	Certified reference material
Cu	Copper
DD	Diamond Drilling
DTM	Digital terrain model
E(x)	Expected value
EDA	Exploratory data analysis
γ (h)	Semi variogram
GRE	Global relative error
h	Separation vector distance
i(x,zc)	Indicator cut-off grade
IK	Indicator kriging
IPD	Inverse power distance
JORC	Joint Ore Reserve Committee
KE	Kriging efficiency
m	Mean
MINRED	Mineral Resource Evaluation Department
MRE	Mineral Resources Estimation
N(h)	Number of paired samples h distance apart
Ni	Nickel
NN	Nearest neighbour

NI43101	National instrument for the Standards of Disclosure for Mineral Projects within Canada.
OK	Ordinary Kriging
$PdAs_2$	Merenskyite
PGM	Platinum group metals
P-P plots	Probability-Probability plot
$PtAs_2$	Sperylite
QC-QA	Quality assurance and quality control
Q-Q plot	Quantile-Quantile plot
RC Drilling	Reverse circulation drilling
(Rh,Pt)AsS	Hollingworthite
SAMREC	South African Mineral Resources Committee
SG	Specific gravity
SK	Simple kriging
SMU	Smallest mining unit
SRM	Standard reference material
wi	Estimation weight
Z(x)	Value of a regionalized variable at point x
Z*(x)	Point to be estimated
μ	Lagrange multiplier
P(h)	Correlogram
σ^2_ε	Estimation variance

1 Introduction

Reconciliation of estimated mineral resources against actual production data is a sine qua non to calibrate and refine a resource model. As defined by Riskie, et al., (2010) reconciliation is a process of identifying, analysing and managing variance between planned and actual results in a manner that highlights opportunities for improvements. It provides assurance of the mineral resource estimate and as a tool enables the system to identify the discrepancies and prompts for model updates when additional data is acquired (CIM Estimation best practice committee, 2002). Thus, Mineral Resource model updates are required to improve the resource estimation as more drilling data becomes available. As mentioned the reconciliation process highlights the discrepancies and these model updates serve to reduce the variances. From the revenue point of view, it is very important that actual production figures should not stray far away from the estimates as this could derail almost the entire business model.

A continuous periodic resource model updates process can improve the mineral resource estimate with time and minimize the reconciliation variances. More sampling data is collected during the life of mine and this sampling data provides an opportunity to carry out a mineral resource update to create better estimates as a way of addressing the identified reconciliation discrepancies. With time causal factors of the reconciliation variance emanating from the resource estimation process will reduce as more data is accumulated and model updates undertaken.

The previous Phoenix resource model update was undertaken in 2011 by Gipro Nickel Consultants as part of a due diligence on the Tati Nickel property. Prior to this, two (2) other updates were completed in 2008 and 2009 by Mineral Resource Evaluation Department (MINRED), a unit of Anglo American Plc group. These updates were routine model updates incorporating additional drillhole and geological data accumulated to improve estimation. Earlier in 2006 SRK consulting were engaged by then owners, Lion ore (Africa) to review the estimation methodology and the resource model with a view of reporting recoverable resources (SRK Consulting, 2006). Recoverable resources provide predictions of location of estimated resources within a particular SMU, which is very important for short term planning of production.

The current update targets recently acquired drill hole, floor and face mapping data to carry out a model update to improve on the last update. To augment drill hole data coverage and to close identified data gaps a drilling campaign was instituted in 2013. The drilling concentrated in the areas within the current pit outline covering several benches (ranging in depth between 60 m to 100 m). With the advent of this additional data and employing appropriate estimation methodologies to undertake another model update the estimated resources are expected to improve. Incorporating as much geological information into the model as possible will assist in constraining of the ore zones and the delimitation of the mineralisation domains.

1.1 Scope of Work

The Phoenix resource model research study update entails reviewing of all collected drillhole data and collating bench and face mapping information to produce updated Mineral Resource model. Drillhole data includes the recently generated sampling information from the 2013 drilling campaign as well as the historical diamond drilling and reverse circulation drilling data available in the Phoenix drillhole database. The geological maps are bench and face maps from the production faces within the pit delineating different geological units exposed. These geological maps inform the distribution and mineralisation variability assessments across and down benches.

1.2 Purpose and Objectives of study

Improved Mineral Resource estimates rely on the continual updating of the resource model as more sampling and mining data is collected. Therefore, as mining progress and more sampling data is collected it prompts for an update of the resource model to improve the resource estimates. With improved estimation the observed reconciliation discrepancies will gradually reduce.

The research study aims to employ different methods of resource estimation to update the resource model in the advent of additional drillhole and mapping data acquired at Tati nickel mine. The update comes in part as routine resource model update assimilating the new data to improve the resource estimate. The performance of the resource model against actual mining data is considered one of the high risk factors in mining projects. In any estimation procedure, the quality of the estimation, assessed through the estimation variance will improve whenever additional sampling information regarding the mineralisation is provided (Sullivan, 1984).

The objectives of the research study are listed below:

1. To undertake geostatistical analyses of all the five mineralisation domains of the Phoenix orebody.
2. To update the mineral resource model through appropriate estimation methodologies.
3. To assess estimated mineral resources against raw data and report optimal estimated resources.

It is a known observation that no single interpolation method is appropriate for all orebodies (Snowden, 1997). Geostatistical analysis is required to characterise the domains and assess the variographic structure of the grade distribution. The selection of appropriate estimation method is based on the results of variography and the generated basic statistics describing the distribution.

2 Literature review

Mineral Resources reconciliation is a process of identifying, analysing and managing variance between estimated resources and actual ore mined in a way that highlights opportunities (Richard & Sulemana, 2015). One of the three objectives highlighted by Rossi & Camacho (2000) of a reconciliation program is to assess the accuracy of the predictive resource models. The other two being to account for the total production and to evaluate the operation's performance. The identified opportunities enable the operation to devise and implement process improvement initiatives across the value chain. Opportunities often highlighted include the selection of improved resource estimation methodologies to create better estimates.

The efficiency of the estimation method improves with additional drillhole data acquired. In producing mines like Tati Nickel, drill hole data coverage improves gradually with time as production continues. More over to address resource model underperformance and reconciliation discrepancies, infill drilling is often undertaken to collect more data to be used in resource model updates. Mineral Resource Estimation (MRE) is a guided process and must to conform to the requirements of international reporting codes for the reporting of exploration results, mineral resources and mineral reserves (SAMREC, JORC and NI 43101).

2.1 Mineral resource estimation guidelines

Mineral Resource estimation provides an estimate of the tonnage and grade of an orebody. The estimate represents a realistic inventory that under justifiable assumptions both technical and economic can be upgraded into mineable reserves (International Accounting Standards Board, Extractive Activities Project team, 2005). Practical considerations to bear in mind during mineral resource estimation process include sampling data quality, drillhole spacing/data density, geological information, assay data analysis, sample support, cut off grades, Mineral Resource model, estimation technique/method and Mineral Resource validation among others. These practical guidelines and several others as outlined in the international reporting codes (SAMREC, JORC and NI 43101) are all aimed at minimizing the risk associated with resource performance. The international reporting codes require a comprehensive understanding of the statistical and geostatistical characteristics of the mineralisation to improve the quality of the estimation (CIM Estimation best practice committee, 2002).

The level of uncertainty on reported mineral resources is graded into three categories namely: - Inferred Indicated and Measured Resources respectively with increasing level of confidence, see figure 1. The subdivisions are a function of the acquired geoscientific information about the mineralisation. The categories are closely linked to the search neighbourhood and drill hole spacing (Rivoirard & Didier, 2015). Specifically, the geoscientific information includes the mapped-out geology hosting the mineralisation and the eventual geological model of the mineralisation, sample assay data quality and the application of an appropriate estimation technique.

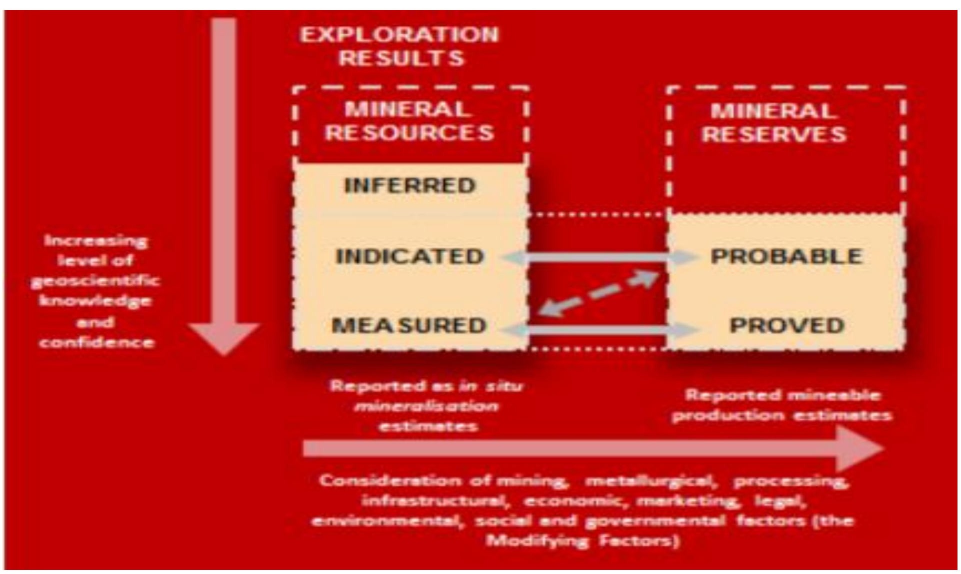


Figure 1: Relationship between Exploration Results, Mineral Resources and Mineral Reserves. Source (SAMREC 2016).

The increase in the confidence level and hence the assigned resource or reserve category is affected by factors such as: -

1. Geology and grade continuity.
2. Spatial distribution of the sampling data.
3. Quality of sampling and assay data.
4. Judgment of the Competent Person (CP).

The onus lies with the competent person to ensure that all material data used in the estimation of the mineral resources and reserves meet the required standards as expounded in the international reporting codes.

A general overview of the resource estimation process is depicted on figure 2. Each stage has its minimum requirements stipulated, a guide though not prescriptive by the international reporting codes (SAMREC, JORC and NI 43 101). For public listed companies these minimum requirements have to be met to disclose the level of financial risk associated with the reported resources or reserves.

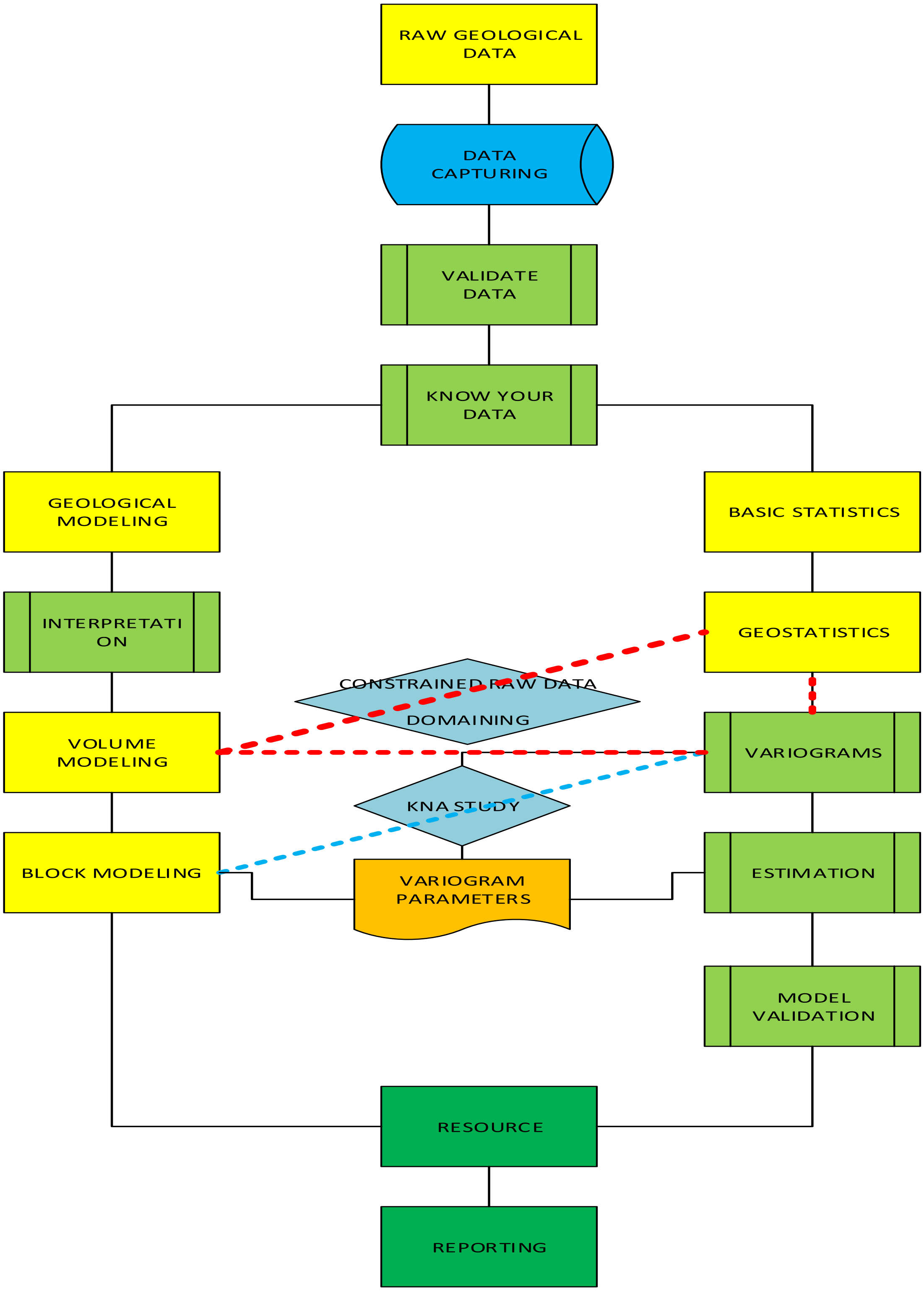


Figure 2: A schematic representation of a resource estimation process. Source: modified from (Vigar, 2013).

2.1.1 Geology and mineralisation controls

There are several geological and mineralisation factors which impact on the accuracy of the estimated resources. Such factors as captured by Dominy, et al., (2002) include:-

- Sampling and assay data;
- Detailed geology and understanding of geological controls; and
- Interpretation of grade distribution characteristics.

Geological data collection required for Mineral Resource estimation must concentrate on defining mineralisation controls. The data collected is interpreted systematically in 3D space to build a geological model. The model captures the extent and the presence of the orebody in relation to the sampling data and known geology (Sinclair & Blackwell, 2004). For purposes of geological modelling mineral deposit styles can be divided in 3 main groups, namely layered, veins and disseminated (Vigar, 2013). The geological characterisation of the orebody improves as the project advances through the different developmental stages. As a result, building a geological model is a dynamic process, revised and amended repeatedly as more geological data is accumulated.

Mineral resource estimation requires the orebody to be compartmentalized into zones of similar geological and mineralisation parameters. This is a fundamental requirement because the estimated resources are constrained by the geological complexity based on the geology, geometry and the grade distribution of the deposit (Chanderman, et al., 2017). These delimited zones are referred to as domains. Hence estimation domains are modelled from the geological variables that control the mineralisation. The definition of the domains should be based on acquired geological knowledge supported by statistical and geostatistical analyses of the sampling data (Erik, 2016). The delimited domains should follow the geology as far as possible. Exceptions do exist where this is not possible, for instance, in orebodies which are structurally controlled the grade distribution often transcends the geology. Therefore, a mineralisation domain is a spatial entity that determines a well-defined portion of an orebody with more or less uniform characteristics (Yunsel & Ersoy, 2013).

Domaining is integral to effective Mineral Resource Estimation. Poor understanding of the geological controls will always lead to a poor resource estimate. In geological modelling and subsequent estimation, a domain's spatial extent is defined by a 3D wireframe. The domain boundaries act as barriers either total or partial depending on their characterisation, to the influence of samples on either side of the boundary during resource estimation (Schofield, 2011). Local estimation procedures such as kriging work on the assumption of the intrinsic hypothesis. This implies that within a domain the mineralisation distribution exhibit consistent statistical properties and it is stationary.

2.1.2 Sampling data quality

Quality assurance and quality control (QA/QC) programs are maintained as part of the geological database. This is a requirement by the above mentioned international reporting codes which stipulates that a comment be made about the "quality of assay data and laboratory tests" and "whether acceptable levels of accuracy and precision have been established". The quality of the estimate depends on quantity and quality of the input data.

A robust sampling protocol is required to ensure acceptable levels of accuracy and precision on the assay data. The designed sampling protocols are specific to the mineralisation being investigated; capturing parameters such as sample size, mass (both wet and dry) and particle size. The protocols must be cost effective without compromising the mentioned parameters (Abzalov, 2011). From the sampling protocols rigorous quality control procedures are required to ensure the protocols are adhered to. The procedures set out the methodology of sample collection, frequency of duplicates samples in the batch, bagging and labelling of the samples and all other field sample preparation and the chain of custody requirements. The procedures inform the number of blanks and standard reference materials to include in the batch prior to submission to the lab.

2.1.3 Sampling errors and bias

Three groups of sampling errors are recognised based on the precision and accuracy of the data (Abzalov, 2011). Group 1 errors stem from sample extraction and preparation procedures and are related to the intrinsic characteristics of the mineralisation. Group 2 errors are a result of the sampling practice. The third group of errors result from analytical and instrumental issues, see table 1.

Table 1: Types of sampling errors and their causes.

Type	Sources of error	Nature of error
Group 1	Material characterization (sampling uncertainties, known, but never eliminated, minimized by strict adherence to principles)	Fundamental sampling error (FSE), related to compositional heterogeneity due to the material properties of the lot
Group 2	Sampling equipment and materials handling (sampling errors, unknown but eliminated by strict adherence to principles)	Increment delimitation error (IDE), geometry of outlined increment is not completely recovered; can be completely eliminated
		Increment extraction error (IEE), material extracted does not coincide with the delineated increment; can be completely eliminated
Group 3	Analytical processes (mainly sampling errors)	Analytical error (AE), all sources of error associated with materials handling and processes in the laboratory

Source: modified from (Cuba, et al., 2012)

Group 1 errors as stated cannot be eliminated but can be minimized through optimized sampling protocols. The errors include grouping and segregation errors emanating from different settling densities and distribution heterogeneity of the material being sampled. Group 2 errors are also managed through optimized sampling protocols and periodic quality assurance monitoring checks on the sampling processes. Group 3 errors relating to calibration of the analytical instruments are managed through periodic instrument calibrations. Figure 3 and 4 show the different types of sampling errors.

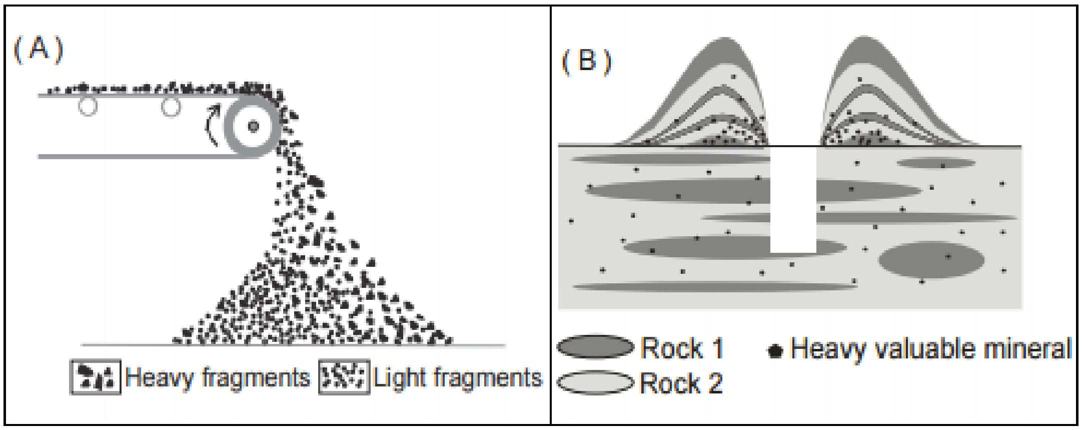


Figure 3: Segregation of rock fragments, heavier particles tend to settle at the base. Source (Abzalov, 2011)

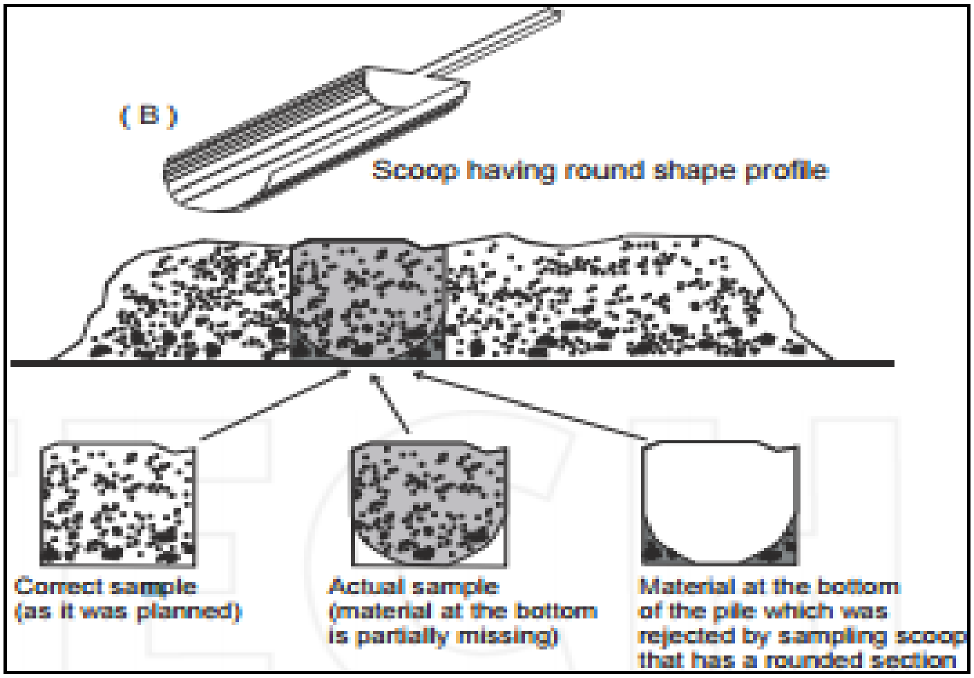


Figure 4: An example of delimitation error, sampling equipment poorly designed. Source (Abzalov, 2011)

Sampling protocols are designed such that every portion of the lot has an equal probability of belonging to the sample to minimise bias. However, a proportion of the error will remain and can be quantified by relative error. This relative error is aggregated into global relative error (GRE) and it is calculated as follows:

$$GRE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{z_s(x_i) - z(x_i)}{z_L(x_i)}\right)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..1$$

Where

n = number of sampled locations

$z_s(x_i)$ = sampled value at location x_i

$z_L(x_i)$ = true value of the lot sampled at location x_i

2.1.4 Precision and Accuracy

To analyse precision levels in assayed data an h-scattergram of original samples against duplicates is plotted. The correlation is assessed against a set tolerance level along the $y = x$ line, see figure 5., Best and acceptable levels of precision for nickel, copper and PGMs are tabulated on table 2.

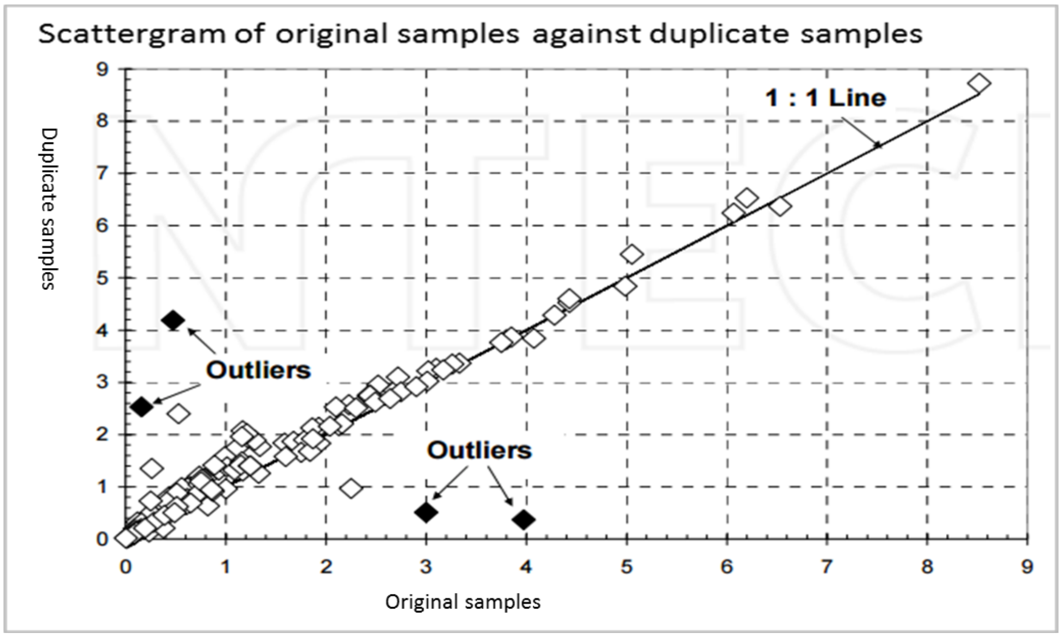


Figure 5: Original samples assays plotted against duplicates assays to analyze precision, modified: (Abzalov, 2011).

Table 2: Acceptable levels of precision for nickel, copper and PGMs.

Mineralisation Type / Deposit	Metal	Best Practise	Acceptable Practise	Sample type
Ni-Cu-PGE - sulphides	Ni (%)	10	15	Coarse rejects
	Cu (%)	10	15	
	PGE(ppm)	15	30	
	Ni (%)	5	10	Pulp duplicate
	Cu (%)	5	10	
	PGE(ppm)	10	20	

Modified from (Abzalov, 2011).

Standard reference materials inserted into a batch are meant to assess the accuracy of the analytical process. The assayed results are plotted against the known average values of the standard reference material with set error margins to assess accuracy.

Blank samples are inserted into a batch of samples dispatched to the laboratory to monitor contamination of samples during sample preparation. Blank samples are devoid of the mineral of interest and therefore their assays must read zero or close to zero considering instrument error limits. The spikes in figure 6 indicate contamination in the samples.

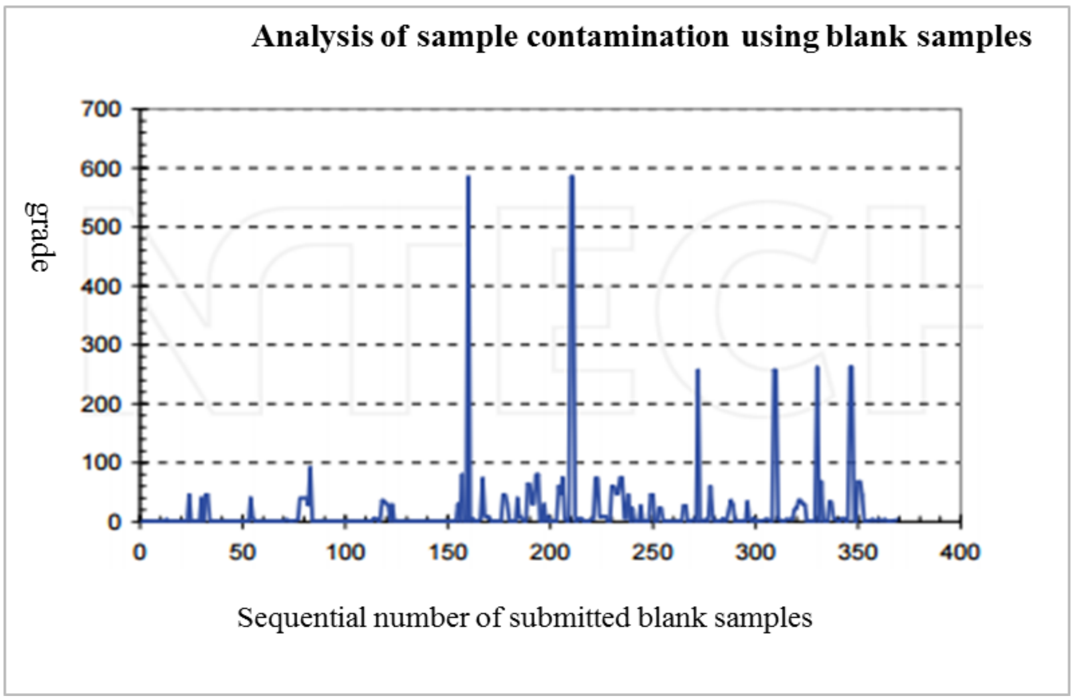


Figure 6: Blank sample assays plotted to analyze sample contamination, modified from (Abzalov, 2011).

2.2 Exploratory data analysis

The purpose of Exploratory Data Analysis (EDA) in mineral inventory evaluation is to improve the quality of estimation by interrogating data and characterizing the variable under investigation (Sinclair, 1999). Sinclair (1999) lists the objectives of the analysis as follows: -

1. To identify and eliminate errors.
2. To provide a statistical description of the variable for resource evaluation.
3. To document and understand the interrelationships between the variables.
4. To recognize systematic spatial variation of variables.
5. To recognize and define distinctive geological domains which require zoning out.
6. To define and characterise outliers.
7. To evaluate similarities or dissimilarity of various types of raw data.

EDA is a general analytical approach, employing graphical tools to reveal the underlying data characteristics and inform the selection of the estimation model. It provides insight into the dataset by uncovering data structures and outliers. The graphical EDA tools usually used include; frequency and cumulative frequency graphs, percentile-percentile and quantile-quantile (Q-Q) plots, box and whisker plots and scatterplots. The graphs are used differently depending on the characteristic under investigation. Scatterplots are used to map the form, direction and strength of association between attributes (Olea, 2009). P-P and Q-Q plots are forms of scatterplots, plotting two distributions against each other to assess similarity.

3 Overview of resource estimation methods

3.1 Classical Polygonal methods

Resource estimation methods vary in complexity, ranging from simple crude traditional methods to more advanced computationally expansive techniques. The less computationally demanding and the simplest include classical estimation methods such as local averaging, polygonal and triangulation methods. These methods use simple geometric principles like area or volume to evaluate the grade and tonnage of an orebody (Kau, 2016). The averaging method or the sample mean weighs all the samples equally and calculates the mean of the samples around a point or block to be estimated. The estimated grade Z_x^* is given by

$$Z_x^* = \frac{1}{n}\sum_{i=1}^{n} Z_i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 2$$

Where Z_i = sample grade at points Z_x (i.... n)
n = number of samples

In triangulation, a sample point is joined to two other closest sampling points through straight lines forming a triangle. The formed triangle is assigned a mean value of the 3 sample values at the corners of the triangle. The grade and tonnage of the block is then taken as the arithmetic mean of the formed triangles (Sinclair & Blackwell, 2004).

Under polygonal method, the entire estimation area is divided into polygons. The polygons are constructed by drawing bisectors of lines joining neighbouring sample points within the block. Each polygon gets assigned grade of the sample point falling within that polygon (Noble, 2011). The grade of the block is taken by averaging the individual grades of the polygons. An example here is the nearest neighbour method (NN). In nearest neighbour estimation the polygon is assigned the grade of the closest sample (Sinclair & Blackwell, 2004). Because the estimation does not average the values from the individual samples the variance of the samples is maintained, and the estimate is not smoothed out.

3.2 Distance weighting methods

Distance weighting methods rely on the assumption that the underlying block to be estimated should be influenced most by nearby samples and less by distant samples (Shahbeik et al., 2014). The estimated grade assigned to the block is the weighted average of the surrounding sample values scaled by their distance to the target block.

The most common weighting function is based on the inverse of the distance to the point or block to be estimated (Glacken & Snowden, 2001). This method is named inverse distance weighting (IDW). The weights assigned are independent of the data values and dependent on the distance between the sampled points and the point or block being estimated. To account for the distance relationship, closer points get more weights than far away samples. This is achieved by raising the inverse of the distance to a certain power. The power is chosen arbitrarily with no bearing to the change in spatial variation with direction as with the variogram.

The IDW estimation weights are assigned as follows:

$$w_i = \frac{\frac{1}{d^{\alpha}}}{\sum_{i=1}^{N}\left(\frac{1}{d_i^{\alpha}}\right)} \qquad \text{..3}$$

Where w_i = weights

d = distance of samples to estimation block

α = power

The weight decays inversely with increase in distance at a rate determined by the power value α. When the α value increase the weight of distant samples diminish and their influence on the estimate become negligible. The power value α can be any number. The most common chosen power value is 2. Normally samples with very little effect on the weight because of the distance to the target point are excluded by restricting the search neighbourhood (ArcGIS Pro, 2017). The search neighbourhood defines the extent of the area containing the samples required to make estimation for a specified target. The size of the search neighbourhood is also chosen arbitrarily. The inverse distance estimated grade (z^*_x) at the estimation location x is obtained by:

$$Z_x^* = \sum_{i=1}^{n} \left(\frac{w_i}{\sum w_i} \right) zi \dots \dots \dots \dots \dots . . \dots \dots \dots 4$$

Where the z_i represents the samples within the search neighbourhood and w_i is defined in equation 3 and z_x is the location to be estimated.

IDW interpolation being deterministic does not account for the sample spatial configuration within the search neighbourhood. Therefore, the estimate is bound to be influenced by the spacing and density of the sampling points. IDW is often preferred over geostatistical interpolators where there are challenges of constructing a meaningful estimate of the field spatial structure (variogram) normally from sparse data (Babak & Deutsch, 2008).

3.3 Geostatistical methods

Geostatistical methods have proved their robustness in resource evaluation and grade estimation over traditional ones. Traditional grade estimation methods include local averaging, geometrical, triangulation, polynomial equations and inverse power of distance. Two forms of geostatistical predictions exist; estimation and simulation. Estimation produces a single estimate of grade and tonnage of block or point based on the sampling data values and the associated model of the spatial distribution correlation of the data. Simulation on the contrary produces possible scenarios of the grade distribution within the block from the sampling data and the associated model of spatial distribution correlation (Zhang, 2011). Figure 7 and 8 show the 2 processes flows. Known limitations plaguing the traditional grade estimation methods such as choice of weighting factors to apply, size of the search radius, and efficiency of the estimation method and the suitability of such method to be applied in other areas are handled well in geostatistics.

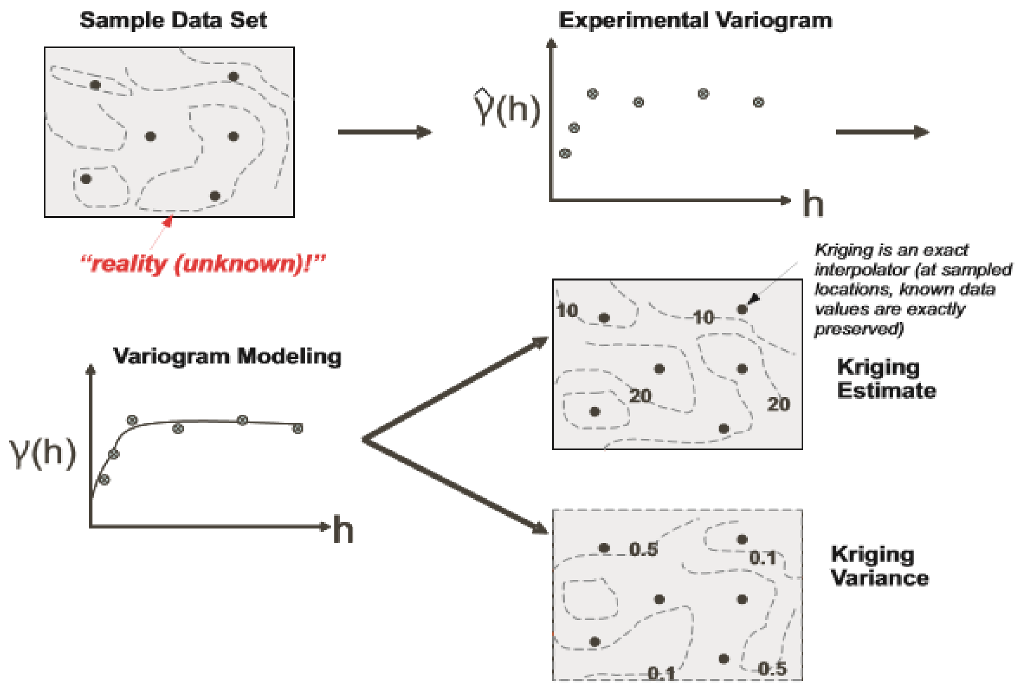


Figure 7: Geostatistical estimation work flow. Source (Zhang, 2011).

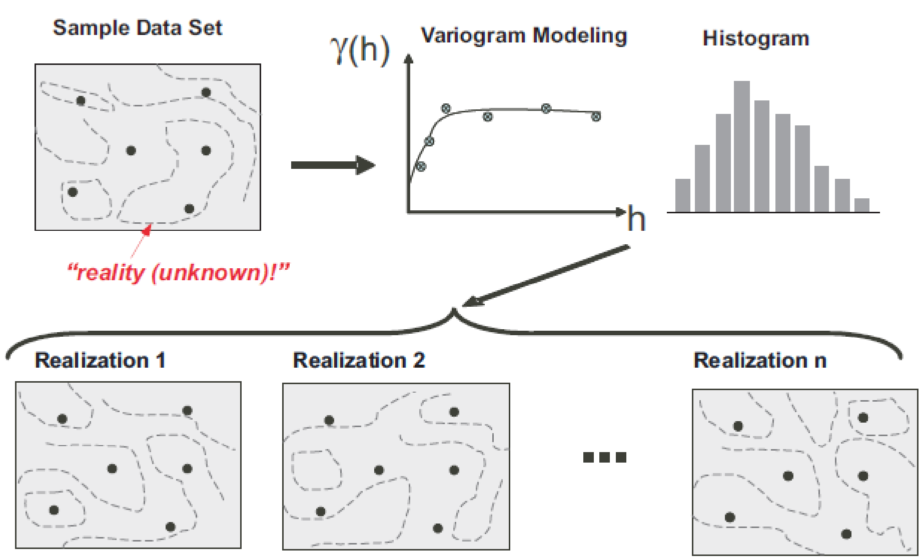


Figure 8: Geostatistical simulation workflow. Source (Zhang, 2011)

Geostatistical methods recognise the following elements of mineral resource evaluation process:

1. Geology of the area under investigation - geological model is required.
2. Numerical values of the data: assay, quality and density.
3. Sample support.
4. Domain geometry: shape and size.
5. Spatial structure of the mineralisation: the variogram.
6. Variability of the data at various supports.
7. Spatial configuration in the data distribution.

Geostatistical estimation is the prediction of the value of an attribute at a location at which it is unknown from measured values of that characteristic at a number of known locations through a function defining the spatial correlation between values (Clark, 2001). The technique works by evaluating the spatial structure of a random variable measured at a point against another value from a point measured a distance away and modelling the obtained experimental form. The process of describing the spatial structure is referred as variography and the subsequent modelling of the structure is called variography modelling. Variography is required to define the intensity of the distribution and the scale at which the distribution is correlated and predict the estimated correlation values at the unsampled locations (Matheron, 1963).

3.3.1 Theory of regionalized variables

The theory of regionalized variables forms the basis of geostatistics. A regionalized variable exhibits a spatial continuity; hence it is not completely random in its distribution. However, its spatial distribution structure is so complex that it cannot be described by a simple deterministic function (Journel, 1983). The theory considers grade distribution in an orebody as one realisation of an order two stationary increment random function (Matheron, 1963). The second order stationarity assumes that the first two moments of the grade distribution (the mean and the covariance) are constant over a domain (Oliver & Webster, 2014). This implies that for any two-grade values Z(x) and Z($x+h$) located at x and $x+h$, where h is a separation vector distance the mean and the covariance are constant such that:-

$$E[Z(x) - Z(x+h)] = m(h) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 5$$

$$E\{[Z(x) - Z(x+h)]^2\} = 2\gamma(h) \ldots..\ldots\ldots\ldots\ldots\ldots..6$$

From equation 5 above the expected value E(x) for all values of x is constant and equal to the mean of all values of x within the domain. Equation 6 introduces an important parameter, the variogram $2\gamma(h)$. The variogram describes the degree of similarity (or dissimilarity) between sample values. It tells us that two data points close to each other within a domain are more likely to have similar values than two points far apart. Both equations indicate that the two moments of the distribution here, that is the mean *m(h)* and the variogram $2\gamma(h)$ are independent of the location x, only dependent on separation vector h within a selected mineralisation domain.

3.3.2 Stationarity and the intrinsic hypothesis

The assumption of stationarity requires autocorrelation between sample values within a domain. Stationarity refers to how well the data is grouped or pooled to fully characterise that portion of the resource to be estimated (Noble, 2011). A variable is auto correlated if it is possible to estimate its value at an unsampled location through measured values at nearby locations. Auto correlation is defined through structure functions that describe the spatial distribution structure of such variable. These structure functions are also referred to as the parameters of a stationary variable. The functions plot the spatial dependence of a variable against the separation or the lag distance of the sampling stations.

In geostatistics a domain is defined where the volume to be kriged is geologically homogeneous. Second order stationarity assumes continuity in sample values across the domain such that the values measured at sampled locations are spatially correlated to values at other unsampled locations. This implies that there are no sudden changes or drift in characteristics of the regionalized variable within the domain. Where stationarity is achieved the expected value *E(x)* or the kriged mean and the kriging variance are constant over the domain and the variogram is dependent only on the lag distance (h) and not the sampling locations (x) (Krige, 1981). From equation 5 under the intrinsic hypothesis the moments are weakly stationary within the domain such that:-

$$\mathrm{E}[\mathrm{Z}(\mathrm{x}) - \mathrm{Z}(\mathrm{x} + \mathrm{h})] = 0 \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots 7$$

From Equation 7, the expected value E(x) is the same everywhere and the variance is constant within a stationary domain.

3.3.3 Parameters of a stationary variable

The spatial structure of a stationary regionalized variable as a function of distance and direction is numerically characterized by the covariance C(h), correlogram ρ(h) and the variogram γ(h). Covariance and correlation measure the similarity of two variables separated by some vector distance (h) apart, whilst the variogram measures dissimilarity between two variables some vector distance (h) apart. Covariance and correlation decreases as h increases but variogram increases as h increases (Oliver & Webster, 2014).

Under second order stationarity defined by a constant mean and variance:-

$$E(Z(x)) = \mu$$

$$VarZ(x) = E\{[Z(x) - \mu]^2\} = C(0),$$

and covariance:-

$$COV(Z(x), Z(x+h) = E[Z(x) - \mu].[Z(x+h) - \mu] = C(h).$$

Correlation between Z(x) and Z(x+h) is

$$\rho(\mathrm{h}) = \frac{\mathrm{C(h)}}{\mathrm{C(0)}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 8$$

Under stationarity condition a regionalized variable is also intrinsic hence it follows from equation 5 and 6 that:-

$$\mathrm{C(h)} = \mathrm{C(0)} - \gamma(\mathrm{h}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .9$$

Graphically the characterization of spatial autocorrelation is presented by an h-scatterplot for univariate response. An h-scatterplot plots the change in correlation as function of the separation distance. The shape of the cloud of the data points indicates correlation between adjacent sample values and it is measured by the linear correlation coefficient (Goovaerts, 1998).

3.3.4 The Variogram

The variogram is the central tool in geostatistical resource estimation. Traditionally the method of characterizing the spatial structure of the grade distribution is through the variogram function. It measures the degree of dissimilarity between measured sample values as a function of separation vector distance (Karl, J. W and Maure B.A, 2010). It measures how quickly grade varies on the average. It simply reflects that closer samples are more similar than samples further apart and thus, their squared differences are smaller than those far apart. The variogram quantifies the range of influence and direction of mineralisation continuity (Oliver & Webster, 2014). The experimental variogram is computed from the raw sampling data. Its reliability is dependent upon factors such as: sample support, lag interval and the band width and the general distribution of sampling data within the domain (Oliver & Webster, 2014). These factors are all but functions of data density within a domain. There are three measures that describe the variogram namely; nugget, sill and the range, see figure 9.

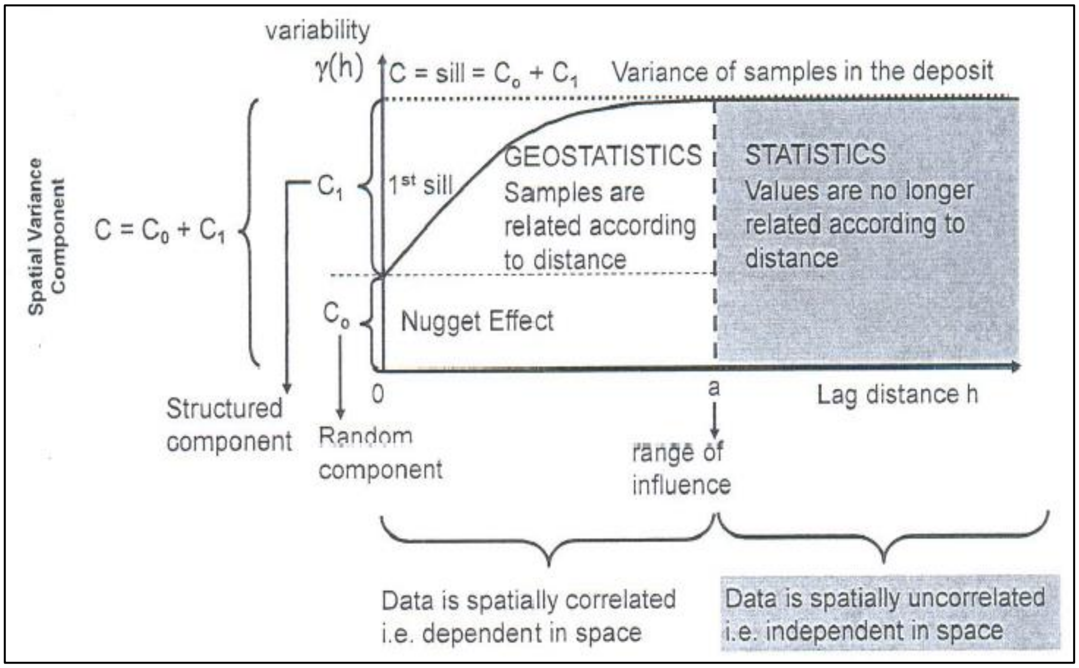


Figure 9: Characteristics of a variogram. Source (Dohm, 2013).

From Figure 9, the total sample variance is composed of two components, the nugget (Co) and the structured component (C_1). Together they make up the sill of the variogram. The nugget effect is the discontinuity in the sample grades at the origin. It is calculated from the vertical variogram which is usually well informed because of the tight sample spacing downhole. The nugget effect reflects the total geological microstructures at distances smaller than the sampling interval and the measurement errors (GSLib.com, 2009). This short scale structures are the most important as they inform the size of geological modelling cells. The separation vector distance (*h*) where the variogram bevels off asymptotically against the sill is called the range (*a*). Within this distance the samples are spatially correlated and beyond, the samples are no longer correlated. For distances beyond the range where the samples are no longer correlated geostatistics cannot be applied.

3.3.4.1 Calculating the variogram

The variogram considers the variance between sample pairs over a range of separation vector distances. It is calculated as follows;

$$\gamma^{*}(h) = \frac{1}{2N(h)} \sum_{i=1} [z_1(x) - z_1(x+h)]^2 \ldots \ldots . \ldots . \ldots \ldots . .10$$

Normally it is recommended that the number of pairs, N(h) be greater than 30 and the separation vector distance h be restricted to halve the sampling domain (Olea, 2009). Often the underlying geological processes have preferred orientation; hence impose a certain manifestation on the variogram shape with direction. To investigate directional variations or anisotropy 3 orthogonal variograms are computed, 2 along the X and Y directions and the 3rd on the Z direction. It is not always practical to have evenly spaced sampling intervals. To cater for irregular h, the samples are grouped into radial distance classes. When calculating the squared differences *h* is partitioned into longitudinal and angular classes defined by lag step and angular tolerance, (figure 10).

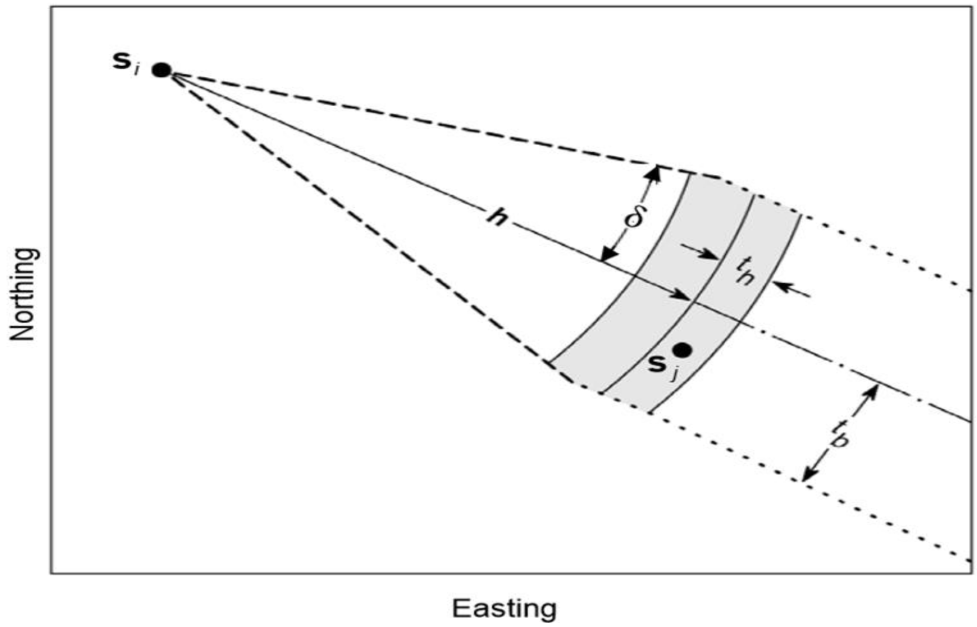


Figure 10: Setting vector distances tolerance limits for the variogram calculation. Source (Olea, 2009).

The horizontal variograms are usually taken along the major and minor axis of anisotropy of the mineralisation. The continuity of the mineralisation can be deduced by plotting the variogram contours to visualize the axis of elongation. Determination of the number of lags and lag spacing is informed by the data spacing and the size of the domain. As a rule of thumb the lag spacing is usually taken as the data spacing and the lag distance equal one half the size the of the domain.

3.3.4.2 Modelling the Variogram

The obtained experimental variogram from the measured values is modelled to derive a mathematical function best describing the continuous variographic shape. The modelling is guided by the underlying geological knowledge applied to the experimental variogram. The purpose of modelling the variogram is to provide a continuous model that describes the variographic structure of the deposit at any given *h*, not only for the multiples of *h* where there are sample values. The nugget is fixed from the vertical variogram because usually the sampling interval is tight downhole.

Depending on the shape of the experimental variogram several structures can be added to best model the shape of the underlying variogram structure.

The shape of the experimental variogram determines the choice of the variogram model. Different models exist each with a different formula. In modelling the variogram the only functions that are conditionally negative definite are permitted to ensure non-negative variance of the estimation error (Goovaerts, 1998). The models must provide a unique solution to the estimation system of equations while meeting the above condition of non-negative estimation variance. The more commonly used models are the Spherical, exponential, Gaussian and the linear model. The spherical model has a more classical shape, rising steadily before levelling off sharply against the sill. In the exponential model the rise is more gradual and parabolic then levels off; the Gaussian model fits well with variograms having smaller nugget and smooth variations. The Linear model is more appropriate for variograms with no sill.

The models fall into 2 categories, the bounded and unbounded variograms. The unbounded models do not have a sill, for example the linear model. Bounded models rise and reach a sill. The spherical, Gaussian and exponential models are all bounded models (figure 11).

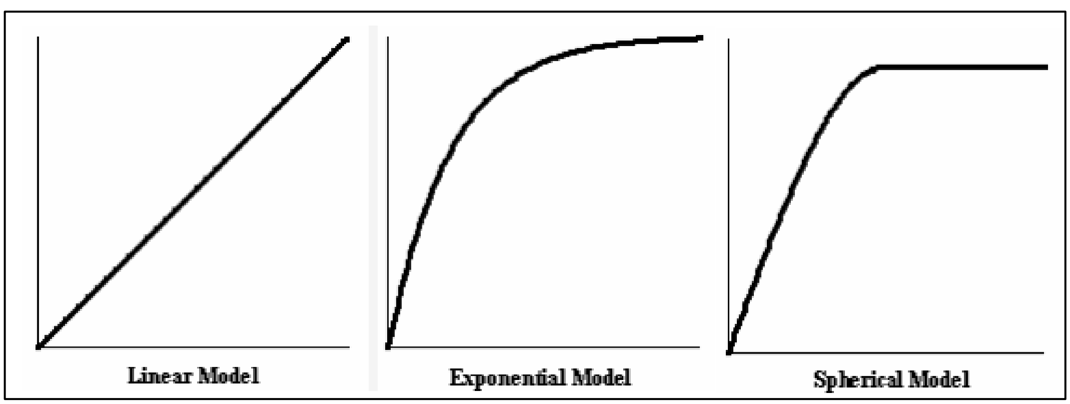


Figure 11: Schematic representation of variogram models. Source: (Barnes, n.d.)

Mathematically the models are expressed as follows: -

Spherical model $\gamma(h) = \begin{cases} 0 & if\ |h| = 0 \\ Co + C1\left[\frac{3h}{2a} - \frac{h^3}{2a^3}\right] & if\ 0 < h \leq a \\ C_o + C_1 & if\ h > a \end{cases}$ ……………..11

Exponential model $\gamma(h) = \begin{cases} 0 & if\ h = 0 \\ C_o + C_1\left[1 - e^{(h/a)}\right] & if\ h > 0 \end{cases}$ ……. …. 12

Gaussian model

$\gamma(h) \begin{cases} 0 & if\ h = 0 \\ C_o + C_1\left[1 - e^{(-h/a)^2}\right] & if\ h > 0 \end{cases}$ ……… 13

Linear Model $\gamma(h) = \begin{cases} C_o + \rho h & if\ h > 0 \\ 0 & if\ h = 0 \end{cases}$ …….. … 14

Where C_0 = nugget effect

C_1 = sill

a = range of influence

h = separation distance

ρ $= regression\ slope$

For direction dependent variation (anisotropy) the modelling should capture the directional effects on the variability. Two types of anisotropy are observed: geometrical and zonal variability. Geometrical anisotropy is shown by an experimental variograms with same shape and sill but different ranges in different directions. A variogram with a sill that varies with direction indicates zonal anisotropy.

3.4 Kriging-Grade interpolation

Kriging is a robust grade interpolation technique capable of delivering an unbiased prediction with minimum estimation variance (σ_ε^2) and utilizing sample spatial autocorrelation (Krige, 1966). It is based on the theory of regionalized variables and therefore requires the calculation and subsequent model of the variogram (Matheron, 1963). The variogram model is required to define coefficients or estimation weights in an optimal linear estimator (Cressie, 1989). It is an exact interpolator, because the kriged estimate at the sampling point is the measured value at that location and the variance is zero. It is a preferred method of estimation because in addition to the estimate of the target variable it provides the estimation variance building some means of confidence on the estimate. If an appropriate variogram model is achieved kriging will always outperform IDW because the variance of estimation will be conditioned by the spatial variability of the data (Vann, 1998). Matheron (1963) named the estimator “kriging” after D.G Krige (South African mining engineer) who first develoved the empirical method and used it for determining true gold grades based on sample grades. Kriging estimates are Best Linear Unbiased Estimates (BLUE) provided the volume being estimated is stationary and an appropriate form of a variogram has been established.

There are several variants of kriging in use, each based on different assumptions made to adjust to varying attribute spatial structure. The different types are:-

- Simple Kriging;
- Ordinary Kriging;
- Universal kriging;
- Indicator kriging; and
- Lognormal kriging;

Indicator kriging and Lognormal kriging basically are any of the first 3 methods above applied to some data which has been transformed (Olea, 2009). These are non-linear kriging methods.

The kriging estimator is a linear weighted average given by:

$$Z_{\mathrm{k}}^*(x) = w_1 z_1 + w_2 z_2 + \cdots + w_n z_n = \sum w_i z_i \ldots\ldots\ldots 15$$

The kriging variance provides a measure of estimation precision at a given location. It is dependent on sample support, location of samples and location, size and shape of the search neighbourhood relative to the target. The kriging variance is calculated as follows:

$$\sigma_k^2 = \sum_x^n w_i \gamma(z_x, T) + \mu \ldots\ldots\ldots\ldots..16$$

The weights are calculated by maintaining the three criteria that the weights sum to one, the estimate is unbiased, and the estimation variance is minimized. With the criteria met, the kriging system of equations is a set of *n*+1 linear equations and *n*+ 1 unknowns to be determined. The weight factors of *n* input points (*n*=1, 2… *n*) for a point Z*(x) to be estimated are calculated by solving the following matrix equation:

$$w_1\gamma(z_1,z_1) + w_2\gamma(z_1,z_2) + w_3\gamma(z_1,z_3) +.....+ w_n\gamma(z_1,z_n) + \mu = \gamma(z_1,A)$$

$$w_z\gamma(z_1,z_1) + w_2\gamma(z_1,z_2) + w_3\gamma(z_1,z_3) +.....+ w_n\gamma(z_1,z_n) + \mu = \gamma(z_1,A)$$

$$w_z\gamma(z_n,z_1) + w_2\gamma(z_n,z_2) + w_3\gamma(z_n,z_3) +.....+ w_n\gamma(z_n,z_n) + \mu = \gamma(z_n,A)$$

$$w_1 + w_2 + w_3 + \ldots\ldots w_n = 1$$

Where

W_i = weight for sample i and j = 1,2,3…, n

$\gamma(z_i,z_j)$ = semi variogram value between points z_i and z_j

and i, j =1,2,3…, n

$\gamma(z_i,A)$ = semi variogram value between z_i and point A to be estimated.

μ = Lagrange multiplier, introduced to ensure $\sum w_i = 1$

The estimate and the estimation variance are dependent only on the spatial characteristics of regionalized variable, vector distance *h* between the sample points and the sampling points relative to each other.

There are two main kriging methods. The methods are distinguished by how the mean value is determined and used during the estimation process. Where the mean is known and held constant across the area of estimation the kriging is referred to as **simple kriging**. The other, **ordinary kriging** the mean is re-estimated from the nearby data values for every point or block to be estimated across the domain (Olea, 2009).

3.4.1 Simple Kriging

For simple kriging estimator is

$$Z^*_{sk}(x_0) = m + \sum_{i=1}^{n} w_i \cdot (Z(x_i) - m) \ldots\ldots\ldots\ldots .17$$

Where x_0 = point where grade is being estimated.

x_i = sample location and i = 1,2,3….n

w_i = weights

n = number of sampling points

m = mean of Z(x)

The estimation variance is calculated as follows:

$$\sigma^2(z_0) = COV(z_0.z_0) - 2\sum_{i=1}^{k} w_i\, COV(z_0.z_i) + \sum_{i=1}^{k}\sum_{j=1}^{k} w_i w_j\, COV(z_i.z_j) \ldots \ldots .18$$

Where σ^2 = sample variance

z_0 = value at estimation point

z_i = value at point *i*

w_i = weight for sample i and j = 1,2,3…, n

Under simple kriging the assumption is that the mean is constant and known across the domain. These assumptions make simple kriging the most restricted form of kriging and so its applicability is limited and prone to suboptimal results when applied. At the estimation stage the mean is not yet known and therefore the variance derivation is calculated through the covariance as shown in equation 18. The set of weights (w) required are those that minimize the estimation variance associated with the estimator $Z_x^*(x)$.

3.4.2 Ordinary Kriging

To satisfy the minimum estimation variance condition, the weights must sum to 1. Rearranging equation 17 for the simple kriging estimator it can be shown that the estimator is independent of the mean when the set above conditions are assumed.

$$Z_x^*(x) = m\left(1 - \sum_{i=1}^{n} w_i\right) + \sum_{i=1}^{n} w_i z(x_i) \ldots \ldots \ldots \ldots \ldots \ldots \ldots .19$$

Thus, under stationarity assumption, constant mean and no trend the Ordinary kriging estimator is:

$$Z^*_{ok}(x_0) = \begin{cases} \sum_{i=1}^{k} w_i\, z(x_i) \\ \sum_{i=1}^{k} w_i = 1 \end{cases} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 20$$

Where Z^*_{ok} = Ordinary kriging estimator

x_i = sample point

w_i = estimation weights

The estimation variance is:

$$\sigma^2_{ok}(z(x_0)) = \sum_{i=1}^{k} w_i\, \gamma(z_i, z_x) - \mu \dots\dots\dots\dots\dots\dots\dots..21$$

Where σ^2_{ok} = estimation variance

$z(x_0)$ = estimation point

w_i = estimation weights

γ = variogram

μ = LaGrange multiplier

Just like in simple kriging the mean is constant but here it is unknown and estimated locally from nearby samples. In this case the mean is recalculated from data points within a moving neighbourhood with the target. This condition has additional improvement over simple kriging of making the estimator unbiased (Rivoirard, 2005). Again, the set of weights required are those that minimize the estimation error under stationarity assumption and the sum of weights must be equal to 1. The weights and the kriging variance are only dependent on the variogram and sample configuration in relation to the block to be estimated (Oliver & Webster, 2014). With the criteria met, the kriging system of equations is a set of n+1 linear equations and n+ 1 unknowns to be determined. The weight factors of n input points (n=1, 2… n) for a point $Z^*(x_o)$ to be estimated are calculated by solving the formulated matrix equations. The LaGrange multiplier (μ) is introduced for optimisation convenience in solving for the unknowns in the set matrix equations.

3.4.3 Indicator Kriging

Linear interpolators such as simple kriging and ordinary kriging have shown limitations in dealing with skewed data such as base metal grade distributions which are highly positively skewed; having long tails. One other limitation is the estimation of recoverable resources in mineralisation interspersed with waste portions. In some natural instances, the arithmetic mean and by extension the linear estimator used to obtain it, is not an appropriate measure of the average of the grade. Non-linear approaches, extensions of kriging themselves can produce optimal estimates under these conditions. Indicator kriging refers to kriging of indicator transformed sample grades through an appropriate indicator variogram (Vann, 1998). The technique was first introduced by Journel (1983) and it has since evolved, with several variants to date.

The original data is transformed into binary form across the grade continuum. The data is coded into series of ones and zeroes depending on their relationship to an indicator cut-off value Z_c (Glacken & Blackney, 1998). Usually the histogram of grades is used to select the cut-off grades. More scrutiny is emphasized on the setting of the cut-off grades to ensure more cut-offs where more information is required, especially the tails in case of highly skewed data. The indicator cut-offs are derived as follows:

$$i(x : z_c) = \begin{cases} 1 \text{ if } z(x) \geq z_c \\ 0 \text{ if } z(x) \leq z_c \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots..22$$

Where z_c = indicator cut-off grade

Indicator variograms are then calculated for the various cut-offs covering the entire range of the input data. The obtained variograms are then modelled across the cut-offs. Implemented in this manner, the method is referred to as multiple indicator kriging referring to the multiple cut-offs generated (Glacken & Blackney, 1998). The indicator data transformation is effective in limiting the effects of extreme values in the data. Values which are barely greater than the cut off receive the same indicator as values much greater than that cut off. Kriging the indicators give an estimate of the proportion of the values which are greater than a certain cut-off. When undertaken at a block size indicator kriging will generate recoverable resources.

Resource classification methods

Mineral Resources are classified into Measured, Indicated and Inferred categories reflecting levels of geological confidence (SAMREC, 2016). The classification into these categories is based on the degree of uncertainty associated with estimates of grade and tonnage of the mineral resource. The uncertainty stems from several sources including inherent geological uncertainty, grade variability and the parameters of the generated model (Emery, et al., 2006). The basis of the classification is to account for these uncertainties through the 3 levels of confidence stated above. Souza and Noppe, 2009 list parameters mostly associated with this degree of uncertainty as follows:

- The amount of information used for the estimate;
- The degree of correlation between the block estimated and the data used for the estimate; and
- The variability in the data used for the estimation.

Resource classification methods can be divided into 2 main types, namely geometrical and geostatistical methods. Geometrical methods include area of influence method and dilation-erosion method (Souza & Noppe, 2009). The search neighbourhood method uses the minimum number of samples within a search neighbourhood. The blocks estimated from the most restrictive neighbourhood, abundant data in the neighbourhood are classified as Measured and the least restrictive are classified as Inferred with the Indicated resources in between (Sinclair & Blackwell, 2004). The slope of regression method classify resources by means of a plot of regression line of estimated values against real values of each estimated block. It ranges between 0 and 1, with 1 being a very good estimate. Lastly the kriging variance which measures estimation precision at a given location can also be used as a classification method. The lower the kriging variance the better the estimate. It is dependent on the size and shape of the sample support, location of the samples and the size and shape of the block being estimated (CUBE Consulting, 2013). The requirement from the international reporting codes concerning the choice of classification method is to "describe and justify criteria and methods used as the basis for classification of the mineral resources".

Tati nickel mine- the case study

4 Property Description and Location

The Phoenix mine is located some 40 km east of Francistown, in the north-east district of Botswana. The mine is accessed through a tarmac road running from Francistown to Matsiloje into Zimbabwe (figure 12).

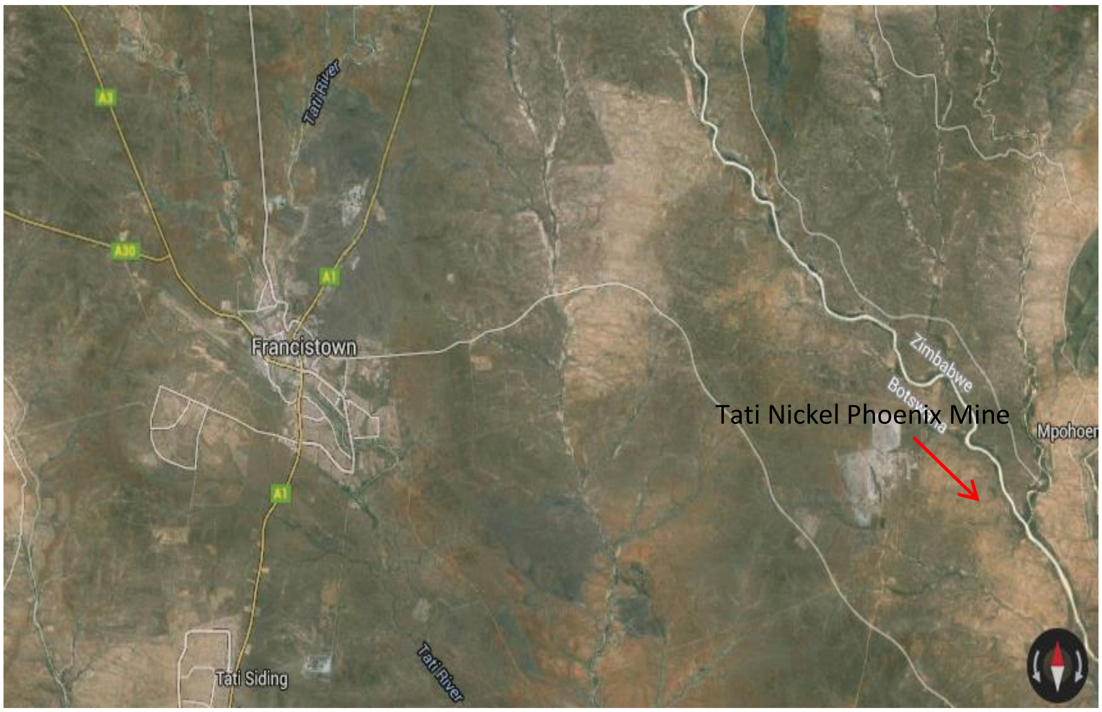
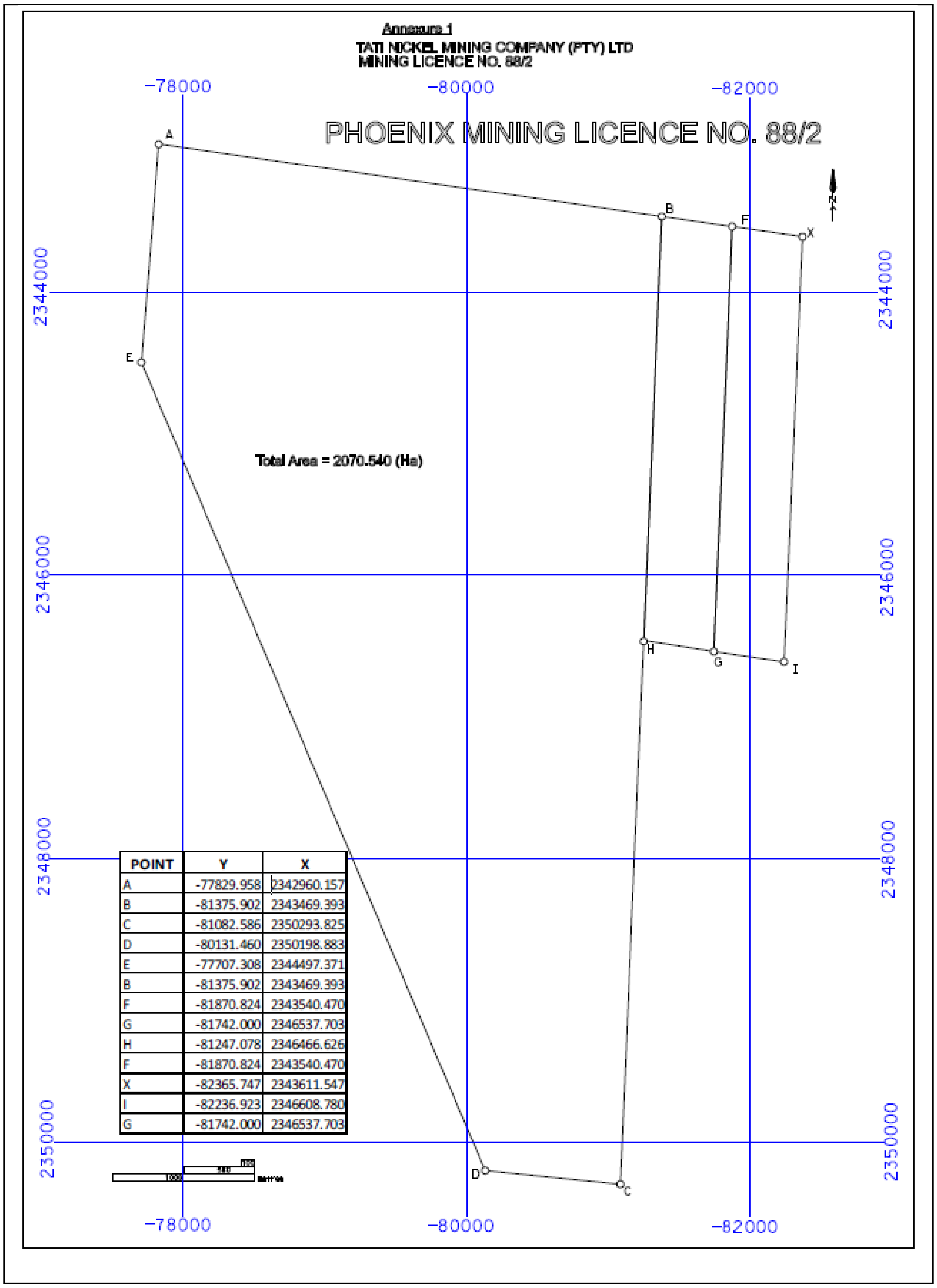


Figure 12: Satellite image of part of the north-east district, Botswana. Source (Google earth).

The mine is defined by beacons as shown in figure 13.



POINT	Y	X
A	-77829.958	2342960.157
B	-81375.902	2343469.393
C	-81082.586	2350293.825
D	-80131.460	2350198.883
E	-77707.308	2344497.371
B	-81375.902	2343469.393
F	-81870.824	2343540.470
G	-81742.000	2346537.703
H	-81247.078	2346466.626
F	-81870.824	2343540.470
X	-82365.747	2343611.547
I	-82236.923	2346608.780
G	-81742.000	2346537.703

Figure 13: Map showing the location of the Phoenix Mine License (Source Tati Nickel survey section).

The corner beacons of the license are listed in table 3. The license has a current surface area of 2070.540 Ha.

Table 3: Co-ordinates for beacons defining the Phoenix Mine License area (88/2).

Beacon ID	X-COORDINATES	Y-COORDINATES
A	2 342 960.157	-77 829.96
B	2 343 469.393	-81 375.90
C	2 350 293.825	-81 082.59
D	2 350 198.883	-80 131.46
E	2 344 497.371	-77 707.31

5 History and Background

The Tati area has a long mining history spanning as far back as ancient copper workings which exploited gossan outcrops of the present operations (Dicks, 2005). Presently, Tati nickel mine consist of 2 deposits, one at Phoenix mine and the other some 15 km south west of Phoenix, namely Selkirk. Other associated Ni-Cu prospects in the vicinity of Phoenix area include the Thekwane and Cinderella exploration prospects. Production at Phoenix started in 1989 after decommissioning of the Selkirk operation which was an underground mine then. The open pit operations at Phoenix mine included a magnetic separation plant which was upgraded in 2006 to a dense media separation plant with an improved plant throughput.

6 Geology and Mineralisation

6.1 Geology

The area underlying the Phoenix mine is a Precambrian greenstone belt terrain forming the south-western margin of the Zimbabwe craton. Two greenstone belts have been mapped in the area: The Tati greenstone belt and the Matsitama/Vumba greenstone belt. The Phoenix mine lies within the Tati greenstone belt which comprises basalts and a calc-alkaline sequence with poorly developed ultra-mafic and felsic units (Tati Nickel exploration section, 2005). The metagabbroic rocks of the Tati greenstone belt intruded into the granitic basement during the later stages of the Limpopo mobile belt tectonism. Outside the greenstone belt to the north and south lie granitic bodies of Shashe gneiss group. These are moderate to highly metamorphosed granites, (figure 14).

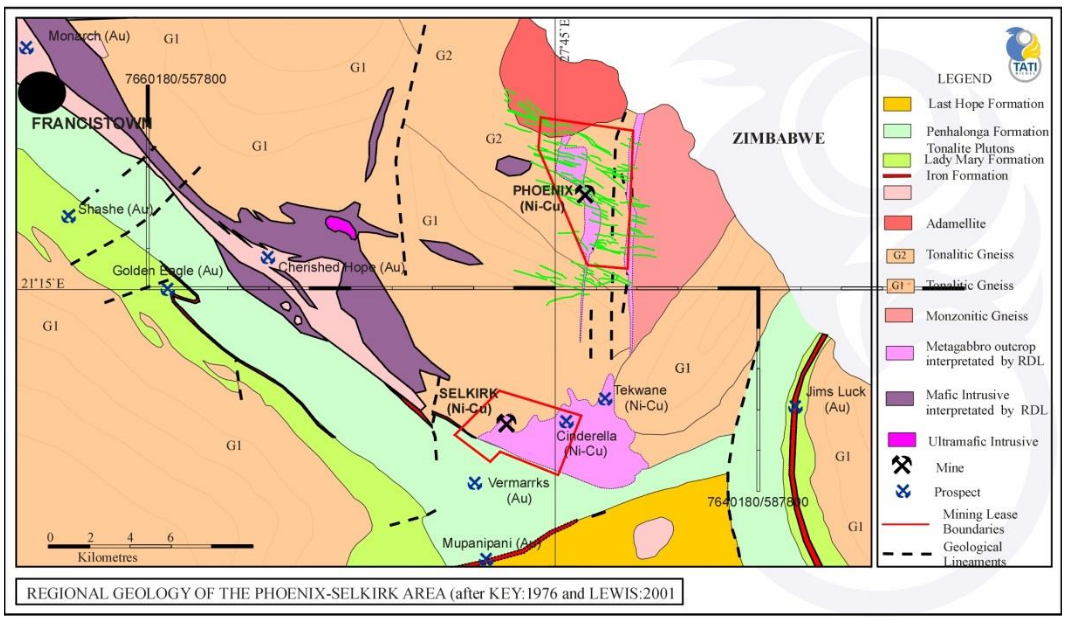


Figure 14: Generalized geology map of North eastern Botswana. Note the location of Phoenix mine. Source (Tati nickel, Geology section).

Locally the Tati greenstone belt is divided into three formations. The Lady Mary Formation which is the oldest lies to the south and east within the area. It comprises of metamorphosed ultamafics and metasediments. Above lies metavolcanics and metasediments of the Penhalonga Formation which in turn is overlain by the Selkirk Formation to the north. The Selkirk formation is made up of felsic and mafic volcanics with mafic gabbroic intrusions. The Phoenix orebody is hosted by an altered metagabbroic intrusion of the Selkirk formation. Later stage magmatism marked by granodiorites, quartz porphyry veins and dolerite dykes cut into the metagabbroic intrusion. The dominant dolerite dykes follow major shear and fault zones striking west-north west (SRK Consulting, 2006). The late intrusions followed existing shear zones striking WNW. Within the pit (figure 15) the wall rock is tonalitic gneiss, medium to coarse grained and locally sheared. The contact with the intrusive metagabbro is often sheared. A typical shear zone is shown on figure 16 cutting across the tonalites on the western pit wall.

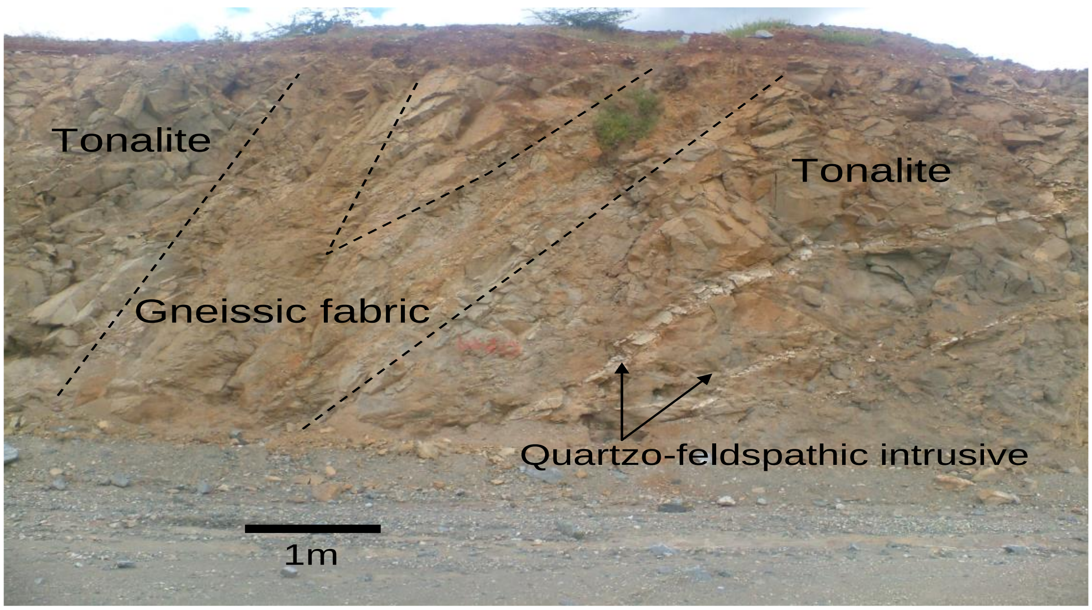


Figure 15: western edge of the pit showing the enclosing tonalite gneiss. Source (TWP, 2006)

Figure 16: Steeply dipping shear zone, northern portion of the Phoenix pit. Source (SRK, 2006)

The metagabbro is subdivided into two units namely the Pit gabbro and the western marginal gabbro which is more restricted to the western peripherals of the Phoenix pit (Dicks, 2005). The subdivisions as described by Dicks (2005) are based on the alteration or altered fragments with the main gabbro unit.

6.2 Mineralisation

The Phoenix deposit is mainly a disseminated Nickel-Copper-PGE sulphide mineralization with discontinuous veins and lenses of massive sulphide (TWP, 2006). The two photos in Figure 17 and 18 show the different styles of mineralization present in the Phoenix ore body. It is hosted in the Pit gabbro as described above. It appears to be structurally controlled. This is evidenced on the exposed E-W face of the pit where the mineralisation is concentrated along fracture zones. The prominent structures, faults and shear zones trend NNE-SSW and northwest-southeast. The sulphide mineralization is concentrated within the intersection of these structures. Late aplitic and pegmatitic intrusions remobilized and concentrated some of the disseminated sulphides into massive sulphide lenses forming the core of the orebody. The five structural mineralization domains in the geological model are defined by these faults and shear zones. Figure 19 shows the layout of the five structural domains superimposed on the pit outline.

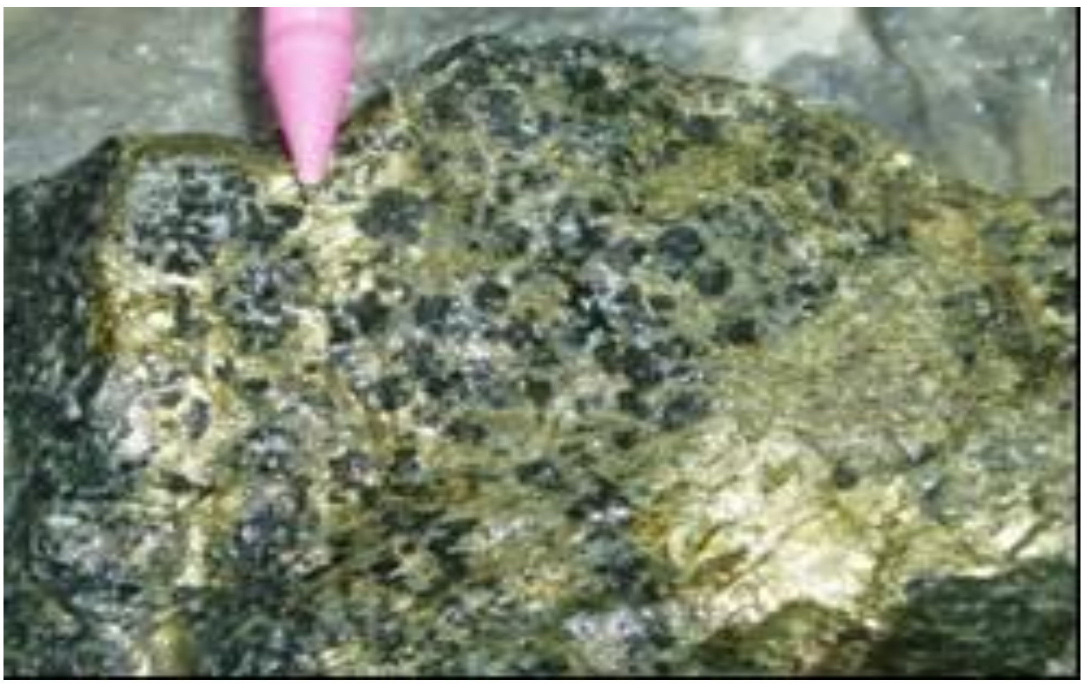


Figure 17: Semi-massive sulphide mineralization in pit metagabbro. Source (TWP, 2006)

The outward extend of the orebody is not fully constrained because its grades into the barren granodiorites country rocks. In the Phoenix geological model, the limit of the mineralisation is based on a probabilistic approach defined by a chosen volume of interest (VOI). The VOI is set based on a certain assay cut off or pay limit, which is a factor of the plant recovery efficiency at the time. The introduction of a more efficient Dense media separation plant saw the revision of this pay limit reduced from 0.15% Ni to 0.10% Ni.

Figure 18: Medium grained Pit gabbro with massive sulphide pods. source Dicks (2005)

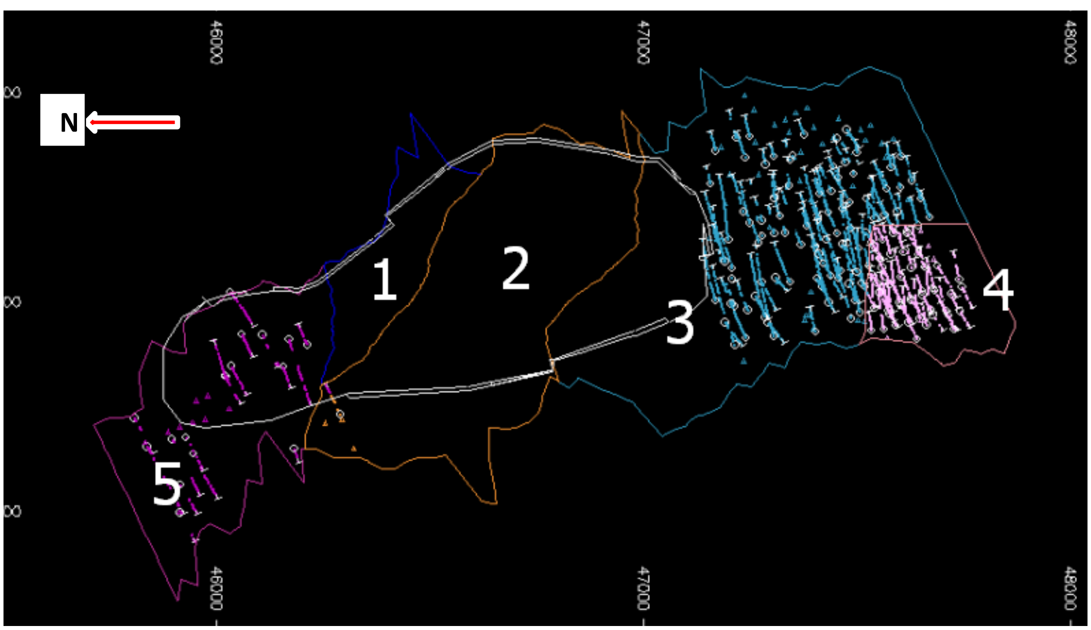


Figure 19: Structural domains of the Phoenix orebody superimposed on the pit outline. Source (TWP, 2006).

The main ore minerals are pentlandite, chalcopyrite and pyrrhotite. Platinum group elements are mainly platinum, palladium and gold hosted in trace amounts by merenskyite [$PdAs_2$], hollingworthite [(Rh, Pt)AsS] and speryllite [$PtAs_2$]. The mineralization formed as a direct magma segregation of immiscible sulphide liquid from the metagabbro (TWP, 2006).

7 Principal Sources of information

This investigation is based on data and information provided by Tati Nickel. The required information was requested from the four (4) Sections within the Mining Department, namely Geology Production, Exploration Geology, Geotechnical and Survey Sections. The data was subsequently housed onto an internal online depository folder created for this work. Some of the information acquired from the respective sections is shown in table 4.

Table 4: Data availed for the 2015 Phoenix resource model update

Section	**Input data requested**	**Data received (File name)**	**Format**
Geology Production	Reverse circulation drilling (RC) data	RC-Holes (updated to end of 2013)	DM file
		Geological domains	DM file
	Corresponding QA-QC reports		
	Relevant geological reports	Feasibility analysis study on optimisation of open-cut mining at Tati Nickel Phoenix and Selkirk deposits.	PDF document
		2009 mineral resource-update for Phoenix Nickel mine, Botswana	PDF document
Geology Exploration	Exploration drilling borehole data	PHX_EX_COLLAR	EXCEL Spreadsheet
		PHX_EX_SURVEY	EXCEL Spreadsheet
		PHX_EX_LITH	EXCEL Spreadsheet
		PHX_EX_ASSAY	EXCEL Spreadsheet
	Corresponding QA-QC reports		
	Mineralisation shell/envelope.	Gabbropt/tr	DM file
	Relevant geological reports		
Geotechnical	Geotechnical data	Dolerite dykes Granodiorite dykes	DM file DXF file
	Relevant geotechnical reports		
Survey	Topographic file	Phoenixtopo_2008pt/tr	DM file
	End of May 2015 pitshell	End of May 2015 pitshell (tbl1505pt/tr)	DM file
	Phoenix lease area	Phoenix mine lease	DM file

7.1 Data Review and Validation

Three sets of drillhole data exist at the Phoenix Mine:

- Diamond Drillhole (DDH) data;
- Reverse Circulation (RC) drillhole data; and
- Blast drillhole data.

These are stored in an industry standard Micromine database, namely GeoBank. However, the data was retrieved into a spreadsheet for review. A decision was made to use only the Diamond drilling and the Reverse circulation drilling data in this study to align to the previous model updates process for ease of comparison of the results. Consequently, only these were subjected to review and validation.

7.1.1 Data validation of Diamond Drill Holes (DDH) exploration data

The diamond drillhole data (DDH) is mainly historical exploration data while the RC data was a combination of exploration and production data. Only the DDH had a full complement of input (Survey, Collar, Assay and lithology) data; the RC data was availed as a complete drillhole data file. Consequently, a full data validation could only be undertaken on the DDH data. The results of the validation are discussed in the following sections focusing on the individual files (survey, collar, assay and lithology) then on the relationships between them.

7.1.2 Drillhole collars

There was a total of 736 collars in the database. These were reviewed, and comments tabulated in table 5. No material issues were noted as fatal flaws. Even though a collar plot was not availed, it was generated during this study. The generated collar plot appeared consistent with the topography and lease area, (figure 20).

Table 5: Data review and validation

Check	Outcome	Comments	Follow up
Collar plot provided	No	The plot was not provided, to be checked at base. But the lease area was provided, and the collars plotted.	
Grid for modelling identified	Yes	Local coordinate based on LO 27	
Duplicate hole identifiers	No	Checked in excel, with a filter formula.	
Duplicate X-Y collar positions	No	Checked in excel, with a filter formula.	
Duplicate X-Y-Z collar positions	No		
X-Y collar locations within bounds	Yes	To check against the lease boundary-checked	
-client to provide bounds			
Total hole length in collar table	Yes		
Down hole surveys in collar table	No	Separate survey file provided	
-separate survey table preferred			
Collar elevations at same level	Yes	Some holes drilled inside the pit	
-acceptable if all nominal			
Collars checked against DTM	Yes	No issues identified	
Cross section check completed	No	Not necessary	
Planned collar locations excluded	Yes	All collar locations drilled	

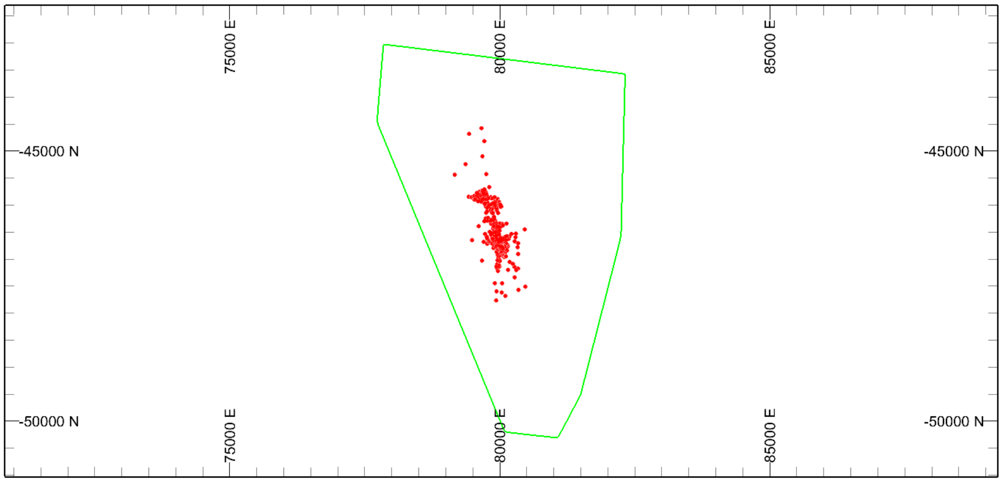


Figure 20: Plot of DDH collars relative to the license area

7.1.3 Downhole Surveys

A survey file was provided for validation (table 6). The only noteworthy consideration was that the Lo 27 coordinates was used, and down plunging holes had negative dip.

Table 6: Downhole surveys for DDH data

Check	**Outcome**	**Comments**	**Follow up**
Down hole survey table provided	Yes		
HoleID, depth, dip and azimuth provided	Yes		
Azimuth corrected to grid system	No	Not necessary	
- need to match grid for collars			
Survey record at collar (depth =0)	Yes	Datamine calls for each hole to start at 0 depth. Not for all collar id.	
Down plunging holes have negative dip	Yes		
Up plunging holes have positive dip	No	No up plunging holes present	
Duplicate survey records	No	No duplicate. BHID = PN057 to be rechecked. (hole length).	

Paths checked in plan and section	No	Not checked, will be revisited when holes3d is run.	
Anomalies removed from paths	No	As above.	
Convention for de-surveying specified	Yes	Use – negative DIP Method	
All depth records less than hole length	Yes	Not checked, will be revisited when holes3d is run.	

7.1.4 Lithology

A lithology file provided for validation yielded no material errors (table 7). Missing intervals were checked in the modelling software and turned out to represent un-logged portions of the drillhole nearer to the surface. No specific lithology is targeted for modelling, as a grade based model is preferred.

Table 7: Lithology for DDH data

Check	Outcome	Comments	Follow up
Geology table provided	Yes		
HoleID, from, to and geocode (s) provided	Yes		
Geocode legend supplied	Yes	Legend available	
Geocode(s) for modelling identified	Yes	Model based on grade cut-off in specific unit	
Geocodes all match legend	Yes		
Overlapping from-to records	No		
Zero thickness records	No		
Missing/unspecified intervals	No	To be checked in Datamine	

7.1.5 Assays

The assays were validated at the same time as density and the results of the validation are shown in (table 8**Table 8**). No duplicate entries were present. The target commodity is Nickel (Ni) and Copper (Cu), although only Ni would be modelled. The units and detection limits for these grade attributes were not provided but were known. A legend for alpha values was not supplied. Therefore a decision was made to treat dashes (“-“) as absent values.

A number of holes (BHIDs MS06, MS16 and PS303) were isolated for further investigation as they had grades that could be regarded as higher than the stoichiometric values. These grades coincided with areas logged as massive sulphide (MGS) on the lithology log file indicative of concentrated pockets of mineralisation possibly massive sulphide veins. Consequently, they were retained as part of the data to be used in the analysis. A single hole (BHID = PN079) had geology entries but no assays, and this was reserved for further investigation.

Table 8: Assays and density for DDH data

Check	Outcome	Comments	Follow up
Assay table provided	Yes		
HoleID, from, to, assay(s) provided	Yes		
Modelling assay(s) fields identified	Yes		
Units and detection limits identified	Yes	Not provided but known	
- all modelling fields			
Unit conversions have been correctly applied	Yes	Not applicable	
e.g. conversions from ppm to percent			
Units for modelling specified	Yes		
Legend for negative values supplied	No	Not applicable	
Legend for alpha values supplied	Yes	"-" to be treated as absent values	To be investigated
Duplicate records	No		
Averaged fields used for modelling	No	Not applicable	
Preferred assay selection explained	Yes	Major commodity	
Compound attributes identified	No		
e.g. Mg is actually MgO			
Overlapping assay records	No		
Zero length records	No		
Missing or unspecified intervals	Yes	Single hole has geology but no Assay	BHID PN079
Total length = hole length in collar table	Yes	To be checked in Datamine	To be investigated in HOLES3D
All depth to records < total hole length	Yes	To be checked in Datamine	To be investigated in HOLES3D
Sum of main oxides < 100%	Yes	N/A	

Highest grades are within stoichiometric limits	Yes	Yes for Ni, but not for Cu	BHIDs MS06, MS16 and PS303 to investigated
Below detection limit values identified	No		To be confirmed
Blank intervals identified and explained	No	No blanks	

7.1.6 Relationships between the various inputs

Having validated the individual files, a cross-validation was undertaken to check the relationships between these inputs as shown in table 9. No material errors were detected. However, 259 collars were removed from the database after it was confirmed that they had no corresponding assays; it appears the holes were planned but not drilled. Only a single hole (BHID = PN071) had a collar entry but no corresponding down hole survey. Therefore, no further follow-up was needed.

Table 9: Relationships between input files

Check	Outcome	Comments	Follow up
Collars without assays	yes	259 collars removed because there were no corresponding assays, confirmed that they were planned and not drilled.	
Collars without down hole surveys	Yes	Only PN071	
Collars without geology	yes		
Collars without density	Yes		
Assays without collars	No		
Surveys without collars	Yes		
Geology without collars	No		
Density without collars	No		

7.1.7 Software validation

Following the visual and spread sheet validation the drillhole data was imported into Datamine^{TM} Software for further validation and desurveying. 12 samples (0.0063%) had a value of -9% Ni and these were deleted from the data. The sample intervals (FROM and TO) were checked for overlaps and the results are presented intable 10. The errors were nominal, and the data was accepted as valid.

Table 10: Validation in Datamine^{TM} Software

FILE	PROBLEM	BHID	FROM	TO
SURVEY	No Survey AT=0	PN071	-	-
SURVEY	No Survey AT=0	231122	-	-
SURVEY	No Survey AT=0	234133	-	-
SURVEY	No Survey AT=0	237120	-	-
SURVEY	No Survey AT=0	237127	-	-
SURVEY	No Survey AT=0	240128	-	-
SURVEY	No Survey AT=0	243126	-	-
SURVEY	No Survey Data	PN079	-	-

7.2 Comment on Data validation

Data validation was undertaken with an aim of showing whether this data was useable in a Mineral Resource Estimation exercise. In the aforementioned case, validation was only carried out on DDH data, for which individual files were presented. Based on the validation exercises undertaken, no material errors were noted in the data. Consequently, the data was accepted as of sufficient quality to be used in Mineral Resource estimation.

7.3 Review of geological interpretation

The geological model relied on the interpretation provided by Tati Nickel from the previous updates. The Phoenix geological model makes provision for five structural domains, separated by structural bodies and dykes. These five domains are shown in figure 21. From internal company documents, the domains are structurally controlled with some dolerite dykes separating the individual domains. The dolerite dykes are barren, except along contacts with the host pit gabbro.

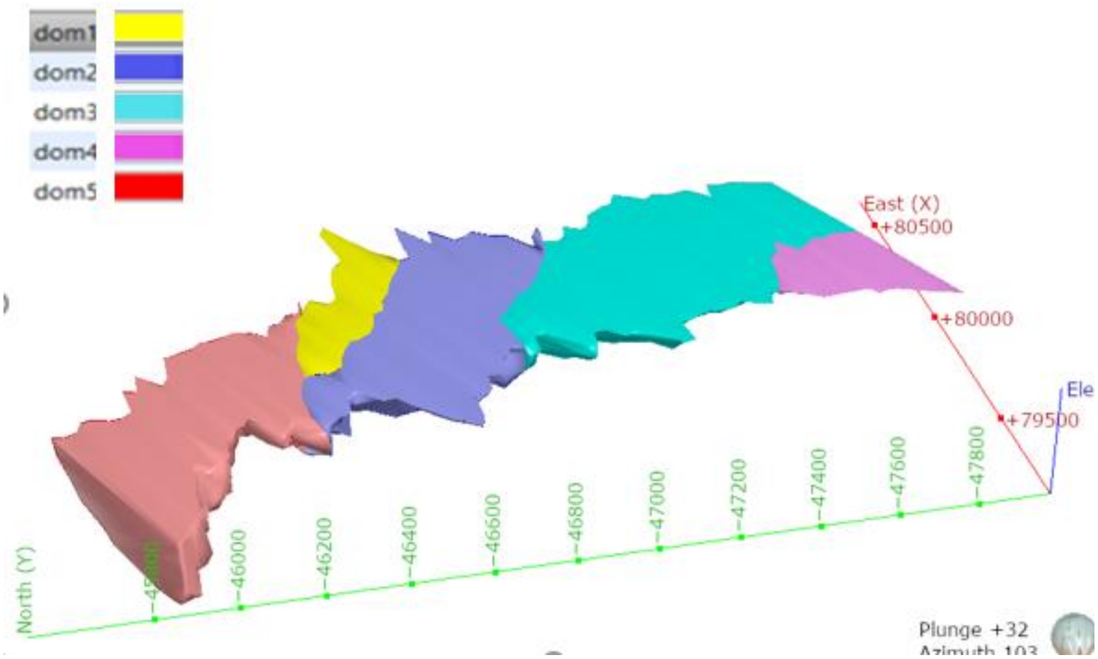


Figure 21: The spatial relationship between the 5 geological domains. Source (Dicks, 2005).

8 Exploratory Data Analysis

For EDA, data from the two data sets was selected based on the existing geological domains. The exploration (DDH) data was drilled on a spacing of ~100 m, whereas the production (RC) data ranged from 5 – 20 m drill spacing. DDH are inclined mostly 45° and 55° to the east in the central and southern portions and to the west in the north zone. The sample spacing in DDH data varied whereas the RC data had 1 m spacing.

The five structural domains were inherited from the existing geological model as mentioned which has been used in the previous mineral resource estimation exercises.

8.1 Statistics

The spatial drill hole data coverage across the five geological domains is shown in figure 22 through to figure 26. Basic statistics for Ni were computed for each domain per data set (table 11). The statistics are summarized and plotted into histograms (Appendix 1) depicting the underlying distributions within each domain. Note that Domain 4 does not have RC data coverage, so statistics shown are only from the exploration data. As stated above sampling support varies, with widely spaced sampling points for the DDH data and tight support for the RC data. This variance in support is expected. The DDH exploration data is used produce a global resource model for long-term life of mine planning whilst the RC data is used to update the dynamic resource model for short term planning and grade control.

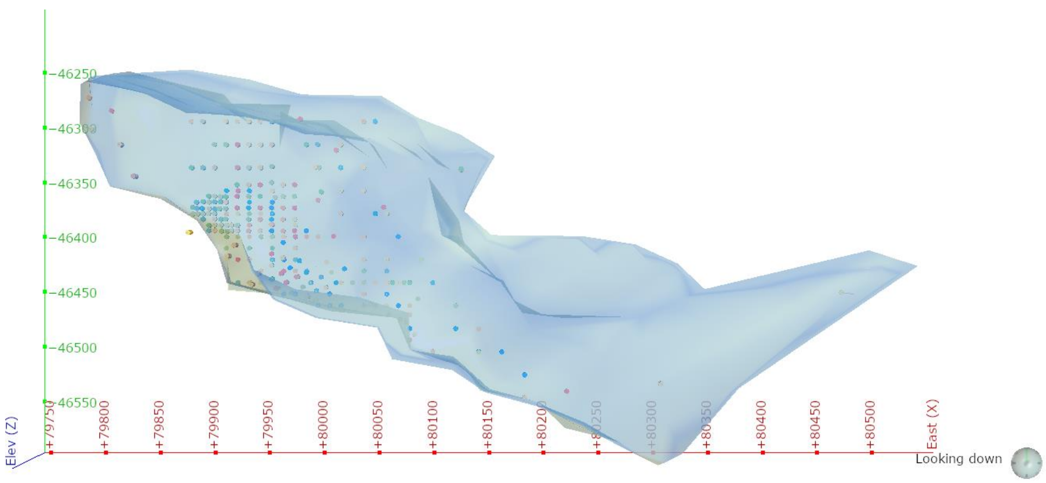


Figure 22: drill hole data coverage in domain 1 (plan view)

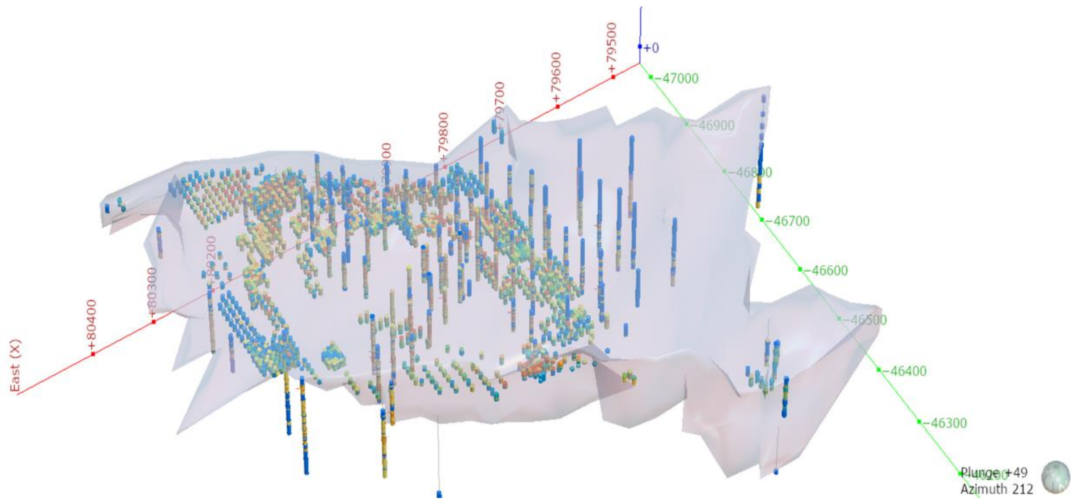


Figure 23: Drill hole data coverage in domain 2

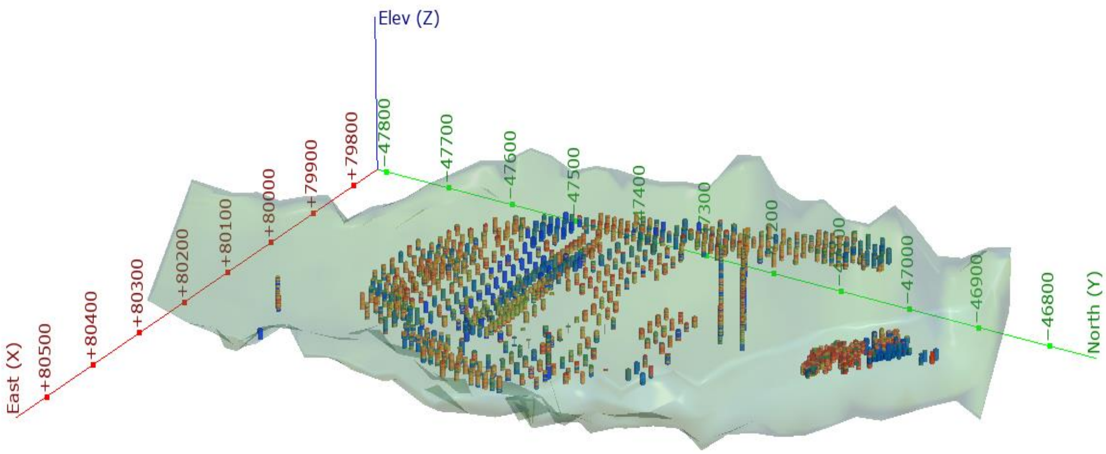


Figure 24: Drill hole data coverage in domain 3

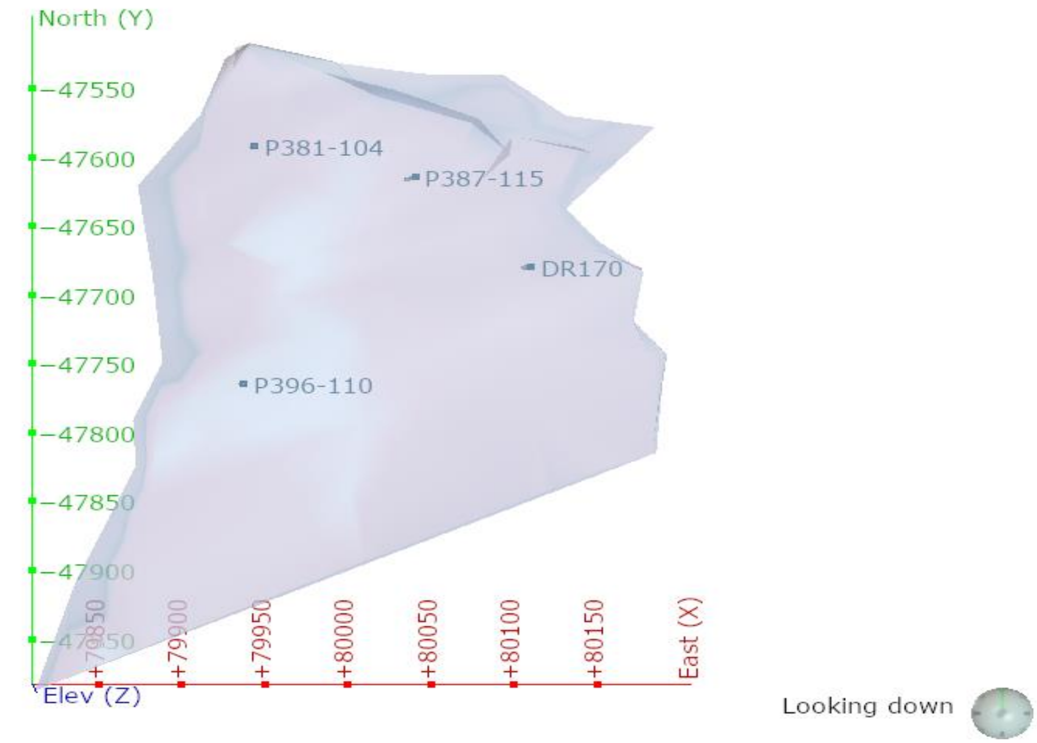


Figure 25: Drill hole data coverage in domain 4 (plan view)

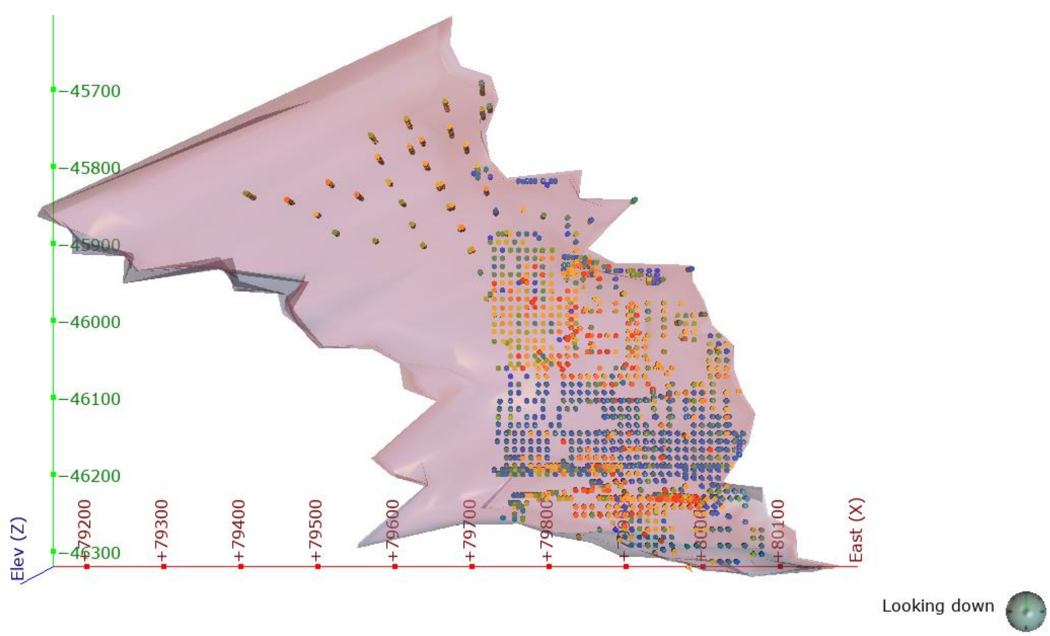


Figure 26: Drill hole data coverage in domain 5 (plan view)

Table 11: Statistics per domain and drill type for %Ni.

Domain and	NSamples	Minimum	Maximum	Mean	Standdev	COV
D 1 – DDH	2328	0.01	8.40	0.60	1.39	2.31
D 1 – RC	7263	0	8.23	0.17	0.59	3.53
D 2 – DDH	13593	0.01	9.90	0.58	1.33	2.30
D 2 – RC	40739	0	8.89	0.16	0.49	3.08
D 3 – DDH	3053	0.01	8.10	0.31	0.81	2.64
D 3 – RC	62445	0	8.19	0.11	0.25	2.26
D 4 – DDH	308	0.01	2.50	0.17	0.28	1.64
D 5 – DDH	35729	0.01	10.54	0.17	0.42	2.46
D 5 – RC	56660	0	9.42	0.11	0.33	3.12

From the Statistics shown of table 11, the DDH data has comparatively higher mean values than the RC data. Notably also, the Coefficient of Variation (COV) is correspondingly higher for RC data than the DDH data in most cases.

The shape of the histogram distribution is typical of this type of mineralization with few very high outlier values resulting in a long tail and a positive skew. For all the five domains on both data sets (exclusion of domain 4 for RC data) COV is consistently high (above 1.5), this is indicative of a wide variation in the Ni grades. The range is almost similar in both RC and DDH data. However, a notable difference is in the mean between the two data types, with DDH data always higher than the RC data. This presents a challenge because the data gives incongruent description of the underlying mineralization.

To evaluate these discrepancies, areas of equal support were evaluated separately to determine if the behaviour is true for all domains. One such area in Domain 1, an area of equal support where there is adequate sampling data from both RC and DDH datasets was selected as shown in figure 27; the resultant statistics at tabulated (table 12) and the histograms are shown in figure 28.

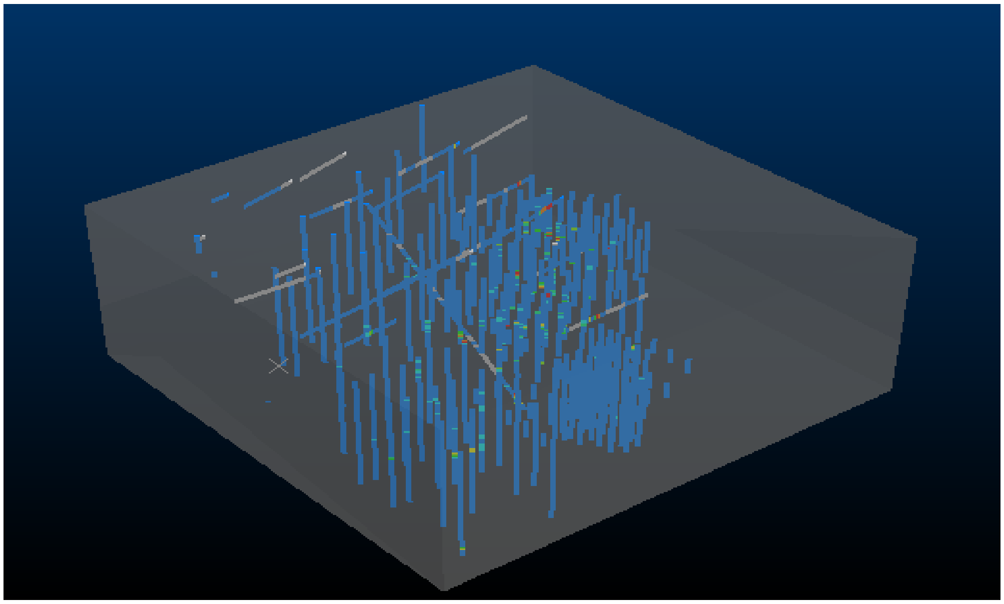


Figure 27: Digitized area around the drill holes for same support investigation (inclined holes = DDH and vertical holes = RC)

It is clear from the comparison that the exploration data (DDH) has a higher mean than the RC data. In the area selected, there is as much as 0.2% difference in average grade between the two datasets. Quantile – Quantile (QQ) plots (Appendix 1) of this distribution also confirmed the positive biasness towards the exploration data. It is assumed that the variance is related to the sampling methods, the DDH sampling focuses only on mineralized zones exclude barren portions whereas RC sampling is continuous downhole and sampling support.

Table 12: Statistics from area of equal support

Equal support area data type	NSamples	Minimum	Maximum	Mean	Standdev	COV
DDH data_1s	647	0.01	8.4	0.37	1.14	3.11
RC data_1s	6857	0.00	8.23	0.17	0.60	3.46

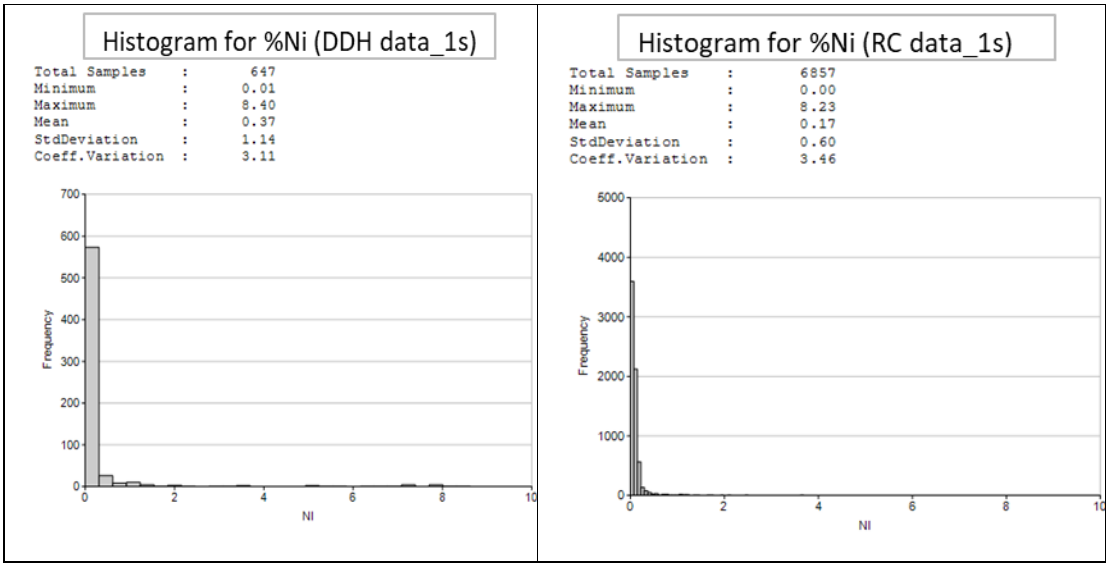


Figure 28: Population statistics within the digitized equal support area in Domain 1.

8.2 Composite statistics

Compositing of data is an important statistical tool to reduce bias in grade during estimation. Determination of optimal compositing length requires insight into the distribution of metal grades by compositing length intervals (Abzalov, 2016). One key factor of cognizance is that the compositing should not change the mean grade of the samples. It is also important that even after compositing the COV should be no greater than the 1.5 threshold, otherwise the data cannot be used confidently for resource estimation, as this is an indication of mixed population.

A composite length of 1 m was chosen for the DDH data. As indicated RC data sampling interval is already 1m. A comparison between the statistics of raw data and composite data for DDH only is shown in table 13. This was done to check for any changes that might skew the interpretations from the composited data which are not characteristic of the orebody but introduced by the compositing. This assessment provided assurance on the selected composite length that it did not introduce any bias into the data.

While compositing harmonised the sample support between RC and DDH data, the mean grades were still higher in DDH data. Also, the COV was still above 2 in Domain 1 – Domain 3. The COV changes vary nominally, even after compositing. The nature of the mineralization, on the other hand, is such that the COV may not reduce further, and that these outliers would need to be investigated by grade-capping.

Table 13: Comparison between original Raw data and Composited data

		NSamples	Minimum	Maximum	Mean	Standdev	COV
DOM1	Raw data	2328	0.01	8.40	0.60	1.39	2.31
	Composite	2654	0.01	8.40	0.36	0.99	2.74
DOM2	Raw data	13593	0.01	9.90	0.58	1.33	2.30
	Composite	16167	0.01	9.00	0.33	0.83	2.51
DOM3	Raw data	3053	0.01	8.10	0.31	0.81	2.64
	Composite	3159	0.01	0.97	0.17	0.38	2.16
DOM4	Raw data	308	0.01	2.50	0.17	0.28	1.64
	Composite	283	0.01	0.64	0.12	0.08	0.68
DOM5	Raw data	35729	0.01	10.54	0.17	0.42	2.46
	Composite	20986	0.01	7.39	0.13	0.25	1.91

8.3 Domain Analysis

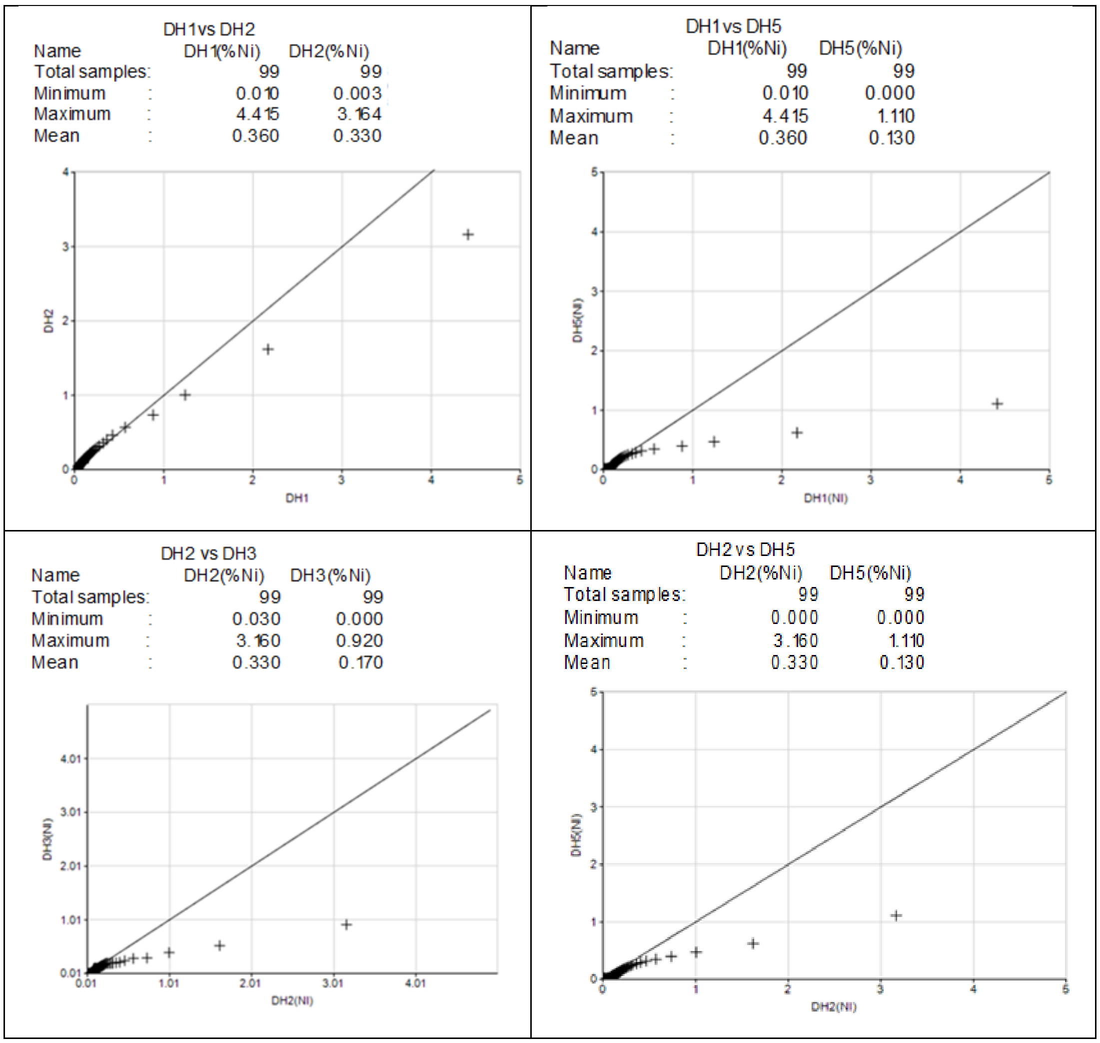
As mentioned earlier, domains were based on historical structural domains that are separated by dykes, major faults and shear zones. However, there is no information in the literature showing whether a statistical test had been undertaken to determine the stationarity (*data is from a single statistical population and the mean and variance are consistent throughout the domain*) of these domains. Consequently, a domain analysis ware undertaken in this study to test for stationarity.

Statistical comparative analyses across the domains were undertaken to determine any notable differences justifying domain separation. Only those domains adjacent to each other were compared. This was achieved through Q-Q plots on %Ni across adjacent domains (figure 29. The comparisons were as follows

1. Domain 1 and Domain 2

2. Domain 1 and Domain 5
3. Domain 2 and Domain 5
4. Domain 2 and Domain 3
5. Domain 3 and Domain 4

The results showed good correlation between compared domains. The correlation is close one across the compared domains.



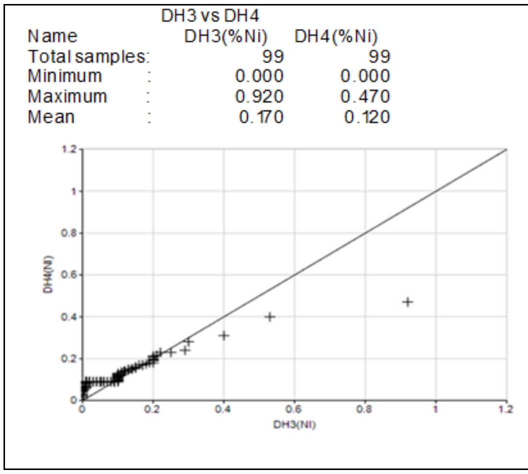


Figure 29: Domain analysis – Q-Q plot of adjacent domains

At lower grades, up to 0.5 %Ni the plots lie along the y = x reference line. At higher grades the plots deviates away from the 45º line indicating some dissimilarity in the compared domains across all the graphs. Statistically all the domains are almost the same as shown in figure 29 and provide no justification for separation. To cross check the result the different domains were plotted on a Box and Whisker plot for visual representation of the data as shown in figure 30. The exercise was used to check for similarities within the populations. Domain 1 and 2 show close similarities, having equal mean and range and the almost similar inter quartile range, so do domain 3 and 5. Domain 4 has a short inter quantile range probably because of the fewer data than the rest of the domains.

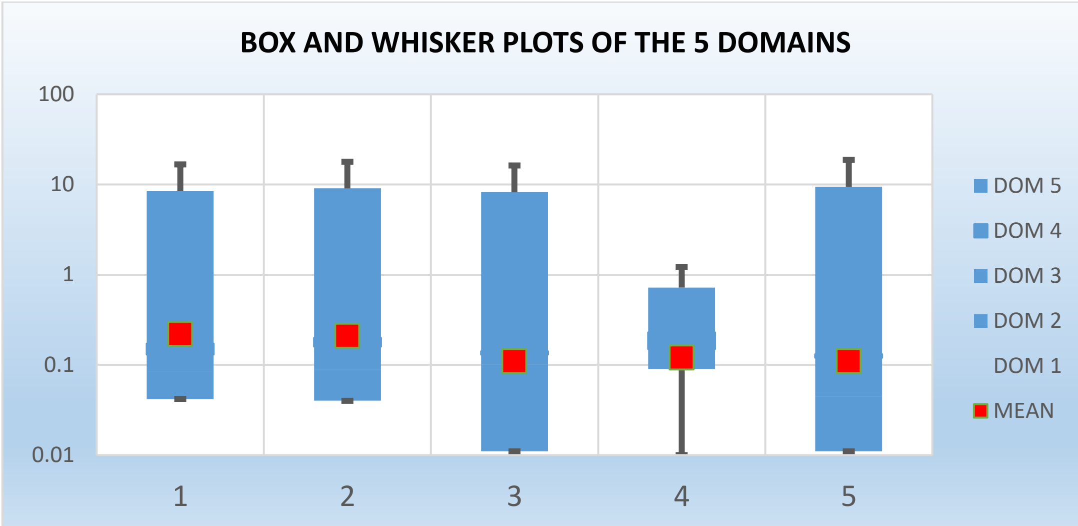


Figure 30: Box and whisker plots of the domains

From this exercise, based on statistical comparisons only, a number of domains could be consolidated. However, the domains are spatial separated by dolerite intrusions as mentioned, structurally controlled defining distinct geological compartments within the orebody. The domaining follows this compartmentalisation. Therefore, for this work the five domains were maintained as in the previous exercises pending further geological domain analysis across this structural divides to investigate these observations further.

9 Mineral Resource Estimation

The Phoenix Resource Model update is based on the block model parameters used in a previous model update (m-PHO-11). The block sizes were evaluated previously during the derivation of the m- PHO-11 model through kriging neighbourhood analysis. Ideally a block size height conforming to a bench height is desired to aid in resource and reserve reconciliations. The tested block sizes were as follows:-

- 60m × 60m × 30m

- 60m × 60m × 10m
- 60m × 30m × 10m
- 30m × 30m × 30m
- 30m × 30m × 10m
- 15m × 15m × 10m

The obtained kriging variances were plotted and an optimal block size selected honouring the mining bench height but not too small, because the kriging variance will be too high (figure 31). For this research work, the selected model properties were maintained.

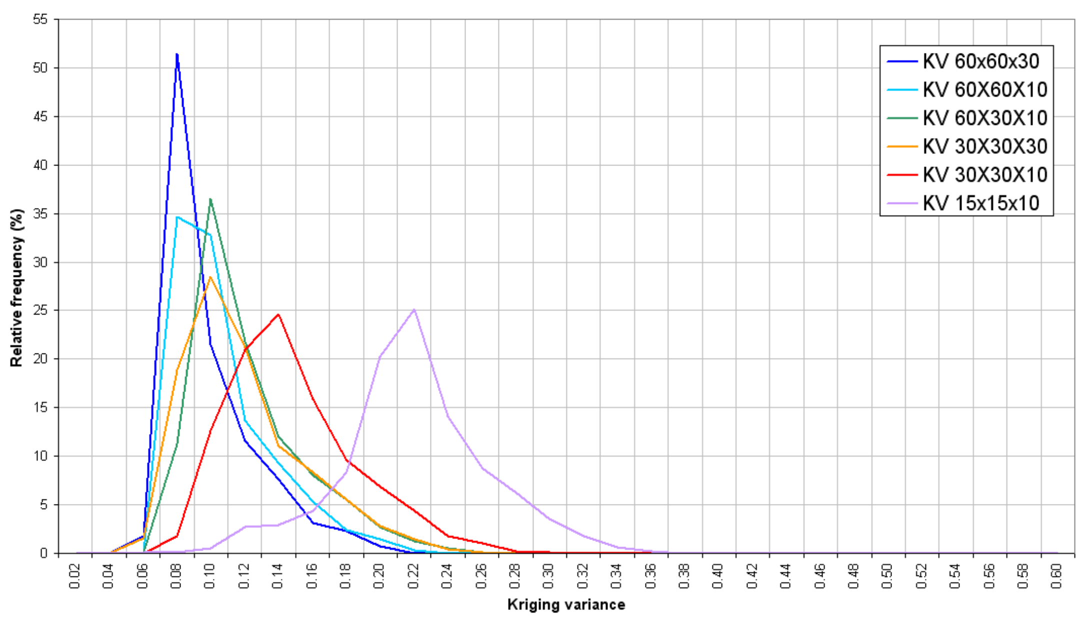


Figure 31: Relative kriging variance for the different block sizes. Source (TWP, 2006)

9.1 Evaluation of the Database

The current data is stored in *Micromine Geobank Database* which appropriately represents all the available data at the Phoenix Resource project. The quality of the data is considered appropriate for the Mineral Resource estimation procedures.

9.2 Block Modelling, Estimation Method and Parameters

9.2.1 Block modelling

A rectangular 3-dimensional (3D) block model was used to fill the geological models using Datamine^{TM}. The block model encloses the entire mineralization envelope as defined by the five geological domains described earlier. A block size of 30 m N by 30 m E by 10 m RL was chosen following review of the kriging neighbourhood analysis undertaken in the previous model update. The block model origin is defined by the minimum easting, northing and elevation. The parameters shown in table 14 below were used for the block model prototype:

Table 14: Model Parameters for all zones

Model setting	Parameters
X origin (mE)	78950
Y origin (mN)	-48110
Z origin (mRL)	240
Block size in X direction (m)	30
Block size in Y direction (m)	30
Block size in Z direction (m)	10
Number of blocks in X direction	57
Number of blocks in Y direction	104
Number of blocks in Z direction	78

9.2.2 Variogram parameters

Anisotropy was investigated to generate variograms for each domain. For each domain three variograms were created, 1 in the vertical direction and 2 orthogonal variograms on the horizontal. The three variograms were modelled and the resultant anisotropy parameters formed the variogram parameter file, per domain. For validation of the modelled parameters an ellipse was plotted and visually assessed for alignment with the dip and dip direction of the mineralisation in the domain. The graphical plots of the Ni variograms are presented in Appendix 3. Variography was also performed for Density for each domain as well following the same procedure as above. The variograms per model are shown in table 15. Note that normal variograms were obtained only for Domains 1 – 3 and 5; median indicator variograms were modelled for Domain 1 and 3. No variograms could be obtained for Domain 4.

Table 15: Variography results for Domains 1- 3 and 5

Domain	**Nugget Effect**	**Structure 1**				**Structure 2**			
		Sill	**Range 1 (m)**	**Range 2 (m)**	**Range 3 (m)**	**Sill**	**Range 1 (m)**	**Range 2 (m)**	**Range 3 (m)**
1	0.176	0.009	12	12	6	0.338	43	37	17
2	0.099	0.010	37	23	4	0.265	84	50	17
3	0.065	0.036	6	8	6	0.115	40	52	23
5	0.020	0.018	3	6	4	0.060	10	19	13

9.2.3 Search parameters

As variography was carried out on all the domains, the variogram range and angular search distance were used to generate the search parameter files (table 16). In the absence of a variogram, the search directions for Domain 4 were based on the visual dip and dip direction of the domain whereas the search distances were copied from the adjacent Domain 5. The primary search volume was only expanded to a factor of 2 while the minimum/maximum number of samples was restricted to 10 and 20, 3 and

20 for the first and second searches, respectively. For the third search, a search factor up to 10 times was used with minimum/maximum 3 and 20 samples to fill the blocks.

Table 16: Search Parameters used for Estimation parameters

Domains	Search angles - X	Search angles – Y	Search angles – Z	Search Range X (m)	Search Range Y (m)	Search Range Z (m)
Domain 1	26	-87	-20	41	38	26
Domain 2	30.18	-89	-10	100	60	10
Domain 3	69	-90	0	39	53	39
Domain 4	40	-89	-20	11	20	17
Domain 5	40	-89	-20	11	20	17

9.2.4 Estimation parameters

The grade estimation *ESTIMATE* procedure in Datamine *Studio 3* was utilised for estimating Ni and Density (SG) into the block models. The estimation filled each block falling within the range of influence as defined by the search parameters with the estimated Ni and SG values. Blocks falling beyond search volume 3 are out of range and could not be estimated. Such blocks were assigned waste Ni grade of 0.005%. It should be noted that, this potentially could lead to a lowering of the overall grade in each domain due to the introduction of lower, waste grade blocks in tonnage calculations. It is anticipated this is a short-term solution and those blocks will be populated as more drilling is undertaken. For blocks with absent SG, a regression line based on the equation below was used.

$$SG = (0.1594739 * NI\ \%) + 2.96$$

The estimation parameters based on block size, search strategy, estimation method, number of sample points and discretization are summarized in table 17.

Table 17: Summary of estimation parameters

Estimation parameter	Details of 30 mN by 30 mE block
Block model geometry	See Table 13
Estimation method	OK, IK, IPD and NN; Table 14
Variogram directions	See Table 15
Variogram parameters	See Table 15
Search strategy	See Section 7.2.4; Table 16
Discretisation	4 X by 4 Y by 4 Z
Minimum number of composites	10
Maximum number of composites	20

9.2.5 Grade Capping

Grade (usually Top) – capping is usually applied to a sample data set to prevent overestimation in small sub-sample sets due to disproportionately high-grade samples. The impact of the lower probability values is lessened by capping of these values to the next highest non-outlier value. This process is subjective and may be based on a variety of factors, including inflection points on the mean variance plots and log probability plot curves, percentiles and other statistics as well as examination of the data for disintegration. Outlier values are also capped if there is a question as to the reproducibility and accuracy of the outlier values. The process of capping of the data attempts to reduce the coefficient of variation (COV) of the data while keeping the mean as close as possible to the mean of raw data. Capping should be applied to the minimum number of samples possible. Capping of the lower values is called Bottom-capping.

The composited DDH data were merged with the RC data per domain into files DH1 to DH5. Further statistics were computed for each domain using merged data sets. COV still remained high in the merged file, prompting Top and Bottom capping to be attempted in order to minimize the effects of top and bottom outliers on the COV.

A number of Log-Log probability plots were constructed for both top and bottom capping, per domain. These are listed in the Appendix 2. The observation was that the capping exercise was futile as the COV remained high above the threshold value of 1.5. The decision was taken to proceed with the data without any capping despite the high COV.

9.2.6 Estimation method

Ordinary Kriging (OK) was employed as the primary method of estimation. OK requires a variogram, which relies on similar data support and is effective when the data are abundant. In the Inverse Power of Distance (IPD) method, a spatial correlation between samples is assumed, and samples closer to the unknown point are assigned a higher weighting. Indicator kriging (IK) is an estimation method developed to weight outliers in skewed distributions, such as the domains in the current work. As it is a non-parametric method it can handle multiple populations or data with very high COV.

Grade estimation was undertaken on %Ni and Density (SG). Choice of grade estimation method used was guided by the results of the variography. Each domain was treated as a separate entity and assessed separately. In almost all the five domains more than one method was used to estimate the Ni grade. This was done to compare the estimation results with the sample grades to ultimately settle for the estimation that honours the sample grades. The primary method of choice was OK and it was applied across all the domains. Other methods such as Nearest Neighbour (NN), IPD and IK were used as appropriate. For density estimation OK was used for all domains. The estimation method, per domain is shown in table 18.

Table 18: Estimation methods used in each domain

Domains	Estimation method	Results
Domain 1	*Ordinary Kriging*	*NI_OK*
	Inverse power of distance	*NI_IPD*
	Indicator kriging	*NI_IK*
Domain 2	*Ordinary Kriging*	*NI_OK*
	Inverse power of distance	*NI_IPD*
Domain 3	*Nearest Neighbour*	*NI_NN*
	Indicator kriging	*NI_IK*
	Ordinary Kriging	*NI_OK*
Domain 4	*Nearest Neighbour*	*NI_NN*
	Inverse power of distance	*NI_IPD*
Domain 5	*Ordinary Kriging*	*NI_OK*
	Nearest Neighbour	*NI_NN*
	Inverse power of distance	*NI_IPD*

9.3 Model Validation

The block models were validated against input composite data to develop confidence in the modelling procedure. The model validation process demonstrates the robustness of the block model estimate against the data used to inform it. The model validation was performed utilising the following methodology:

1. Visual comparison of the estimated block grades against the sample grades.
2. Global comparison of the average block model grades and average sample grades.
3. Sectional (swath) plots comparing the number of samples, block model estimated grades and the raw sample grades occurring within a specified distance on either side of a section.

Visually, there is a good correlation between the estimated block grades and the sample grades with high grade samples spatially informing high grade block estimates and vice-versa. This is true for all domains, although in areas with poor sample coverage there is poor correlation.

The global comparison is summarised in terms of the differences between average input data and resultant block model as shown in table 19. There is very good correlation in Domain 1, 4 and 5 and less so in Domains 2 and 3. This difference is attributed to lack of samples in areas beyond search radius such that the nominal value of % Ni (0.005%) must be inserted, consequently, lowering the grade.

Table 19: Model validation – Mean %Ni and SG comparison

Domains	**Data**		**Model**		**Difference**	
	%Ni	SG (g/cm^3)	%Ni	SG (g/cm^3)	Ni	SG
Domain 1	0.22	2.91	0.21	2.9	5%	0%
Domain 2	0.21	2.92	0.17	2.89	19%	1%
Domain 3	0.12	2.92	0.1	2.98	17%	-2%
Domain 4	0.13	2.87	0.14	2.91	-8%	-1%
Domain 5	0.11	2.97	0.11	2.94	0%	1%

Swath analysis was done by comparing model slices in step-wise fashion with drillhole data within the slices. The estimated mean per slice in the 3 orthogonal directions were plotted in excel against the sample grades within each slice.

For Domain 1, the swaths occurring within a slice of 5 m in the Eastings direction is shown in Figure 32. Each estimation method (M_NI_OK, M_NI_IPD and M_NI_IK) used was compared with the sample grades (S_NI) and number of samples (#SAMPS) in the swath analysis (figure 32).

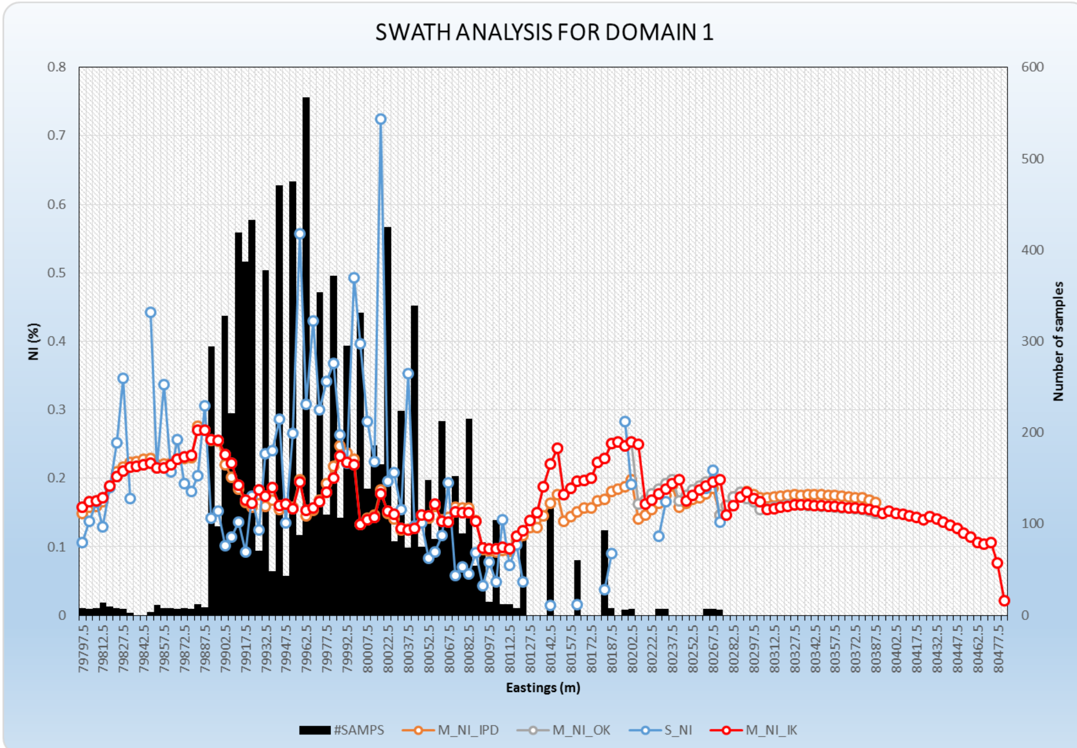


Figure 32: Swath Analysis for Domain 1

The analysis for Domain 1 shows some interesting trends for all the estimation methods. In general, where there is very good sample coverage the correlation is good, and in areas of poor sample coverage the differences are higher. There is no particular difference in any of the estimation methods used. This shows that in this domain, even with high COV, the estimation improves only nominally when a non-parametric estimation method such as IK is used.

In Domain 2, only OK and IPD estimates were produced. The swath plot for both shows a good correlation in trend, with the one significant difference in values between the model and composite data at Eastings = 79972.5 – 80022.5 m (figure 33).

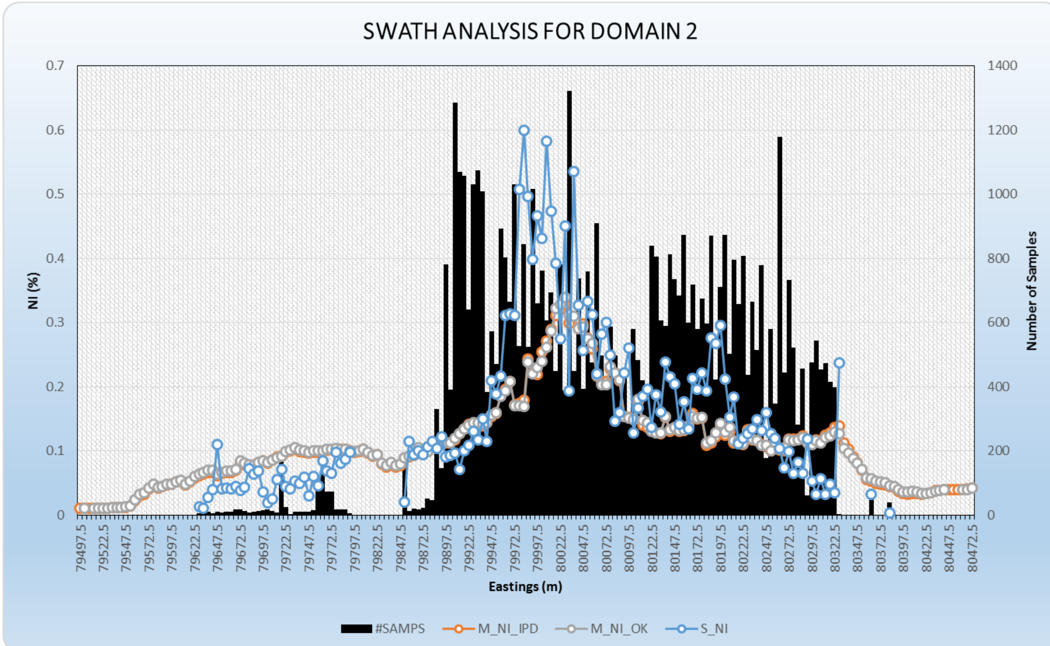


Figure 33: Swath Analysis for Domain 2

Domain 3 swath analysis considered OK and IK, with the resultant plot illustrated in in figure 34**Figure 34**. The superiority of IK as a preferred estimation method is clearly shown in this domain. Whereas OK consistently overestimates the composite data in all areas except the area around Eastings = 80067.5 – 80097.5, IK is closer to the composite data. In areas of poor sample coverage, IK outperforms OK. Even though both estimation methods follow the trend of the data, only IK is closer to the data. NN and IPD were evaluated but are not displayed in Figure 34, and perform poorly, being closer to OK than to IK. The reason why OK performs poorly is because it depends on a linear (parametric) distribution of the data, and because this distribution is skew, with high COV, the method falls. Consequently, IK, being non-parametric should be the preferred method for estimation in this domain.

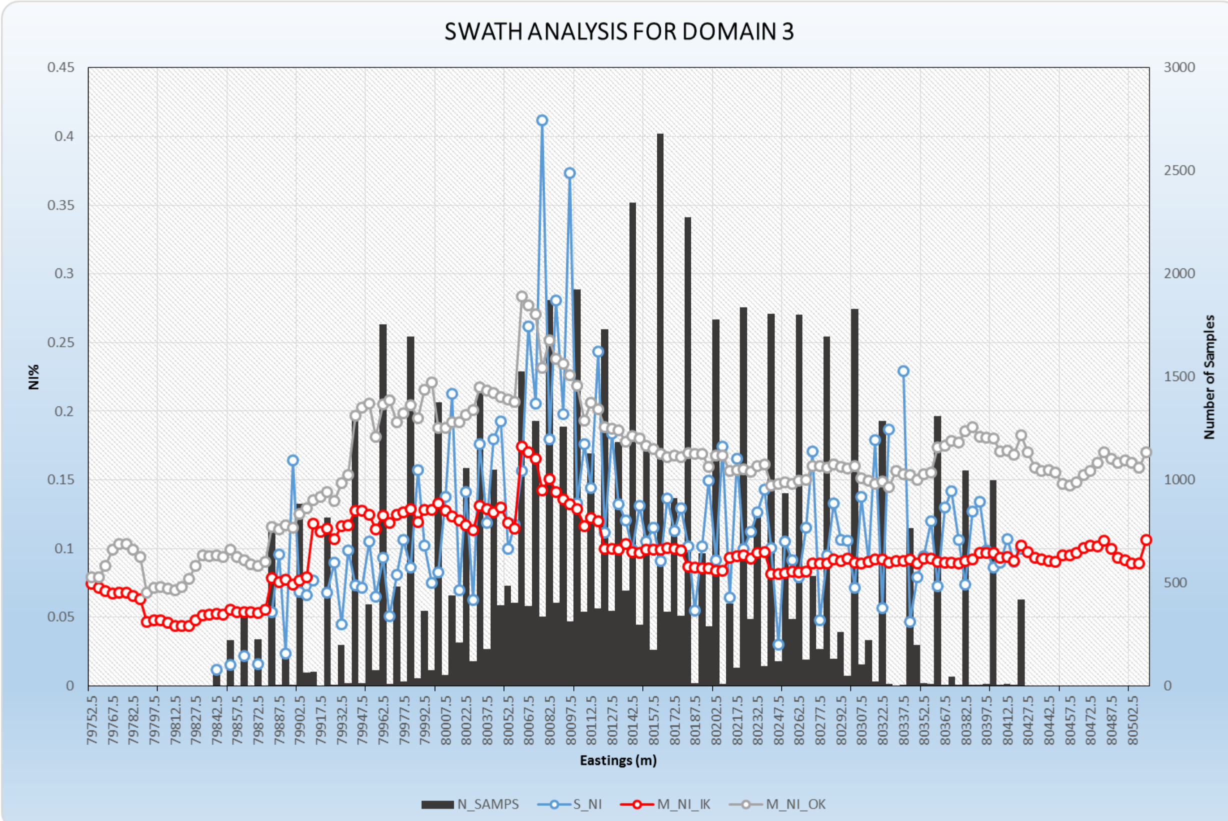


Figure 34: Swath Analysis for Domain 3

For Domain 4 only IPD was considered as no variogram could be obtained; the swath plot is illustrated in Figure 35 with IPD and NN plotted for comparison. In the absence of a large sample set, the Z-direction (elevation) was used for generating the swath plot. IPD is clearly the better method, to some extent correlating well with the data. The NN method falls off as the depth increases (i.e. elevation 952.5 m onwards).

In Domain 5 swath analysis NN, IPD and OK estimations were all plotted resulting in the plot illustrated in figure 36. IPD and OK are consistently close, while NN falls away, poorly correlating with the composite data. In area of high sample coverage, there is good correlation between the model and the data for both OK and IPD; the converse is also true.

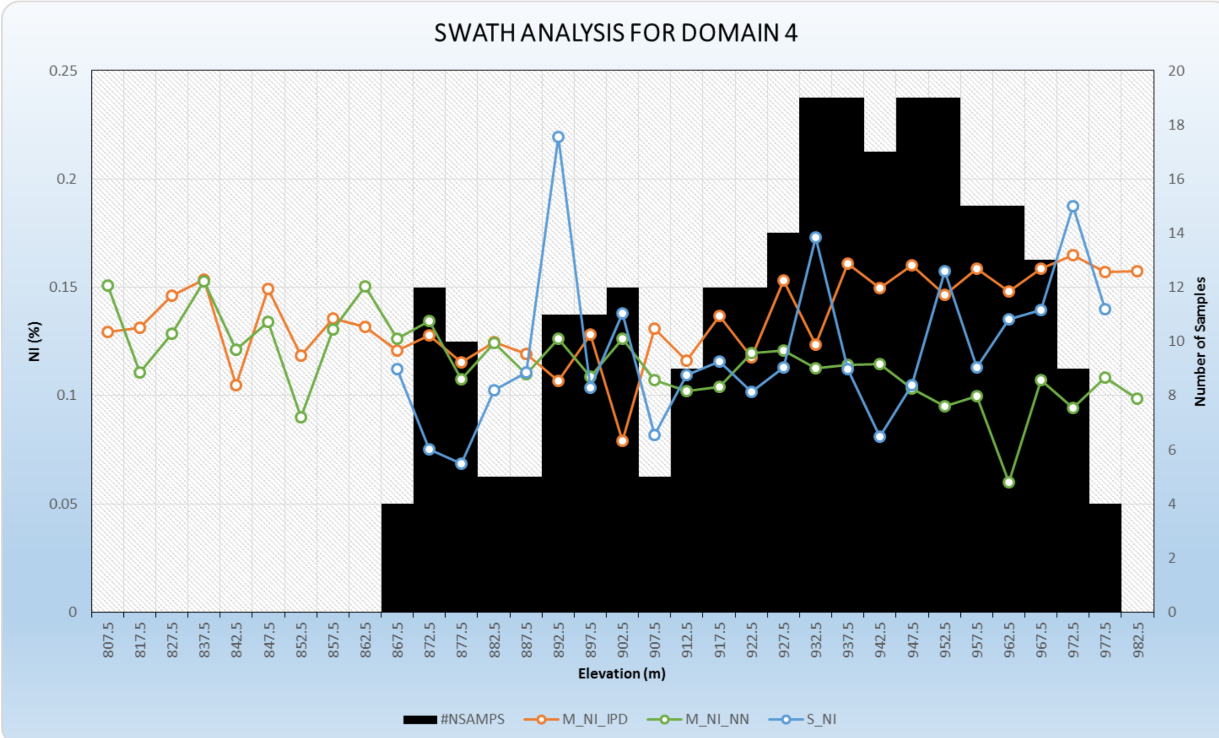


Figure 35: Swath Analysis for Domain 4

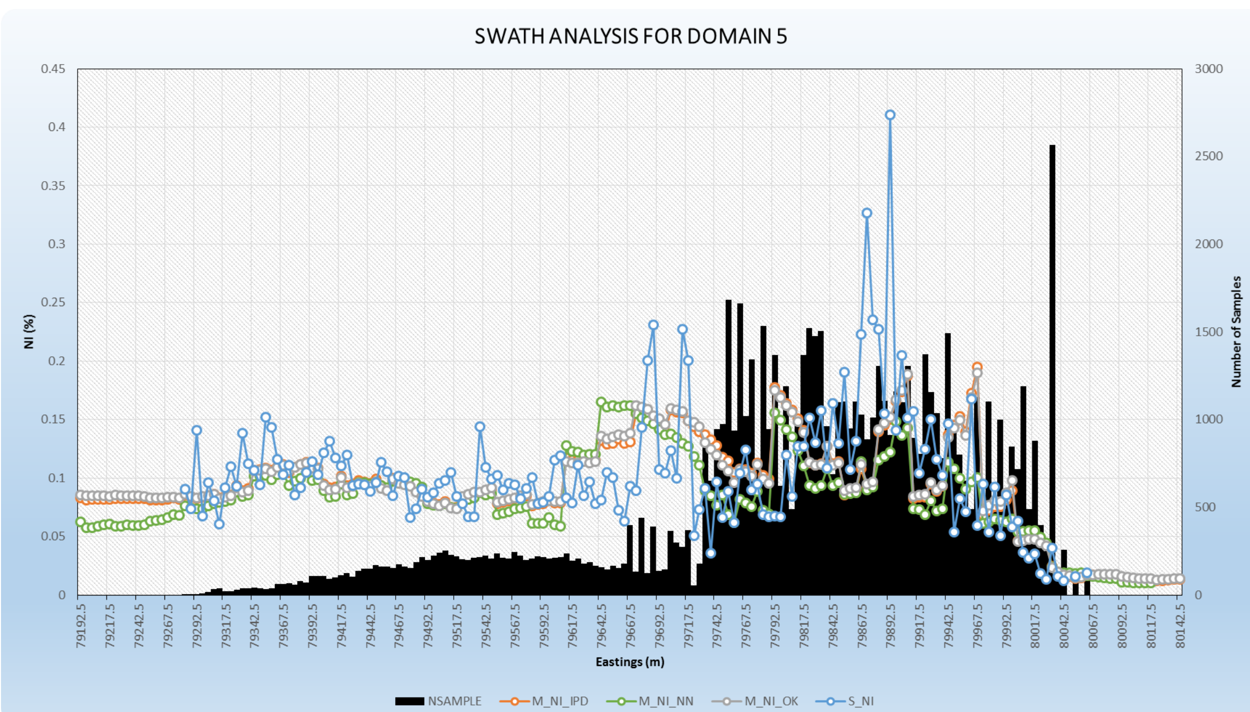


Figure 36: Swath Analysis for Domain 5

10 Resource Evaluations

In general, Mineral Resources are classified as **Measured**, **Indicated**, and **Inferred Resources**, based on the confidence attached by the CP. Below are some of the classification criteria usually employed to report the estimated resource, in line with the South African Code for Reporting of Mineral Resources and Mineral Reserves (SAMREC, 2016), including the following:

- Geological and grade continuity
- Quality Assurance and Quality Control (QAQC)
- Data quality:
- Drillhole spacing
- Number of samples and search volumes
- Slope of Regression (SE) and Kriging Efficiency (KE)

Since none of these criteria were considered in the current work, it has been decided not to alter the existing classification. However, the number of samples per search volume was used to give an indicative level of confidence on the reported resources per domain. The results are summarised in the Appendix 5 and Appendix 6.

10.1 Depleted Mineral Resources Statement

The validated models for the domains were added together to produce one final model for the Phoenix deposit named m-pho-17.dm. Dykes that separate the domains have been excluded from the model. This model was truncated against the end of May 2016 pit shell. The total resources are shown in table 20. A field was introduced in the final model to represent mined out resources, and these mined out resources are tabulated in table 21. The remaining portions of the resource are shown in table 22.

It is the five domains was included in the model, irrespective of grade. And in those areas where the model cells where not populated noted that a lot of low grade material has been introduced because all the data within, a nominal value of 0.005% Ni was introduced, consequently lowering the average grade.

Table 20: Estimated Tonnage and Grade – Total Resources

DOMAIN	VOLUME(m^3)	TONNES	SG(g/cm^3)	Ni (%)
1	19 883 811	57 625 200	2.90	0.21
2	87 367 175	252 091 986	2.89	0.17
3	85 481 707	254 380 140	2.98	0.10
4	7 002 885	20 405 016	2.91	0.14
5	83 929 590	246 956 824	2.94	0.11
Total	283 665 170	831 459 166	2.93	0.13

Table 21: Estimated Tonnage and Grade – Mined Out

DOMAIN	VOLUME(m^3)	TONNES	SG(g/cm^3)	Ni (%)
1	8 112 780	23 689 985	2.92	0.28
2	33 220 254	96 489 694	2.90	0.26
3	25 622 510	76 293 364	2.98	0.11
4	-	-	-	-
5	12 081 438	35 725 278	2.96	0.14
Total	79 036 983	232 198 321	2.94	0.19

Table 22: Estimated Tonnage and Grade – Unmined

DOMAIN	VOLUME(m^3)	TONNES	SG (g/cm^3)	Ni (%)
1	11 771 031	33 935 215	2.88	0.16
2	54 146 921	155 602 292	2.87	0.11
3	59 859 198	178 086 775	2.98	0.09
4	7 002 885	20 405 016	2.91	0.14
5	71 848 152	211 231 546	2.94	0.11
Total	204 628 187	599 260 845	2.93	0.11

10.2 Estimated Grade - Tonnage curves for the unmined resource

10.2.1 The Estimated Total Resource

Grade tonnage curves were generated for the global model. The results are shown in figure 37 and 38. This gives a better description of the grade-tonnage relationship. For example, at a cut-off of 0.1 Ni% there are ~410 Mt with an average grade of 0.21 Ni% (figure 37 and table 23).

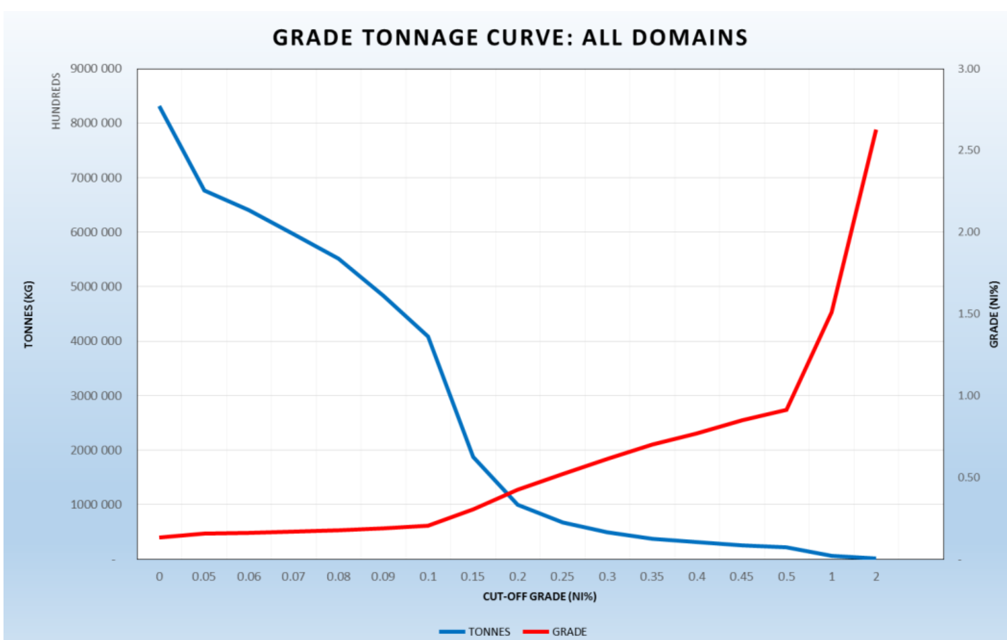


Figure 37: Grade – Tonnage curve for all the domains for the m-pho-17.dm model

Table 23: Estimated Grade – Tonnage figures for the m-pho-17.dm model

CUT-OFF GRADE (Ni %)	TONNES	AVERAGE GRADE ABOVE CUT OFF (Ni %)
0	831 459 166	0.13
0.05	676 950 942	0.16
0.06	640 503 305	0.16
0.07	596 089 124	0.17
0.08	551 106 930	0.18
0.09	483 489 472	0.19
0.1	409 032 753	0.21
0.15	187 505 257	0.31
0.2	99 324 431	0.43
0.25	67 696 908	0.52
0.3	48 959 936	0.61
0.35	37 870 161	0.70
0.4	31 385 194	0.77
0.45	25 358 341	0.85
0.5	21 677 076	0.91
1	6 348 124	1.51
2	847 547	2.63

10.2.2 The Unmined Resource

The Grade – Tonnage curve for the unmined resource is presented in Figure 38, with corresponding tabulation in table 24. From both illustrations, at a cut-off grade of 0.1 Ni %, it is expected that ~216 Mt are available at an average grade of 0.17 Ni %.

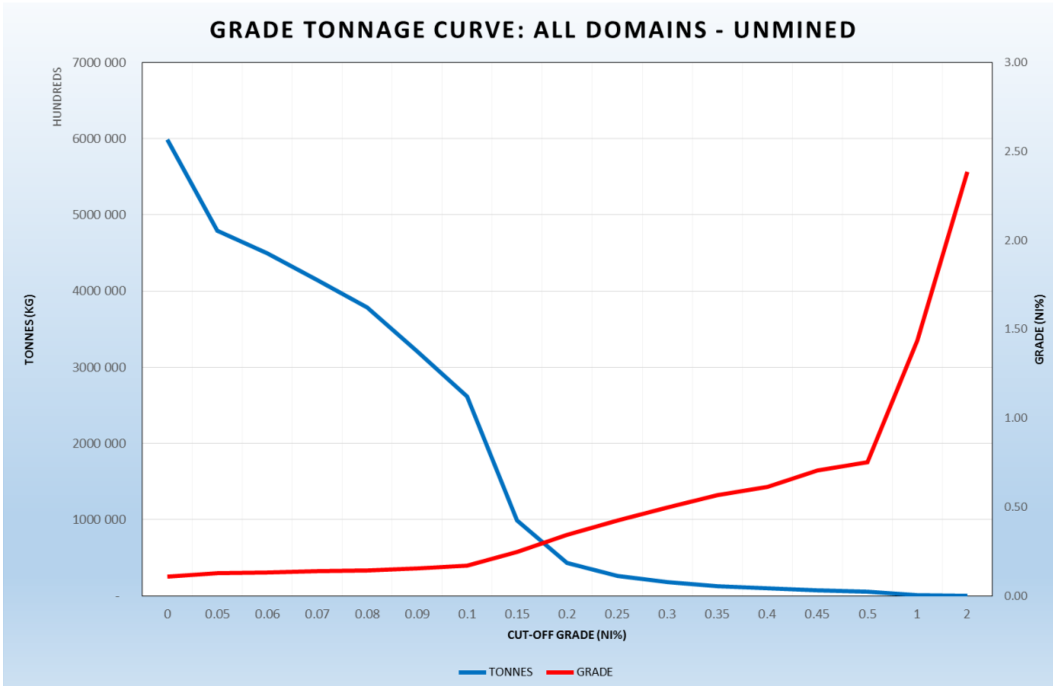


Figure 38: Estimated Grade – Tonnage curve for all the domains for the UNMINED resource

Table 24: Estimated Grade – Tonnage figures for the m-pho-17.dm model – UNMINED resource

CUT-OFF GRADE (Ni %)	TONNES	AVERAGE GRADE ABOVE CUT OFF Ni %
0	599 260 845	0.11
0.05	479 196 425	0.13
0.06	449 999 849	0.13
0.07	414 523 003	0.14
0.08	378 222 364	0.14
0.09	321 093 814	0.15
0.1	261 459 530	0.17
0.15	99 141 902	0.25
0.2	43 569 053	0.34
0.25	26 261 644	0.43
0.3	17 762 614	0.50
0.35	12 822 106	0.57
0.4	10 285 233	0.61
0.45	6 938 128	0.71
0.5	5 795 981	0.75
1	873 836	1.44
2	52 539	2.38

10.3 Comparison to previous model

An attempt has been made to compare the current 2017 (m-pho-17.dm) model with the previous model, produced by Gipro Nickel in 2011, called mpho-11.dm (hereafter called the 2011 model). However, true comparison for the models is not entirely possible at this stage for the following reasons:

- The current (2017) model has not been classified into any of the required categories, whereas the 2011 model specified these categories.

- The input drillhole file used to generate the 2011 model is not available for comparison.

- In the 2011 model the northern flank of Domain 5 was not included in the Resource due to low exploration potential.

- It appears the 2011 model only utilised NN and IPD method, with omni-directional searches. Beyond the search radius, a nominal value of 0.005 Ni% was inserted into the model cells.

- Also the 2011 model used a lower density (SG = 2.84 g/cm^3) for areas with no density, whereas the 2017 model used a regression line equation which yielded higher density for similar blocks.

The two models have significantly different volumes, making comparison untenable. However, to get an idea of the relationship between the two, a decision has been made to deplete the bigger 2011 model using the Domain wireframes (1 – 5) that form the basis for the 2017 model. This approach gives a better view, and since the volume of the Domains is well-defined, the model comparison is shown in table 25.

Table 25: Estimated Tonnage and Grade – Comparison for 2011 and 2017 models

MODEL	VOLUME (m^3)	TONNES	SG (g/cm^3)	Ni (%)
2011	282 086 635	816 576 454	2.90	0.09
2017	283 665 170	831 459 166	2.93	0.13
%DIFFERENCES	-1%	-2%	-1%	-44%

It is clear from the figures that there is very little difference in volume and tonnes for the material lying with the domains, with the 2017 model showing a slight increase in tonnage but a much higher increase in grade. This grade disparity is attributed to the longer search radii used in estimation for the 2017 model. The 2011 model used a standard distance for each domain (30 m by 30 m by 30 m) and an omnidirectional search whereas the 2017 model used individual search radii.

A further comparison is shown in figure 39, which takes E-W slices through both models, based on a similar legend. The 2011 model is shown on the left (1A, 2A and 3A) whereas the 2015 model is on the right (1B, 2B and 3B). It is noted from the image that the 2011 model has a ring of very low grade (i.e. Ni %= 0.005) around the edges of the domains. In the 2017 model, however, the extended search radius allows for slightly higher grades due to extended searches.

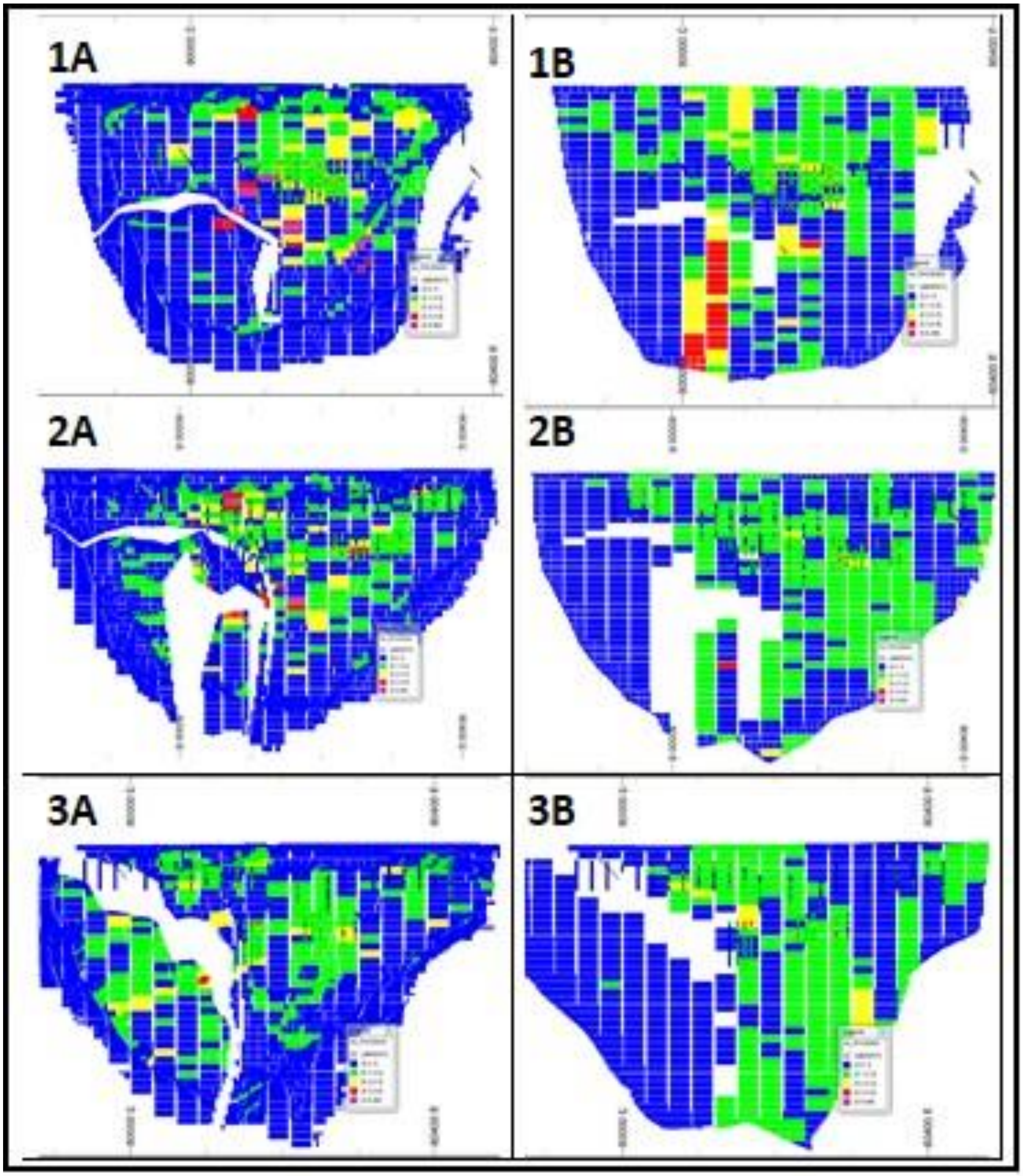


Figure 39: E – W sections across selected parts of the two models. m –PHO-11on the left and 2017 model on the right.

11 Conclusions and Recommendations

Two main sources of data (exploration data [DDH] and production data [RC]) were combined to inform the block model. The supplied exploration data was carefully checked for errors and verified. No major errors were found, and the data was deemed of sufficient quality to be used for estimation. No geological and/or structural modelling was undertaken.

EDA showed that the data across all domains is almost always ‘mixed’, yielding high variance and high COV. Efforts to reduce the COV by compositing or grade-capping were futile. Consequently, the high COV was considered a feature of the mineralization and the data was used for estimation without the need for grade capping. As two data were used in estimation, it was found that DDH data consistently yielded higher Ni % grades than RC data.

Estimation methods including IPD, OK and IK were employed to populate the blocks. Of these IK, appeared the most robust, and is evident in the model validation exercise across all the domains. The depleted Mineral Resource with unmined resources only, is shown in table 26:

Table 26: Estimated Tonnage and Grade for the Phoenix deposit – Unmined (cut-off Ni %)

DOMAIN	VOLUME (m^3)	TONNES	SG (g/cm^3)	Ni (%)
1	11 771 031	33 935 215	2.88	0.16
2	54 146 921	155 602 292	2.87	0.11
3	59 859 198	178 086 775	2.98	0.09
4	7 002 885	20 405 016	2.91	0.14
5	71 848 152	211 231 546	2.94	0.11
Total	204 628 187	599 260 845	2.93	0.11

No classification of the resource has been undertaken at this stage and the depleted Mineral Resource is based on the May 2016 pit shell. However, at a cut-off of 0.1 Ni %, the tonnage is ~261 Mt with an average grade of 0.17 Ni %.

In general, the following were found to be commendable areas regarding the modelling of the Phoenix Resource:

- Good quality data: The validated and reviewed data is of very good quality. No area of concern was noted during the process of verification

- Industry Standard Database: In general, International Reporting codes require that the data be housed in an acceptable systemic database. The exploration data was retrieved from such a data set, which is be well-managed.

- Choice of Estimation Method: It appears that in the past, other estimation methods other than Ok have been used for estimating the domains. IK in particular seems to have been used in the past, and should be used going forward.

A number of observations made during this study could, potentially, benefit the project:

- Review of the geological modelling: It appears the geological models have never been reviewed since the deposit was first modelled, even though more data exists at present. A thorough review and check may be warranted to aid in interpretation.

- Review of Domains: Domain analysis has shown that the initial domaining could potentially be reviewed. Careful domaining could yield information on dip and dip directions of the deposit, which could be applied to other, newer parts of the deposits. This in turn would improve the estimation process. However, this is mitigated by the fact that a lot of production has occurred already, and a lot of data exists already to warrant further refinement.

- RC vs DDH data under estimation. It is clear that there is underestimation in the more dense RC data compared to the exploration DDH data. To keep within the confines of the previous classification, this discrepancy has not been used to penalize the data. However, it is suggested that a more robust, non-linear estimation method such as CO-KRIGGING, be considered to evaluate the estimation satisfactorily.

- The existence of multiple populations in the data has in the past been attributed to the nature of the mineralisation. Limited statistical domain analyses, however, shows that a more refined domaining could, potentially, limit the multiplicity in domains and the resultant mixing of different populations of data

- The Estimation method of choice should continue to be IK, although other no-linear estimation methods such as Conditional Simulations and Uniform Conditioning could add value, if applied.

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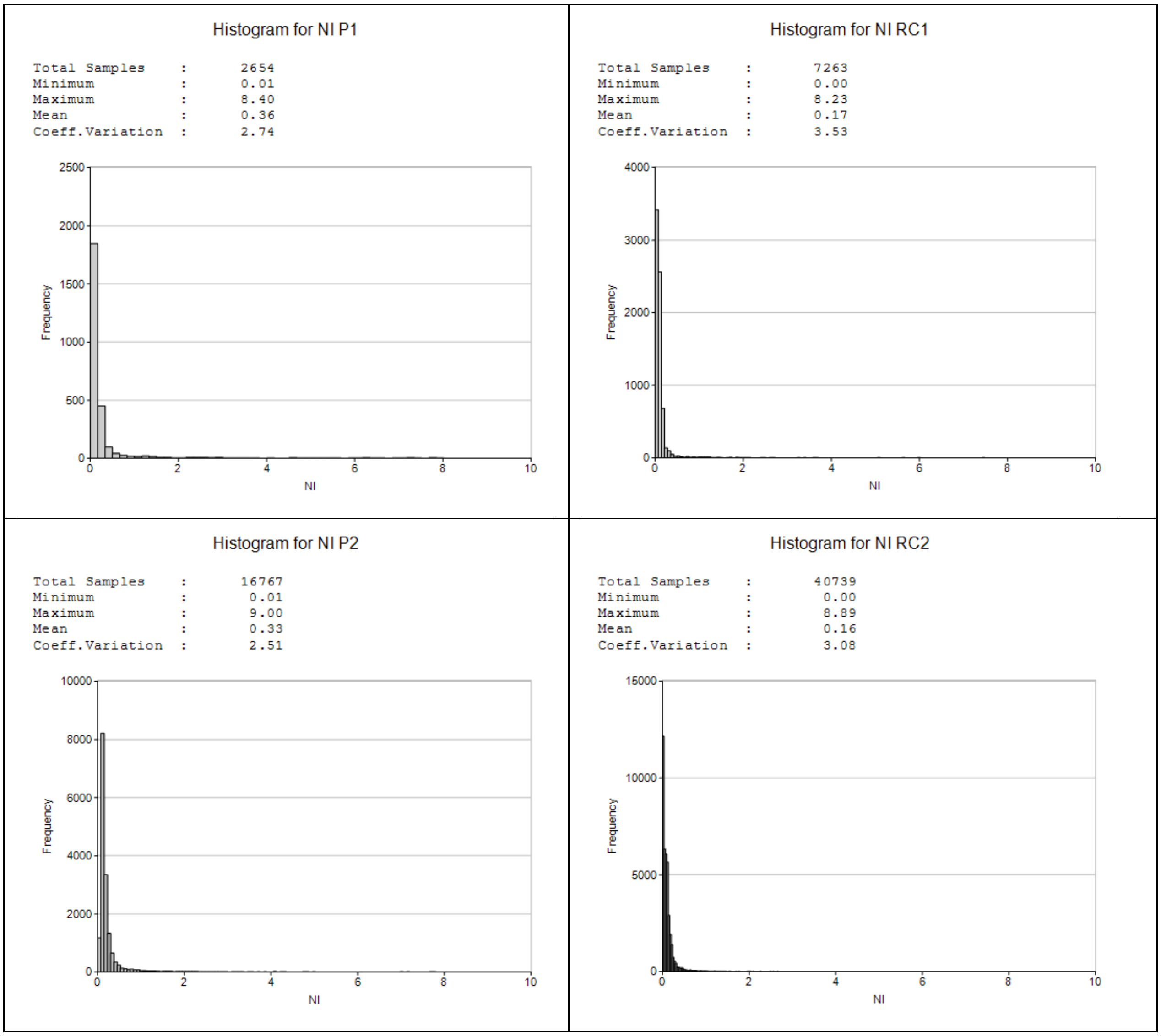
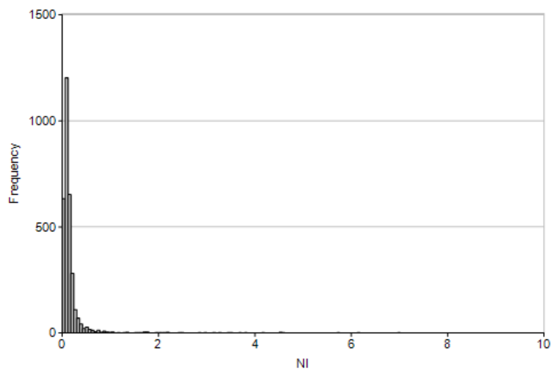
Appendix

Appendix 1: Histograms of Ni per domain



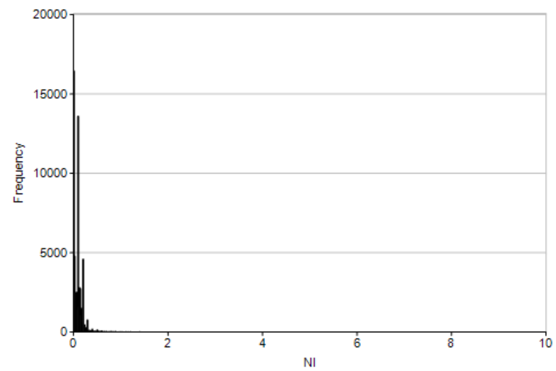
Histogram for NI P3

```
Total Samples    :     3159
Minimum          :     0.01
Maximum          :     6.97
Mean             :     0.17
Coeff.Variation  :     2.16
```



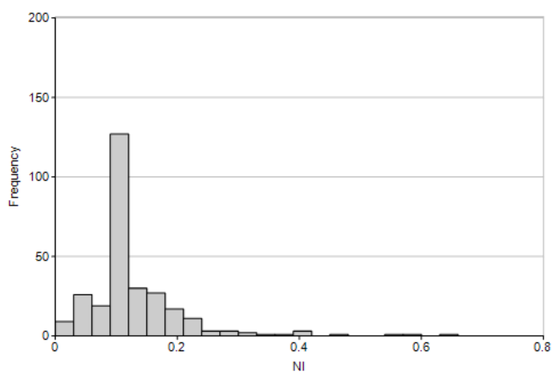
Histogram for NI RC3

```
Total Samples    :     62445
Minimum          :      0.00
Maximum          :      8.19
Mean             :      0.11
Coeff.Variation  :      2.26
```



Histogram for NI P4

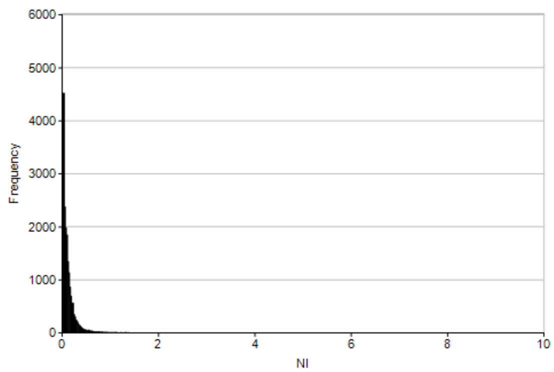
```
Total Samples    :     283
Minimum          :    0.01
Maximum          :    0.64
Mean             :    0.12
Coeff.Variation  :    0.68
```



Domain 4 has no RC borehole data hence no histogram to compare with DDH

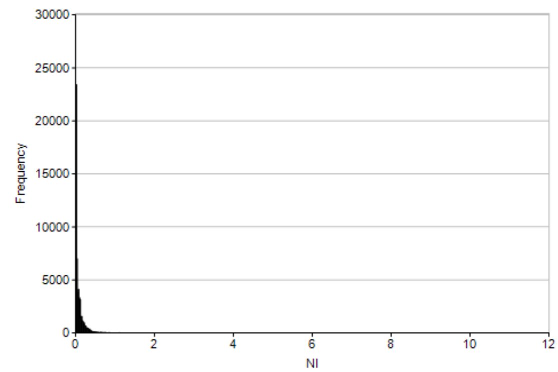
Histogram for NI P5

Total Samples	:	20986
Minimum	:	0.01
Maximum	:	7.39
Mean	:	0.13
Coeff.Variation	:	1.91



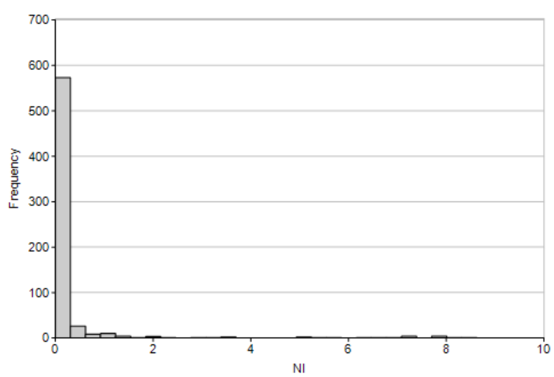
Histogram for NI RC5

Total Samples	:	56660
Minimum	:	0.00
Maximum	:	9.42
Mean	:	0.11
Coeff.Variation	:	3.12



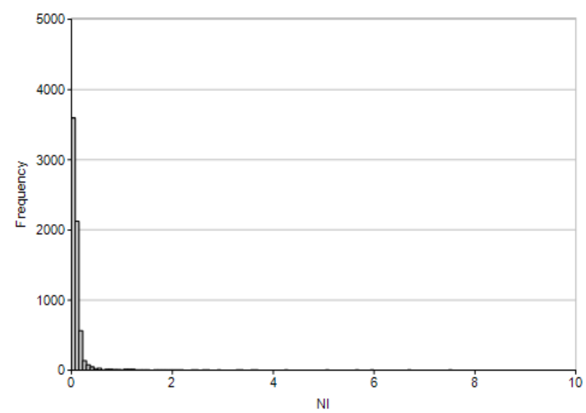
Histogram for NI P1S

Total Samples	:	647
Minimum	:	0.01
Maximum	:	8.40
Mean	:	0.37
Coeff.Variation	:	3.11

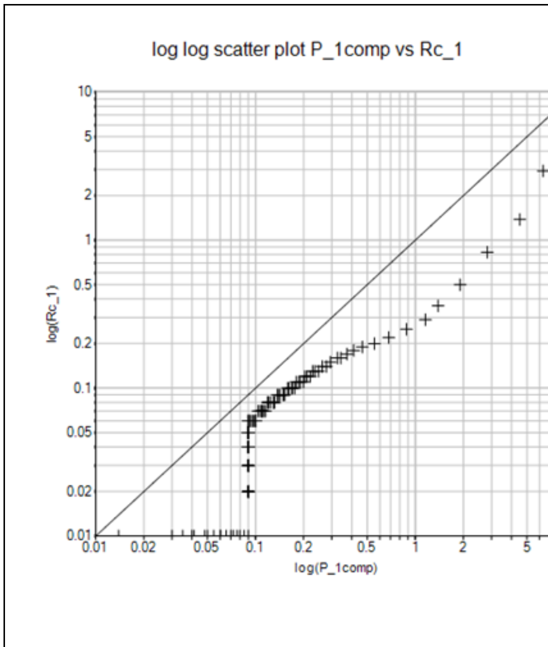


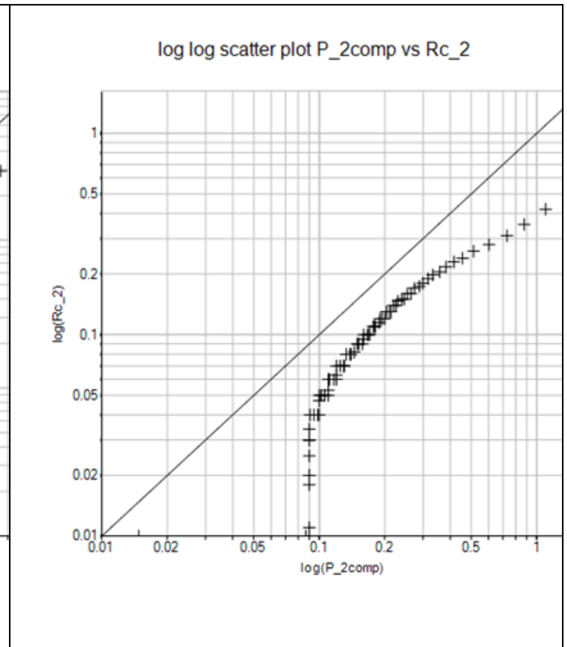
Histogram for NI RC1S

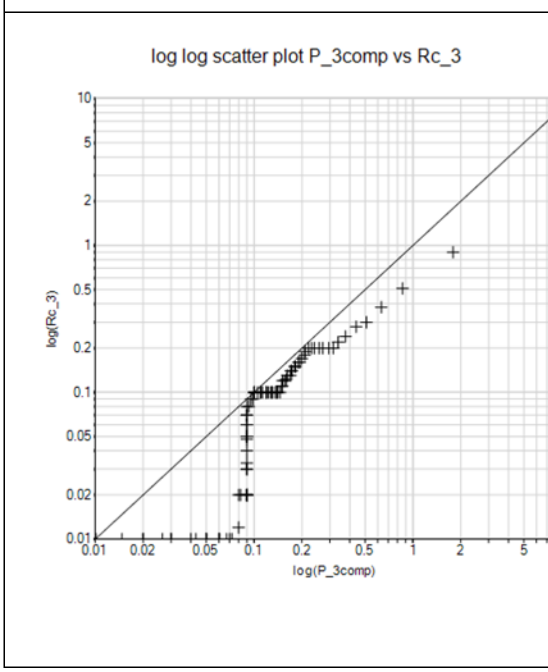
Total Samples	:	6857
Minimum	:	0.00
Maximum	:	8.23
Mean	:	0.17
Coeff.Variation	:	3.46

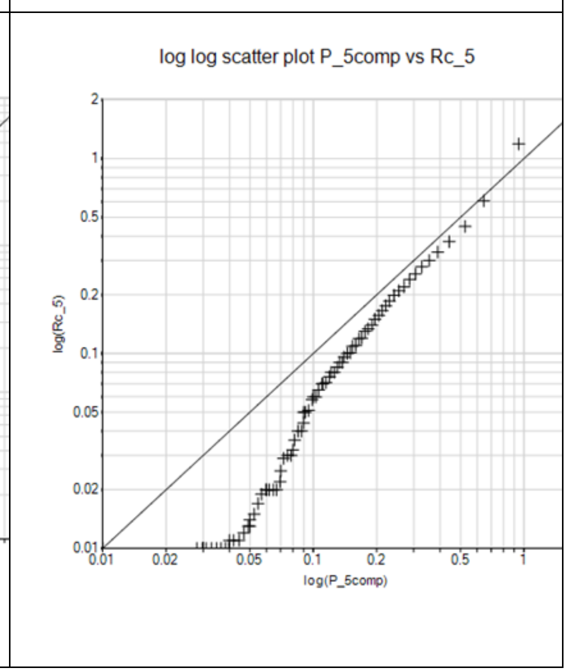


Appendix 2: Log-Log probability plots

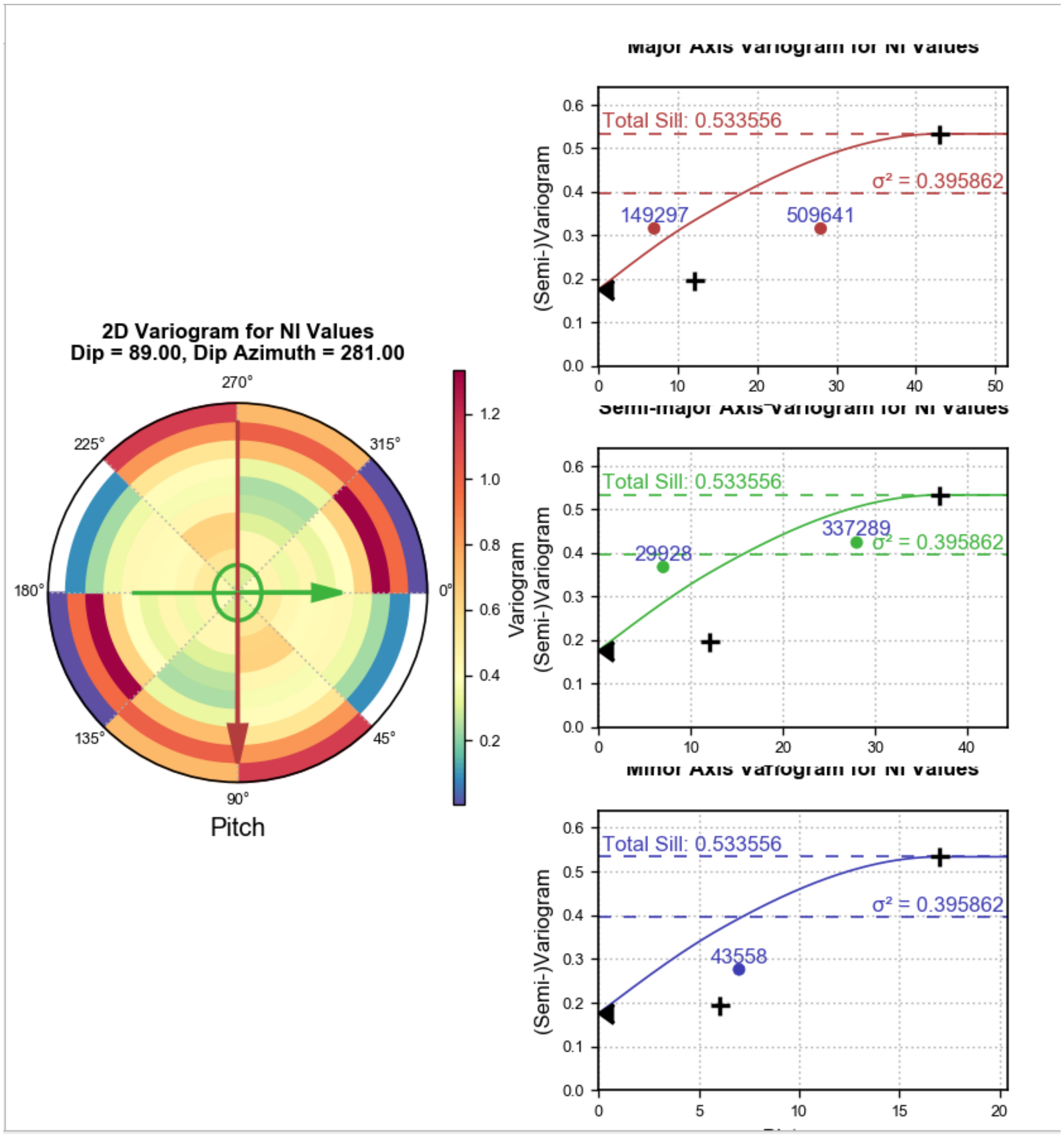




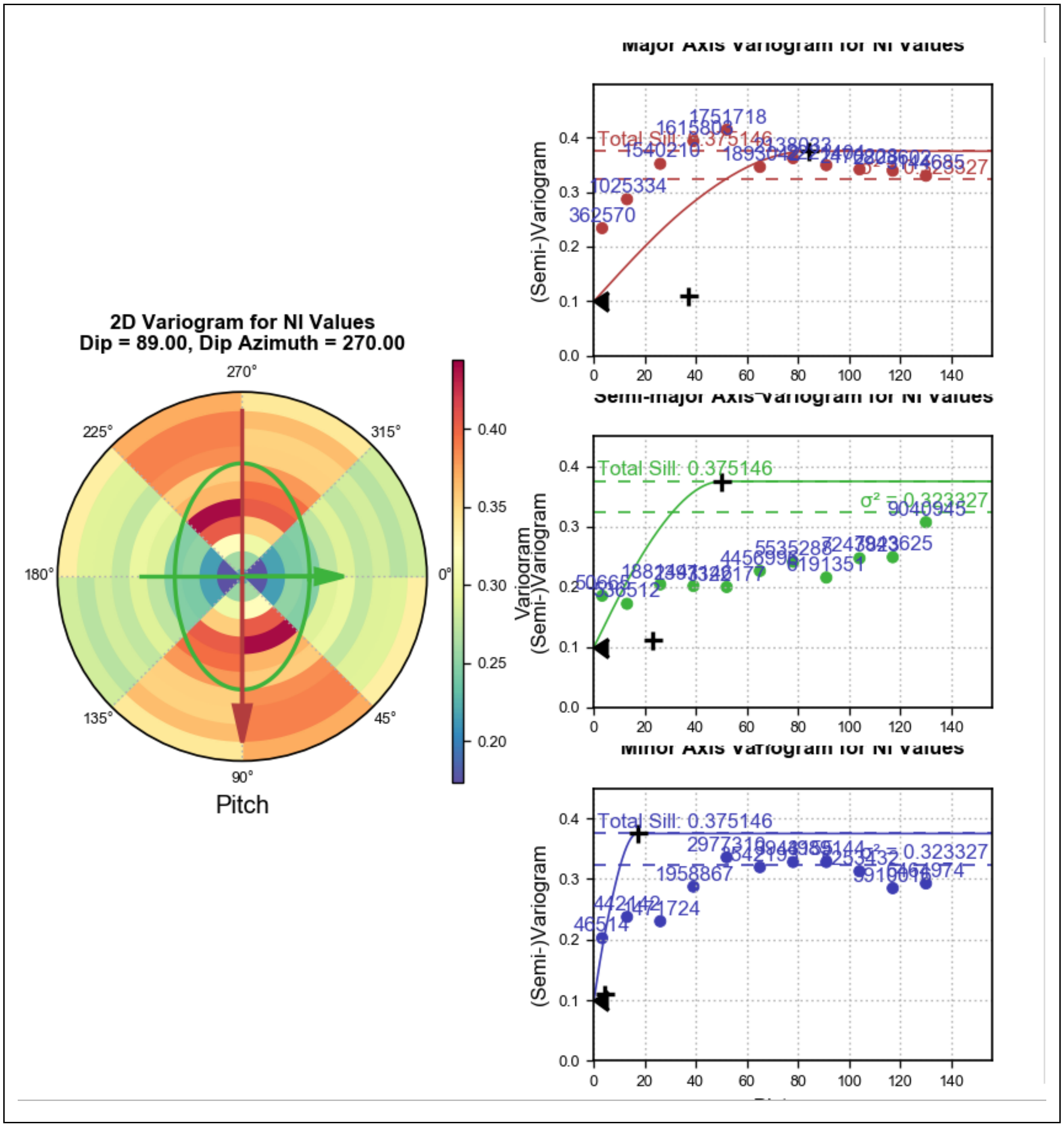




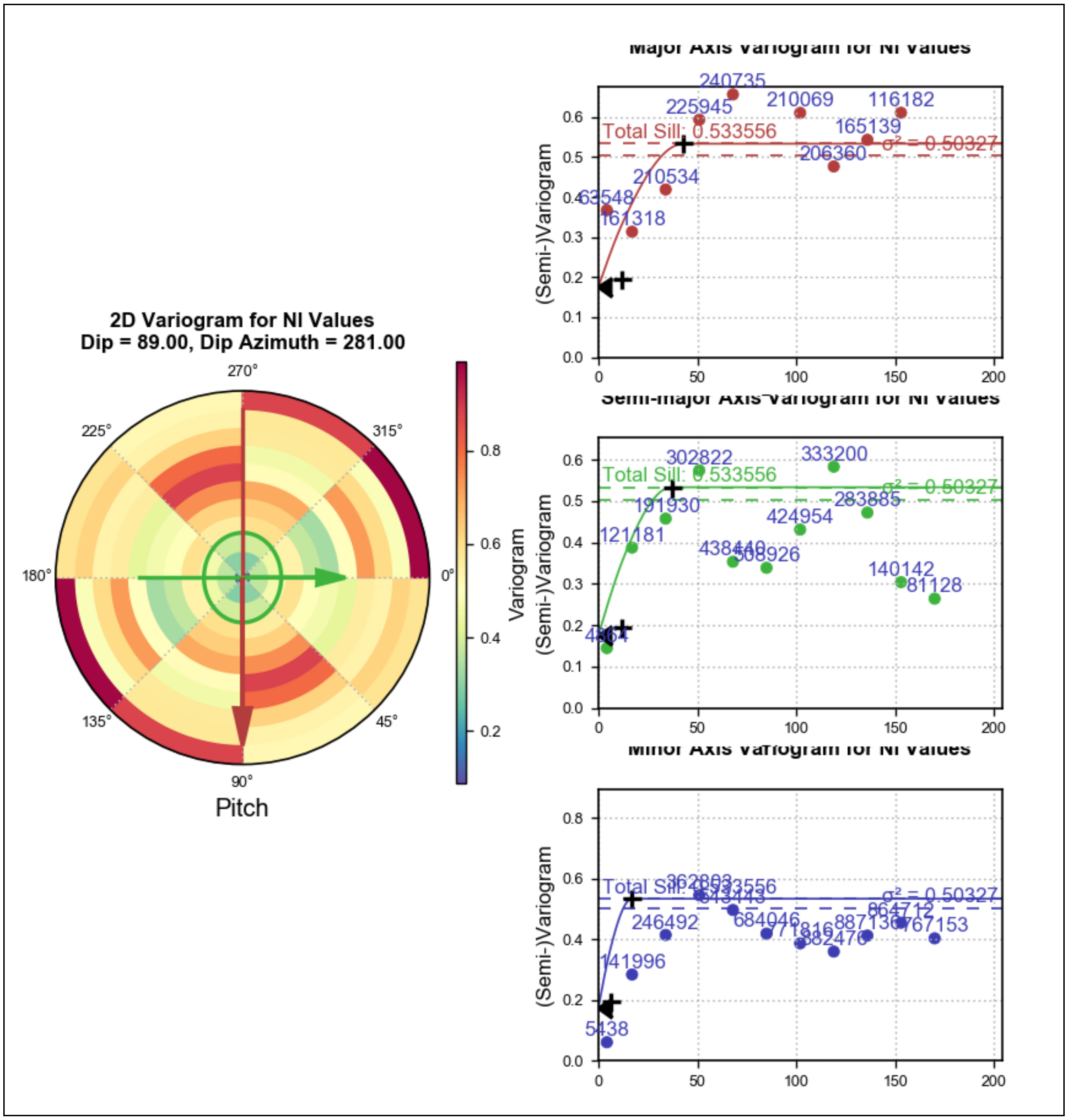
Appendix 3: Experimental variograms plots from the 5 geological domains



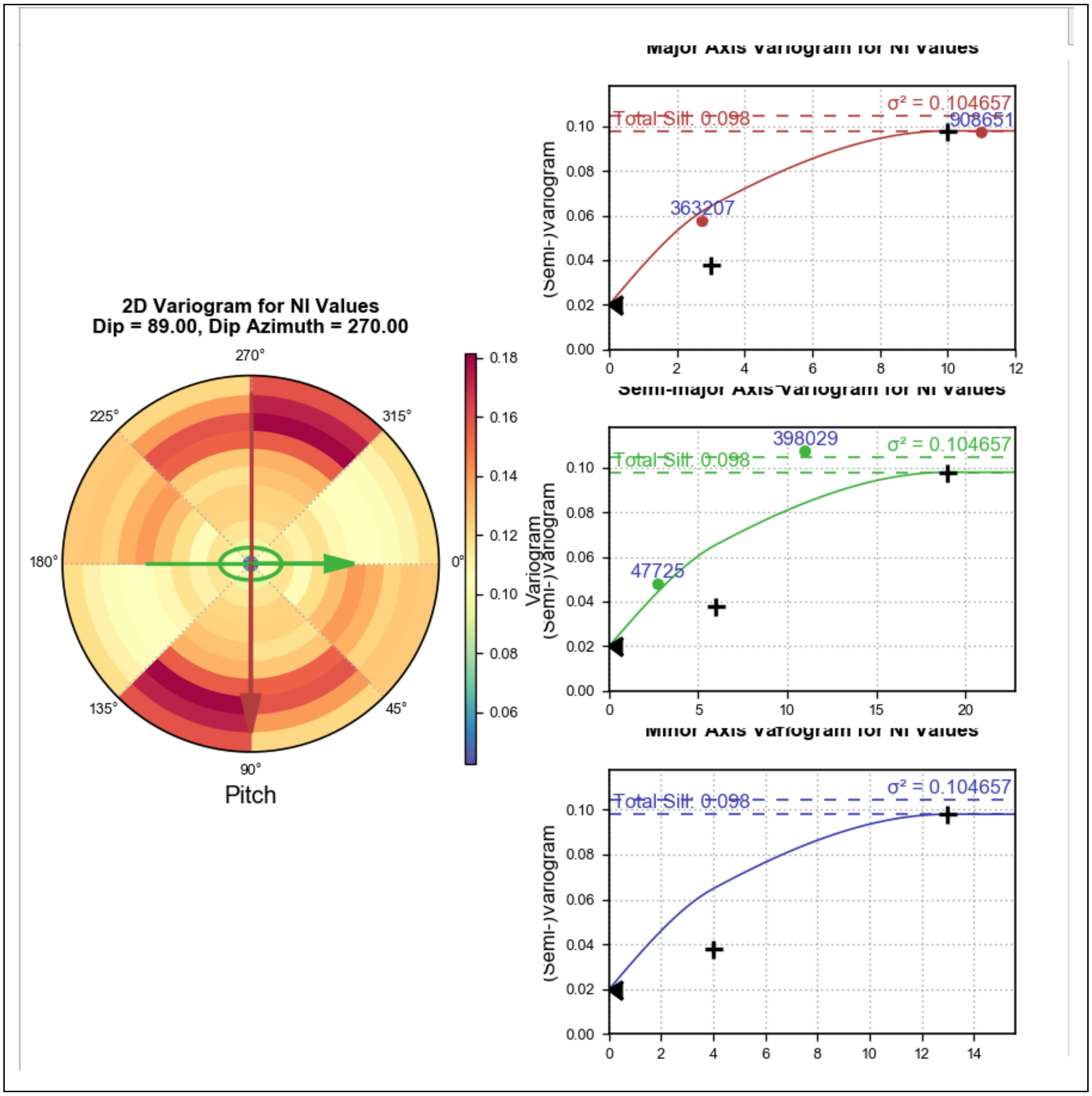
Domain 1 directional variograms



Domain 2 directional variograms

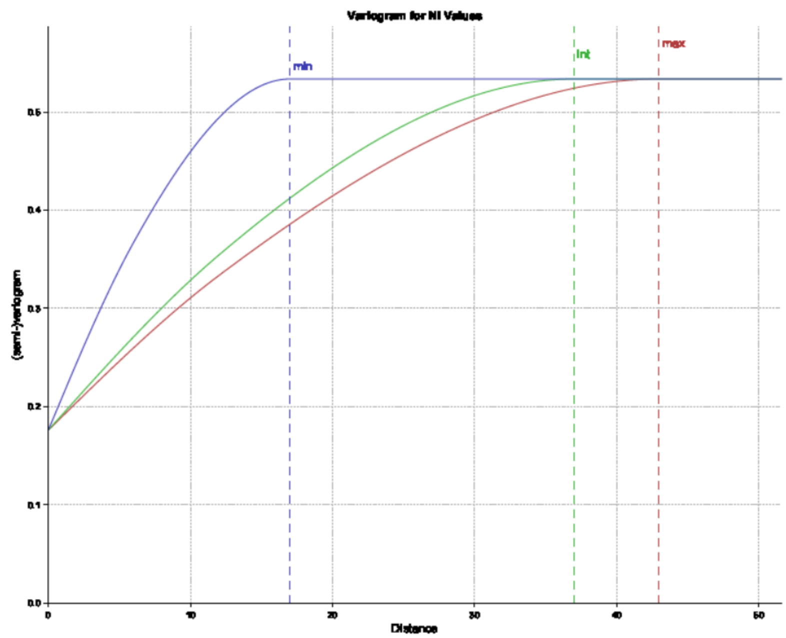


Domain 3 directional variograms

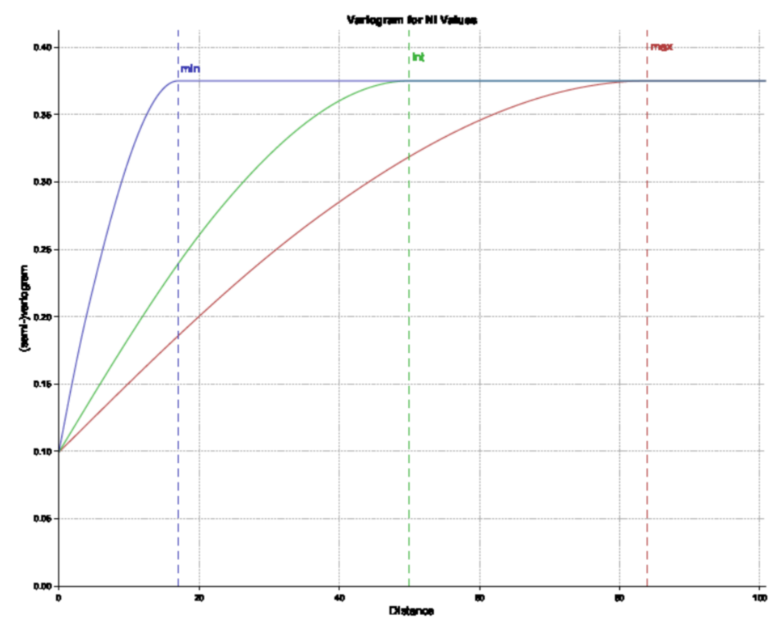


Domain 5 Ni directional variograms

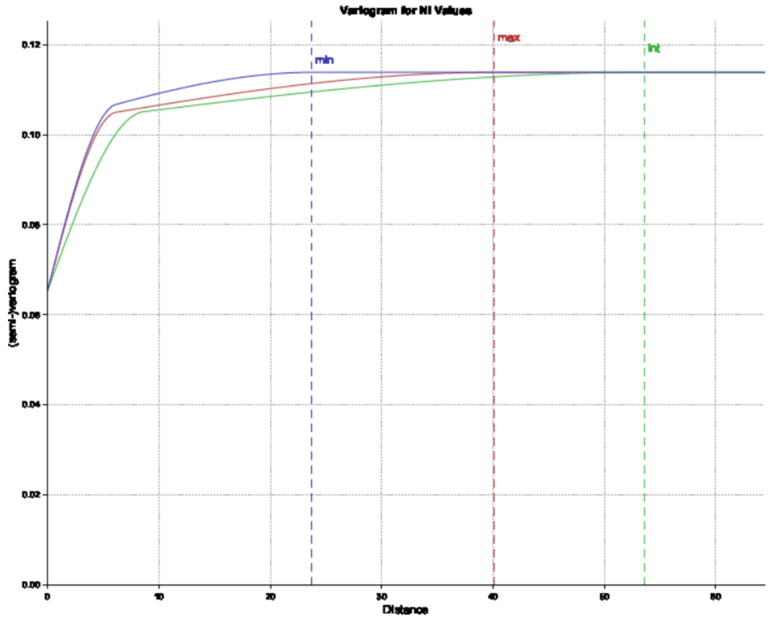
Appendix 4: Modelled variograms for Ni values for the domains.



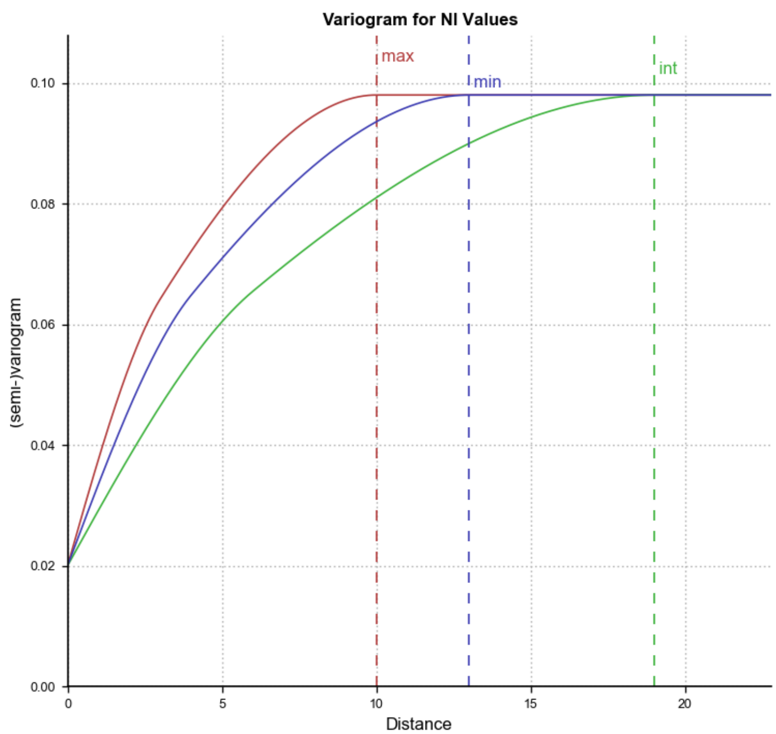
Domain 1



Domain 2



Domain 3



Domain 5

Appendix 5: Total resources per domain, unmined.

Tonnage and Grade – Total Resources Domain 1

DOMAIN	SVOL	MINEDOUT	VOLUME	TONNES	DENSITY	NI%
1	1	NO	2,422,949	6,974,895	2.88	0.12
	2	NO	4,054,490	11,698,878	2.89	0.16
	3	NO	5,293,592	15,261,441	2.88	0.18

Tonnage and Grade – Total Resources Domain 2

DOMAIN	SVOL	MINEDOUT	VOLUME	TONNES	DENSITY	NI%
2	1	NO	17,623,980	51,037,029	2.90	0.11
	2	NO	22,220,139	63,834,126	2.87	0.11
	3	NO	14,302,802	40,731,136	2.85	0.10

Tonnage and Grade – Total Resources Domain 3

DOMAIN	SVOL	MINEDOUT	VOLUME	TONNES	DENSITY	NI%
3	1	NO	18,146,091	54,000,853	2.98	0.10
	2	NO	23,647,075	70,361,727	2.98	0.10
	3	NO	18,066,033	53,724,195	2.97	0.09

Tonnage and Grade – Total Resources Domain 4

DOMAIN	SVOL	MINEDOUT	VOLUME	TONNES	DENSITY	NI%
4	1	NO	185,704	561,589	3.02	0.13
	2	NO	2,949,260	8,560,394	2.90	0.13
	3	NO	3,867,921	11,283,034	2.92	0.14

Tonnage and Grade – Total Resources Domain 5

DOMAIN	SVOL	MINEDOUT	VOLUME	TONNES	DENSITY	NI%
5	1	NO	7,911,553	23,335,478	2.95	0.11
	2	NO	19,059,960	56,106,041	2.94	0.11
	3	NO	44,876,639	131,790,027	2.94	0.10

Appendix 6: Total resources per domain-Mined out.

Tonnage and Grade – Total Resources Domain 1

DOMAIN	SVOL	MINEDOUT	VOLUME	TONNES	DENSITY	NI%
1	1	YES	5,297,173	15,559,583	2.94	0.28
	2	YES	2,222,002	6,408,365	2.88	0.26
	3	YES	593,606	1,722,036	2.90	0.27

Tonnage and Grade – Total Resources Domain 2

DOMAIN	SVOL	MINEDOUT	VOLUME	TONNES	DENSITY	NI%
2	1	YES	29,277,997	85,297,672	2.91	0.27
	2	YES	3,706,905	10,537,886	2.84	0.16
	3	YES	235,352	654,136	2.78	0.10

Tonnage and Grade – Total Resources Domain 3

DOMAIN	SVOL	MINEDOUT	VOLUME	TONNES	DENSITY	NI%
3	1	YES	23,679,904	70,512,869	2.98	0.11
	2	YES	1,942,483	5,780,130	2.98	0.10
	3	YES	123	366	2.97	0.08

Tonnage and Grade – Total Resources Domain 5

DOMAIN	SVOL	MINEDOUT	VOLUME	TONNES	DENSITY	NI%
5	1	YES	6,580,498	19,509,435	2.96	0.15
	2	YES	4,252,436	12,528,654	2.95	0.12
	3	YES	1,248,505	3,687,190	2.95	0.12