The appropriateness of the Localised Uniform Conditioning technique for high-nugget Birimian-style gold deposits

Emmarentia Maritz

(Student number: 1558714)

School of Mining Engineering

University of the Witwatersrand

Johannesburg, South Africa.

Supervisors:

Prof RCA Minnitt, JCI Professor of Mineral Resources and Reserves

A dissertation submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, in fulfilment of the requirements for the degree of Masters in Engineering.

Johannesburg 2017

DECLARATION

I declare that this dissertation is my own unaided work. It is being submitted to the Degree of Masters of Science in Engineering to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination to any other university. The dataset that informs the dissertation has been obtained while employed by AngloGold Ashanti.

____

2nd day of JUNE 2017

ABSTRACT

The localized uniform conditioning (LUC) technique converts conventional Uniform Conditioning (UC) grade-tonnage curves into single grade values attached to each smallest mining unit (SMU). This is achieved by ranking the SMUs within a panel in increasing order of their grade based on the local grade patterns predicted by direct kriging of the SMUs. However, the quality of this localization process will depend heavily on the validity of the predicted grade patterns. A study was undertaken to determine how valid the predicted grade patterns of a typical Birimian-style gold deposit (with high nugget effect and strong short-range variability) might be expected to be. The direct SMU kriging rankings (based on sparse data) were compared with the grade control model ranking (based on close-spaced data and the best available estimate of the deposit). The results showed a satisfactory correlation and relationship between these rankings. It was concluded that the application of the LUC technique is still useful and appropriate for this style of deposit.

ACKNOWLEDGEMENT

I would like to thank AngloGold Ashanti and my colleagues Tom Gell, Vasu Govindsammy, Geoff Gushée, Vaughan Chamberlain and Richard Peattie for their support.

TABLE OF CONTENTS

DECLARATION 2

ABSTRACT 3

ACKNOWLEDGEMENT 4

LIST OF FIGURES 7

LIST OF TABLES 9

LIST OF SYMBOLS 10

LIST OF ACRONYMS 11

1 INTRODUCTION 12

2 THE THEORY OF LOCALISED UNIFORM CONDITIONING 16

2.1 Non-linear geostatistics 16

2.2 Uniform Conditioning 18

2.2.1 Estimation of the panel grade 19

2.2.2 Fitting the Discrete Gaussian Model (DGM) to the data 19

2.2.3 Determine the change of support coefficients 20

2.2.4 Transformation of the panel estimates and cut-offs to Gaussian units 21

2.2.5 Calculation of the proportion and quantity of metal above each cut-off 21

2.2.6 Discussion 22

2.3 Localised Uniform Conditioning 23

2.4 Contribution to knowledge 29

3 CASE STUDY LOCATION AND GEOLOGY 30

4 GEOLOGICAL INTERPRETATION AND DATA ANALYSES 34

4.1 Mineralisation model and sample data 34

4.2 Compositing and bias 36

4.3 Grade capping 39

4.4 Boundary analysis 39

5 ORDINARY KRIGING ESTIMATION 41
5.1 Semi-variogram modelling 42
5.2 Optimising the estimation parameters 43
5.3 Ordinary Kriging estimation 44
6 LUC ESTIMATION 47
6.1 LUC estimation 47
6.2 Results 48
7 THE QUALITY OF THE LOCALISATION 52
7.1 True versus predicted ranking 52
7.2 Accuracy of LUC ore-waste prediction 55
7.3 Reconciliation with the Grade Control model 57
8 ALTERNATIVES FOR GRADE PATTERN ESTIMATION 58
9 SUMMARY AND CONCLUSION 61
REFERENCES 63

LIST OF FIGURES

Figure 1. Sketch explaining the definition of the grade classes and assigning the grade values to the SMU blocks (Abzalov, 2006).. 26

Figure 2. Locality map of the Sadiola Gold Mine located in Mali................................ 30

Figure 3. Isometric view looking approximately North showing the case study area with respect to the north and south pits; the drilling and mineralisation model..................... 31

Figure 4. Simplified geological map of the Tambali north pit (Masurel et al, 2014) 32

Figure 5. Plan view showing (A) all samples and (B) exploration samples in the study area.. 34

Figure 6. Histograms of gold grade – All data (A) vs. Exploration data (B) 36

Figure 7. Bias test area 37

Figure 8. Log Histograms – GC vs. EX 38

Figure 9. QQ Plot – GC vs. EX 38

Figure 10. Histograms of de-clustered and top capped gold grade – All data (A) vs. Exploration data (B) 39

Figure 11. Boundary analysis across mineralisation model contact.............................. 40

Figure 12. Directional semi-variograms of gold composite grades along the major (A), semi-major (B) and minor (C) directions of continuity.. 42

Figure 13. Slope of Regression and Kriging Efficiency for block size and number of composites 44

Figure 14. Panel (A) and SMU (B) grades estimated by Ordinary Kriging with sparse exploration data 45

Figure 15. SMU grades estimated by Ordinary Kriging with (A) sparse exploration data and (B) dense exploration plus grade control data ('true' grades) 46

Figure 16. Mean Grade and Total Tonnage curves: Panel Kriging vs. UC.................. 48

Figure 17. Mean Grade and Total Tonnage curves: "true" grades vs. UC and OK grades 49

Figure 18. SMU grades estimated by the LUC technique with sparse data 49

Figure 19. Mean Grade and Total Tonnage curves: "true" grades vs. UC, LUC and OK grades.. 50

Figure 20. Plan view comparison of the panel kriging (A), the direct SMU kriging with sparse data (B), the LUC model (C) and the "true" grades (D)...................................... 51

Figure 21 Scatter Plot of LUC vs. True rankings 53
Figure 22. Plot of the number of occurrences of “true” vs. LUC rankings shown in (A) plan and (B) 3-Dimensional view 54
Figure 23 Plan view comparison showing the ranking models (left) and the corresponding LUC result (right) for Ordinary Kriging (A), IDW2 (B) and IDW5 (C) 59
Figure 24 Comparison of the number of occurrences of ‘true’ vs. LUC rankings based on rankings from (A) Ordinary Kriging, (B) IDW2 and (C) IDW5 60

LIST OF TABLES

Table 1. Estimation parameters for Ordinary Kriging estimation 41

Table 2. Tonnes, grade and metal comparisons of Grade Control and LUC within the study area 56

Table 3. Tonnes, grade and metal comparisons of Grade Control and LUC within the study area 57

LIST OF SYMBOLS

Z	random function
Y	Gaussian random function
u	location in space
z(u)	value that the function takes at u
y(u)	Gaussian transform of z(u)
$Z^*(u)$	an estimate of the panel grade Z at u
φ(y)	anamorphosis function of Z
v	a block (larger support size)
V	a larger block
ρ	correlation coefficient
Var{Zu}	variance of Z at the point support
Var{Zv}	variance of Z at the block v support
r	smu change of support coefficient
R	panel change of support coefficient
zc	cutoff grade
yc	Gaussian cutoff grade
Q(zc)	quantity of metal above cutoff
P(zc)	proportion of the panel above cutoff
M(zc)	grade of the panel above cutoff
λα	indicates the weights of linear combinations
$C(h)$	a stationary covariance function
$\overline{C}$	the mean value of the coviance function $C(h)$
μ	Lagrange parameter
$P\ (z_c)$	proportion above the cut-off c
$Q\ (z_c)$	metal quantity above the cut-off c
$M\ (z_c)$	mean grade above the cut-off c
φ_n	hermite polynomial coefficients
$H_n[Y(\mathbf{u})]$	the hermite polynomial value for expansion of the Y value
σ_v^2	dispcersion variance of blocks
σ_u^2	dispersion variance of points
$\overline{\gamma}_{v,v}$	average variogram value for the blocks

LIST OF ACRONYMS

AAS	Atomic Absorption Spectrometry
AU	Gold
DD	Diamond core
DGM	Discrete Gaussian Model
EX	Exploration
FGO	Full Grade Ore
GC	Grade control
KNA	Kriging Neighbourhood Analysis
LUC	Localized Uniform Conditioning
MGO	Marginal Grade Ore
MW	Mineralised Waste
OK	Ordinary Kriging
RC	Reverse Circulation
SMU	Smallest Mining Unit
UC	Uniform Conditioning

1 INTRODUCTION

For adequate technical and financial evaluation of a project, attempts should be made to estimate the recoverable resources – the portion of the in-situ resource that can be economically extracted by mining. To achieve this, the estimates of the tonnage and grade of the mineralisation should be produced above a given economic cut-off and should take into consideration the proposed mining selectivity.

At the early stages of exploration, we often only have broad spaced sample data to estimate with. Ordinary Kriging (OK), a commonly used linear interpolator, may be used to estimate grades into larger panels (estimation into smaller panels that are not adequately supported by dense data may result in smoothed and conditionally biased estimates). These larger panels, that are suitable for the broadly spaced data, often do not adequately represent the selectivity expected at the time of mining. The mining selectivity (represented by the Smallest Mining Unit or SMU) is based on the deposit type and the chosen mining equipment.

Non-linear techniques, such as Uniform Conditioning (UC) and Multiple Indicator Kriging (MIK), are used to generate estimates at SMU scale reflecting the proposed mining selectivity. With these techniques, the portion of the mineralisation that can be economically extracted is estimated by determining the distribution of SMUs within each panel based on a change of support model. Estimates of the grades and proportions extractable above a given cut-off are provided for each panel without specifying precise spatial locations for this recoverable mineralisation. Having a better understanding of the actual spatial locations of the SMUs would significantly simplify the handling of the results for Mine Planning purposes and would simplify and potentially enhance the technical and financial evaluation of the project.

In 2006, Marat Abzalov (2006) proposed a method called Localised Uniform Conditioning for predicting the spatial locations of the economically extractable mineralisation by assigning a single grade to each SMU sized block. LUC enhances the conventional UC approach by localising the model results. The grades of the SMUs are derived from the conventional UC grade-tonnage relationships. For each panel, the UC grade-tonnage function is divided into grade classes and the mean grades of the grade classes are assigned to the SMUs in the panel. The method of mean grade assignment is based on a predicted grade pattern within each panel. The grade pattern is determined by an Ordinary Kriging of the SMUs from the sparse dataset and is used to rank the SMUs within each panel in increasing order of their grade before assigning the mean grades of the UC grade classes.

Abzalov (2006) noted that spatial grade distribution patterns are often recognised by geoscientists in deposits even when drill spacing is still too broad for direct accurate modelling of small block grades, but sufficient for identification of the major distribution trends. He suggested that, even when drill spacing is too broad to avoid a smoothed SMU grade estimate, direct kriging of the small blocks can be used to obtain reliable grade patterns and resultant SMU ranking within the panels. Abzalov deemed that this was particularly applicable to continuous mineralisation characterised by a low nugget effect, such as disseminated base-metal sulphides, bauxites and iron-oxide deposits. He cautioned that where the data is sparse and not close to a panel, or their distribution is characterised by strong short-range variability, there could be less of a meaningful pattern. Accordingly, if the predictions of the SMU rankings by Ordinary Kriging (or any other technique) are inadequate, the advantages of using the LUC approach will be more limited or even entirely unsuitable. A basic assumption of the conventional UC approach is that the locations of ore and waste within the panels are unknown (the SMUs are distributed randomly within the panels). The LUC method aims to overcome this theoretical constraint by attempting to predict the spatial locations of the SMUs, but the quality of the localisation process will depend heavily on the validity of the grade patterns predicted by the direct kriging of the SMUs. The concern is that the use of the LUC technique may be inappropriate for deposits with high nugget and strong short range variability. Strong short range variability, i.e. a high Nugget Effect, might result in poor prediction of the local grade patterns which are used to rank the SMUs within the panels. In addition, drill spacing also plays an important role in the quality of the localisation achieved – the closer the distances between drillholes, the better the quality of the ranking is expected to be.

As a result of this background, a study was undertaken to test the appropriateness of the application of the LUC technique to a typical Birimian-style gold deposit with a high nugget effect and strong short range continuity (typically around 25-30 m in the main direction of continuity). The LUC technique was applied using the sparse drillhole dataset (early stage/exploration) which followed a 25 m x 25 m x 2 m drilling grid. This grid was used for the classification of Mineral Resources of the Indicated category for the chosen deposit.

The research aimed to determine whether or not the use of the LUC technique is appropriate for deposits exhibiting high nugget and strong short-range variability. The validity of the predicted grade patterns was measured by comparing the direct SMU kriging ranking (based on sparse data) with the Grade Control model ranking (based on close spaced data and the "best available estimate" of the deposit).

The methodology that was used to complete the research was as follows:

- Exploratory Data Analyses: Two datasets were compiled for the study: one including all exploration data and one including both exploration and grade control data. These datasets were composited to 2 m intervals and domained into mineralised and un-mineralised samples according to the mineralisation interpretation. Grade capping was performed to control the effect of outliers and the two datasets were de-clustered. Finally, the statistical grade distributions and summary statistics for the two domains of the two datasets were described.
- Boundary Analysis: To determine whether the use of hard or soft boundaries during grade estimation would be appropriate, the grade variation across the mineralisation boundary was investigated.
- Generated an Ordinary Kriging panel estimate for a panel size of 30 mN by 30 mE by 10 mRL using the exploration dataset: Modelled semi-variograms; completed a Kriging Neighbourhood Analysis to determine the optimal set of estimation parameters and generated an Ordinary Kriging panel estimate from the exploration data.
- Generated an Ordinary Kriging SMU estimate for SMU ranking using the exploration dataset: Used the same set of estimation parameters to generate an

Ordinary Kriging SMU estimate from the exploration data (used for the LUC ranking). The SMU size was 10 mN by 10 mE by 3.33 mRL.

- Generated a recoverable LUC estimate: Transformed the de-clustered point data of the exploration dataset to Gaussian space; performed change of support from point to SMU; completed Uniform Conditioning (UC); localised the UC results with the LUC approach and validated the results.
- Determined the quality of the localisation: The quality of the LUC localisation is dependent on the meaningfulness of the grade pattern predicted by the direct kriging of the SMU. This was measured by comparing the rankings of the "true" SMU grades with the LUC rankings and determining if there was a positive correlation between the actual and predicted rankings. If there was a positive correlation, then it could be said that there was some confidence in the local positioning achieved by the LUC technique – that it was not random, but that it showed a positive correlation with the true positioning. The "true" SMU grades were estimated using the exploration plus grade control dataset.

This methodology was applied to a real example of a typical Birimian style gold deposit. These types of deposits are good examples of data with high nugget and strong short-range continuity.

2 THE THEORY OF LOCALISED UNIFORM CONDITIONING

In this section the theory of LUC is presented. LUC is derived from the conventional UC technique which is a non-linear geostatistical method used for the estimation of recoverable resources.

2.1 Non-linear geostatistics

Linear geostatistics makes use of linear combinations of weighted data to provide an estimate of a regionalized variable (such as gold grade or thickness of a layer). Ordinary Kriging is an example of a linear estimation technique and it is widely known and used by resource practitioners in industry. It is an estimator that generates estimates by minimising estimation variance.

However, where data spacing is broad in comparison with the desired estimation block size, a linear estimation based technique will be unsuitable. When estimating into small blocks - which are not supported by adequately dense data - it will typically produce an overly smoothed and conditionally biased assessment of the recoverable resource. Hence, an adequately larger block/panel will need to be reverted to, given the broad data spacing. For many deposits, estimates of these larger panels will be unsuitable for technical and financial valuation of a mining project as it is necessary to estimate tonnage and grade of mineralisation above a given economic cut-off grade taking into account a proposed mining selectivity. The mining selectivity may be much smaller than the estimated panels and the panel estimates will therefore not be representative of the recoverable resource (Abzalov, 2006).

The mining selectivity is defined by the Smallest Mining Unit (SMU). The SMU is the smallest block at which ore-waste selection can be made during mining and it is generally a function of the selected mining equipment and the nature of the orebody.

Non-linear geostatistics allows the practitioner to not just estimate the value of a variable, but also a non-linear function of it. Being able to derive the non-linear function of a grade variable allows the estimation of tonnage and grade of mineralisation above a given economic cut-off grade taking into account a proposed mining selectivity. This is commonly achieved by modelling the grade-tonnage relationships for a given mining selectivity by using change-of-support techniques. Given a particular mining selectivity, the proportion of mineralisation that can be economically extracted from a particular panel is predicted without attempting to provide precise spatial locations for the recoverable resources within the panels. This is achieved by calculating the grade-tonnage relationships of the selectively minable units from the available sample distribution using a suitable non-linear geostatistical method (Abzalov, 2006).

The work on non-linear geostatistics commenced in the sixties by Sichel and Krige. Sichel proposed an estimator and gave confidence intervals for the mean assuming the sample values were independent and distributed according to lognormal law. Danie Krige proposed a lognormal regression, which later led to lognormal kriging. Non-linear techniques were further developed in the seventies in trying to solve the problem of selectivity during mining.

In 1990, Rivoirard described non-linear geostatistics in more detail in a book which provided an introduction to disjunctive kriging and non-linear geostatistics (Rivoirard, 1990).

Since Rivoirard's book was published, various authors have shown that non-linear estimators can be used to correct for smoothing and numerous publications covering these topics are available.

In 1992, Ravenscroft published a paper in which he proposed the use of the conditional simulation method for the estimation of recoverable reserves (Ravenscroft, 1992).

In 1998, Vann and Guibal (1998) provided an overview of non-linear estimation. They compared linear and non-linear estimation and provided the motivations for non-linear approaches. A summary of the main non-linear estimators was included in the paper.

Vann, Guibal and Harley also described the Multiple Indicator Kriging (MIK) approach in 2000 and showed how to determine whether MIK is suitable for a deposit. The technique was described in the paper and a number of theoretical and practical implementation issues were examined (Vann et al, 2000).

Krige and Assibey-Bonsu in 2001 compared a number of techniques for the estimation of recoverable resources and analysed the results to rate the relative efficiencies and uncertainties of the different techniques (Krige et al, 2001).

A number of other authors ok the use of various non-linear techniques with practical case studies such as Abzalov and Humphreys in 2002 who estimated a recoverable resource for a mesothermal gold deposit using non-linear Geostatistics (Abzalov et al, 2002) and De-Vitry, Vann and Arvindson in 2007 who showed how to select the optimal method of resource estimation for multivariate iron ore deposits (De-Vitry et al, 2007).

In conclusion, the understanding and practical application of non-linear geostatistics to estimate recoverable resources have progressed significantly since its inception in the 1960s and it is now well understood and applied in practice.

2.2 Uniform Conditioning

UC is one of the more common non-linear geostatistical methods used for the estimation of recoverable resources. This approach has been around since the 1970s and 1980s and it is also extensively covered in literature.

The second part of Rivoirards 1990 book “Introduction to disjunctive kriging and nonlinear geostatistics” deals with Change of Support and UC and was written to provide understanding and guidance for the use of non-linear techniques.

An easy to understand study on the UC technique was completed by Chad Neufeld of the University of Alberta in 2005. The general idea of the project was to dive into the details of UC and present UC in an easy to understand format. Neufeld determined that the workflow for UC could be summarised in five steps which are discussed in further detail below (Neufeld, 2005).

2.2.1 Estimation of the panel grade

UC relies on a robust estimate of the panel grade denominated by $Z^*(\mathbf{u})$. This panel grade is estimated as follows by the linear combinations of the samples denoted by $z(\mathbf{u}_\alpha)$ and the OK weights (λ_α):

$$Z^*(\mathbf{u}) = \sum_{\alpha=1}^{n} \lambda_\alpha(\mathbf{u}) z(\mathbf{u}_\alpha) \tag{1}$$

The OK system of equations (or "kriging system") is used with the kriging estimator (Eq. 1) to minimise estimation variance. This "kriging system" is expressed in Eq. (2) and it provides a system of (n+1) linear equations which includes the weights λ, the Lagrange parameter μ, the covariance function C and the mean value of the covariance function C. The λ_β weights should sum to 1 (Journel, 1978).

$$\begin{aligned} \sum_{\beta}^{n} \lambda_\beta C(\mathbf{u}_\beta, \mathbf{u}_\alpha) + \mu(\mathbf{u}) &= \overline{C}(V(\mathbf{u}), \mathbf{u}_\alpha), \quad \alpha = 1, \ldots, n \\ &\approx \frac{1}{N} \sum_{j=1}^{N} C(\mathbf{u}'_j, \mathbf{u}_\alpha) \\ \sum_{\beta}^{n} \lambda_\beta &= 1 \end{aligned} \tag{2}$$

2.2.2 Fitting the Discrete Gaussian Model (DGM) to the data

The sample distribution is at point scale (not representative of block or panel scale). The sample distribution is fit using a Hermite polynomial expansion.

$$\begin{aligned} Z(\mathbf{u}) &= \Phi(Y(u)) \\ &\approx \sum_{n=0}^{np} \phi_n H_n[Y(\mathbf{u})] \end{aligned} \tag{3}$$

This function maps point variable Z to Gaussian variable Y in order to work further in Gaussian space. The equation is referred to as the Gaussian anamorphosis function where *np* is the highest order term in the polynomial expansion, φ_n is a fitted coefficient for each term, and $H_n[Y(\mathbf{u})]$ is the hermite polynomial value defined by the term of the expansion and the Y value. The φ coefficients must be calculated for the anamorphosis function. The first coefficient is:

$$\phi_0 = E\{Z(\mathbf{u})\} \tag{4}$$

or the expected value of *Z(**u**)*. Higher order coefficients can be calculated using:

$$\begin{aligned}\phi_p &= E\{Z(\mathbf{u})\cdot H_p(Y(\mathbf{u}))\} \\ &= \int \Phi(y(\mathbf{u}))\cdot H_p(y(\mathbf{u}))\cdot g(y(\mathbf{u}))\cdot dy(\mathbf{u})\end{aligned} \tag{5}$$

The higher order coefficients of Eq. (5) can be estimated as a finite summation as follows:

$$\phi_p = \sum_{\alpha=2}^{N}\left(z(\mathbf{u}_{\alpha\text{-}1}) - z(\mathbf{u}_\alpha)\right)\cdot\frac{1}{\sqrt{p}}H_{p-1}(y(\mathbf{u}_\alpha))\cdot g(y(\mathbf{u}_\alpha)) \tag{6}$$

The fitted coefficients must satisfy the following equality:

$$Var\{Z(\mathbf{u})\} = \sum_{p=1}^{np}\phi_p^2 \tag{7}$$

where $Var\{Z(\mathbf{u})\}$ is the variance of Z at the point support (Neufeld, 2005).

2.2.3 Determine the change of support coefficients

The Discrete Gaussian Model is used for calculating the change of support. It controls the shape and variability of the distribution at the larger scale. The anamorphosis function in Eq. (3) can be modified to account for the change of support from point data to block data by the addition of a change of support coefficient *r*:

$$\begin{aligned}Z(v) &= \Phi(Y(V)) \\ &\approx \sum_{n=0}^{np} r^n\phi_n H_n[Y(V)]\end{aligned} \tag{8}$$

The distribution of grades for large volumes can be determined by calculating *r*, which requires the variance of the larger support volumes. Neufeld noted that “typically, there is not enough data available to do this explicitly”. The dispersion variance of the larger blocks can be estimated using the modelled variogram of the point data:

$$\sigma_v^2 = \sigma_{\mathbf{u}}^2 - \bar{\gamma}_{v,v} \tag{9}$$

where V is the SMU support volume, σ_V^2 is the variance of the SMU sized blocks, $\sigma_{\mathbf{u}}^2$ is the variance of the point data, and $\bar{\gamma}_{v,v}$ is the average variogram value for the SMU. This equality is true for the point support and the block support:

$$
\begin{aligned}
Var\{Z_v\} &= \sigma_v^2 \\
&= \sigma_{\mathbf{u}}^2 - \overline{\gamma}_{v,v} \\
&= \sum_{n=1}^{np} r^{2n} \phi_n^2
\end{aligned}
\tag{10}
$$

where $Var\{Z_V\}$ is the variance of Z at the SMU support. The only unknown parameter is r and the value of r that satisfies the equality can be determined. The panel anamorphosis function is shown in Eq. (11) and the change of support parameter r' can be estimated by solving the equation.

$$
\begin{aligned}
Z(V) &= \Phi(Y(V)) \\
&\approx \sum_{n=0}^{np} (r')^n \phi_n H_n\left[Y(V)\right]
\end{aligned}
\tag{11}
$$

The panel variance should be estimated from the variance of the panels. The panel change of support coefficient can be calculated by solving the following equation:

$$
\begin{aligned}
Var\{Z_V\} &= \sigma_V^2 \\
&= \sum_{n=1}^{np} (r')^{2n} \phi_n^2
\end{aligned}
\tag{12}
$$

2.2.4 Transformation of the panel estimates and cut-offs to Gaussian units

If the panel estimation was done in original grade units, each estimate will need to be transformed to Gaussian units using the panel anamorphosis function from Eq. (11). Each cut-off grade also needs to be transformed to Gaussian units. The cut-off grades should be transformed using the SMU anamorphosis from Eq. (8).

2.2.5 Calculation of the proportion and quantity of metal above each cut-off

Given that the panel grade is known, the distribution of the SMUs within that panel can be calculated. By definition, the average of the SMUs within the panel is the panel grade, and the variance is based on the change of support model.

The recoverable reserves are defined by the proportion $P(z_c)$ and quantity $Q(z_c)$ of metal above the cut-off grade which can be derived from the distribution of the SMUs within the panels. Lastly, the mean grade above cut-off $M(z_c)$ is calculated from these (i.e. the quantity of metal and the proportion above the cut-off):

$$M(z_c) = \frac{Q(z_c)}{P(z_c)} \tag{13}$$

2.2.6 Discussion

The focus of Neufeld's work described above was on the theory for UC, but various other publications covered the practical application.

In 1998, Humpreys completed a practical case study for the estimation of the large, low grade Wandoo Deposit at Boddington Gold Mine using the UC technique. Ordinary kriging was performed, but this could not be used to give a resource reflecting the real mining selectivity. Kriging of smaller blocks would seriously understate the true variability. Therefore, UC was applied to obtain a more realistic resource estimate corresponding to the intended mining selectivity (Humphreys, 1998).

Another example of later case studies included a case study in UC of local recoverable reserves estimation for Jelsava Magnesite deposit in Slovakia – Level 220. The case study discussed the results of UC which was implemented for the first time on the deposit in question. This methodology (i.e. UC) was necessitated by a change to the exploitation method of the deposit from chamber-pillar to slicing bench with emphasis on selectivity and recoverability for more effective exploitation of the deposit. They reported that the application of UC resulted in quicker comparisons between the estimates and the real extraction results and allowing for more frequent resource model updates, subsequent estimation and scheduling (Vizi, 2008).

A Recoverable Uranium Resource was estimated for the Mkuju River Uranium Project, Tanzania using UC. The authors noted that the use of a non-linear estimation method increased the reliability of the grade-tonnage curves and UC was the method chosen for estimation of the recoverable resource. The case study showed how UC could be used to convert the panel grade tonnage curves into SMU grade tonnage curves for use in pit optimisation and detailed mine planning studies (O'Connor et al, 2012).

2.3 Localised Uniform Conditioning

The main disadvantage of the conventional UC method is its inability to predict a spatial location of the economically extractable mineralisation. In addition to knowing which portion of a panel contains mineralisation exceeding the cut-off, it would practically be useful to have a better understanding of the precise spatial distribution of the recoverable resources within the panels.

In 2006, Marat Abzalov proposed the LUC method for predicting the spatial locations of the economically extractable mineralisation by assigning a single grade to each SMU sized block. LUC enhances the UC approach by localising the model results. The grades of the SMUs are derived from the conventional UC grade-tonnage relationships (Abzalov, 2006).

The key steps involved in generating an LUC estimate include:

1. Estimate the panel grades using Ordinary Kriging (as per Section 2.2.1).
2. Fit the Discrete Gaussian Model to the data (as per Section 2.2.2).
3. Determine the change of support (as per Section 2.2.3). The Discrete Gaussian Model is used for calculating the change of support.
4. Transformation of the panel estimates and cut-off grades to Gaussian units (as per Section 2.2.4).
5. Perform Uniform Conditioning (i.e. calculate the proportion and quantity of metal above cut-off as per Section 2.2.5).
6. Estimate the SMU grades using an appropriate estimation technique such as Ordinary Kriging (used for ranking of the SMUs within the panels).
7. Run the LUC step to localise the conventional UC grade-tonnage relationships (assign a single grade to each SMU sized block).

Compared with conventional UC estimation (steps 1 to 5), the additional steps to generate an LUC model includes steps 6 and 7 - generation of an Ordinary Kriging model at SMU scale and the localisation of the UC results (LUC).

Abazalov describes the concept and theory of the LUC method in his paper of 2006. The concept is outlined by Abzalov as follows: *"The conventional UC method estimates a tonnage and grade of mineralisation which can be recovered using SMU of size (v) at the chosen cut-off value. A set of grade tonnage distributions is constructed for each studied panel by applying several cut-off values (z_{CN}). The LUC algorithm then estimates the mean grades of the grade classes in each panel at the given SMU support. The grade class is the portion of the panel whose grade is higher than a given cut-off (z_{Ci}), but lower than the next cut-off (z_{Ci+1}). The next step is to rank the SMU blocks distributed in each panel in their grade increasing order. Finally, the mean grades of the grade class which have been deduced from the UC model are assigned to the SMU blocks whose rank matches the grade class. Thus, the key features of the LUC approach are the ability to calculate the mean grade of the grade class and assign these means grades to the SMU size blocks which have been ranked in each panel in increasing order of their grade."*

The underlying idea of the LUC method is the ranking of the SMU blocks in increasing order of their grade. It is deemed that reasonably accurate ranks of SMU blocks within the panels can be derived from the spatial distribution patterns predicted by the direct kriging of the SMU from sparse data (Abzalov, 2006). The accuracy of these predicted rankings is expected to be better for more continuous mineralisation (characterised by a low nugget effect such as bauxites or iron oxide deposits) than for discontinuous mineralisation (deposits with a high nugget effect such as orogenic gold deposits). In addition, the drill spacing relative to the spatial variance plays an important role – the closer the distances between drillholes, the better the quality of the ranking is expected to be (Abzalov, 2006).

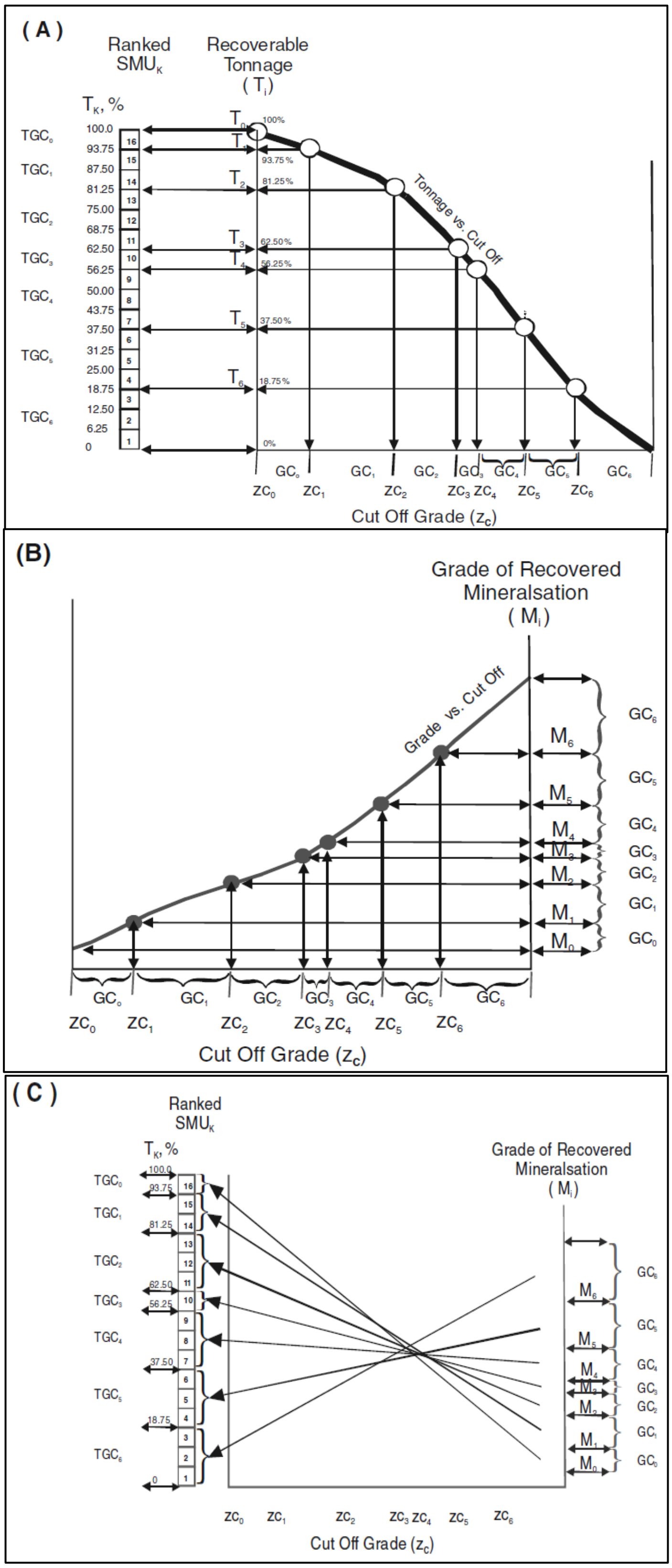
The outputs of the UC method forms the basis of LUC and includes the grade-tonnage relationships of the recoverable resources distributed within a panel. The LUC procedure is illustrated on the process map of Figure 1 (Abzalov, 2006). In the example, there are 16 SMUs (v) within a panel (V) and six different cut-off grades (z_C) are applied. The SMUs within each panel are ranked in increasing order of their grade based on a direct kriging of the SMUs.

Once the SMU ranks (SMU_K) for each panel have been determined, grade classes (GC_i) are then defined. The grade class (GC_i) represents a proportion of a panel which grade is above the given cut-off (z_{Ci}) and less than the next cut-off value (z_{Ci+1}) – see Figure 1A. The SMU ranks (SMU_K) are then converted to the grade classes. The grade class (GC_i) can be determined for each SMU_K by comparing its (T_K, T_{K+1}) intervals with the intervals of the grade classes (T_i (z_{Ci}), $T_{i+1}(z_{Ci+1})$). SMU_K will be assigned grade class (GC_i) if (T_K–T_{K+1}) $\subset$ (T_i–T_{i+1}).

The mean grades (M_i) of each grade class (GC_i) can then be derived from the UC grade vs cut-off curve by separating the grade curve into the various grade classes – see Figure 1 B.

Figure 1 C demonstrates how the mean grade (Mi) of each class can then be transferred to the SMUK blocks by matching their grade class indexes MGCi and TGCi. This is done in an “opposite” fashion in that high grades are assigned to the lower ranks and vice versa (as the SMUs are ranked in increasing order of their grade).

An important aspect to take note of is that the abovementioned procedure assumes an exact match between the grade class intervals and intervals of SMU blocks. Practically, this will rarely be the case and this can be dealt with by weighting grades of the classes to their proportions of the SMU to estimate the mean SMU grade (Abzalov, 2006).



(A) This figure shows the cut-off grades on the x-axis (Z_c) and the tonnage proportions (T^i) of mineralisation above cut-off on the y-axis (derived from the UC results). The GC^i values (shown on the x-axis) are the grade classes signifying the portion of the mineralisation distributed in the panel which grade lies within the range of $\geq z_{Ci}$ and $< z_{Ci+1}$. The TGC_i values (shown on the y-axis) signifies the grade class indexes assigned to the SMU blocks falling within the range from T_i to T_{i+1}.

(B) This figure shows the cut-off grades on the x-axis (Z_c) and the definition of the mean grades (M_i) of the grade class (GC_i) on the y-axis.

(C) The mean grades (M_i) of the grade class (GC_i) are transferred to the SMU blocks which index (TGC_i) is matching the grade class (GC_i) as illustrated on the figure.

Figure 1. Sketch explaining the definition of the grade classes and assigning the grade values to the SMU blocks (Abzalov, 2006)

Since Abzalov developed the LUC method in 2006, compared to other non-linear techniques (such as conventional UC and MIK), relatively few papers and case studies have been published describing and demonstrating the use of the LUC technique. In 2011, Assibey-Bonsu and Deraisme published a paper which provided a brief review of the multivariate uniform conditioning and the localised multivariate uniform conditioning techniques and presented a case study based on a porphyry copper gold deposit in Peru. The study showed that, in the multivariate case, Gaussian models used for calculating recoverable resources provide consistent results in modelling the change of support and the information effect. The UC method met the goal of reproducing the correlation existing between the different grade elements at the panel scale. The study further showed that, the Localised Multivariate Uniform Conditioning (LMUC) technique provided adequate initial individual post-processed localised multivariate SMU recoverable estimates (Deraisme et al, 2011).

The authors followed this work up with another paper published in 2012 wherein they tested further techniques on the same porphyry copper gold deposit in an attempt to improve the LMUC estimates through multivariate block simulations which incorporate all the correlations of the secondary and main elements. The technique is referred to as Localised Multivariate Simulated Estimates (LMSE) and its results were compared with that of LMUC. The study showed that both approaches led to similar results, but the LMUC approach is straightforward and less time consuming whilst the LMSE approach provides access to the quantification of the uncertainty in the estimates (Deraisme et al, 2012).

In 2014, Abzalov published a paper on LUC in which two case studies were presented – one for an iron ore deposit and one for a bauxite deposit. The case studies were used to illustrate the results of several years of study on the LUC method and its application to different geological environments. It allowed identification of the strengths and weaknesses of the method. The strengths identified included that the method produced accurate grade-tonnage functions; that the method can be useful even at the early stages of exploration and that block ranking can be improved with auxiliary data such as geophysical or geochemical information. The weaknesses included that block ranks produced by kriging can significantly differ from their "true" distribution if the variogram is characterised by a high nugget effect (Abzalov, 2014).

In the same year, Millad and Zammit implemented the LUC technique for the recoverable resource estimation of the Kipoi Copper Project located in the DRC. The paper discussed the implementation of an estimate using LUC and compared the results based on resource definition drilling to those obtained by close spaced grade control drilling and actual mill production. The authors concluded that the LUC method was able to generate quantifiably more accurate predictions than a linear method such as Ordinary Kriging (Millad et al, 2014).

In her Masters dissertation of 2015, Kathleen Hansmann applied the LUC technique to two hypothetical datasets representing two types of distributions – the first a symmetrical distribution (approaching normality) with a low nugget and well defined continuity and the second, an approximate log-normal distribution with high nugget effect and short range continuity. The LUC technique was implemented to produce localised SMU estimates for the two datasets. The resultant estimates were compared with the "actual" grade-tonnage curves (i.e. the close spaced hypothetical data) to determine the success of LUC for the two datasets. The results showed that LUC performed well when there was an underlying normal distribution and there was sufficient data falling within the range of the variogram model, but there was only a slight benefit offered by UC for global grade tonnage (GT) predictions (the estimated results from the linear estimator OK were also reasonable). However, when predicting the grades and tonnage of log-normally distributed data with poor data coverage in the ranges of the variograms, LUC performed better than OK. In these circumstances OK performed poorly due to conditional bias which may have been amplified by a high nugget effect and/or small blocks. The author concluded that when there is poor data coverage within the ranges of the variogram, UC is better at predicting the grades and tonnage of material above cut-off than the linear estimator OK (Hansmann, 2015).

2.4 Contribution to knowledge

The validity of the LUC approach depends greatly on the ability to generate meaningful grade patterns to inform the ranking of the SMUs within the panels. Abzalov cautioned that where the data is sparse and not close to a panel, or their distribution is characterised by strong short-range variability, there could be less of a meaningful pattern. Accordingly, if the predictions of the SMU rankings by Ordinary Kriging (or any other technique) are inadequate, the advantages of using the LUC approach will be more limited or even entirely unsuitable as there will be low confidence in the spatial positioning of the SMUs (Abzalov, 2006).

During the review of current research on the topic, it was found that few of the existing publications focused on demonstrating the validity of the predicted local grade patterns for real world deposits exhibiting high nugget and strong short range variability. There therefore appeared to be a need to complete more research around this aspect of the LUC technique. The research presented in this dissertation attempts to address this shortfall in current research. In addition to this, the presented research will also help practitioners to understand and correctly apply the LUC technique.

3 CASE STUDY LOCATION AND GEOLOGY

In this chapter, the case study dataset is introduced. It comprises a real world gold deposit exhibiting high nugget and strong short range variability.

The Tambali gold deposit was chosen for the study and it forms part of the Sadiola Gold Mine located in Mali close to the border with Senegal and approximately 440km north-west of the capital Bamako (Figure 2).

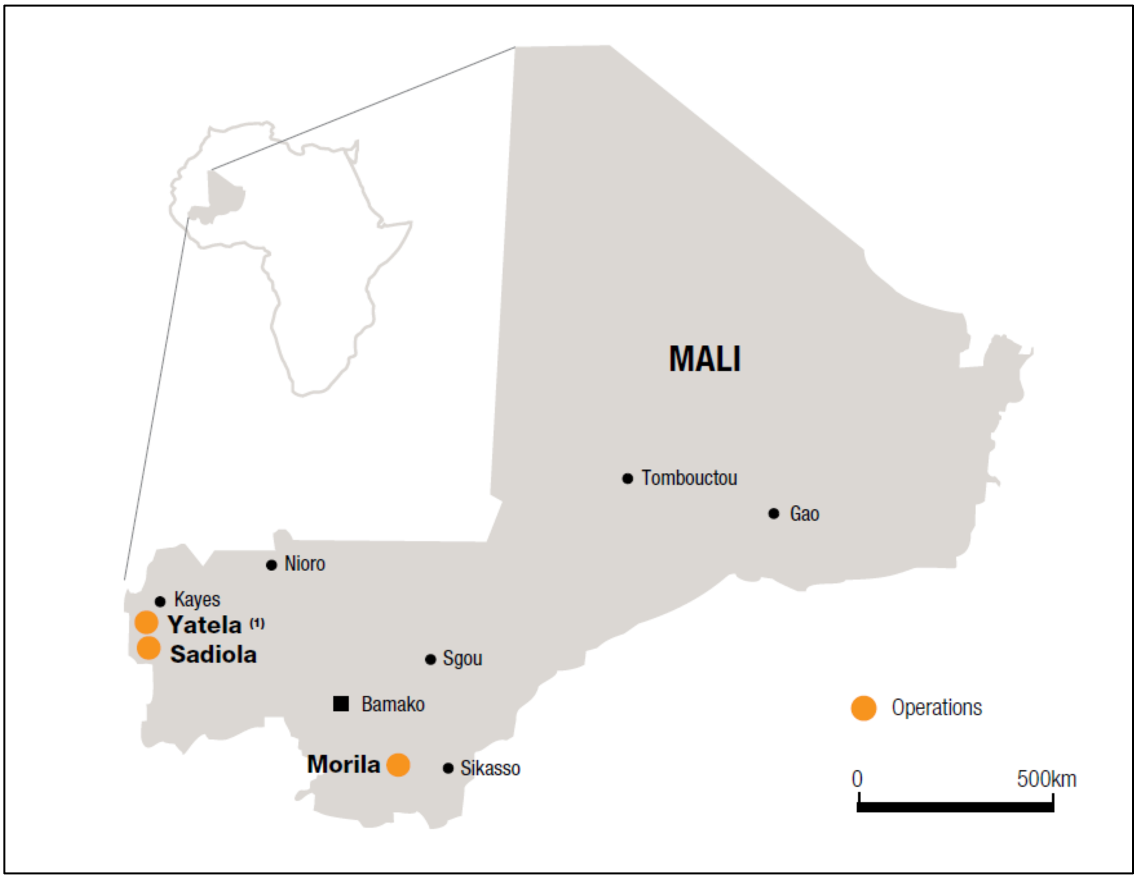


Figure 2. Locality map of the Sadiola Gold Mine located in Mali

Two pits have been mined at Tambali - the north and south pits. Data from the mined out portion of the north pit was selected for the study and represented about two to three month's production (Figure 3).

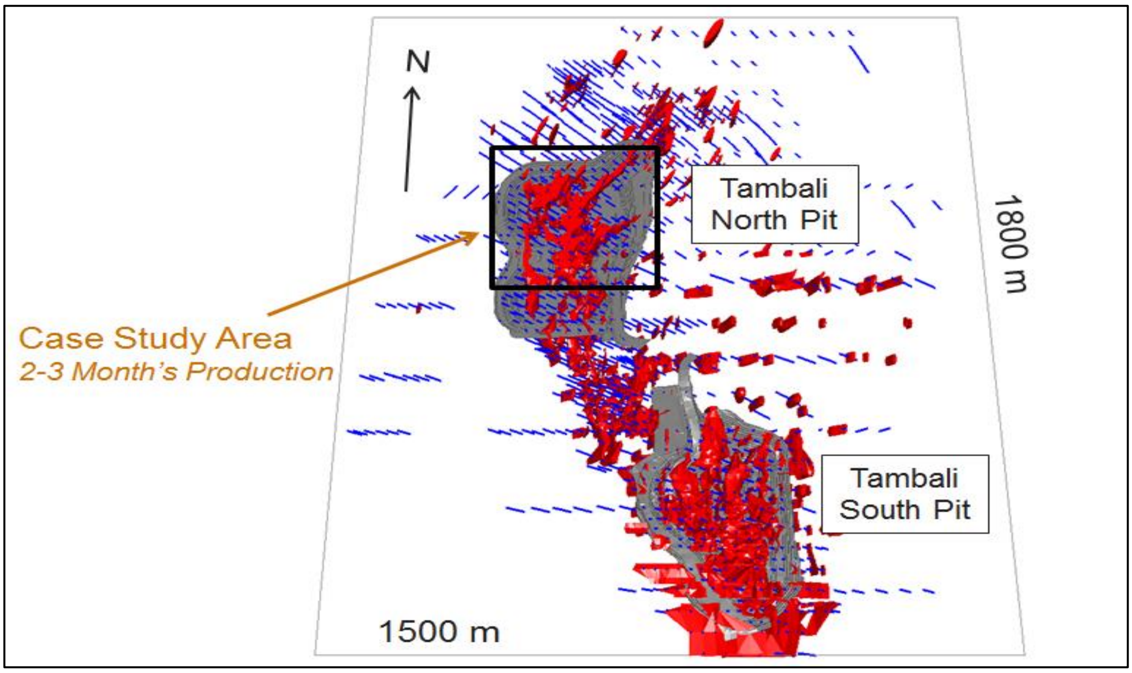


Figure 3. Isometric view looking approximately North showing the case study area with respect to the north and south pits; the drilling and mineralisation model

The Sadiola gold deposits geologically lie within the Kenieba Kedougou Birimian greenstone belt of south-western Mali (± 2.2 Ga). The deposits are hosted by the Kofi Formation – a dominantly meta-sedimentary unit. At Tambali, the host rocks comprise of moderately-sorted meta-sandstone with minor meta-siltstone interbeds and a finely-bedded siltstone-shale unit with minor sandstone interbeds. These meta-sedimentary units are north trending, but are intruded by numerous NNE-trending QFP dykes and plugs. The weathering profile is deep and extends to depths of about 80-90 m.

A simplified geological map of the Tambali north pit is shown in Figure 4.

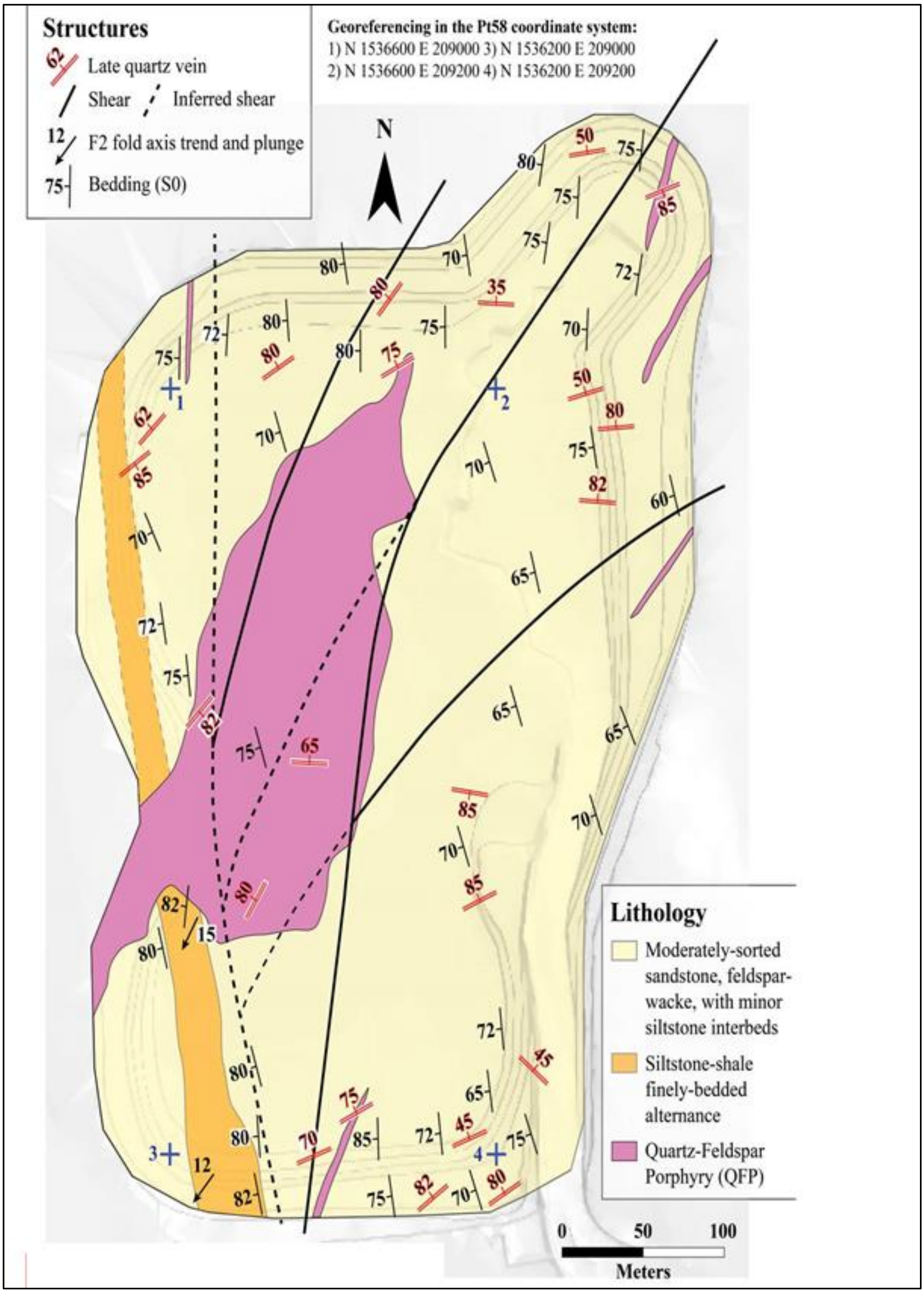


Figure 4. Simplified geological map of the Tambali north pit (Masurel et al, 2014)

The mineralisation is developed in all host rocks and the mineralisation trends are associated with north-east trending shear zones marked by veining and alteration. The dominant ore mineral is arsenopyrite although pyrite, and in lesser extent pyrrhotite, have also been observed in core. Antimony-bearing minerals are present in traces to minor amounts. The pathfinder element association of the ore typically comprise As-Au-Sb ± Ag-Bi-Mo (Masurel et al, 2014).

4 GEOLOGICAL INTERPRETATION AND DATA ANALYSES

Having introduced the location and geology of the case study in the previous chapter, this chapter describes the sampling techniques and geological modelling method employed. It is followed by descriptions of the mineralisation's sample distribution; statistical characteristics and the behaviour of grades along the mineralisation boundaries.

4.1 Mineralisation model and sample data

Gold grade and structural trends were used to interpret the mineralisation using Leapfrog© software. The interpretation was generated using the implicit Leapfrog© Grade Interpolation technique which involves the 3D contouring of grades whilst taking into account a chosen grade threshold and defined structural trends. The output envelope based on a threshold (or lower grade limit) of 0.35 g/t was selected as it was deemed to best represent the mineralisation. Before finalising, it was adjusted by a few manual edits where required.

All available exploration and grade control data from the mined out portion of the Tambali North pit informed the study. The exploration drillhole spacing was approximately 25 mE by 25 mN and the grade control drillhole spacing approximately 6.25 mE by 12.5 mN (Figure 5).

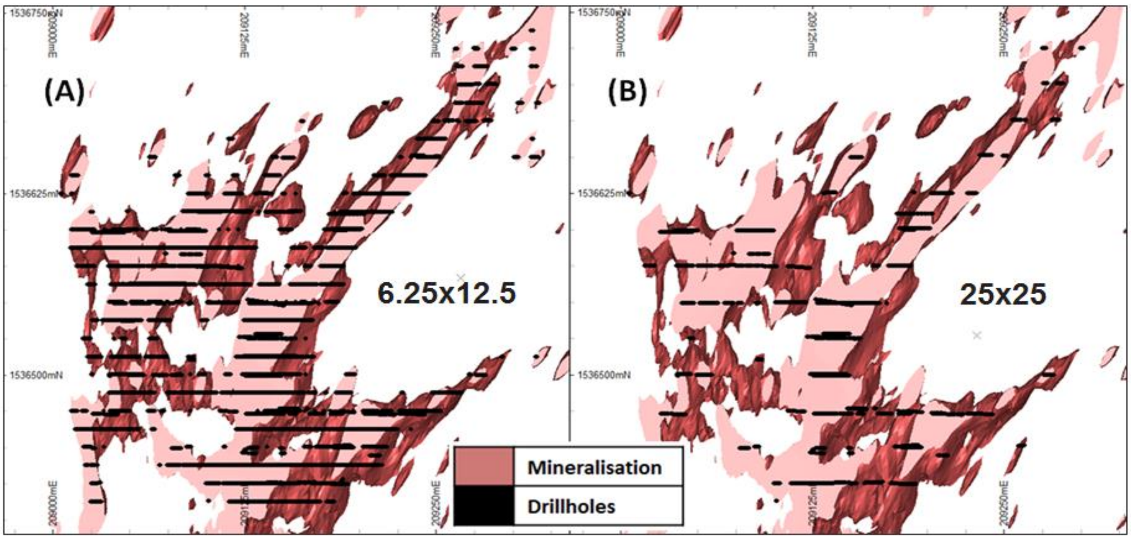


Figure 5. Plan view showing (A) all samples and (B) exploration samples in the study area

Exploration samples were collected by Reverse Circulation (RC) or Diamond Core (DD) drilling techniques:

- Diamond core drilling was by conventional wireline method with HQ (63.5 mm) or NQ (47.6 mm) sized drill bits. Double and triple tube core barrels were used to capture the soft, friable saprolite material. The core samples were cut in half using a diamond saw. The half core was sampled (generally over 1 m intervals honouring geological contacts) and submitted to the laboratory for further preparation and analysis.
- RC drilling was undertaken using either 90 mm or 125 mm dual tube drill rods fitted with a tungsten carbide drag bit. Chip samples were collected over 2 m intervals down the hole and split using a stacked riffle splitter for exploration samples and an automatic rotary cone splitter for grade control samples. Samples of approximately 3 kg were submitted to the laboratory for further preparation and analysis.

All collar locations were surveyed with Differential GPS and downhole surveys were completed with a Reflex survey tool which provided azimuth, dip and magnetic readings for each sample point. Surveys were collected about every 30 m down the hole. Sample recoveries were generally acceptable (in excess of 90%) for both diamond core and RC drilling.

All grade control drilling was by RC technique. Routine grade control drilling was carried out with Drilltech D45KS rigs which provided a 146 mm hole whilst the deeper advanced grade control holes were drilled with the Schramm 685s or KWL 1600 using 4 1/2 to 5 inch hammer bit sizes varying from 124 mm to 133 mm for the 4 1/2 inch hammer and 133mm to 140mm for the 5 inch hammer.

Samples were dispatched to the analytical laboratory for analysis. At the laboratory both drill core and RC samples were placed in an oven until dry (typically for 8 hours), then passed through a jaw crusher which reduced the maximum size to <6 mm. A riffle splitter was used to reduce the sample size to 500 g, which was then pulverized for a minimum of 3 minutes in a Labtech LM2 chrome steel pulveriser. The gold concentration was determined using Fire Assay (for a 50 g aliquot) with Atomic Absorption Spectrometry (AAS) finish. The minimum detection limit was 0.005 g/t Au.

4.2 Compositing and bias

The majority of the Tambali sampling was at either 1 m or 2 m intervals. The samples were therefore composited to 2 m intervals within the interpreted mineralisation model to ensure equal sample support. Datamine© software was used for compositing and mode 1 was selected. This mode forces most samples to be included during compositing by slightly adjusting the composite length, whilst keeping it as close as possible to the specified composite interval. For instance, if the use of mode 0 (fixed composite interval) would have result in three 2 m composites and a 30 cm residual (which would have been discarded) for a particular drillhole and zone, use of mode 1 (for the same interval) would have resulted in three 2.1 m intervals (three slightly larger composites, but no residual or sample discarding).

Two different composite datasets were compiled – the first containing all available data (exploration plus grade control – the dense dataset) and the second containing only the exploration samples (i.e. the sparse dataset). The summary statistics for the two datasets are shown in Figure 5. In total, there were 4,851 composited drillhole samples in the dense dataset and 806 composited exploration samples in the sparse dataset.

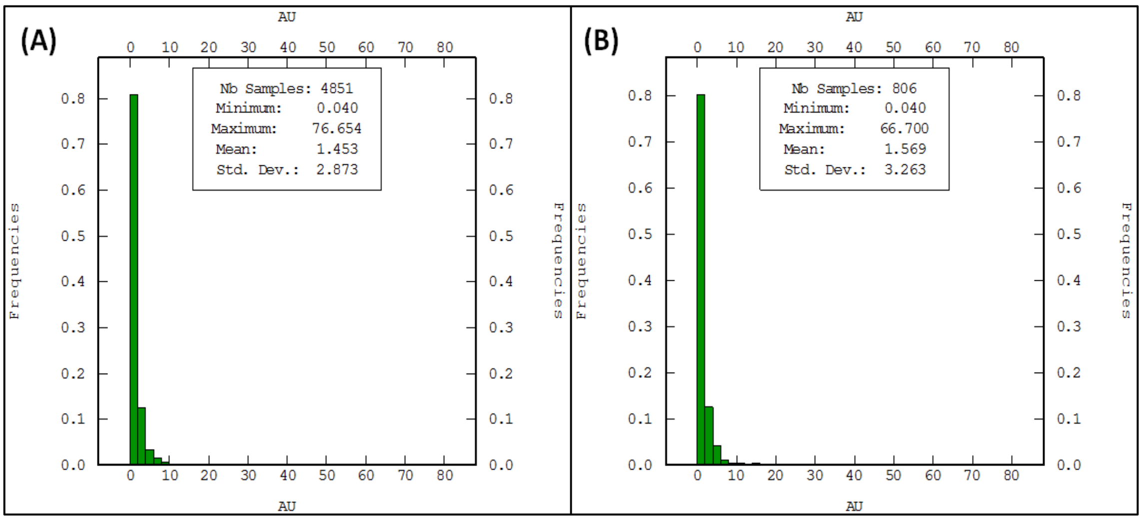


Figure 6. Histograms of gold grade – All data (A) vs. Exploration data (B)

A bias test was completed to check for bias between the grade control (GC) and exploration (EX) grades. The selected bias test area (Figure 7) was well informed by both datasets down to an elevation of about 90 mRL (formed the lower elevation limit of the bias test area). The selected bias test area occurred in the north pit and was a well-informed subset of the study area.

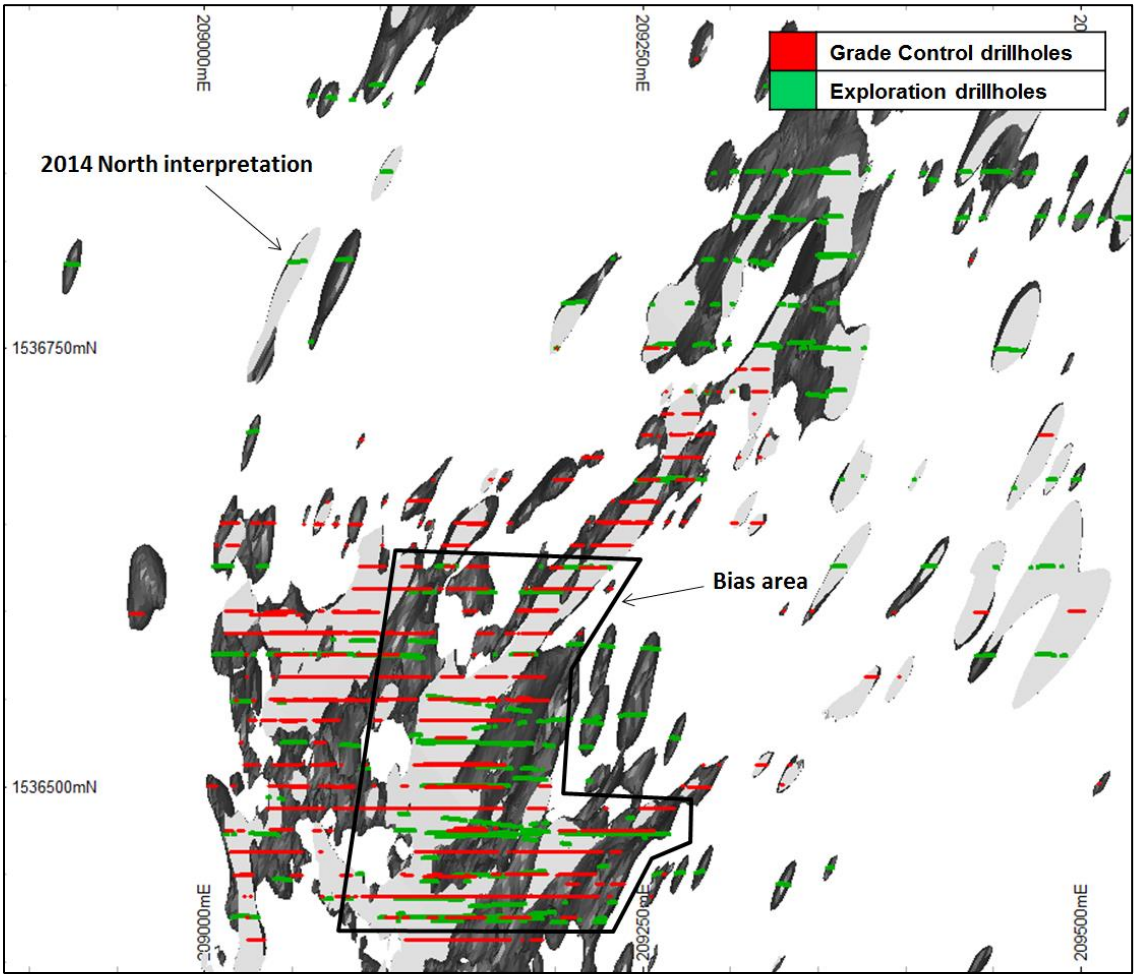


Figure 7. Bias test area

The basic statistics of the two datasets (after top capping) compared well with the means within 2% of each other (Figure 8).

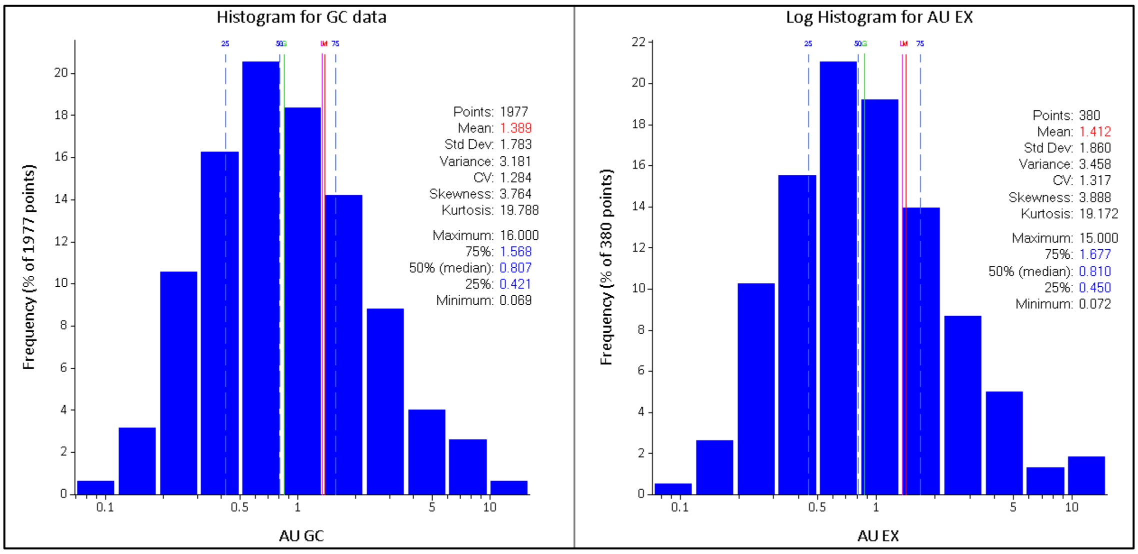


Figure 8. Log Histograms – GC vs. EX

A QQ Plot (Figure 9) further supported the observation that there was no significant bias between grade control and exploration sample grades.

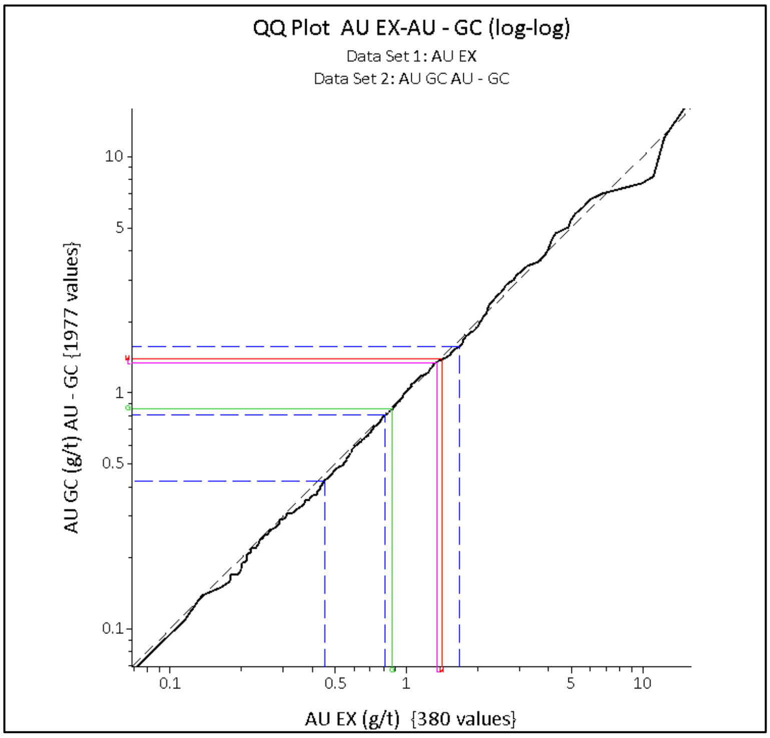


Figure 9. QQ Plot – GC vs. EX

4.3 Grade capping

A grade capping exercise showed that, within the study area, capping the exploration dataset to 15 g/t and the total dataset to 25 g/t would be appropriate for estimation. The investigation of histograms, log probability plots and mean and variance plots were used to determine suitable grade cap values. A total of four values were capped for the exploration dataset (representing about 0.5% of the dataset) and eleven values for the total dataset (representing about 0.2% of the total dataset). The two datasets were de-clustered with the ISATIS© software which makes use of a moving window to assign de-clustered weights to the samples. The moving window dimensions were set to the approximate sample spacings of 25 mE by 25 mN by 2 mRL for exploration and 6.25 mE by 12.5 mN by 2 mRL for the total dataset.

The de-clustered statistics of the two datasets were found to be similar (Figure 10) with the mean grade of the total dataset (1.4 g/t) comparing well with that of the exploration dataset (1.46 g/t).

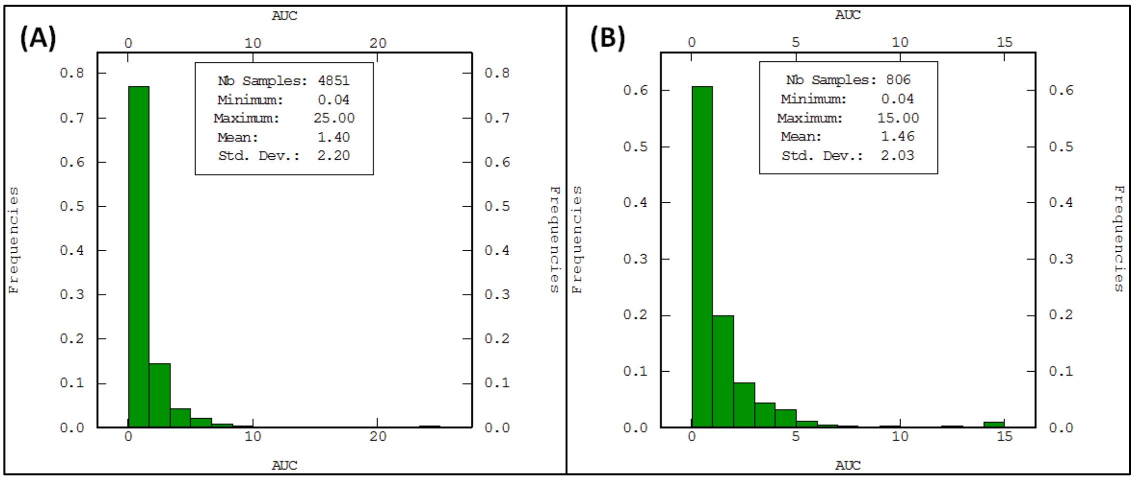


Figure 10. Histograms of de-clustered and top capped gold grade – All data (A) vs. Exploration data (B)

4.4 Boundary analysis

To determine whether the use of hard or soft boundaries during grade estimation would be appropriate, the grade variation across the mineralisation boundary was investigated.

A hard boundary refers to a situation where no samples outside of the mineralisation envelope is seen during estimation (the grade variation across the boundary is sharp). A "soft boundary" refers to a gradational change of the grade across the boundary and includes the distance from the boundary that samples, falling outside of a particular domain, will still be seen when estimating the domain.

The result of the boundary analysis across the mineralisation model contact is shown in Figure 11. The distance from the boundary is plotted on the y-axis and the grade on the x-axis. The mineralisation contact is at zero distance with negative distances occurring outside of the mineralisation model and positive distances inside of it.

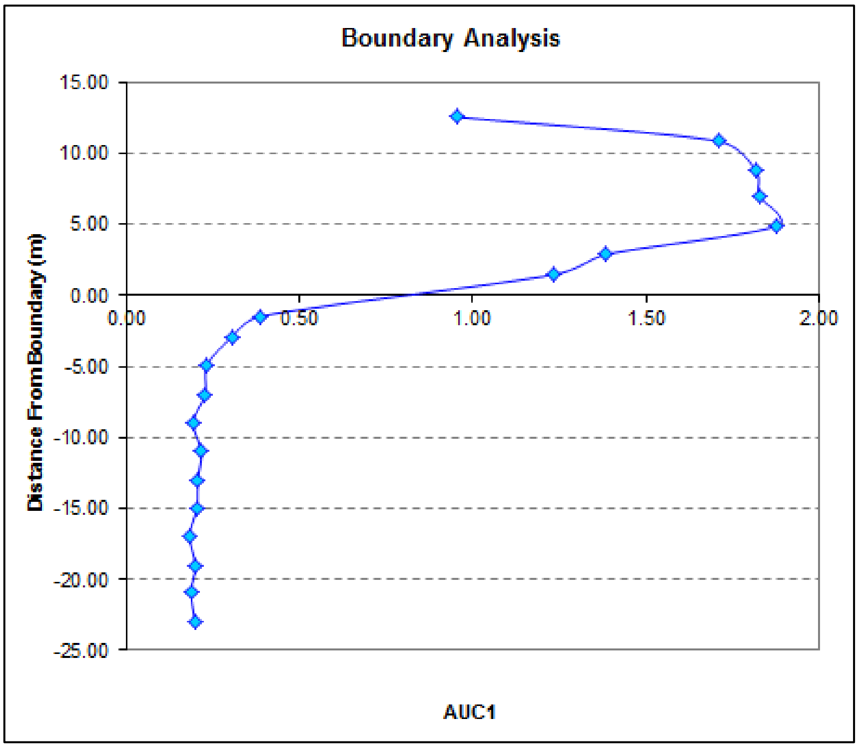


Figure 11. Boundary analysis across mineralisation model contact

The plot shows that the grade change across the boundary is reasonably sharp and hence, a hard boundary (including no samples outside of the mineralisation model) was selected for estimation.

5 ORDINARY KRIGING ESTIMATION

This chapter deals with the process followed to generate the Ordinary Kriging estimates. These form inputs into the LUC process and the quality of the LUC estimates are dependent on them. The methods used to derive the estimation parameters are described and include variogram modelling and Kriging Neighbourhood Analysis (Vann et al, 2003).

The Tambali mining equipment supports a Selective Mining Unit (SMU) of 10 mN by 10 mE by 3.33 mRL (mining takes place on 10 m benches in 3.33 m flitches). As a result, a total of 27 SMUs (10x10x3.33) fits within each panel (30x30x10).

Three different Ordinary Kriging estimates were produced for the study:

- An Ordinary Kriging panel estimate from the sparse/exploration data: this estimate informed and conditioned the non-linear conventional UC estimate.
- An Ordinary Kriging SMU estimate from the sparse/exploration data: this estimate was used to predict the local grade patterns for localisation (LUC).
- An Ordinary Kriging SMU estimate from the dense dataset (grade control plus exploration): this estimate was considered the "truth" or best available estimate of the deposit. It was ultimately used to evaluate the quality of the LUC estimate from sparse data.

A summary of the estimation parameters used for producing these various Ordinary Kriging estimates are shown in Table 1. The parameters for panel and SMU estimation from sparse data were the same whereas the parameters for estimation of the "truth" (i.e. SMU estimate from dense data) used fewer samples and a smaller search.

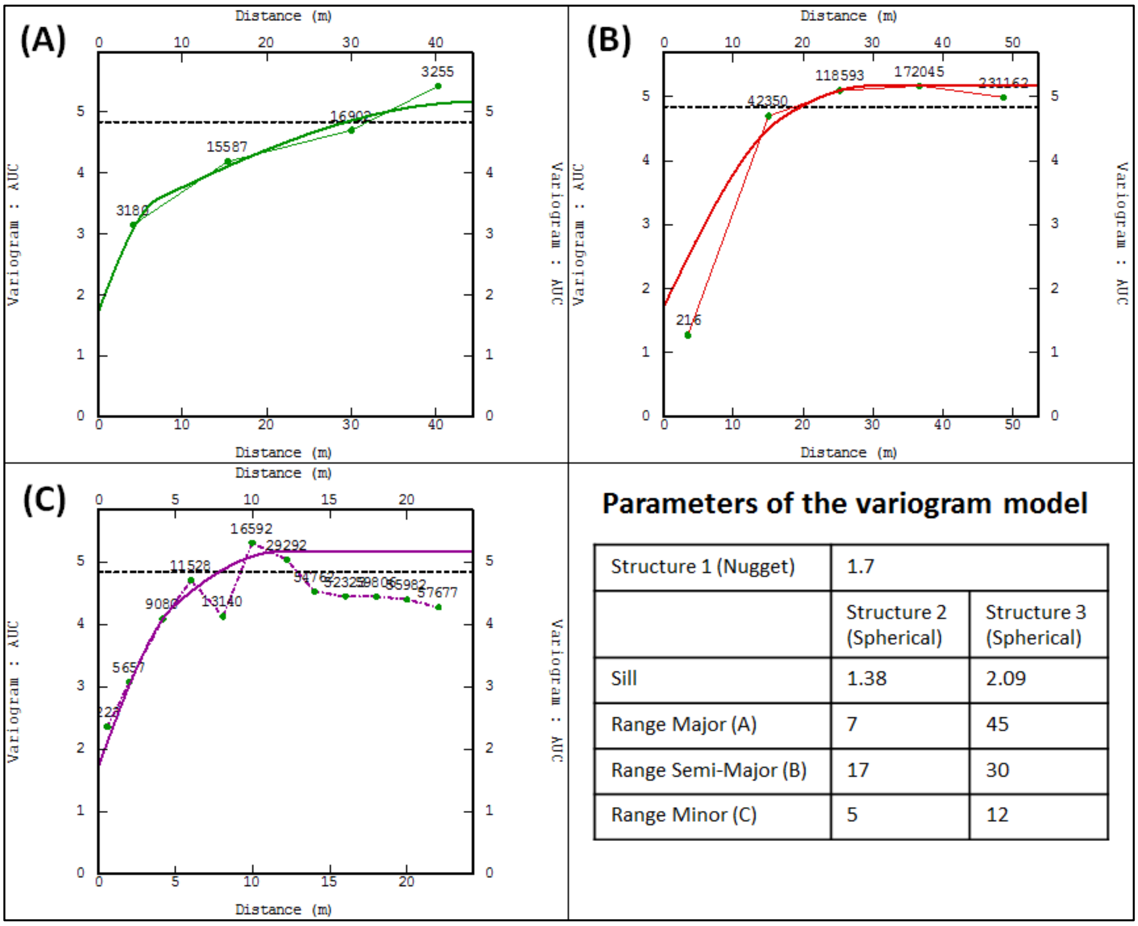
Parameter	OK panels: sparse data	OK SMU: sparse data	OK SMU: all data ('truth')
Minimum number of composites	10	10	10
Maximum number of composites	80	80	40
Search Ellipsoid Rotation	Azimuth: 35 Dip: 75 Dip Direction: 125	Azimuth: 35 Dip: 75 Dip Direction: 125	Azimuth: 35 Dip: 75 Dip Direction: 125
Search Ellipse Dimensions	70x50x20	70x50x20	35x25x15
Discretisation	5x5x5	5x5x5	5x5x5

Table 1. Estimation parameters for Ordinary Kriging estimation

In the following sections, the process to derive these parameters and the resultant estimates are described.

5.1 Semi-variogram modelling

Experimental semi-variograms of gold (Au) grade values distributed in the study area were calculated using all available drillhole samples. The semi-variograms showed distinct anisotropy with the main direction of continuity being along an azimuth of 35 degrees representing the strike direction (or dominant NNE-trending shear fabric). Across this strike direction (azimuth of 125 degrees with a 75 degree dip) a semi-major axis of continuity was defined. The largest variability occurred in the third direction (perpendicular to the major and semi-major plane). The experimental semi-variogram was modelled with a nugget effect and 2 spherical structures (Figure 12).



Structure 1 (Nugget)	1.7	
	Structure 2 (Spherical)	Structure 3 (Spherical)
Sill	1.38	2.09
Range Major (A)	7	45
Range Semi-Major (B)	17	30
Range Minor (C)	5	12

Figure 12. Directional semi-variograms of gold composite grades along the major (A), semi-major (B) and minor (C) directions of continuity

The relative nugget effect of this semi-variogram (calculated as a ratio of nugget to the global sill) is approximately 33%. This semi-variogram model has been used further in this study for all the block grade estimation using Ordinary Kriging (OK) or UC techniques.

5.2 Optimising the estimation parameters

The optimal set of estimation parameters to use was determined by a Kriging Neighbourhood Analysis (KNA). During a KNA, kriging efficiency and slope of regression are used to investigate conditional bias for a given set of estimation parameters. Kriging efficiency compares kriging variance against block variance. If the kriging variance is low compared to the block variance, the degree of smoothing is minimised and the grade tonnage relationship is best reflected. The slope of regression statistic describes the linear relationship between actual and estimated grades. If the slope statistic is close to one, then an unbiased relationship is expected.

For the block size optimisation, a discretisation of 5x5x5 and a minimum of 4 and maximum of 100 samples were used. The semi-variogram model presented in the previous section was used. Search ellipses were oriented according to the approximate orientation of the mineralisation with search distances set to approximate the variogram ranges. The block sizes were then varied and the results for each block size recorded and graphed (Figure 13). The optimal blocks size is considered to be the one with best Slope of Regression and Kriging Efficiency and consequently, 30x30x10 was selected as the block size for estimation.

For the number of composites optimisation, the block size was fixed to the optimal one (i.e. 30x30x10); the maximum number of composites were varied and the result for each recorded and graphed (Figure 13). The maximum number of samples to use was considered to be 80 - the point at which the slope of regression and kriging efficiency graphs flattened out (beyond which point the use of more samples would only increase processing time, but would give no benefit in terms of estimation quality). Usually, one would also consider the amount of negative kriging weights, but none were encountered for these tests. At the chosen block size of 30 mN by 30 mE by 10 mRL and a maximum number of composites of 80, the Slope of Regression and Kriging Efficiency were satisfactory at about 0.95 and 0.82 respectively.

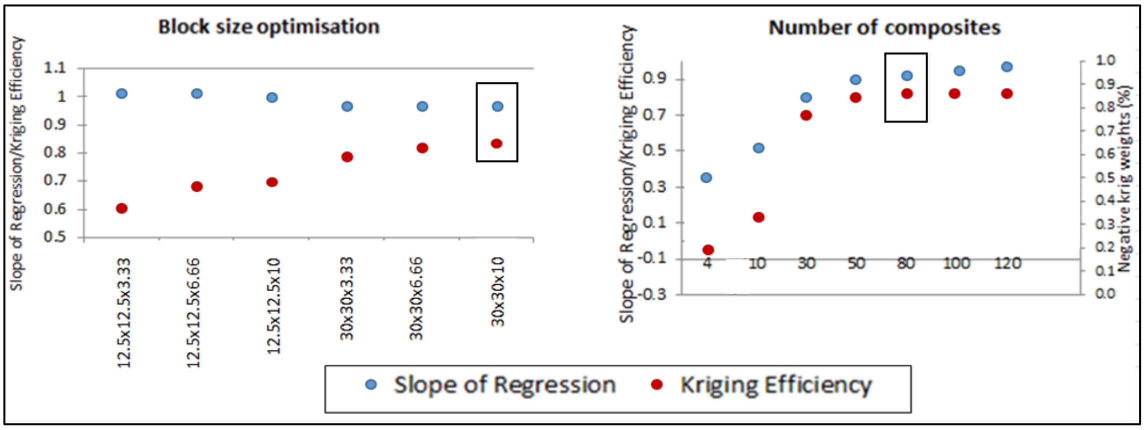


Figure 13. Slope of Regression and Kriging Efficiency for block size and number of composites

5.3 Ordinary Kriging estimation

The sparse dataset (early stage/exploration) was used for kriging both the SMUs and the panels. The same variogram model and the same search neighbourhoods were used for both (as per Table 1). The distributions of these two estimates are compared in Figure 14 together with a visual representation (typical plan views of the block estimates).

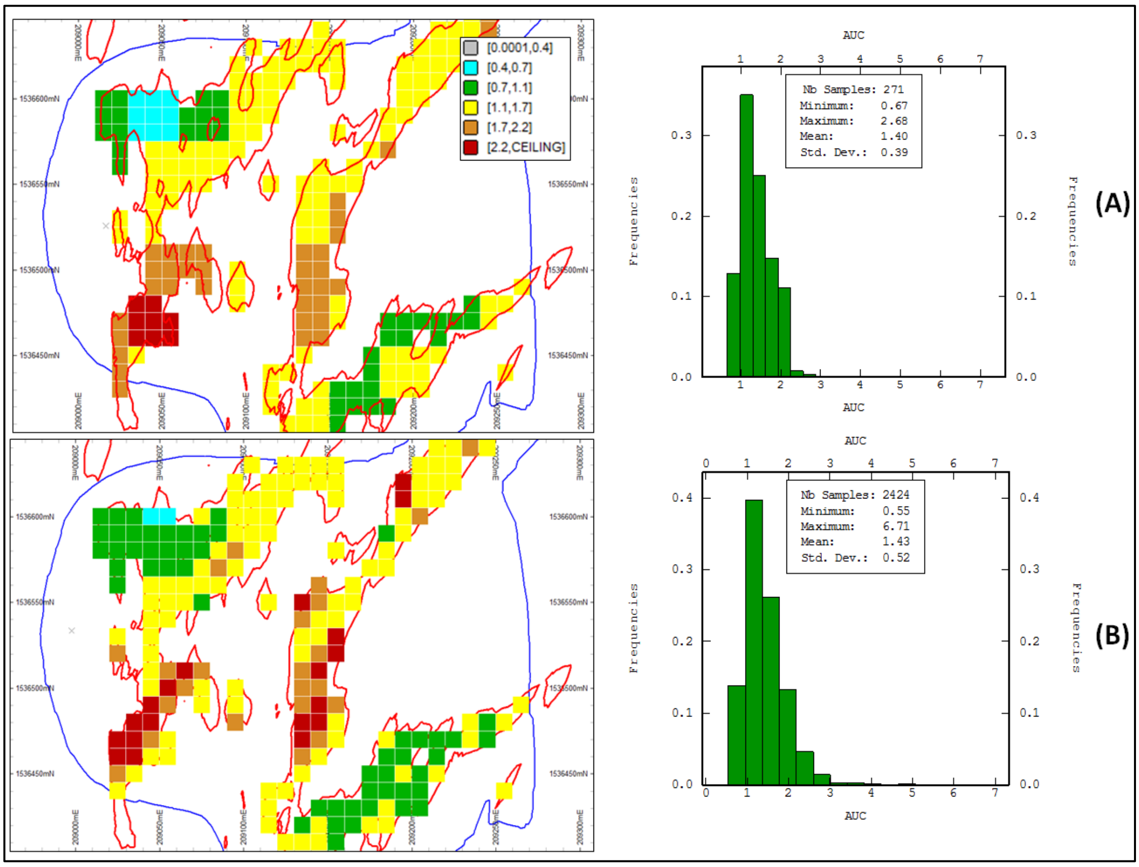


Figure 14. Panel (A) and SMU (B) grades estimated by Ordinary Kriging with sparse exploration data

Ordinary Kriging estimates of the SMUs based on all available data (dense dataset: grade control plus exploration samples) were also generated and were considered to represent the best available estimate of the SMU grades. For the purposes of this study; they were referred to as the ‘true’ SMU grades. The SMU estimates from sparse data were excessively smoothed in comparison with these ‘true’ SMU grades shown by a comparison in Figure 15.

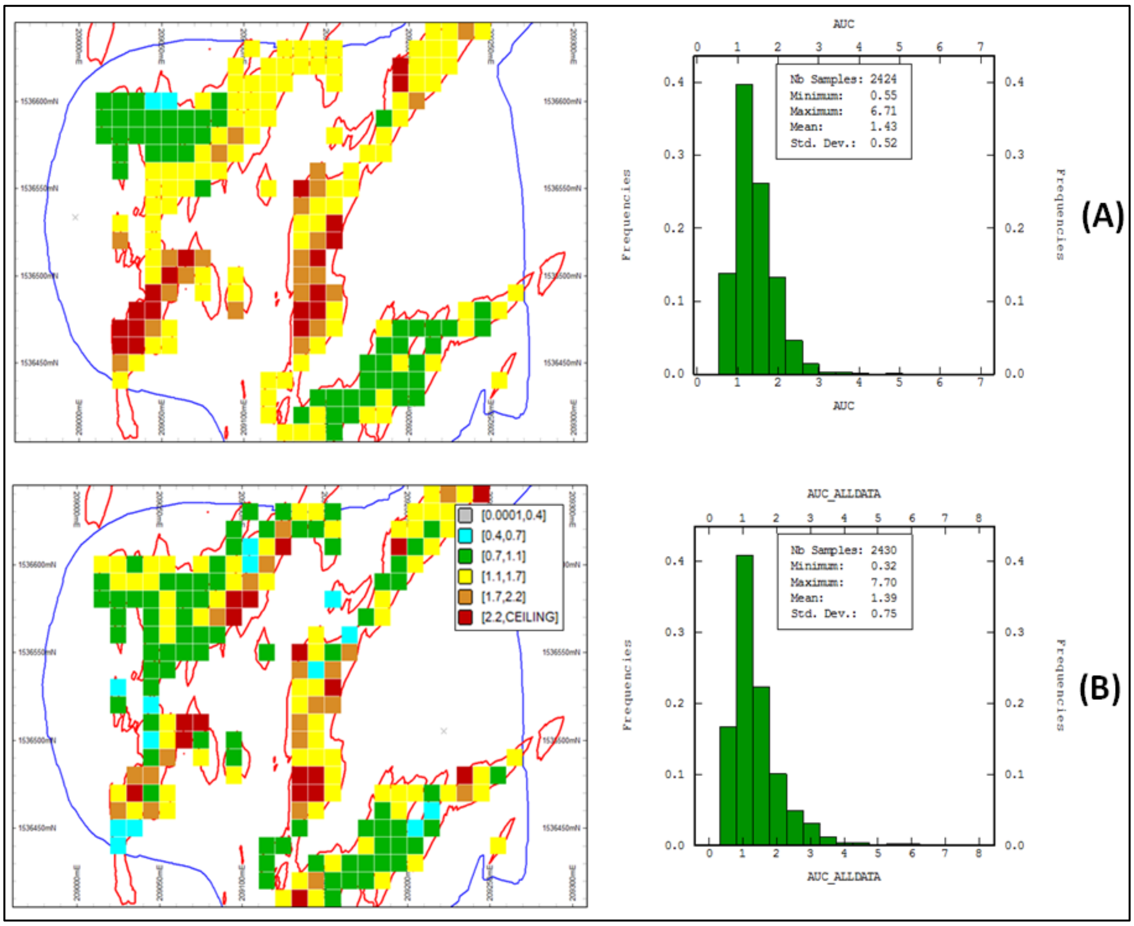


Figure 15. SMU grades estimated by Ordinary Kriging with (A) sparse exploration data and (B) dense exploration plus grade control data ('true' grades)

The global mean grades were found to be similar, but the variances differed markedly with the 'true' grade standard deviation of 0.75 much greater than the standard deviation of the sparse data estimates (0.52). As noted by Abzalov (2006), an attempt to use SMU grades obtained by kriging with the sparsely distributed data can lead to very inaccurate assumptions regarding the optimal mining scenarios.

6 LUC ESTIMATION

The previous chapter covered the generation of the following Ordinary Kriging estimates:

- An Ordinary Kriging panel estimate from the sparse/exploration data: to inform and condition the non-linear conventional UC estimate.
- An Ordinary Kriging SMU estimate from the sparse/exploration data: to predict the local grade patterns for localisation of the UC results (LUC).
- An Ordinary Kriging SMU estimate from the dense dataset (grade control plus exploration): this estimate was considered the "truth" or best available estimate of the deposit. It was ultimately used to evaluate the quality of the estimates from sparse data.

The current chapter describes the process followed to generate the LUC estimate – from the anamorphosis modelling and change of support to the UC and its localisation (LUC). At the end of the chapter, the resultant LUC estimate is visually compared with the Ordinary Kriging estimates and the "truth".

6.1 LUC estimation

ISATIS© software was used to model the recoverable resources from the sparse data using the conventional UC method. The steps in the process included the following:

- the de-clustered point data was transformed to Gaussian space (Gaussian Anamorphosis modelling)
- change of support from point to SMU was performed using the Discrete Gaussian Model for change of support
- UC was applied and
- the UC results were localised with the LUC approach.

Correction for the information effect was made during the Change of Support procedure. The information effect makes provision for the fact that the SMUs will ultimately still be selected on an estimated grade (based on the Grade Control samples) instead of the real grade. Hence, some ore blocks will be misclassified as waste and some waste blocks as ore. In order to get a more realistic recoverable estimate that takes account of this misclassification, a correction for the information effect was made by assuming that the final sampling mesh will be 6.25 mE by 12.5 mN by 2 mRL (i.e. the production or grade control sample spacing). Even at the production stage, a difference between the estimated values of the mining blocks and the real grades can be expected (the estimates are still not based on “perfect” information). As a result, we will still misclassify some of our mining blocks (i.e. actual ore blocks predicted to be waste or actual waste blocks predicted to be ore). The information effect quantifies the amount and effect of misclassification of SMU blocks and a correction for it can then be made during estimation.

6.2 Results

The grade-tonnage curves of the OK panel grades; the block anamorphosis function (at SMU support) and the UC grades are compared in Figure 16. Compared with the panel estimate, the block anamorphosis and the UC estimate showed greater selectivity (initial lower tonnes at higher grade).

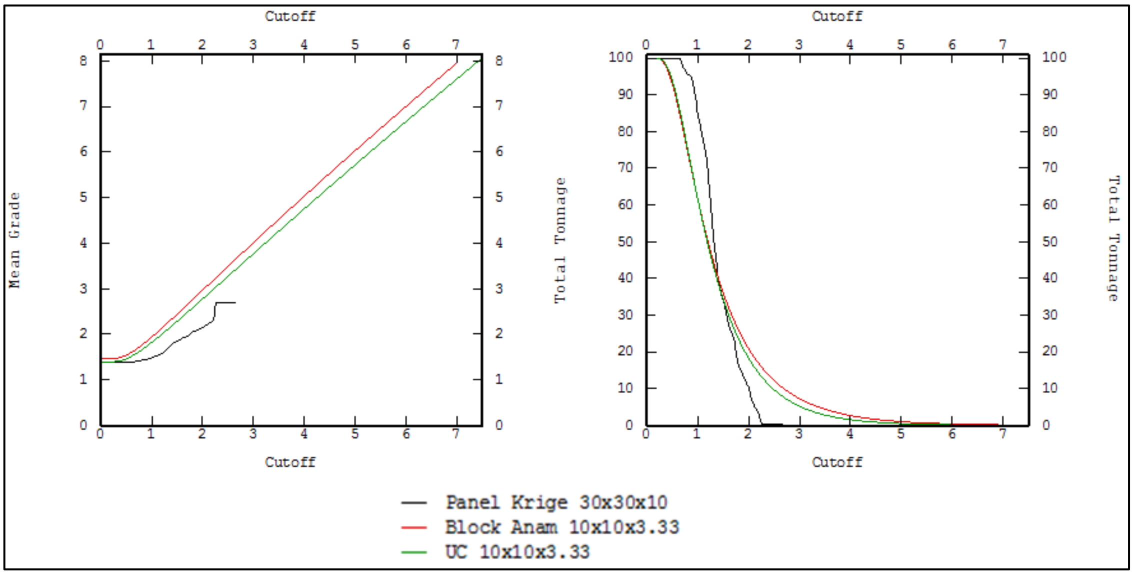


Figure 16. Mean Grade and Total Tonnage curves: Panel Kriging vs. UC

The conventional UC grade-tonnage relationships corresponded significantly better with the grade-tonnage relationships of the ‘true’ SMU grades than that obtained with the

OK estimates from sparse data (Figure 17). The UC model represents a significant improvement in comparison with the ‘unconditioned’ OK estimates from sparse data.

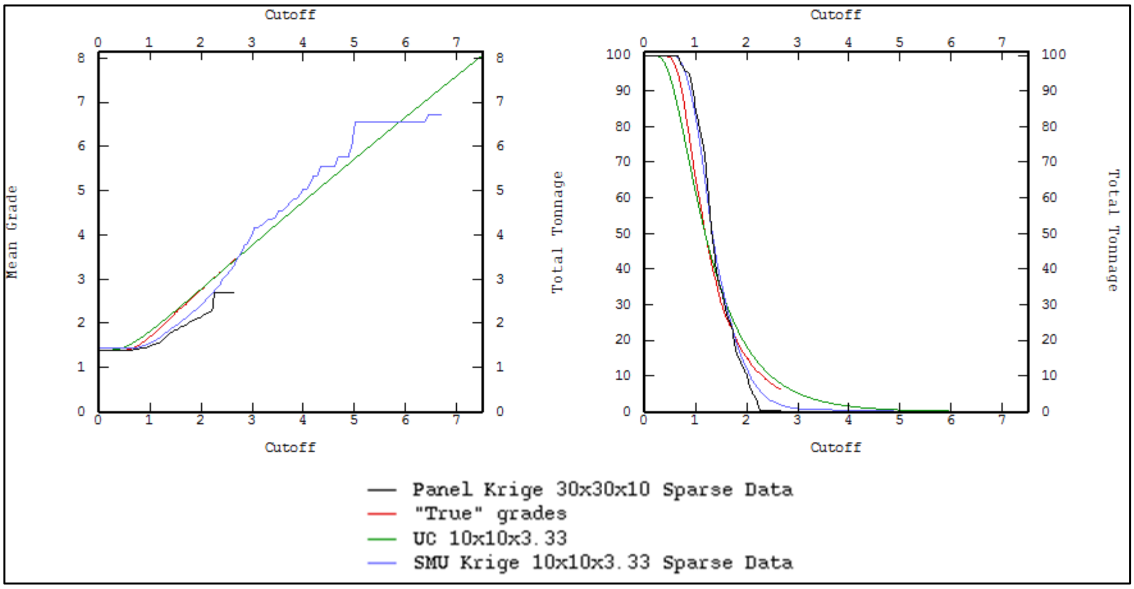


Figure 17. Mean Grade and Total Tonnage curves: “true” grades vs. UC and OK grades

The conventional UC results were localised by the LUC technique which involved ranking the SMU blocks within each panel (based on the OK SMU grades from sparse data) and deriving the grades of the SMU ranks from the UC model and assigning them to the corresponding SMU blocks (Figure 18).

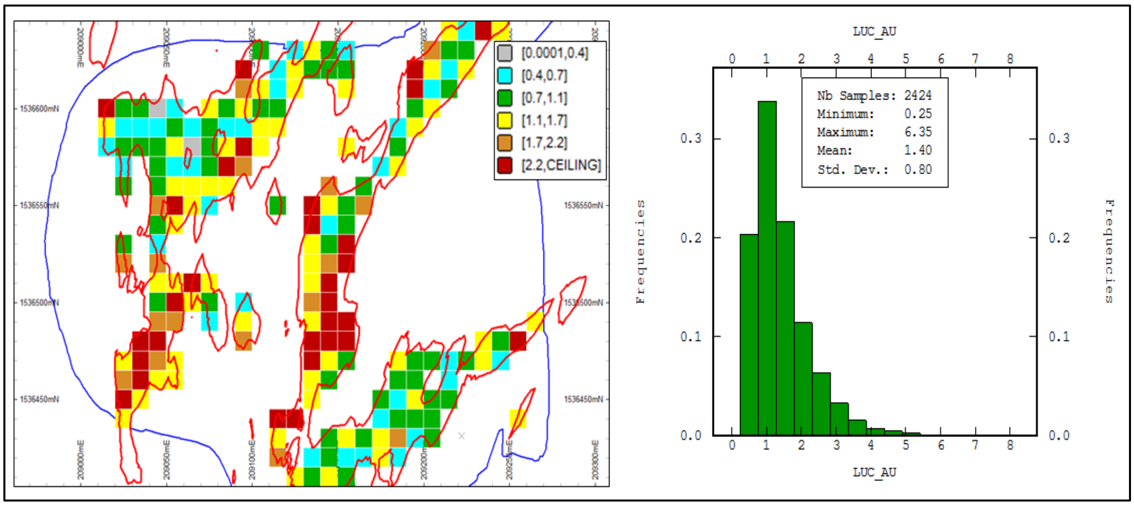


Figure 18. SMU grades estimated by the LUC technique with sparse data

The grade-tonnage curves of the LUC estimate were very similar to that of the UC estimate (Figure 19). The good match between the grade–tonnage curves derived from UC and LUC is expected as the LUC algorithm simply localises the UC results maintaining the grade–tonnage relationships predicted by the conventional UC model.

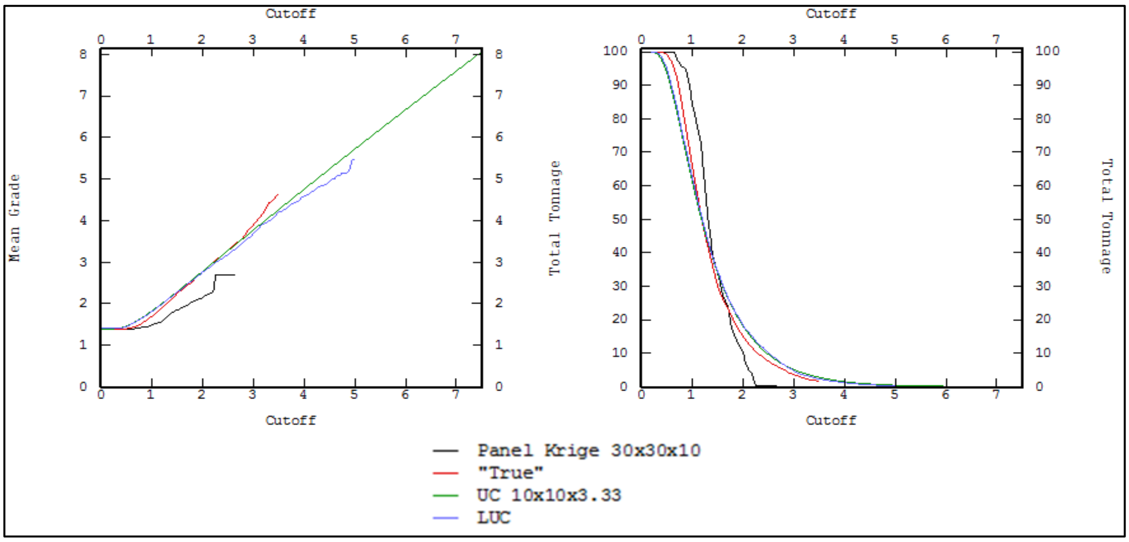


Figure 19. Mean Grade and Total Tonnage curves: “true” grades vs. UC, LUC and OK grades

The grade distribution of the LUC estimates was less smoothed than that of the sparse data OK estimates and compared with the ‘true’ SMU grades; it better represented the variability of the deposit (Figure 20). The standard deviation of the SMU grades modelled by the LUC method (SD = 0.80) was also closer to that of the ‘true’ grades (SD = 0.75) and significantly larger than that obtained by direct kriging from a sparse data grid (SD = 0.52).

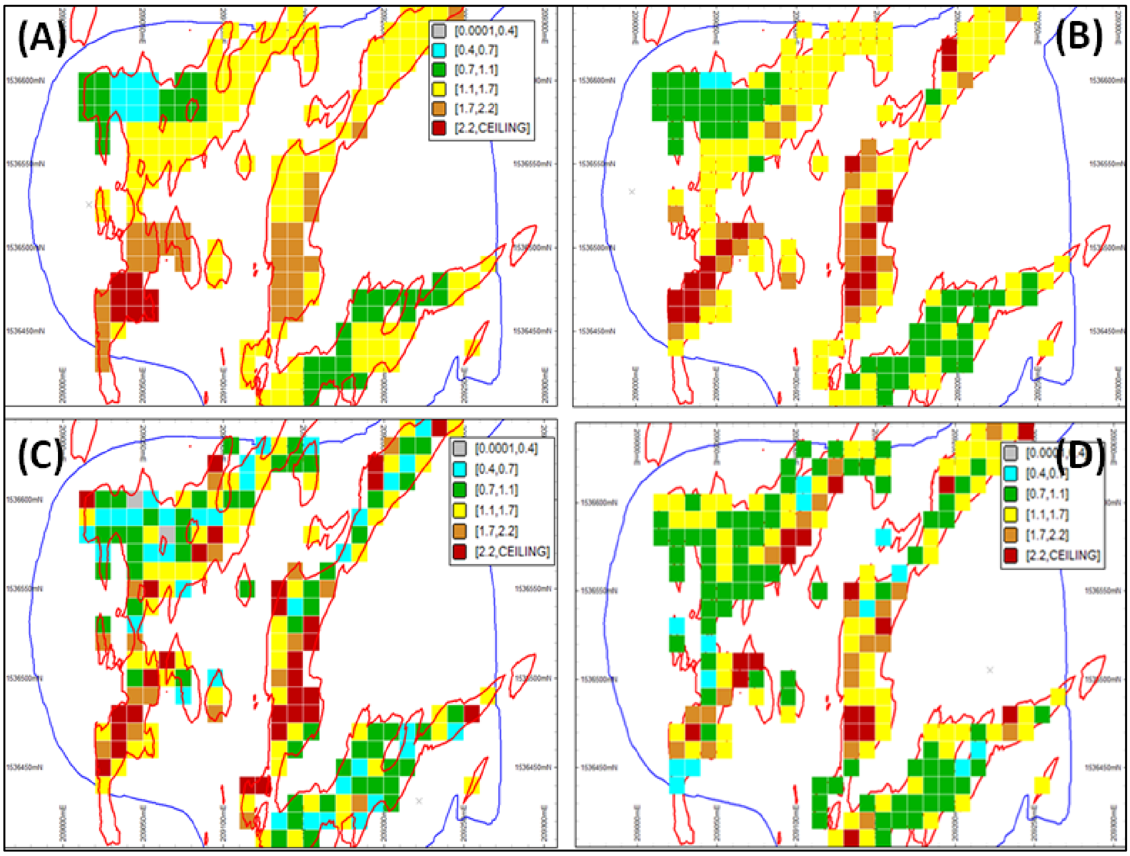


Figure 20. Plan view comparison of the panel kriging (A), the direct SMU kriging with sparse data (B), the LUC model (C) and the "true" grades (D)

Compared with the OK estimates from sparse data, the LUC estimate better represents the variability expected at the time of mining. The LUC estimate is still noticeably different from the 'true' grades. The technique itself does not make up for the lack of data at the early stages (the LUC estimate is still based on sparse data and the LUC result depends heavily on the grade pattern predicted by the direct kriging of the SMU - also from sparse data).

A reconciliation of the LUC estimate with the Grade Control model over the study area is presented in Section 7.3 of this document.

7 THE QUALITY OF THE LOCALISATION

The previous chapter described the process followed to generate the LUC estimate and concluded with a visual comparison of the LUC estimates with the “truth”. The quality of the localisation is dependent on the meaningfulness of the grade pattern predicted by the direct kriging of the SMU (Abzalov, 2006). This grade pattern is used for ranking of the SMUs into increasing order of their grade which determines the order in which the mean grades of the UC grade classes are assigned to the SMUs.

In this chapter, the quality of the localisation was quantitatively assessed by comparing the rankings of the ‘true’ grades with the LUC rankings and determining if there is a relationship between the actual and predicted rankings. If there was a relationship, then it could be said that there was some confidence in the local positioning achieved by the LUC technique – that it was not random, but that it showed a convincing relationship with the true positioning. In addition to this, it was determined how often the ore-waste prediction of the LUC estimate was correct. This provided another measure of the “success” of the local positioning of the SMUs achieved by the LUC technique. Finally, the LUC estimate was reconciled against the Grade Control model over the study area.

7.1 True versus predicted ranking

For both datasets, the 27 SMUs within each panel were sorted in increasing order of their grade. Thus, each SMU was assigned a ‘true’ ranking as well as a ‘predicted’ (or LUC) ranking between 1 and 27. The SMUs that fell outside of the estimation domain were disregarded (the affected panels therefore had fever ranking pairs). A Scatter Plot showed a reasonable correlation between the ‘true’ and LUC rankings with a correlation coefficient of 0.6 (Figure 21).

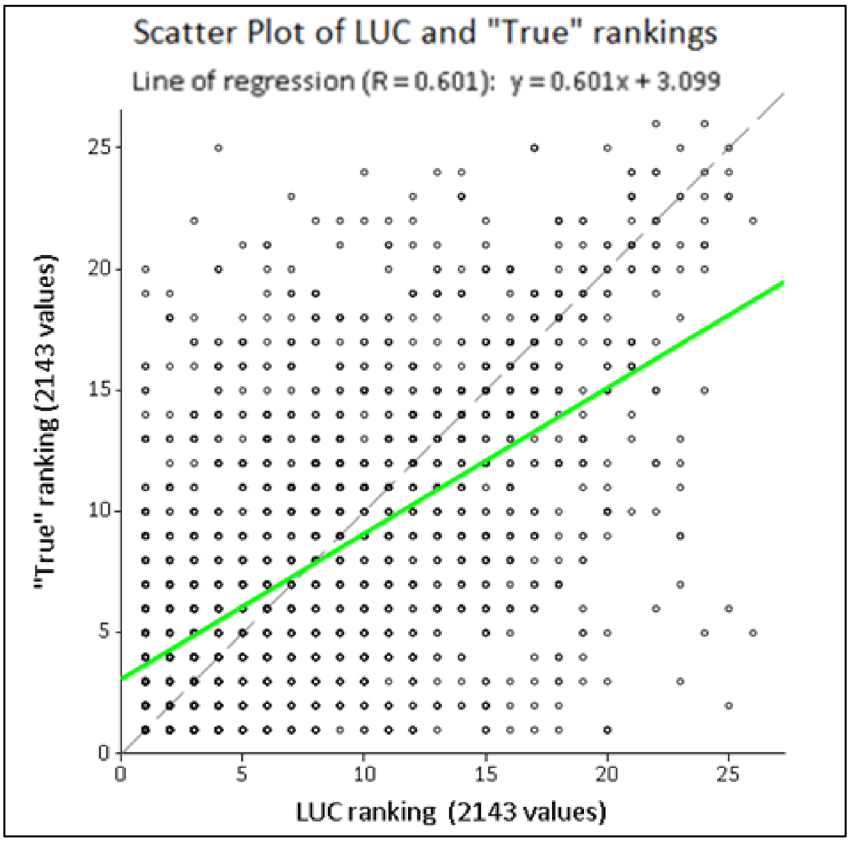


Figure 21 Scatter Plot of LUC vs. True rankings

The number of occurrences of each ranking combination (‘true’ vs. LUC) was subsequently counted across all panels. For example, counting the number of instances where the actual and predicted ranks were both 1; then the number of instances where the actual rank was 1, but the predicted rank was 2; and so forth. The result is presented in Figure 22 and shows all possible ranking combinations for up to 27 SMUs. The actual (or ‘true’) ranking is shown on the X-axis and the predicted (or LUC) ranking on the Y-axis. The colouring is based on the number of instances that a rank pair occurred.

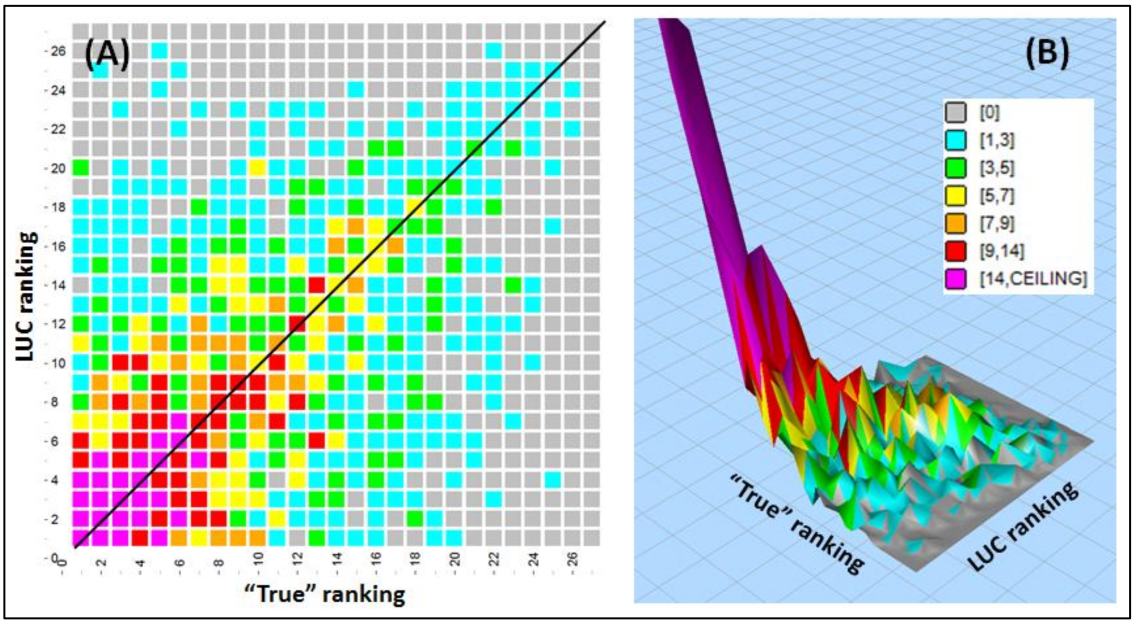


Figure 22. Plot of the number of occurrences of "true" vs. LUC rankings shown in (A) plan and (B) 3-Dimensional view

Overall, the results showed a reasonable relationship between the actual and predicted rankings with a significantly greater amount of predicted SMU rankings being closer to the actual rankings than further away. It can be concluded that, even though we are dealing with a deposit exhibiting high nugget and strong short range variability, there nevertheless appears to be some confidence in the local positioning achieved by the LUC technique i.e. it does not appear to be random, but shows a convincing relationship with the 'true' positioning.

The LUC technique was applied using the sparse drillhole dataset (early stage/exploration) which followed a 25x25x2 m drilling grid. This grid is conventionally used for classification of Mineral Resources of the Indicated category for this deposit. Drill spacing plays an important role in the quality of the localisation achieved – the closer the distances between drillholes, the better the quality of the ranking is expected to be. Conversely, wider drillhole spacing would be expected to reduce the quality of the localisation achieved.

7.2 Accuracy of LUC ore-waste prediction

Another check on the quality of the localisation achieved by the LUC technique involved determining how often the ore-waste prediction of the LUC estimate was correct. A particular SMU was deemed to be waste if it was below the cut-off grade and ore if it was above the cut-off grade. To achieve this, the following was determined over all the SMUs within the study area:

- A correct classification: the number of SMUs that were predicted to be waste by the LUC estimate and were actually waste as measured against the 'true' grades.
- A misclassification: the number of SMUs that were predicted to be waste by the LUC estimate, but that turned out to be ore as measured by the 'true' grades.
- A correct classification: the number of SMUs that were predicted to be ore by the LUC estimate and were actually ore as measured against the 'true' grades.
- A misclassification: the number of SMUs that were predicted to be ore by the LUC estimate and were actually waste as measured against the 'true' grades.

This exercise was undertaken for three different cut-off grades. In order of increasing cut-off grade it included the Mineralised Waste (MW) cut-off grade of 0.65 g/t; the Marginal Grade Ore (MGO) cut-off grade of 1 g/t and the Full Grade Ore (FGO) cut-off grade of 1.2 g/t. The MGO and FGO material are mined and stockpiled separately, but blended and fed to the plant as scheduled (blending gives flexibility in terms of delivered grade). MW material is stockpiled separately, but generally forms part of only the Mineral Resource, not the declared Ore Reserve (stockpiled for potential processing at the end of the life of the mine). This MW material may become an Ore Reserve and be fed to the plant at any time should the economics (for example gold price or costs) improve to such an extent, that they become economically viable.

The result of the study is shown in Table 2 and is separated by the MW, MGO and FGO cut-off grades.

Actual	Predictio n	Number	Percentage of total	Comment
Mineralised Waste cut-off grade – 0.65 g/t				
Waste	Waste	26	1%	Correct classification
Waste	Ore	88	4%	Misclassification
Ore	Waste	251	12%	Misclassification
Ore	Ore	1778	83%	Correct classification
Total correct	84%			
Total incorrect	16%			
Marginal Grade Ore cut-off grade – 1 g/t				
Waste	Waste	407	19%	Correct classification
Waste	Ore	337	16%	Misclassification
Ore	Waste	384	18%	Misclassification
Ore	Ore	1015	47%	Correct classification
Total correct	66%			
Total incorrect	34%			
Full Grade Ore cut-off grade – 1.2 g/t				
Waste	Waste	684	32%	Correct classification
Waste	Ore	398	19%	Misclassification
Ore	Waste	379	18%	Misclassification
Ore	Ore	682	32%	Correct classification
Total correct	64%			
Total incorrect	36%			

Table 2. Tonnes, grade and metal comparisons of Grade Control and LUC within the study area

At the lower MW cut-off grade, the ore-waste prediction achieved by the LUC estimate was very good at about 84% accuracy. This reduced to 66% and 64% accuracy for the higher MGO and FGO cut-off grades respectively. For the level of information that the LUC estimate is based on (i.e. sparse exploration data) and considering what it will be used for (i.e. the technical and financial valuation of the project and/or long term mine planning and scheduling) the achieved LUC prediction is considered very good.

7.3 Reconciliation with the Grade Control model

Finally, the LUC estimate was reconciled against the Grade Control model over the entire study area (Table 3). The short term mine plans are based on the Grade Control model and it is used for designing the shapes for mining.

Cut-off grade (g/t)	Grade Control Model			LUC Model			Percentage Difference		
	TONS	GRADE (g/t)	METAL (g)	TONS	GRADE (g/t)	METAL (g)	TONS	GRADE (g/t)	METAL (g)
0.0	778,083	1.39	1,084,858	713,083	1.41	1,005,692	-8%	1%	-7%
0.4	777,472	1.40	1,084,658	711,667	1.41	1,005,208	-8%	1%	-7%
0.5	775,528	1.40	1,083,744	706,583	1.42	1,002,855	-9%	2%	-7%
0.6	757,944	1.42	1,073,911	691,083	1.44	994,202	-9%	2%	-7%
0.7	718,417	1.46	1,048,128	650,417	1.49	967,707	-9%	2%	-8%
0.8	651,805	1.53	998,432	590,333	1.56	922,518	-9%	2%	-8%
0.9	575,139	1.62	933,577	529,833	1.64	871,178	-8%	1%	-7%
1.0	510,944	1.71	872,971	470,417	1.73	814,883	-8%	1%	-7%
1.1	445,139	1.81	804,089	412,833	1.83	754,347	-7%	1%	-6%
1.2	384,000	1.91	733,918	355,000	1.94	687,977	-8%	1%	-6%
1.3	330,444	2.02	667,239	308,000	2.04	629,348	-7%	1%	-6%
1.4	286,139	2.12	607,876	267,833	2.15	575,153	-6%	1%	-5%
1.5	242,917	2.24	545,271	231,250	2.26	522,203	-5%	1%	-4%
2.0	121,722	2.78	337,940	115,917	2.80	324,365	-5%	1%	-4%

Table 3. Tonnes, grade and metal comparisons of Grade Control and LUC within the study area

The Grade Control and LUC models compared very well with tonnes and metal within about 4 to 9 percent of each other and grades within 1 to 2 percent. This is considered especially good considering that the study area represented only about two to three month’s production (reconciliations over smaller volumes are expected to be poorer than over larger volumes).

8 ALTERNATIVES FOR GRADE PATTERN ESTIMATION

In the previous chapters, the LUC estimation process and results were described and the quality of the localisation achieved – by the direct kriging of the SMU – was evaluated.

LUC can also incorporate external information such as high resolution geophysical data or alternative estimation techniques (other than Ordinary Kriging) for prediction of local grade patterns. In light of this, an alternative technique for the estimation of the grade patterns used for SMU ranking was tested and compared with that achieved by the direct kriging of the SMUs. Inverse Distance Weighting (IDW) was used and its application and results are described in this chapter.

Two IDW estimates were produced - one to the power of two (IDW^2) and one to the power of 5 (IDW^5). The LUC ranking determined by OK was compared with rankings obtained by Inverse Distance Weighting (IDW) to evaluate the robustness of the OK estimation technique for determination of the rankings (Figure 23).

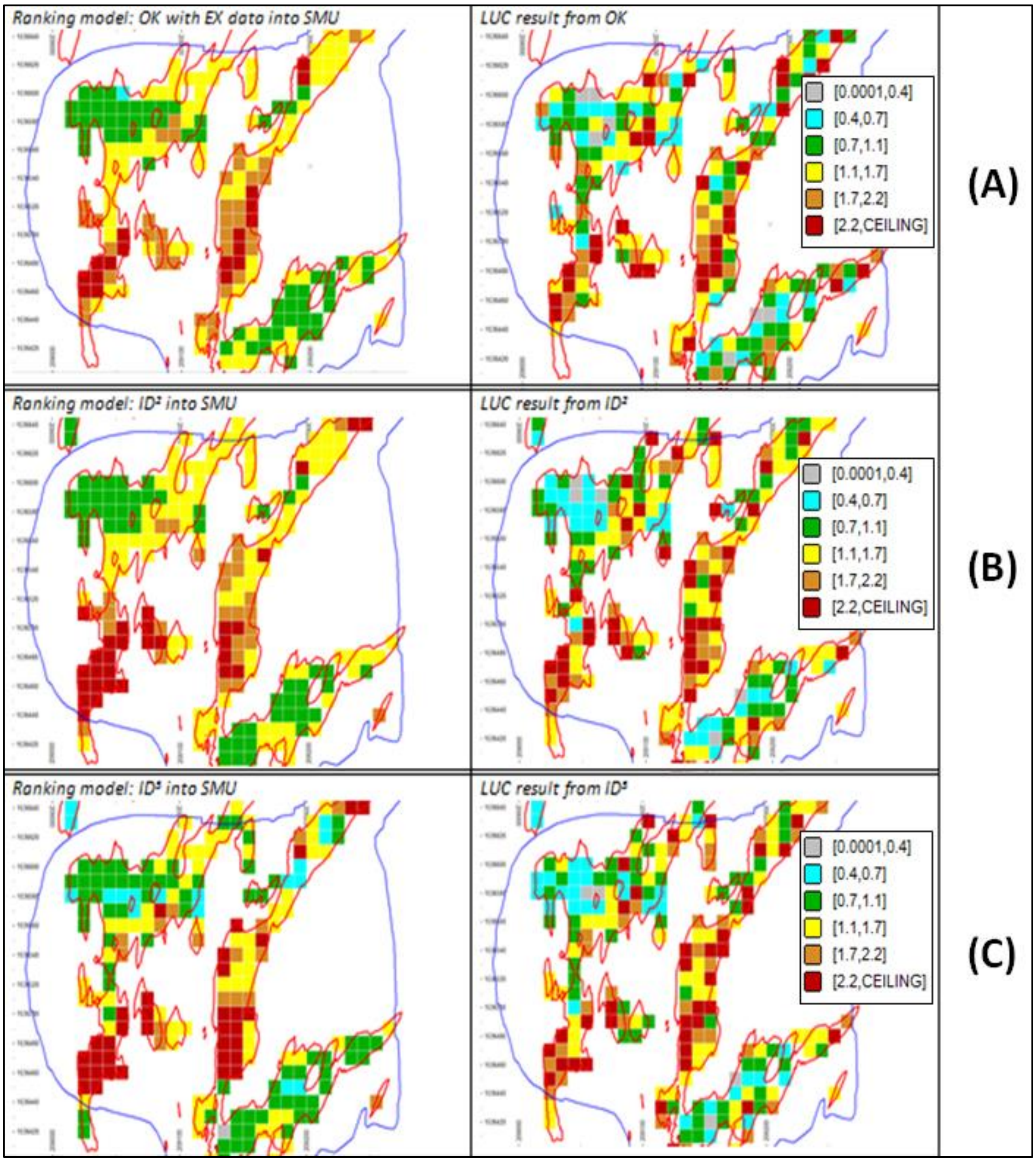


Figure 23 Plan view comparison showing the ranking models (left) and the corresponding LUC result (right) for Ordinary Kriging (A), IDW2 (B) and IDW5 (C)

Visually the results from the OK and IDW rankings looked similar with the LUC model based on IDW rankings slightly more smoothed in comparison with that based on OK rankings. However, when comparing the rank count plots for the three scenarios (counting the number of occurrences of each ranking combination) the LUC ranking based on OK appeared to be better correlated with the 'true' rankings than those based on IDW^2 and IDW^5 (Figure 24) – a greater amount of rank pairs occurred closer to the

45 degree line (where prediction = actual) for the LUC estimate based on OK, than for those based on IDW.

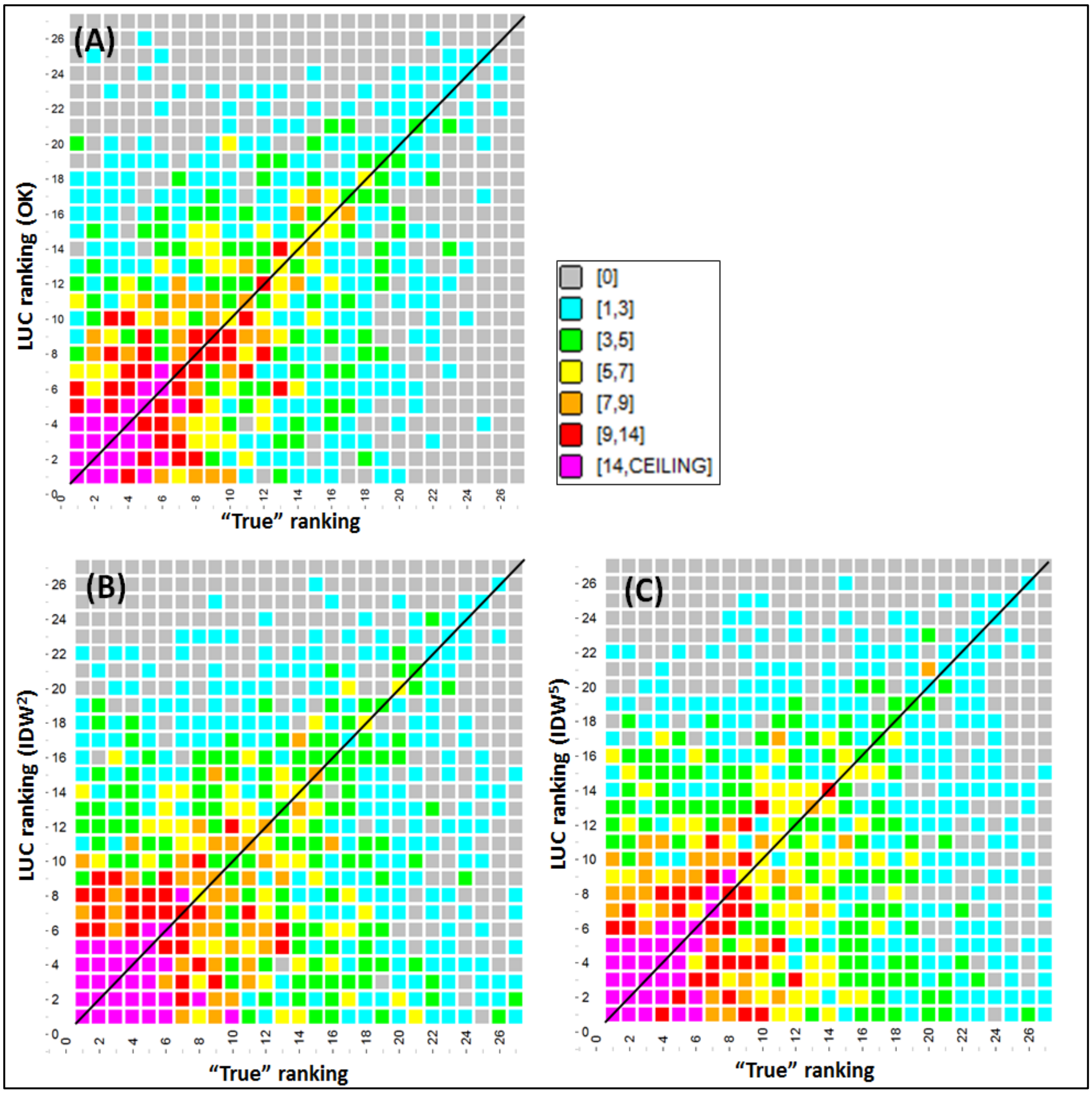


Figure 24 Comparison of the number of occurrences of 'true' vs. LUC rankings based on rankings from (A) Ordinary Kriging, (B) IDW2 and (C) IDW5

In conclusion, the use of IDW for SMU ranking did not produce a better result than that achieved with the direct kriging of the SMU. For ranking of the SMUs, one should always use the best available technique or data.

9 SUMMARY AND CONCLUSION

A basic assumption of the conventional UC approach is that the locations of ore and waste within the panels are unknown. The LUC method aims to overcome this theoretical constraint by attempting to predict the spatial locations of the SMUs, but its validity is strongly dependent on the ability to confidently estimate the rankings of the SMUs within the panels.

Since 2006, the LUC method has been implemented in commercial software and has been commonly used for the estimation of recoverable resources. The LUC technique is an enhancement of the conventional UC technique and it re-produces the conventional UC grade-tonnage relationships. Even though this is the case, the validity of the localisation is heavily reliant on the ability to reasonably predict SMU rankings from sparse data and the accuracy of this localisation depends on the techniques used for the SMU ranking (Abzalov, 2014).

It is considered that, when using the direct kriging of the SMU for ranking, the presence of a high nugget and strong short range variability could potentially result in inadequate localisation. In addition, this could be aggravated if drill spacing is too broad to achieve adequate localisation. Drill spacing plays an important role in the quality of the localisation achieved by LUC – the closer the distances between drillholes – the better the quality of the ranking is expected to be. Accordingly, if the predictions of the SMU rankings by Ordinary Kriging (or any other technique) are inadequate, the advantages of using the LUC approach will be more limited or even entirely unsuitable. It is therefore deemed necessary to assess the quality of the localisation before accepting an LUC result. In the mined out area of an active open pit, one could achieve this by comparing the rankings of the SMUs based on close spaced Grade Control data with the rankings based on sparse exploration data (as was done in this study). In an unmined pit with no close spaced data, it is more difficult to assess the quality of the localisation. However, one could attempt to improve the rankings from the direct kriging of the SMUs by integrating it with auxiliary data such as geophysical or geochemical information as proposed by Abzalov (Abzalov, 2014).

In the current study, the LUC technique was implemented for the mined out portion of a typical Birimian style gold deposit (mined by open pit methods) to model the grades of SMU sized blocks from sparse, early stage data which followed a 25x25x2 m drilling grid. This grid is conventionally used for classification of Mineral Resources of the Indicated category for this deposit. Drill spacing plays an important role in the quality of the localisation achieved – the closer the distances between drillholes, the better the quality of the ranking is expected to be. Conversely, wider drillhole spacing would be expected to reduce the quality of the localisation achieved.

The LUC grade-tonnage relationships closely matched the conventional UC grade-tonnage relationships and better predicted the grade-tonnage relationship of the 'true' grades than that derived from Ordinary Kriging. In order to assess the quality of the LUC localisation, the direct SMU kriging rankings (based on sparse data) were compared with the Grade Control model rankings (based on close spaced data and the best available estimate of the deposit). The results showed a reasonable relationship between the actual and predicted rankings and it was concluded that, even though the grade patterns predicted by the direct kriging of the SMUs may be less meaningful for deposits exhibiting strong short range continuity, there nevertheless appears to be some confidence in the local positioning achieved by the LUC technique. Therefore, it is considered that the use of the LUC technique may still be useful for this style of deposits.

It is recommended that, if possible, the quality of the localisation achieved by the LUC technique should be determined for each LUC study undertaken. This is to ensure that the LUC estimates are acceptable - that there is a relationship between the spatial positioning predicted by the LUC technique and that which will be encountered at the time of mining.

REFERENCES

Abzalov, M.Z., 2006, Localised Uniform Conditioning (LUC): A New Approach for Direct Modelling of Small Blocks: Mathematical Geology, v. 38, no. 4, p. 393-410.

Abzalov, M.Z., and Humphreys, M., 2002, Resource estimation of structurally complex and discontinuous mineralisation using non-linear Geostatistics; Case study of a mesothermal gold deposit in northern Canada: Explor. Min. Geol., v.11, no. 1-4, p.19-29.

Abzalov, M.Z., 2014, Localised Uniform Conditioning (LUC): Localized uniform conditioning: method and application case studies: Journal of the Southern African Institute of Mining and Metallurgy, vol. 114, n.3.

Assibey-Bonsu, W., and Krige, D., 1999, Use of direct and indirect distributions of selective mining units for estimation of recoverable resources/reserves for new mining projects, in Proceedings of 28th APCOM Symposium: Colorado School of Mines, Golden, p. 239-244.

Assibey-Bonsu, W., and Deraisme, J., 2011, Localised Uniform Conditioning in the Multivariate Case: An Application to a Porphyry Copper Gold deposit: in Proceedings of 35th APCOM Symposium.

Assibey-Bonsu, W., and Deraisme, J., 2012, Comparative study of Localized Block Simulations and Localized Uniform Conditioning in the Multivariate case.

Assibey-Bonsu, W., Deraisme, J., Garcia, E., Gomez, P., and Rios, H., 2014, Production reconciliation of a multivariate uniform conditioning technique for mineral resource modelling of a porphyry copper gold deposit: The Journal of The Southern African Institute of Mining and Metallurgy, vol. 114, p.285-292.

De-Vitry, C., Vann, J., and Arvindson, H., 2007, A Guide to Selecting the Optimal Method of Resource Estimation for Multivariate Iron Ore Deposits: in Proceedings of Iron Ore Conference, August 2007.

Hansmann, K., 2015, Application of a Localised Uniform Conditioning on two hypothetical datasets: A dissertation submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg.

Humphreys, M., 1998, Local recoverable estimation: A case study in uniform conditioning on the Wandoo Project for Boddington Gold Mine in Proceedings of a one day symposium: Beyond Ordinary Kriging, Australia, p. 63-75.

Journel, A.G., Huijbregts, C.J., 1978, Mining Geostatistics: Academic Press, New York.

Krige, D., and Assibey-Bonsu, W., 2001, Valuation of recoverable resources by Kriging, direct conditioning or simulation, in Proceedings of 29th APCOM Symposium: Beijing, p. 3-8.

Masurel, Q., Thebaud, N., Miller, J., and Ulrich, S., 2014, Tambali Quarterly Report July 2014: Controls on the genesis, geometery and location of the Sadiola gold system, Mali, West Africa (internal AGA report by the Centre for Exploration and Targeting).

Millad, M.G., and Zammit, M., 2014, Implementation of Localised Uniform Conditioning for Recoverable Resource Estimation at the Kipoi Copper Project, DRC: in Proceedings of the Ninth International Mining Geology Conference.

Neufeld, C.T, 2005, Guide to Recoverable Reserves with Uniform Conditioning, Guidebook Series Volume 4, Centre for Computational Geostatistics (CCG), Canada.

Neufeld, C., and Deutsch, C.V., 2005, Calculating Recoverable Reserves with Uniform conditioning in Proceedings of IAMG '05: GIS and Spatial Analysis, vol. 2, p. 1065-1070.

O’Connor, M., Bertoli, O., and Titley, M., 2012, Estimating Recoverable Uranium Resources using Uniform Conditioning – A Case Study on the Mkuju River Uranium

Project, Tanzania: in Proceedings of the 2012 AusIMM International Uranium Conference.

Ravenscroft, P., 1992, Recoverable reserve estimation by conditional simulation: Annels, A.E. (ed.), 1992, Case Histories and Methods in Mineral Resource Evaluation: a Geological Society Special Publication, No. 63, pp. 289-298.

Remacre, A.Z., 1984, L'estimation du R´ecup´erable local, le conditionnement uniforme. PhD thesis, Ecole Nationale Sup´erieure des Mines de Paris.

Remacre, A.Z., 1989, Uniform conditioning versus indicator kriging: A comparative study with the actual data: Geostatistics, Volume 2, pages 947–960.

Rivoirard J, 1990, Introduction to disjunctive kriging and nonlinear geostatistics, Centre deGeostatistique, Ecole des mines, France.

Vann, J. and Guibal, D., 1998, Beyond ordinary kriging – An overview of non-linear estimation, Mineral Resource and Ore Reserve Estimation: The AusIMM Guide to Good Practice, p. 6-23.

Vann, J., Guibal, D. and Harley, M., 2000. Multiple indicator kriging: is it suited to my deposit: 4th International Mining Geology Conference, Australia, p. 9-17.

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

Vizi, L., 2008, A case study in Uniform Conditioning of local recoverable reserves estimation for Jelsava Magnesite deposit – Level 220: Geoscience Engineering, vol. 1, p. 41-53.