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Localised Uniform Conditioning (LUC): A New Approach for Direct Modelling of Small Blocks[1]

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Recoverable mineralisation at a given mining selectivity is traditionally modelled from sparse data grids by non-linear geostatistical techniques such as Uniform Conditioning. This method estimates the tonnage and grade of mineralisation which can be extracted as small selective minable blocks from large blocks (panels), whose grade is modelled by Ordinary Kriging. Uniform Conditioning technique estimates the proportions of recoverable mineralisation in each panel without specifying the actual locations of the economically extractable blocks. This inability to predict a spatial location of the recoverable mineralisation is a major disadvantage of the conventional Uniform Conditioning method. A new approach, called Localised Uniform Conditioning, has been developed to overcome this limitation. This method applies the grade–tonnage relationships modelled by the Uniform Conditioning technique to the spatial grade distribution patterns approximated by direct kriging of the small blocks from the sparse data grid. This approach estimates localised selective mining units grades conforming to the proper grade–tonnage curves obtained by the Uniform Conditioning method as well as maintaining the relative spatial grade distribution pattern indicated by the directly kriged small block grades. The advantage of this approach is essentially dependent upon the data available for ranking the small blocks within a panel in increasing order of their grade. Ordinary Kriging of the small blocks can be used for their ranking providing the kriged estimates produce a meaningful indication of the relative grade pattern. Where the data is sparse and not close to a panel, or their distribution is characterised by a strong short-range variability, the advantages of using the Localised Uniform Conditioning approach are more limited.

KEY WORDS: geostatistics; Uniform Conditioning; ore reserves.

INTRODUCTION

It is well known by the geostatistical community that linear regression based techniques are unsuitable for modelling grades of small blocks when data spacing is too broad in comparison with the estimated block sizes. All linear estimators, including Ordinary Kriging (OK) (Journel and Huijbregts, 1978), which is a popular method among resource industry practitioners, can produce smoothed assessments

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of the recoverable resources when applied to model small blocks which are not supported adequately by dense data spacing (Armstrong and Champigny, 1989; Ravenscroft and Armstrong, 1990; Pan, 1998).

Estimating the grade of the large blocks (panels) whose size is adequate to a given data spacing is impractical for technical and financial valuation of a mining project because it is necessary to estimate tonnage (T_v) and grade (Z_v) of mineralisation above a given economic cut-off (z_C) taking into account a proposed mining selectivity. In geostatistical terms, this task is known as estimation of the 'recoverable resources' of support (v), where a block of size (v) represents the smallest selectively minable unit (SMU).

At present, the common practise of estimating the 'recoverable resources' consists of modelling the grade–tonnage relationships for the given mining selectivity applying the change-of-support techniques. This approach predicts what portion of mineralisation can be economically extracted (i.e. above the given cut-off) at the given mining selectivity without the application of precise spatial locations of the recoverable resources. Tonnage (T_v) and grade (Z_v) of recoverable resources are estimated by a suitable non-linear geostatistical method (Rivoirard, 1994) which calculates the grade–tonnage relationships of the selectively minable units of size (v) from an empirically available sample (quasi-point) distribution. Uniform Conditioning (UC) is one of such non-linear geostatistical methods (Rivoirard, 1994; Chiles and Delfiner, 1999), which is often used in the mining industry for the modelling of recoverable resources (Assibey-Bonsu and Krige, 1999; Krige and Assibey-Bonsu, 2001; Abzalov and Humphreys, 2002a, 2002b).

The main disadvantage of the conventional UC method is its inability to predict a spatial location of the economically extractable mineralisation. The practical needs of the modern mining industry require a better understanding of a spatial distribution of the recoverable resources for a more accurate assessment of the technical and economic merits of the mining project. In other words, it is not sufficient to only know what portion of a panel contains mineralisation exceeding the economic cut-off value but it is also important to predict the local spatial locations of these economically extractable blocks of ore. Pioneering work of Assibey-Bonsu and Krige (1999) has explored the various opportunities to model direct and indirect distribution of recoverable resources based on volume–variance relationships. There were numerous attempts to model the 'recoverable resources' using the Conditional Simulation techniques (Ravenscroft, 1992; Krige and Assibey-Bonsu, 2001), which produced, in general, very encouraging results. However, this approach still remains very time consuming.

A new method for modelling grades of selectively minable units (SMU) called Localised Uniform Conditioning (LUC) is proposed in this paper. LUC enhances the Uniform Conditioning approach by localising the model results. Firstly, this technique calculates the grade distribution functions using a conventional UC method and then uses the calculated grade–tonnage relationships in the panels to assign a single grade value to each SMU size block. Assigning grades from the UC model to the SMU blocks is based on a ranking of the SMU within each panel in increasing order of their grade. LUC approximates the spatial grade distribution patterns within the panels by direct kriging SMU from the sparse data grid. This paper discusses the methodology of the proposed LUC technique and provides a case study of Cu-mineralisation.

UNIFORM CONDITIONING: OVERVIEW

Uniform Conditioning (Rivoirard, 1994; Chiles and Delfiner, 1999; Wackernagel, 2002) is a non-linear geostatistical technique of calculating tonnage (T_v) and mean grade (M_v) of recoverable resources distributed in a large panel (V) as the small blocks of size (v) representing a partitioning of this panel (Fig. 1). These small blocks of support (v) represent selectively minable units (SMU) which can be selectively extracted from a panel (Z_V). They are classified as 'ore' if the SMU grade ($z(v)$) is equal to or exceeds the cut-off value ($z_C(v)$) and is a 'waste' otherwise.

In geostatistical terms the UC technique (Rivoirard, 1994; Wackernagel, 2002) involves calculating a conditional expectation of a non-linear function $\Psi(Z(v))$ of the blocks (v) with respect to the corresponding panel grade $Z(V)$. In other words, the UC methods assumes that the grade of the panel ($Z(V)$) is

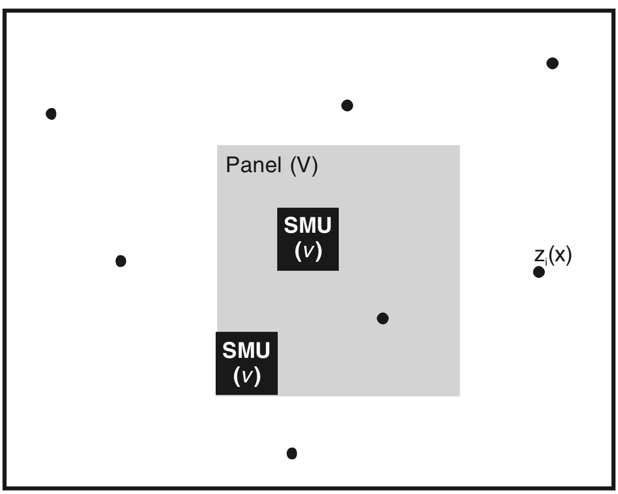


Figure 1. Sketch explaining distribution of the selective mining units of support (v) in the panel (V). Data nodes ($z(x)$) are denoted as the black dots.

known. In practise, as the true panel grades $Z(V)$ are not available they are substituted in the UC models by the $Z(V)^*$ panel grades estimated by Ordinary Kriging (OK).

Estimation of a non-linear function $\Psi(Z(v))$ from the available point (i.e. sample) variable $Z(\mathbf{x})$ uses a Discrete Gaussian Point-Block Model (Lantuejoul, 1988; Rivoirard, 1994; Wackernagel, 2002). The UC method uses the Discrete-Gaussian Point-Block model to calculate a Point-to-SMU(v) anamorphosis (Eq. (1)) and a Point-to-Panel(V) anamorphosis (Eq. (2)).

$$Z(v) = \phi_V(Y(v)) = \sum_{k=1}^{\infty} \frac{\varphi_k}{k!} r^k H_k(Y(v)) \tag{1}$$

$$Z(V) = \phi_V(Y(V)) = \sum_{k=1}^{\infty} \frac{\varphi_k}{k!} s^k H_k(Y^*(V)) \tag{2}$$

These models are further used for the calculation of recoverable tonnage (T) (Eq. (3)).

$$T_V(z_{\mathrm{C}}) = \mathrm{E}\left[I_{Z(V)\geq z_{\mathrm{C}}} \left| Z^*(V)\right.\right] = E\left[I_{Y_V \geq y_{\mathrm{C}}} \left| Y_V^*\right.\right] = 1 - G\left\{\frac{y_C - \frac{s}{r}Y_V^*}{\sqrt{1-\left(\frac{s}{r}\right)^2}}\right\} \tag{3}$$

and Contained Metal (Q) (Eq. (4))

$$\begin{aligned} Q_V(z_{\mathrm{C}}) &= \mathrm{E}\left[Z(v) I_{Z(V)\geq z_{\mathrm{C}}} \left| Z^*(\mathrm{V})\right.\right] \\ &= \sum_{k=1}^{N} \left(\frac{s}{r}\right)^k H_k(Y_{\mathrm{V}}^*) \sum_{j=1}^{N} \varphi_j r^j \int_{y_{\mathrm{C}}}^{+\infty} H_k(y) H_j(y) g(y)\, dy \end{aligned} \tag{4}$$

where $Y_{\mathrm{V}}^* = \phi_{\mathrm{V}}^{-1}(Z^*(\mathrm{V}))$ and $y_{\mathrm{C}} = \phi_V^{-1}(z_{\mathrm{C}})$.

Finally, the mean grade (M) (Eq. (5)) of the recovered mineralisation whose SMU grades are above a given cut-off z_{C}, is estimated as

$$M_V(z_{\mathrm{C}}) = \frac{Q_V(z_{\mathrm{C}})}{T_V(z_{\mathrm{C}})} \tag{5}$$

Additional correction for insufficient information, known as Information Effect is usually applied to further improve a given change-of-support model (Bleines and others, 2001; Wackernagel, 2002; Journel and Kyriakidis, 2004).

LOCALISED UNIFORM CONDITIONING

Concept

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 then 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.

Assigning Grade to SMU According to Their Ranks

The procedure of calculating the mean grade for each grade class and assigning these grades to the corresponding SMU blocks is shown schematically on the process map (Fig. 2).

Firstly, the UC method is used to estimate the grade–tonnage relationships of recoverable resources distributed as SMU of size (v) in the panels (V).

Then, the 3D panels need to be split (partitioned) on sub-cells whose size are equal to that of the chosen SMU size. All SMU size blocks distributed in a panel are ranked in increasing order of their grade. Ranking procedure is explained further in the next section.

The next step is to define the grade classes using relationships between the tonnage of recoverable mineralisation (T_v) and the cut-off grade (z_C) estimated by UC technique for each panel (Fig. 2A). The grade class (GC_i) represents a proportion of a panel whose grade is above the given cut-off (z_{Ci}) and less than the next cut-off value (z_{Ci+1}). Each grade class is defined by its lower (z_{Ci}) and upper (z_{Ci+1}) cut-off values and by corresponding $T_i(z_{Ci})$ and $T_{i+1}(z_{Ci+1})$ values representing a recoverable tonnage at lower and upper cut-offs defining the given grade class.

In other words,

$$GC_i \subset \{T_i(z_{Ci}), \quad T_{i+1}(z_{Ci+1})\}, \quad \text{and} \quad GC_i \subset \{z_{Ci}, z_{Ci+1}\},$$

where $T_i(z_{Ci})$ is recoverable tonnage at cut-off (z_{Ci}) and $T_{i+1}(z_{Ci+1})$ is recoverable tonnage at cut-off (z_{Ci+1}).

Then, the SMU ranks need to be converted to the grade classes (Fig. 2A). This is achieved by defining the SMU ranks as proportions of the panel tonnage T_V.

$$\mathrm{SMU}_K \subset (T_K, T_{K+1}),$$

where SMU_K is the SMU of a rank (K), T_K is the proportion of the panel tonnage distributed in SMU blocks whose rank is equal or lower than (K), and T_{K+1} is the proportion of the panel distributed in SMU blocks having higher rank.

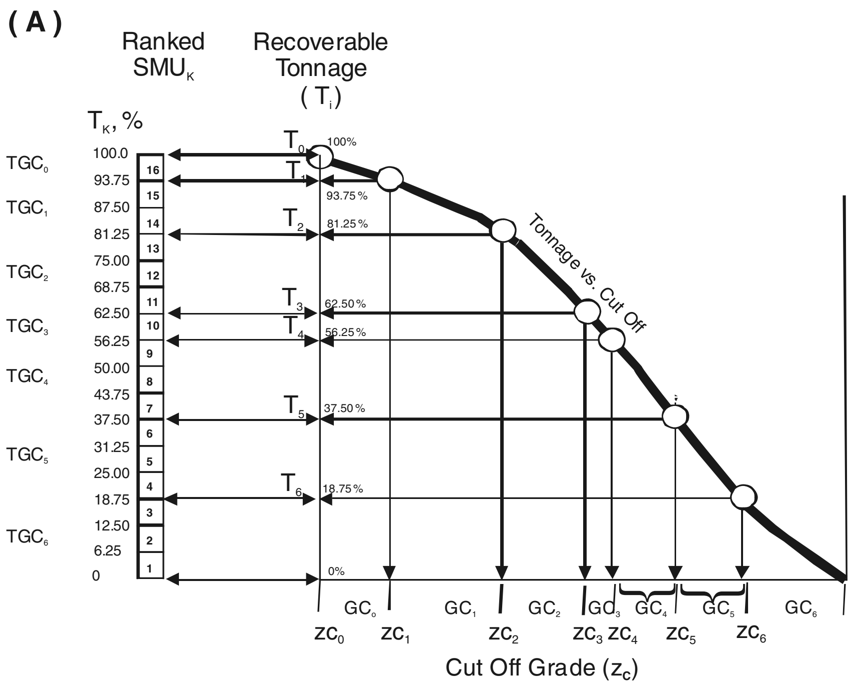
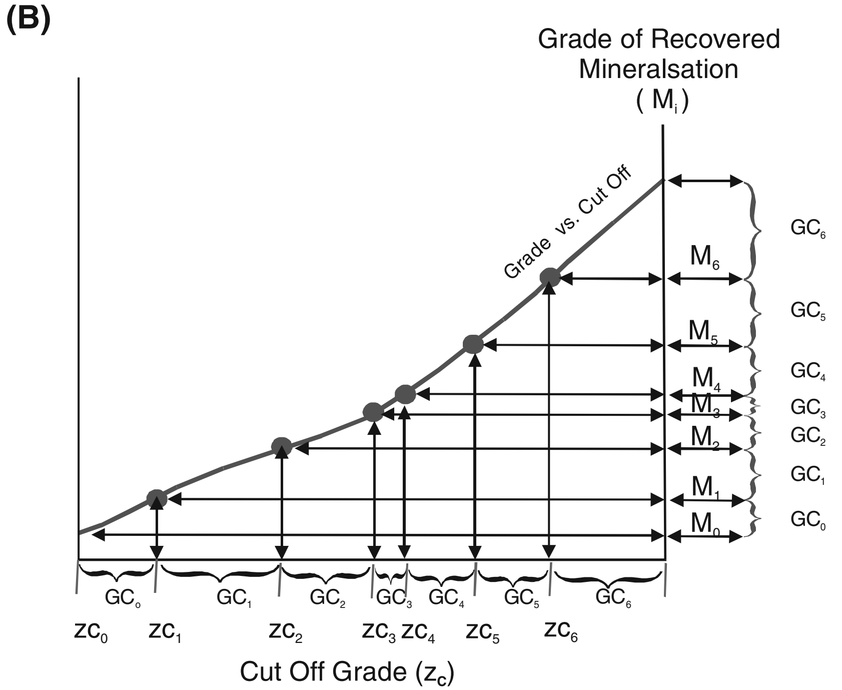


Figure 2. Sketch explaining definition of the grade classes and assigning the grade values to the SMU blocks. Presented example uses 16 SMU blocks in panel and six cut-off values used in the UC model. (A) Definition of the grade classes (GC_i) from UC results. z_{Ci}—cut-off values, T_i—tonnage of mineralisation above the cut-off z_{Ci} expressed as proportion (%) of the panel, GC_i—grade class representing a portion of mineralisation distributed in the panel as the SMU size blocks which grade lies within the range of $\geq z_{Ci}$ and $< z_{Ci+1}$. Grade class (GC_i) encompasses mineralisation from T_i to T_{i+1}. TGC_i—is the grade class indexes assigned to the SMU blocks falling within the range from T_i to T_{i+1}; (B) Definition of the mean grades (M_i) of the grade class (GC_i); (C) Assigning the mean grades (M_i) of the grade class (GC_i) to the SMU blocks which index (TGC_i) is matching the grade class (GC_i).



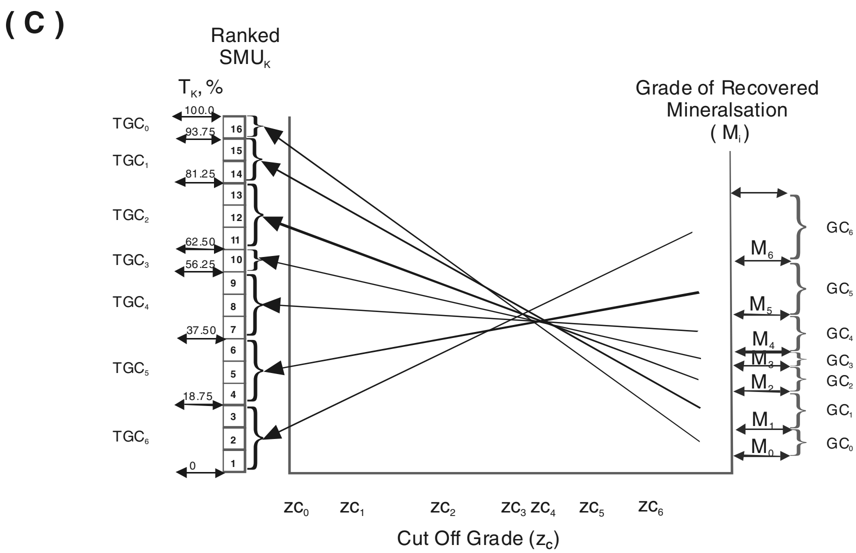


Figure 2. Continued.

The grade class can be determined for each SMU_K by comparing its (T_K, T_{K+1}) intervals with the intervals of the grade classes ($T_i(z_{Ci})$, $T_{i+1}(z_{Ci+1})$) (Fig. 2A). SMU_K will be assigned grade class (GC_i) if (T_K–T $_{K+1}$) $\subset$ (T_i–T_{i+1})

The next step is to calculate the mean grades (M_i) of the grade classes (MGC_i) in the panels using the UC model (Fig. 2B).

Finally, a mean grade (M_i) of each class can be transferred to the SMU_K blocks by matching their grade class indexes (MGC_i and TGC_i) (Fig. 2C).

The above explained procedure of assigning the grade values to the SMU blocks (Fig. 2) assumes an exact match between grade class intervals $\{T_i(z_{Ci}), T_{i+1}(z_{Ci+1})\}$ and intervals of SMU bocks (T_K, T_{K+1}). When the range of SMU (T_K–T_{K+1}) does not precisely match that of the grade classes (T_i–T_{i+1}), the mean SMU grade is estimated by weighting grades of the classes to their proportions of the SMU.

Ranking SMU in Increasing Order of Their Grade

The underlying concept of the LUC method is an ability to rank the SMU blocks in increasing order of their grade (Fig. 3). Accurate rankings would require high density information. However, in some cases reasonably accurate ranks of the SMU blocks in the panels can be deduced from the spatial distribution patterns of

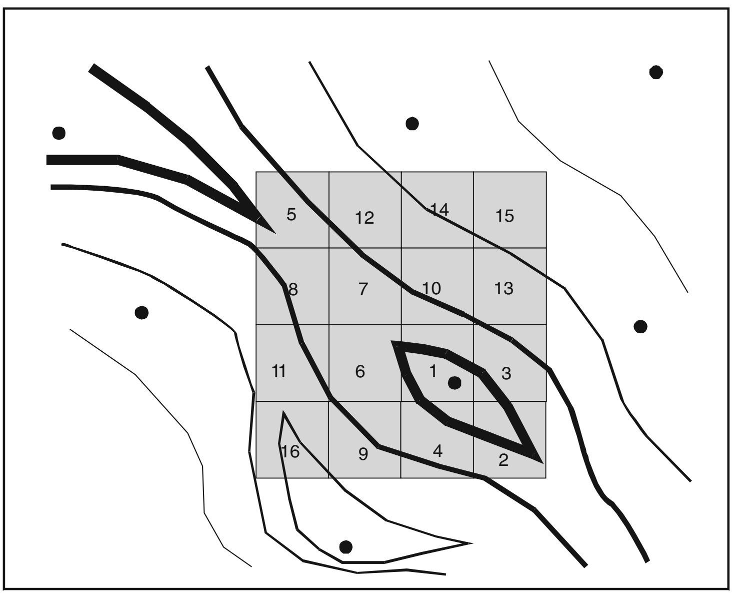


Figure 3. 17pcSketch explaining definition of the SMU grade ranks from the sparsely distributed data.

the grade values, such as zoning or grade trends. The latter approach is particularly relevant for continuous mineralisation, characterised by a low nugget effect, such as disseminated base-metal sulphides, bauxites and iron-oxide deposits. Spatial grade distribution patterns are often recognised by geoscientists in such 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.

The global distribution features of the grade variables exhibiting a strong continuity can be reconstructed by interpolating available data nodes using a conventional linear interpolator, such as OK. In other words, it is suggested that direct kriging of the small blocks can be used for their approximate ranking in grade increasing order in the panels even when drill spacing is too broad to avoid a smoothed SMU grade estimation. The proposed approach of ranking the SMU blocks in the panels using a linear estimator is demonstrated in the case study from a copper mine.

The validity of the obtained grade ranks depends on complexity of the grade distribution patterns. Further, studies are required to quantify limitations of the application of linear estimators (e.g. OK) for ranking the SMU size blocks. At this stage it is assumed that the above assumption is applicable to grade variables whose spatial distribution satisfies a border effect condition and which are also characterised by a low nugget effect and exhibit good continuity at their variogram origins and also where the available data grid is not too sparse or remote from the panel.

The OK based ranking of SMU blocks can be further enhanced using suitable high-resolution geophysical techniques. Precision of geophysical methods is usually insufficient for a quantitative interpretation of the geophysical responses. However, it can be adequate for generating the relative grade distribution patterns of the SMU blocks in the panels which then can be used for the definition of the relative grade relationships between the SMU blocks.

CASE STUDY: CU-MINERALISATION

The proposed Localised Uniform Conditioning (LUC) methodology has been tested using data collected from an operating Cu mine (Fig. 4A). Due to confidentiality reasons the name of the mine is not disclosed and all sample grades have been multiplied by a constant.

The purpose of the case study was to reproduce using a broadly spaced drilling data the actual true grades of the SMU size blocks, which are 10 m × 10 m × 10 m, by applying the LUC approach. The true block grades are not known therefore, they had to be replaced by their best available estimates obtained using all the available samples. The central part of the deposit, chosen for the present case-study, contains 12,587 composited drill hole samples. All composites are 5 m long. Spatial distribution of composites varies between 10 m × 10 m × 5 m and 5 m × 5 m × 5 m (Fig. 4B). Using this nearly exhaustive dataset the grade of 10 m × 10 m × 10 m

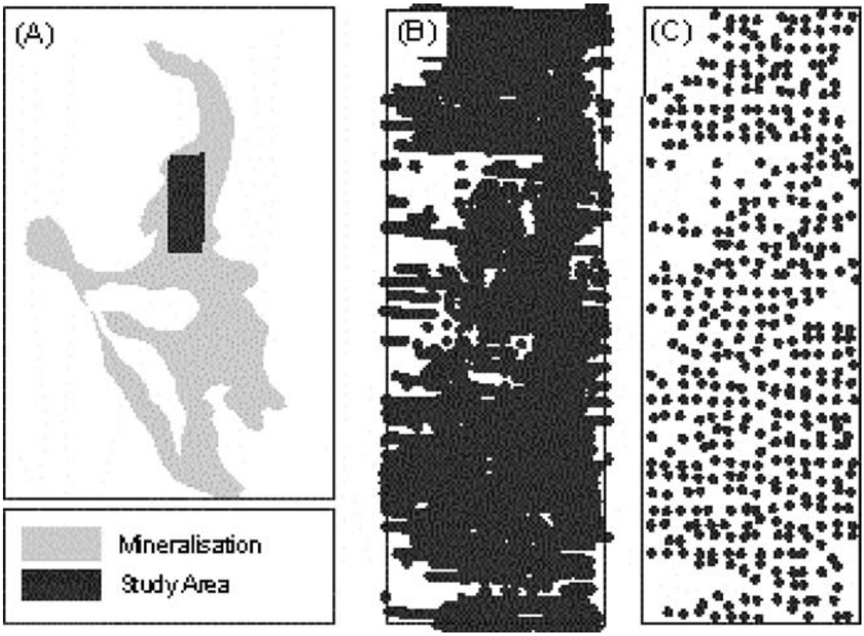


Figure 4. (A) Schematic map of the deposit showing location of the study area; (B) All samples (composites) distributed in the study area; (C) Subset of the data selected as one sample per 30 m × 30 m × 30 m block.

SMU size blocks have been estimated using OK technique. These kriged block grades represent the best available estimates of the SMU grades and therefore, for convenience they are referenced throughout this study as the "true" SMU grades.

The original database has been sub-sampled by selecting a single composite in each of the 30 m × 30 m × 30 m blocks (Fig. 4C). In total, this subset of the data contains 439 composites. The statistical parameters of this subset are similar to that of the original exhaustive dataset (Fig. 5) and given their equal spatial coverage, this subset of data is representative of the global grade for the study area.

Experimental variograms of Cu grade values distributed in the study area have been calculated using all the drill hole samples (Fig. 6A). The variograms exhibit a distinct directional anisotropy with direction of the main continuity being along 0°N representing the strike direction of the Cu mineralisation. Across the strike direction (90°E) is a semi-major axis of continuity. The largest variability (shortest range) occurs in the vertical down direction (D90). This experimental variogram has been best represented by a model containing nugget effect and three nested spherical structures (Fig. 6B). It is noteworthy that the relative nugget effect of this variogram, calculated as a ratio of nugget to the global sill, is approximately

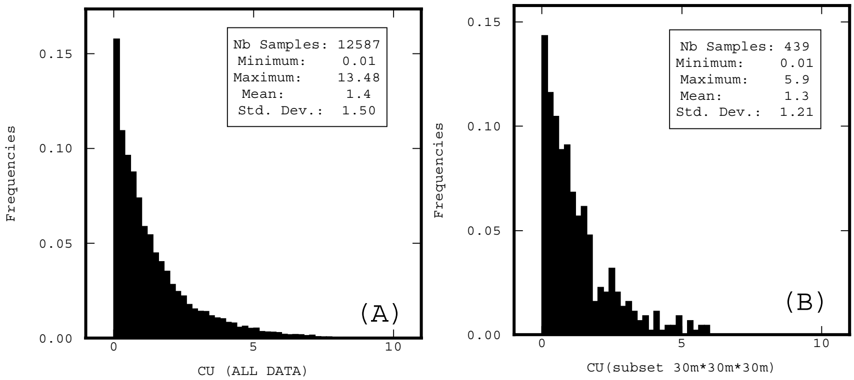


Figure 5. Histograms of the composited drill samples in the study area. (A) All data; (B) Subset of the data selected as one sample per 30 m × 30 m × 30 m block.

15% (Fig. 6B). This variogram model has been used further in this study for the block grade estimation using OK and UC techniques.

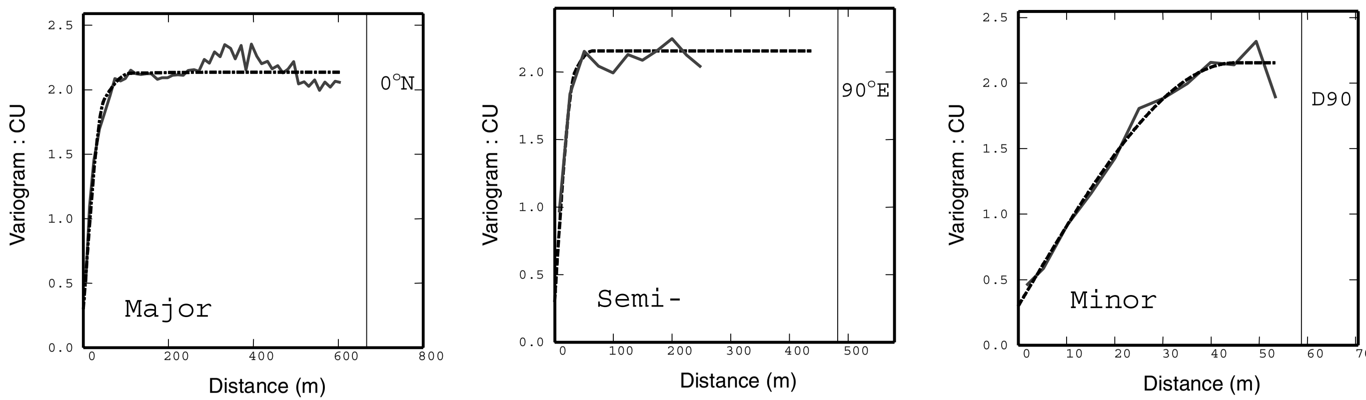
Firstly, the SMU grades were kriged (OK) using all available data. Distribution of the kriged SMU grades in the study area is shown on the map (Fig. 7A) representing a 10 m thick slice drawn through the block model. A histogram of the SMU grades is shown in Fig. 7B. For comparison, the same blocks were kriged using the data subset (Fig. 8). The same search neighbourhood was used in both estimates.

Global mean values of the two models are similar (Figs. 7B and 8B). However, the shapes of the histograms and the variances of the estimated block grades (Figs. 7B and 8B) are noticeably different. As it could be envisaged, the grade of the SMU size blocks kriged using sparsely distributed data (i.e. 30 m × 30 m × 30 m selection) are excessively smoothed in comparison with their 'true' grades.

Another striking difference between the two models is a spatial distribution of the ore grade (>2% Cu) mineralisation (Figs. 7A and 8A). Kriging of the SMU grades using broadly distributed data has created a distorted image of the spatial distribution of the ore grade blocks (Fig. 8A) which noticeably differ from the distribution pattern of the "true" ore grade blocks (Fig. 7A). In other words, an attempt to use the SMU grades obtained by kriging the sparsely distributed data, such as the 30 m × 30 m × 30 m selection, can lead to very inaccurate assumptions regarding the optimal mining scenarios.

The results presented in the Figures 7 and 8 are in good agreement with the well-known smoothing effect of kriging (Pan, 1998), which is particularly intense when kriging is applied to sparsely distributed data for interpolating them to inadequately small blocks (Armstrong and Champigny, 1989; Ravenscroft and Armstrong, 1990; Krige and Assibey-Bonsu, 2001).

(A)



(B)

Structure	Sill	RANGE Major	RANGE Semi-	RANGE Minor
Nugget	0.3			
Spherical 1	1.3	60	35	45
Spherical 2	0.54	150	65	45
Spherical 3	0.015	250	65	55

Figure 6. (A) Directional variograms of the Cu grades in the study area. Solid line—experimental variogram, dashed line—model; (B) Parameters of the variogram model.

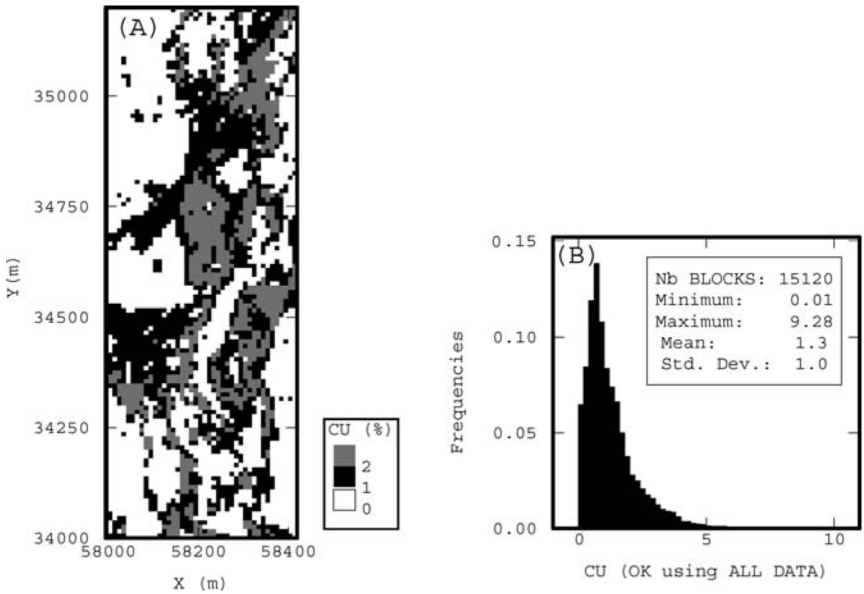


Figure 7. SMU grades estimated by Ordinary kriging technique using all data in the study area. (A) Map showing spatial distribution of the SMU grades in the study area (10 m thick slice through the model centred at −385 mRL); (B) Histogram of the SMU grades.

The recoverable resources were further modelled by the UC method using ISATIS®, which is a commercial geostatistical software (Bleines and others, 2001). The edge effect (Rivoirard, 1994) and a multiGaussianity (Goovaerts, 1997) assumptions, required by the UC method, have been checked and confirmed as parts of this study. A detailed description of tests used for checking these assumptions are described elsewhere (Abzalov and Humphreys, 2002a; Goovaerts, 1997).

The panel size was chosen as 30 m(X) × 30 m(Y) × 30 m(Z) as this grid assures the presence of at least one datum in each panel. One of the underlying conditions for application of the UC technique is a robust estimate of the panel grades. Block by block comparison of the kriged grades with their 'true' grades shows a good correlation between these two values (Fig. 9) with no conditional biases. Therefore, application of UC method to the kriged 30 m(X) × 30 m(Y) × 30 m(Z) panels is warranted.

Accurate modelling of grade–tonnage relationships using non-linear geostatistical change-of-support techniques, including the UC method, requires a correction for an information effect. A procedure of correcting for insufficient information (information effect) is explained in (Bleines and others, 2001) and it was followed in this study.

Grade–tonnage relationships modelled by the UC method have been plotted (Fig. 10) together with the grade–tonnage curve derived from the SMU grades

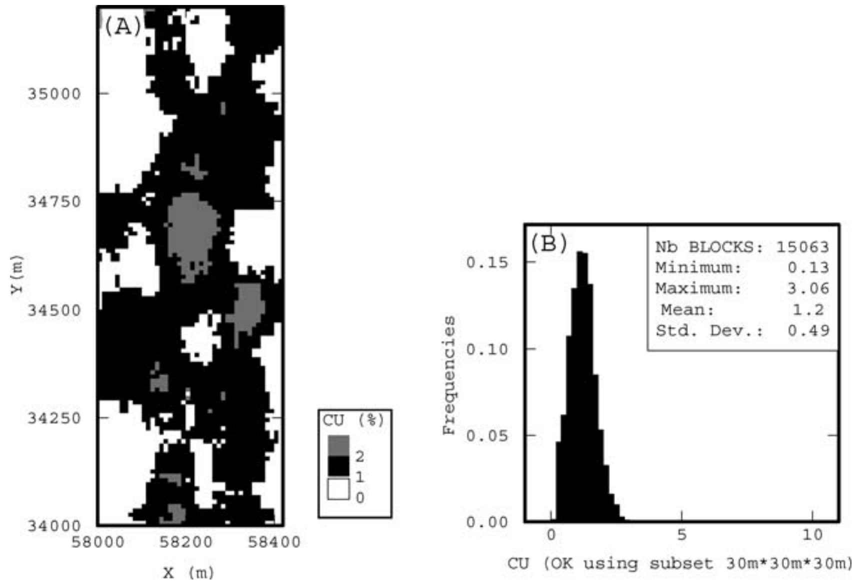


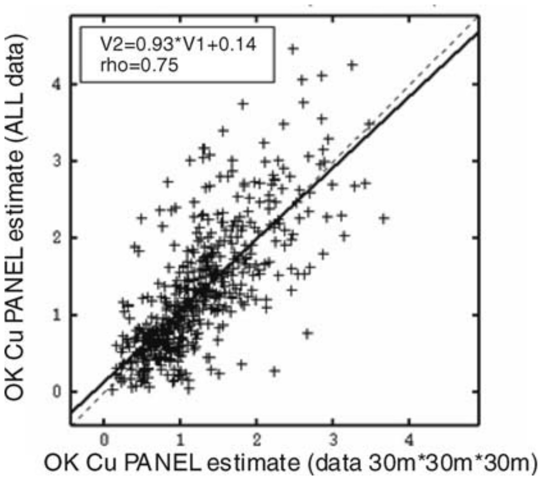
Figure 8. SMU grades estimated by Ordinary kriging technique applied to the sparsely distributed data subset. The data nodes are distributed as 30 m × 30 m × 30 m random stratified grid in the study area. (A) Map showing spatial distribution of the SMU grades in the study area (the same area as on the Fig. 7); (B) Histogram of the SMU grades.

kriged from a sparse (30 m × 30 m × 30 m) data grid and also with the grade–tonnage relationships of the 'true' SMU grades. It is obvious that the grade–tonnage relationships modelled by UC method are close to that of the 'true' SMU grades and both noticeably differ from the kriged grades of the sparsely distributed data. Thus, the UC model represents a significant improvement in comparison with the SMU grades without conditioning, obtained by kriging of the sparsely distributed data (Fig. 10).

Finally, localisation of the UC results by the LUC technique has been implemented (Fig. 11). In other words, all SMU blocks have been ranked in each panel. The grades of the SMU ranks (i.e. grade classes) have been derived from the UC model and then assigned to the corresponding SMU blocks (Fig. 2).

Grade–tonnage relationships obtained by LUC method are practically the same as the UC model results (Fig. 10). The good match between the grade–tonnage diagrams derived from UC and LUC models is natural as the LUC algorithm simply localises the UC results maintaining the grade–tonnage relationships predicted by conventional UC model.

The histogram of the SMU grades estimated by LUC method (Fig. 11B) has the same shape as the histogram of the 'true' SMU grades (Fig. 7B). Dispersion



Summary statistics of the OK Cu PANEL estimates:

(using data 30m x30mx 30m)
mean = 1.2
St.Dev = 0.6
min = 0.1
max = 3.6

(using ALL data)
mean = 1.2
St.Dev = 0.8
min = 0.02
max = 4.5

Figure 9. Estimated (OK method) Cu grades of the panels (30 m × 30 m × 30 m blocks). Estimates obtained using all available data vs. estimates obtained using data subset (30 m × 30 m × 30 m random stratified grid). Solid line denotes linear regression between these two estimates, their 1:1 relationships (dashed line) is also shown for a reference.

variance of the SMU grades (Fig. 11B) modelled by LUC method (SD = 0.88) is lower, but reasonably close to their 'true' grade variance (SD = 1.0) and significantly larger than the variance of the SMU grades (SD = 0.49) obtained by their direct kriging from a sparse data grid (Fig. 8B).

Given the fact that the LUC model closely reproduces the actual histogram of the SMU supported grades, it provides a significantly better estimate of the recoverable resources at the given economic cut-offs than SMU grades directly kriged from the sparse data grid (Fig. 10).

The improvement obtained by the LUC method is because it accounts for the spatial distribution of the recoverable mineralisation. Distribution of the SMU grades estimated by LUC technique is shown on the map (Fig. 11A). This represents the same 10 m thick slice through the block model which has been used in Figures 7A and 8A displaying the SMU Ordinary Kriging grades. Comparison of the different models shows that LUC model (Fig. 11A) has better reproduced the true spatial distribution pattern of the ore grade (>2% Cu) SMU blocks (Fig. 7A) than the OK method applied to this sparsely distributed data (Fig. 8A). In comparison with the SMU grades directly kriged from sparsely distributed data, the LUC method represents a significant improvement in resolution of the local resource model. These findings suggest that LUC method can be a very useful tool during the early stages of a mining project evaluation, when sparsely distributed data is usually the only information available.

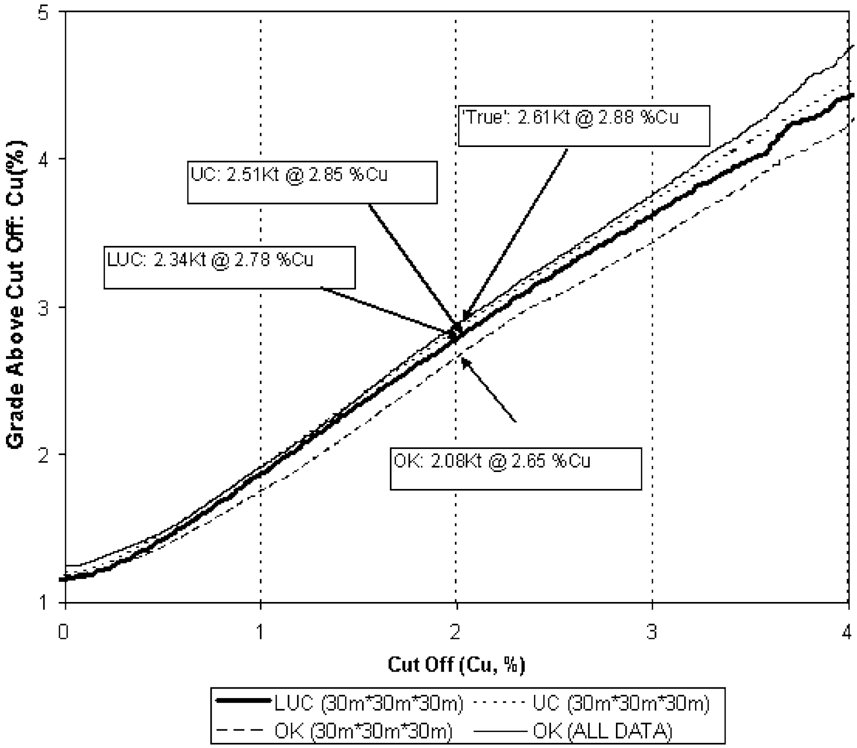


Figure 10. Recovered SMU Grades (above cut-off) vs. Cut-Off relationships estimated by OK, UC and LUC techniques applied to the sparsely distributed data subset (i.e. 30 m × 30 m × 30 m random stratified grid). Inserts show the different estimates of the tonnage and grade of the ore grade (≥2% Cu) mineralisation.

It is important to note that results obtained by the LUC method (Fig. 11A) still noticeably differ from the actual grade distribution pattern (Fig. 7A). This difference clearly shows limitations of the LUC method which cannot exactly reproduce an actual SMU grades despite a noticeable improvement in comparison with directly kriged SMU grade estimates.

Accuracy of spatial distribution of the SMU grades modelled by LUC method depend on the ability to accurately reconstruct the SMU grade ranks from the limited information available. Our preliminary tests show that direct kriging of the SMU grades can produce a reasonable spatial distribution pattern of the grade values in case of a continuous mineralisation, characterised by a low nugget effect, such as disseminated base-metal sulphides, bauxites and iron-oxide deposits. SMU ranking can be further improved by the use of additional auxiliary information, such as semi-quantitative high-resolution geophysical data. In that case, the proposed LUC approach can be considered an alternative technique to the

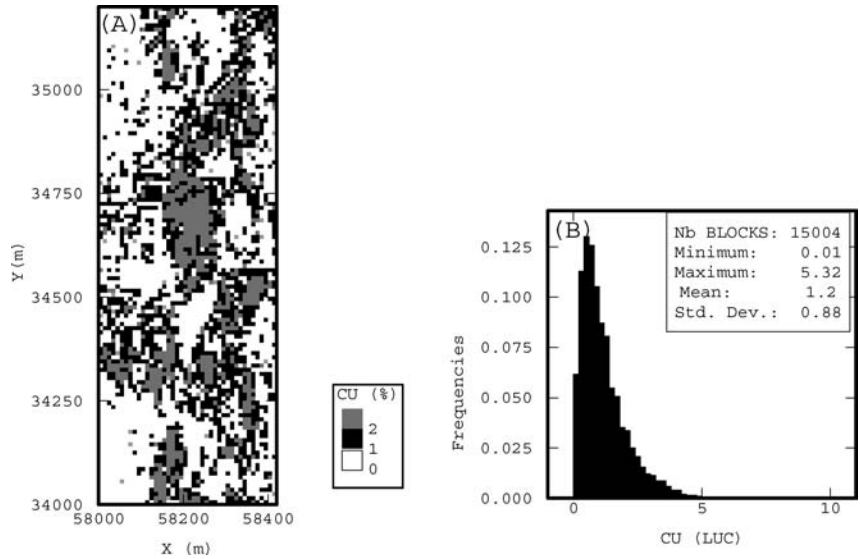


Figure 11. SMU grades estimated by LUC technique applied to the sparsely distributed data subset (i.e. 30 m × 30 m × 30 m random stratified grid). (A) Map showing spatial distribution of the SMU grades in the study area (the same area as on the Fig. 7); (B) Histogram of the SMU grades.

far more routinely used methods of the co-kriging family. Implementation of the LUC method is less time consuming, and does not require a robust cross-variogram between the target and auxiliary variables.

SUMMARY AND CONCLUSIONS

The proposed LUC approach is based on ranking of the SMU blocks in increasing order of their grade, and then assigning the mean grade of a grade class of a UC model to the SMU blocks whose ranks match to a grade class. LUC approximates the grade distribution patterns within the panels by direct kriging SMU from the sparse data grid. This approach arrives at localised SMU estimates conforming to the proper grade–tonnage curves obtained by the UC method, as well as maintaining the relative SMU grade pattern indicated by their direct OK estimates.

It must be stressed that the validity of LUC approach for this case study, and in general, depends heavily on the extent to which the available data enables meaningful patterns of SMU grade estimates to be realised within each panel. The results are dependent essentially on the data available for ranking the SMU within a panel in their grade increasing order. Ordinary Kriging estimates of the SMU can be used for their ranking, providing the kriged estimates produce a meaningful indication of the relative grade pattern within the panel. Accuracy of the SMU ranking can be further improved by using additional information, such as high-resolution geophysical data.

Where the data is sparse and not close to a panel, or their distribution is characterised by a strong short-range variability, there could be less of a meaningful pattern than that covered in the case study presented and consequently the advantages of using the LUC approach are more limited.

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