Improving Reconciliation and Grade Control by Statistical and Geostatistical Analysis

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Introduction

Accurate recoverable resource estimation and grade control procedures are the foundation of successful mining ventures. Long, medium and short term planning in a mining operation are all dependent upon precise estimations. For example, poor estimation may result in the long term in a pit being incorrectly optimised, in the medium term cash-flow forecasts may be disastrously inaccurate, and in the short term the allocation of ore and waste material by grade control may be erroneous. Many open pit gold mines in Australia suffer from a lack of reconciliation between exploration and in-pit estimates and actual head grades delivered to the mill. This is often despite very good grade control sampling and geological control. Often correction factors are applied to the resource model and grade control estimates in order to approximate reconciliation with production figures. Some of the main reasons for erroneous estimation are the failure to account for one or many of the following:

— the statistical distribution of the sample data,
— the spatial continuity of the sample data,
— the regression-effect and the volume-variance relationship,
— the degree of mining selectivity (*ie.,* dilution) that is practised, and
— the selection of an appropriate estimation method to calculate recoverable tonnes and grade.

Statistical and geostatistical analysis and modelling procedures are capable of investigating and overcoming the problems listed above. It must be emphasised that if there is a sampling bias present, in either the exploration, grade-control or production data, then no method will arrive at the correct answer without correction, or otherwise by chance.

This paper presents the steps involved in improving orebody/grade control modelling and reconciliation and highlights the modelling and reconciliation benefits that a geostatistical approach can give to a mining operation. For this purpose a case study is presented from a typical Western Australian open pit gold mine.

The frequency distribution of sample data

The frequency distribution of sample grades will determine the method used to calculate the average grade of a population of data. The arithmetic mean of normally distributed data will give the average grade, but unfortunately normal distributions are very rare amongst mineralized phenomena. Examples of orebodies with a normal data distribution include some massive copper or manganese deposits. It is more common for sample grades to correspond to a skewed distribution. The arithmetic average of a positively skewed distribution will overestimate the average grade (*e.g.,* lognormally distributed gold mineralisation) and underestimate it if negatively skewed (*e.g.,* iron ore). Positively skewed distributions are common amongst precious metals, base metals, mineral sands and contaminants (*e.g.,* phosphorous in iron ore). The lognormal distribution is characterised by the property that the logarithms of the sample values correspond to a normal distribution. Most observations are small compared to the mean, but a few are very large. A distribution may be positively skewed, but not exactly lognormal, in which case it may be termed mixed-lognormal or pseudo lognormal. In such cases it may be possible to ad a constant to the values of the distribution in order to normalise their natural logarithms. This is known as a three parameter lognormal distribution [*i.e.,* $\log_n$ (value + α) is normally distributed] and is common in stratabound gold deposits of gold accumulation values across a reef of variable width. The failure to separate distinct geological/mineralogical domains may result in a bimodal mixed grade distribution.

Figure 1 displays a histogram of the logarithms of a bench of gold grade control data. Note the normal distribution of the logarithms of the sample values, demonstrating their lognormality. Separate "unmineralised" and "high grade/outlier" sub-populations are visible on either side of the histogram. Figure 2 displays a logarithmic cumulative frequency diagram of the same data. The majority of the data corresponds to a straight line representing a single lognormal population between points A and B. At point A the deflection in this straight line is interpreted as the boundary between the "unmineralized" and "mineralized" sub-populations and is referred to as the mineralization indicator grade. This value is typically between 0.05 and 0.3 g/t in gold deposits. The deflection at point B represents the boundary between the "mineralized" and the "high grade/outlier" sub-

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Vivienne majored in mathematics and geology at the University of Rhodesia in 1970, then worked in applied experimental statistics for five years and lectured in finance and statistics for a year. After completing her Honours and Masters degree in geology at Rhodes University, in 1981 she joined the operations research department of Anglo American Corporation, South Africa. Since 1986 she has been based in Perth, consulting to the minerals industry in the field of resource management.

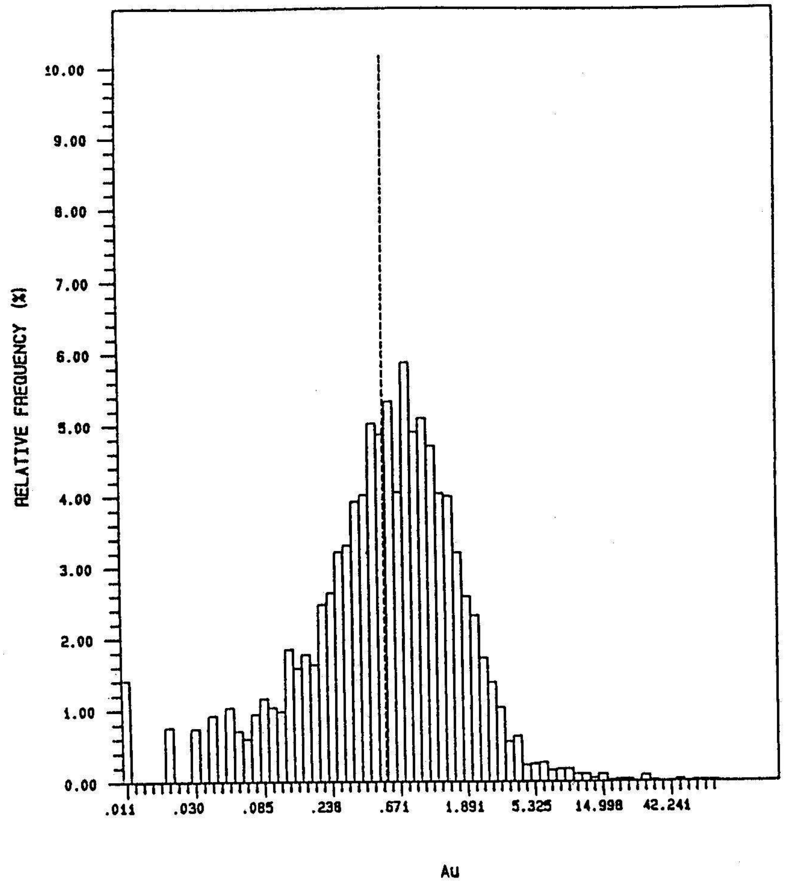

FIGURE 1 Logarithmic histogram of grade control data for gold.

populations. The presence of the latter sub-population may typically be accentuated by assay bias at higher grades.

Negatively skewed distributions are characterised by those where the metal values are mostly very high, with much fewer low values. Iron ore is typically distributed in this fashion and may be converted to equal or approximate a normal distribution by taking the logarithm of (maximum Fe value – Fe value). In this way the tendency to under-estimate the average grade is removed and an unbiased estimate should result after conversion back to a normalised value.

Sichel's 't' estimate (the "Sichel Mean") is the best estimator of the mean of a lognormal distribution. It may be used to arrive at a suitable assay cutting value for high grades in order to avoid overestimation when the arithmetic mean is used.

The Sichel mean = geometric mean * f (V, n),
Where f (V, n) is Sichel's tabulated 't' factor,
V = sample variance, and
N = sample size.

The geometric mean is the antilog of the mean of the logs. For three parameter lognormal distributions:

the Sichel mean = {(geometric mean + α) * f (V, n)} – α,
where α is the third parameter constant.

Therefore by experimentation it is possible to apply a progressively more severe high grade cut until the cut arithmetic mean of a lognormal distribution equals the uncut Sichel mean, in order to arrive at a suitable high grade cut for the sample data.

Semivariogram analysis

One of the most useful tools available to development and mine geologists is the semivariogram. It is a graph of the *variability* between pairs of samples against the *distance* (or lag) between them in a specific direction (Figure 3). It is capable of quantifying the range of influence and direction of geological/mineralogical continuity and as such can be used to investigate and support geological interpretation. Semivariogram analysis is based on the theory of regionalised variables developed by Matheron in the early 1960s. The technique is applicable to any spatially correlated data set, that is, for sample values where the closer spaced samples are likely to be less variable than samples which are spaced further apart.

The semivariogram value for sample pairs at a certain distance (n) apart is half of the average squared difference between grades at this distance.

$\gamma(h) = (1/(2\ n))\ \Sigma(X_i - X_{i+n})^2$ (absolute semivariogram),
where h = lag between members of a sample pair,
X_i = grade of first member,
X_{i+n} = grade of second member, and
n = number of pairs.

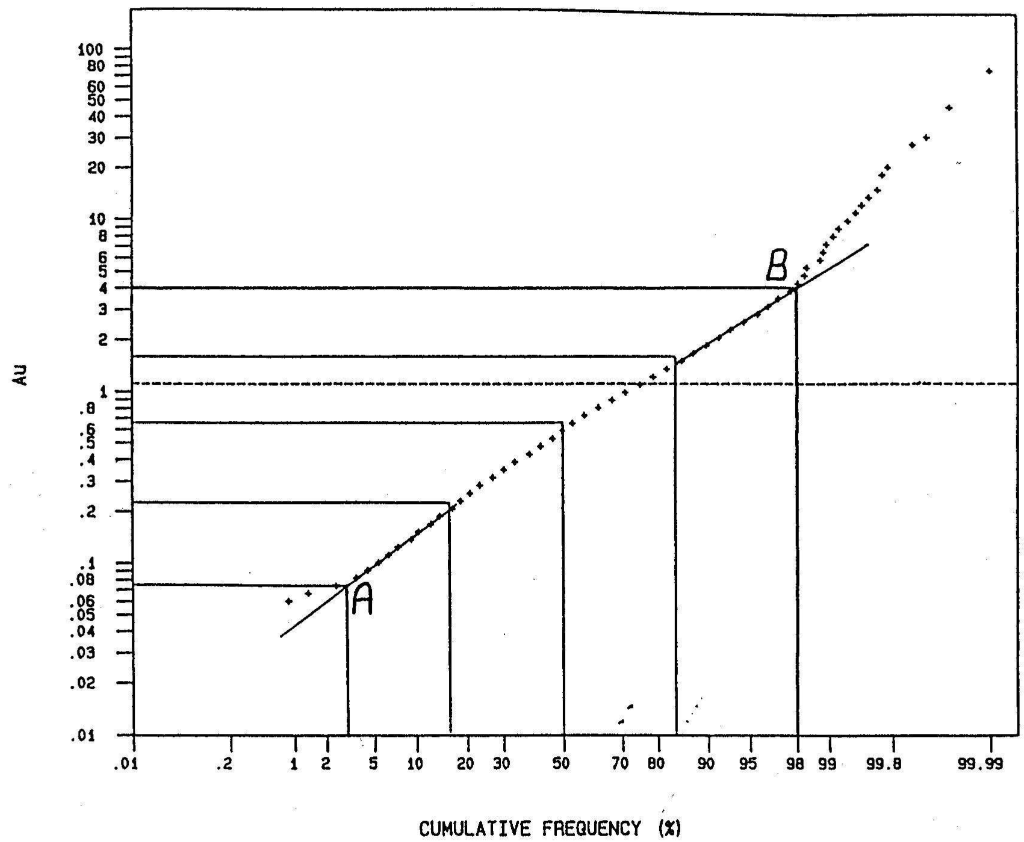

FIGURE 2 Logarithmic cumulative frequency diagram of gold control data for gold.

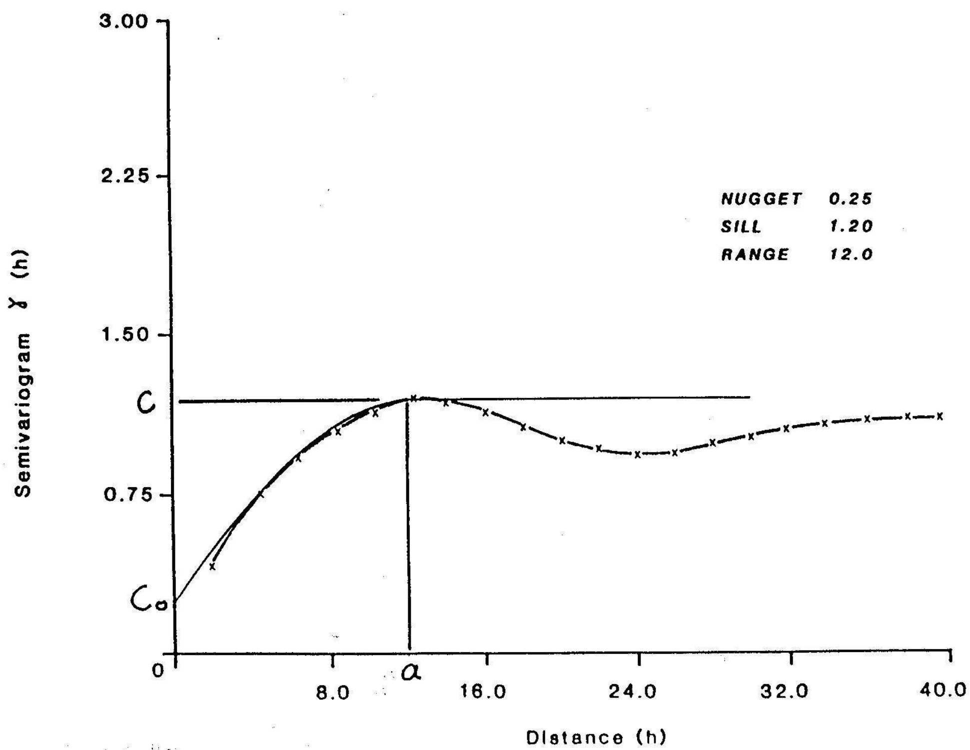

FIGURE 3 Across-strike variogram.

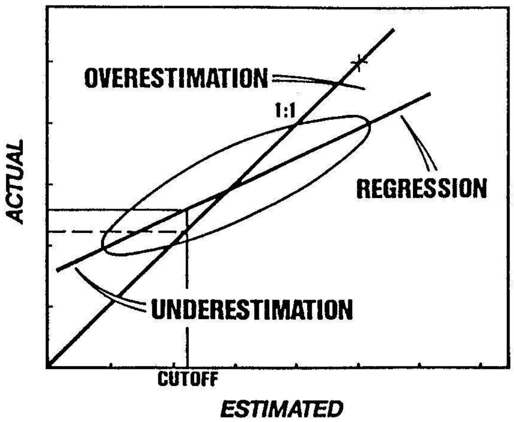

FIGURE 4 Illustration of the regression effect.

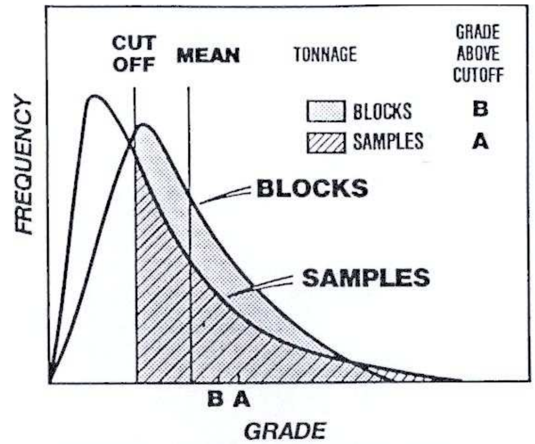

FIGURE 5 Illustration of the volume-variance relationship.

Semivariograms are calculated for specific geological or structural directions (*e.g.,* down dip, down plunge, horizontal strike, perpendicular to strike, *etc.*). The quality of the experimental semivariogram may be improved by its calculation using only data above the mineralisation indicator grade and/or below the high grade/outlier boundary. This results in the definition of semivariogram parameters for only the mineralized material, that is, the continuity of mineralization rather than the continuity of unmineralized material or of abnormally variable mineralization.

When h is equal to zero, that is, the two samples that are compared have exactly coincident location, the variability between them may not be equal to zero. A practical example of this is the difference in assay values that can be expected from two halves of an equal length of diamond drill core. The presence of variability between samples at or very close to zero distance apart is termed the *nugget effect* (Co). This inherent variability is most serious where there are very small scale structures such as coarse gold or small scale veining. The nugget effect is very important in the evaluation of precious metal deposits, but it should be noted that sampling or assaying error may make a significant contribution to its magnitude. The more massive orebodies tend to have a very low nugget effect (*i.e.,* iron ore), where there is a high degree of reproducibility between immediately adjacent samples. The best estimate of the nugget effect is usually obtained from a semivariogram calculated in the direction of closest sample spacing, that is, the down hole/ along drive direction when using exploration data or in the blast hole line/ditch witch trench direction during grade control.

As the distance between samples increases, the semivariogram value rises until it levels off at what is known as the *sill* value (C). This is the distance at which samples are no longer spatially correlated and is known as the *range of influence* (a). More than one sill value may be present, in which case a semivariogram is defined with so called *nested structures.* The first sill (short range structure) defines a range of influence up to which the variance between samples may rise very rapidly with increasing distance (C_1 and a_1). Beyond a_1 the variability may increase less rapidly with distance until the longer range structure is defined at the point where samples are no longer spatially related (C_2 and a_2). Values of C and a are defined for each experimental semivariogram by fitting a theoretical model to the semivariogram trace. A *spherical* model is found most commonly to fit experimental semivariograms, but exponential, Gaussian and linear models may also be appropriate.

Logarithmic variograms may be calculated for negatively skewed data. The method of calculation is the same as for the absolute variogram, except the data is first transformed to the log values. Logarithmic variograms are far less sensitive to data outliers and therefore the resultant variograms are much more robust.

In summary, the semivariogram allows the geologist to investigate and quantify the spatial variability of the mineralisation that is being evaluated or mined. The quality of semivariograms and the parameters that they define allow informed decisions to be made on the sample spacing required to investigate the mineralisation. In this way over or under sampling of the orebody may be prevented. By defining the range of influence and the change in variance with distance for specific directions, parameters may be selected to allow more sophisticated and meaningful grade interpolation to ease the degree of manual intervention and decision making in defining ore/waste boundaries.

The regression effect and the volume-variance relationship

The regression effect is the term applied to the phenomenon of exploration or grade control sampling underestimating the actual grades that are mined in low grade areas and overestimating the head grade produced from high grade areas. This is because real mining units have a different distribution of average grades than the distribution of sample grades. Figure 4 illustrates this effect with the ellipse defined by the scatter of points when sample values are plotted against corresponding actual block values. A regression line may be drawn through the ellipse which does not define a 1:1 relationship between sample and block grades. Thus a cutoff applied to sample grades may be equivalent to a different effective cutoff on production grades. For example in the context of an open pit gold mine, the application of a nominal 1.0 g/t Au cutoff to blast hole samples used to design polygonal ore outlines may result in an effective production cutoff of 1.2 g/t Au. Therefore if the economic cutoff of the deposit at a particular time is 1.0 g/t Au, a significant quantity of profitable material may be allocated to waste because of the imposition of an effective production cutoff of 1.2 g/t Au. Similarly, in an iron ore mine, the selection of saleable ore by interpolation of blast hole assays of contaminant such as phosphorous or silica may result in a higher effective production cutoff being placed on the contaminants than is required, the result of which would be the misallocation of some of the saleable material to the waste dumps.

The regression effect is caused by the change in variance of a data set according to the degree of support (or volume) of the data. Therefore a population of sample grades will have a higher variance than a population of mining block grades. Similarly larger blocks will have a lower variance than smaller blocks. Figure 5 displays combined frequency diagrams of sample grades and block grades from a hypothetical orebody. This diagram demonstrates that if the cutoff grade is below the mean grade of the orebody, the distribution of blocks will define a greater tonnage at a lower average grade than the distribution of samples. The opposite is true if the cutoff grade is higher than the mean grade. This phenomenon is known as the volume-variance relationship. This relationship explains why it is important to standardise the support of exploration and grade control sampling that are combined for statistical and geostatistical analysis. For example if the total data set available for the evaluation of an orebody consisted of 50 reverse circulation drill holes with samples taken at 2 m intervals, and 50 diamond drill holes with samples taken at 0.5 m or smaller intervals, the diamond drill hole samples can be expected to have a higher variance than the reverse circulation drill hole samples because of the variation in support of the two sample sets. Therefore in order to be able to combine the data for analysis, the diamond drill holes have to be composited into 2 m sample lengths.

Mining selectivity

There is more than one way to mine an orebody depending upon the degree of selectivity that is to be practised. The objective of selective mining is to reduce the amount of dilution by waste of the valuable ore material. The controls on selective mining include the following critical parameters:

- the geological or structural complexity of the orebody,
- the cutoff grade that is used,
- the degree of continuity of ore material above the cut- off grade,
- the size and accuracy of mining equipment, and
- the required production rate.

These controls are used in the selection of a selective mining unit (SMU) which represents the minimum resolution capable of being mined. The selection of a large SMU in a structurally complex orebody will result in greater internal and external dilution. The volume-variance relationship has demonstrated that cutoff grades should be placed on SMUs and not sample grades, as SMU grades represent fully diluted estimates that are capable of being recovered. The degree of continuity of the mineralisation will increase with a decrease in cutoff grade. Therefore the selection of the SMU size is related to the operational cutoff that is chosen. For example in a highly variable gold stockwork orebody the selection of a 1.5 g/t cutoff would require a much small SMU than a high volume/low grade operation at a 0.7 g/t cutoff. Similarly if in such an operation it is intended to mine highly selectively above a 1.5 g/t cutoff in order to produce a reasonable head grade, the size of the equipment used may set a restriction on the maximum output of the operation.

Estimating the recoverable tonnes and grade

A recoverable resource/reserve estimate represents the tonnes and grade which can actually be mined above a cutoff set on SMU grades. The calculation of the recoverable tonnes and grade from a bench of grade control data is a relatively straight forward procedure:

- there is a large amount of closely spaced data, and consequently statistical and semivariogram analysis will provide very robust parameters; and
- grades may be estimated for SMU size blocks without severe computational overheads.

In order to calculate estimated grades for each block in the bench, a suitable estimation method has to be chosen. Most people who read this paper will be familiar with the inverse distance weighting method (IDW). With IDW the estimate for the average grade of a block is a weighted average of sample grades in and around the block, with the weight of any given sample inversely proportional to the distance to the power n, between the sample and the centre of the block. Generally a search ellipse is chosen to define those samples to be used in the estimation of the grade of each block, which is shaped according to the geometric anisotropy of the mineralization. This ellipse may of course be provided by the ranges of influence defined from semivariograms calculated in the main structural directions. The selection of the power n is somewhat arbitrary and usually bears little resemblance to the change in variance of the mineralization with distance in each direction as defined by the semivariograms. Some people use just the inverse of the distance, others the inverse squared or cubed. Beyond n = 3 the value of the estimate becomes very similar to a polygonal approach.

Kriging is a distance weighted estimate of the block grade from the surrounding samples. Unlike IDW, the weight of each sample is a function of the distance and orientation from the centre of the block and is defined by the shape of semivariogram models. The advantages of the kriging estimate are that it is unbiased and has the minimum variance. The assumption is made that stationarity of grades exists, that is, the mean grade of the data values is the same as the mean grade of the sample values.

There are a number of different kriging methods available and selection of a suitable estimator should be made according to the distribution of sample data and the robustness of semivariogram parameters. Normally distributed samples may be modelled with *ordinary kriging* using absolute semivariogram parameters.

If the sample data corresponds to a lognormal distribution and logarithmic semivariograms have been calculated, there are two methods available. For the first method the logarithmic semivariogram parameters may be transformed into absolute semivariogram parameters and block estimations may be made using the transformed parameters with ordinary kriging. This has been termed *pseudo-lognormal kriging*. The formula for the transformation is:

$$V(h) = \mu^2 \exp(V^2) \times \{1.0 - \exp[-V_1(h)]\},$$

where $V_1(h)$ is the log variogram,
$V(h)$ is the absolute variogram,
V^2 is the sill of the log variogram, and,
μ is the mean grade of the deposit.

This transformation tends to enhance the relative magnitude of the nugget effect or short range structures, as a function of the size of V^2.

The other alternative is to do *lognormal kriging* where the estimator is obtained by using ordinary kriging of the log-transformed sample data with the lognormal variogram model. The exponent of the log value is then taken and multiplied by a correction factor greater than 1.0. The correction factor is calculated using the kriging variance of the log values and the log variogram. It is therefore important to note that the accuracy of the lognormal variogram model has a direct effect on the final estimate. If the sill of the lognormal variogram is under or over-estimated by X%, the estimate will also be under- or over-estimated by a similar amount. Ordinary kriging or pseudo-lognormal kriging do not suffer from this sensitivity to the variogram sill, but lognormal kriging is much less influenced by outlier values.

Therefore in conclusion, if lognormal variograms are robust and without significant zonal anisotropy (the semivariogram sill changes in different directions), and outliers are present in the distribution (as is often the case in precious metal orebodies), then lognormal kriging may be used.

From the experience of the authors it has been observed that the use of lognormal kriging when modelling a bench of gold grade control data into SMU size blocks will provide the sharpest boundaries between what is clearly ore and waste. That is to say, there is less smoothing and ore outlines may be accurately defined. A general order of decreasing smoothing across such boundaries according to the chosen estimator may be defined as:

IDW* >> ordinary kriging >> pseudo-lognormal kriging >> lognormal kriging
* depending on power chosen

To establish the recoverable tonnes and grade within SMU size blocks for the whole orebody may be more difficult. Even if the orebody is adequately sampled, and robust variograms have been defined, the use of SMU size blocks may result in:

— unacceptably high estimation variances for the block values
— impractical computing overheads

An alternative approach is to use larger blocks that overcome the difficulties given above (so called *bulk blocks*). The selection of the block size is related to the sample spacing. From what we know of the regression effect and the volume variance relationship, kriged bulk block values can be expected to have a different distribution and lower variance than kriged SMU values. Consequently, a resource calculation based on bulk blocks may be expected to define a different estimate of tonnes and grade above a specific cutoff, than that which is actually recoverable using the SMU.

In order to be able to predict the recoverable tonnes and grade above a specific cutoff from bulk blocks, a technique has been defined that uses a recovery function to predict what is recoverable using a specific SMU size. This rationale proposed by David (1977) is the so called *lognormal shortcut*.

The lognormal shortcut uses the concept of SMUs within bulk kriged blocks that have the same lognormal grade distribution (similarly, the *normal shortcut* assumes a normal distribution). The mean of the distribution is the value of the bulk kriged block. The variance of the distribution is *dispersion variance*, which is defined thus:

$$\sigma^2(\text{SMU/Bulk Block}) = \sigma^2(\text{point in bulk block}) - \sigma^2(\text{point in SMU})$$

The semivariogram model is used during the calculation of the point variances for the bulk block and the SMU. Therefore, combining the kriging variance of the kriged bulk block with the dispersion variance and the kriged average grade, will represent the distribution of the SMUs within the bulk block. The probability is then calculated of the proportion of SMUs above the specified cutoff and the selective grade above this cutoff. Similarly the proportion and grade of waste material may also be realised.

The lognormal shortcut technique therefore uses a probabilistic estimate of the grade and proportion of SMUs above the specified cutoff to estimate the recoverable tonnes and grade.If the size of the SMU is changed a new dispersion variance may be calculated and the recoverable tonnes and grade at this new level of mining selectivity may be estimated. For example the change in recoverable reserves may be investigated if it is proposed to change the size of mining equipment.

It must be remembered that it is usually the case that only bulk blocks inside or peripheral to the main ore zone will contain material that will be mined. Therefore in order to obtain a meaningful estimate of what is truly recoverable one must have an idea of which bulk blocks will form the mineable area, that is, the area that will be subject to grade control.

Therefore the selection of bulk blocks for use with the lognormal shortcut technique may be made by the subdividing of the bulk block model, including, say, only those above a certain grade (0.5 g/t Au for example), or within a digitised envelope.

The lognormal shortcut estimate will provide a theoretical maximum recoverable tonnes and grade using the parameters that are provided (*i.e.*, ideal selectivity). In practice the production of a mining operation will be somewhere between the bulk and selective estimate depending on the success achieved in the selective mining. In a carefully controlled mining operation the actual production will be much closer to the selective estimate than the bulk and may even equal it, depending upon the nature of the orebody.

Indicator kriging (Journel, 1982) is another method that may be used to estimate recoverable tonnes and grade. It is especially useful in addressing orebodies with complex distributions as the assignment of ore proportions above indicator grades is distribution independent. An indicator cutoff grade is chosen and all samples above this indicator are set to 1's, and the grades below to 0's. Semivariograms are calculated for the 0's and 1's and these are then kriged. The resulting block values represent the probability (or percentage) of that block that would be above the indicator cutoff grade and hence this represents the recoverable tonnage within a block. The grade of the portion of the block above the cutoff is the arithmetic mean of the sample grades within this indicator category. This procedure may be repeated at numerous indicator grades with proportions and average grade calculated for each indicator bin. This method has been refined by the use of *nested* (or relative) indicators where indicator values for a given cutoff are only defined for samples above the previous cutoff. If twenty indicators are defined to model the orebody, then twenty sets of variograms must be defined, and twenty kriging operations completed. Consequently the time and computational overheads may be significant.

Other more elaborate methods for the estimation of recoverable tonnes and grade include *disjunctive kriging* (Marechal, 1975) and *multigaussian kriging* (Verly and Sullivan, 1985), which both involve the normalisation of sample data. *Probability kriging* (Kim *et al.,* 1987) and *rank order kriging* (Francois-Bongarcon, 1986) are two further estimators that involve conversion of data to rank order transforms, that is, samples are sorted by increasing grade and assigned their respective cumulative frequencies.

Reconciliation and the grade/tonnage relationship

It is possible to explain many reconciliation anomalies by the regression effect and the volume-variance relationship. The classification of ore and waste during mining is sensitive to whether the cutoff grade is based on sample grades or on recoverable block grades. This is due to the regression effect and results in some real waste blocks being falsely classified as ore and some real ore blocks being discarded as waste. Therefore in order to improve this misclassification error, ore and waste should be classified according to recoverable block estimates. This will lead to a reduction in the variance of estimation and hence to less potential misclassification.

When attempting to reconcile exploration estimates with grade control estimates and finally with true head grades and production tonnages, it is important to understand the grade tonnage relationship. For example, considering a hypothetical orebody represented by a bulk kriged block model, if the tonnage estimates are plotted against the estimated grade for various cutoffs, the resulting curve is called a *grade/tonnage diagram*. This will illustrate the relationship between tonnes and grade at different cutoffs. If a more selective estimate for the same deposit is plotted on the grade/tonnage diagram the resulting curve will be above the bulk block curve and will demonstrate the change in tonnes and grade estimated for each cutoff. With increasing selectivity tonnes may either decrease, stay the same or increase, and grade will stay the same or more likely increase. Therefore a line joining a specific cutoff on the bulk curve to the same cutoff on the selective curve will indicate the direction of change in tonnes and grade with increasing selectivity for this cutoff.

For example at a high cutoff, both tonnes and grade may increase with greater selectivity while at a low cutoff the grade may rise while the tonnage falls. It is then possible to plot on the same figure the estimates derived from comparable grade control data, either by manual allocation of blasthole assays or by kriging. In this way the difference between blasthole and SMU size estimates may be compared in order to ascertain the effective mining cutoff and these estimates may be reconciled with bulk and selective exploration models. Finally real production data may be plotted on the diagram in order to investigate how robust the models are and what level of selectivity is actually being achieved.

A thorough reconciliation in this manner, carried out using carefully calculated and at all times comparable data, may provide the following valuable information on the operation.

(i) The selective resource model may (if required) be modified to reconcile with production data. Consequently, optimisation may be carried out on a model that accurately predicts the recoverable tonnes and grade.

(ii) Grade control cutoffs and interpolation methods may be modified in order to arrive at a procedure that accurately defines coherent ore zones using recoverable SMU block cutoffs, that is, the regression effect is minimised and misclassification errors are reduced.

It is of paramount importance to compare “like with like” when attempting to reconcile any aspect of a mining operation. The use of incomparable estimates and assumptions will result in spurious results. Therefore initial difficulties in obtaining satisfactory reconciliation may require that all critical estimates and parameters are reviewed to account for possible error. Sampling bias is by far the greatest problem and can be investigated by reference to the final metallurgical balance of the operation. Where multiple pits are feeding a single mill, the processing of test parcels from each deposit may be required in order to investigate reconciliation difficulties. The effort involved can be very worthwhile if it leads to the meaningful optimisation of each deposit and the imposition of relevant cutoff grades.

It is obviously preferable to carry out much of this work at the feasibility stage or early in the life of the deposit. If this is done, correction may be made to the pit design before it becomes impractical to do so, and the wastage of ore by misclassification will be rapidly addressed. The following example presents a reconciliation study for a typical, shear zone hosted Western Australian, open pit gold mine.

A Western Australian open pit gold mine

Setting

Steeply dipping tabular gold deposit in greenstone hosted shear zone.

Resource model

Exploration data	370 reverse circulation drillholes sampled at 1 m intervals. About 5000 samples.
Software	Geostat Systems International and Micromine.
Statistics	Lognormally distributed above a mineralisation indicator grade of 0.10 g/t Au. Mean grade above 0.1 g/t Au is 1.33 g/t and Sichel mean is 1.14 g/t Au.
Semivariograms	Lognormal semivariograms calculated for all data greater than 0.1 g/t Au. Nested spherical semivariogram models defined for down plunge (-15˚ south), down dip (-80˚ west) and downhole (-60˚ east) directions.
Kriged bulk block model	Lognormally kriged block model using 10 m (N-S) by 4 m (E-W) by 2.5 m (vertical) bulk blocks. Lognormal kriging parameters:

	Co = 0.47 C_1 = 0.45 C_2 = 0.45 rotation = 0, -80, 15 a_1 = 15 x 13 x 3 m a_2 = 60 x 45 x 6.5 m All assays above 0.01 g/t Au used during estimation. Maximum number of samples used per block = 30
Selective mining model	Kriged bulk block model investigated by lognormal shortcut technique using a 5 m (N-S) by 4 m (E-W) by 2.5 m (vertical) SMU – with a calculated dispersion variance of 0.0731, and for bulk blocks $\geq$0.5 g/t Au.

Grade control models

Setting	Bench 837.5 mRL blasthole data.
Software	Geostat Systems International and Micromine.
Statistics	Lognormally distributed above a mineralization indicator grade of 0.1 g/t Au. Mean grade above 0.1 g/t Au is 1.21 g/t Au and Sichel mean is 1.02 g/t Au.
Semivariograms	Lognormal semivariograms calculated using all data $\geq$0.1 g/t Au in N-S and E-W directions.
Kriged grade control model	Lognormally kriged using 10 m by 4 m by 2.5 m blocks and 5 m by 4 m by 2.5 m blocks to produce two models. Lognormal kriging param- eters: Co = 0.45 C_1 = 0.45 C_2 = 0.30 rotation = 90, 0, 0 a_1 = 12 x 5 x 5 m a_2 = 40 x 14 x 18 m All assays above 0.01 g/t Au used during estimation, maximum number of samples used per block = 15.

Reconciliation

The bulk and selective resource models were screened for topography and by the existing pit outline to determine mined and unmined estimates. Figure 6 displays a combined grade tonnage diagram for the total bulk and selective resource models and for material within and outside the pit limits at the time of the study. The bulk and selective curves demonstrate the relationship between recoverable tonnes and grade at various cutoffs for increasing selectivity. For example at a 0.8 g/t Au cutoff the grade increases and the tonnage decreases with greater selectivity, while at a 2.0 g/t Au cutoff the grade and tonnage increase for the same improvement in selectivity. Therefore there is a particular cutoff for each pair of curves where increasing selectivity results in improvement in the grade with no significant change in the tonnage mined, that is, for the total resource model, at a cutoff of between 1.0 and 1.5 g/t Au. Also plotted on Figure 6 is the actual production estimate, comprising the mill throughput tonnage and the head grade, of material mined from within the existing pit outline. This point lies very close to the inpit bulk resource curve at slightly above the 1.0 g/t Au cutoff. Ore selection at the operation was made by manual contouring of blasthole assays using a nominal 0.9 g/t Au cutoff. The position of the actual production point in Figure 6 demonstrates that the operational procedure was approximately equivalent to an effective 1.0 g/t Au resource model bulk block cutoff. The proximity of actual production to the bulk block curve indicates that mining selectivity at the operation was poor. It is known that problems were encountered with post-blasting dilution. The 0.8 g/t Au cutoff on the selective resource model curve demonstrates that if the selective mining procedures had been more successful a significant improvement in head grade would have been achieved.

In order to investigate the improvement in selectivity obtained from the use of closely spaced grade control information, two lognormally kriged models of grade control data from a single bench were constructed, using bulk (10 x 4 x 2.5 m) and SMU (5 x 4 x 2.5 m) sized blocks respectively. Figure 7 displays the grade tonnage curves for these models together with the curves for the same bench of the bulk and selective resource model. The latter two models were constrained by the area of the grade control sampling in order to make all the models comparable.

The bulk block grade control model curve sits above the bulk block resource model curve and therefore demonstrates, as one would expect, that the additional grade control data has improved the potential selectivity. The SMU size block grade control model curve sits above the bulk block grade control model and is positioned very close to the selective resource model curve. This demonstrates the improved selectivity of ore classification using the SMU sized blocks and the successful simulation of the recoverable tonnes and grade on this bench by the selective resource model, that is, if ore selection was made on the basis of the log kriged grade control data using SMU size blocks, and blasting dilution was minimised, the actual production would be close to this curve. The mill throughput estimate for material mined from this bench was not available, but if the relationship observed for the entire pit production is valid for this bench, then it would be expected to fall close to the bulk block resource or grade control models at an effective cutoff of approximately 1.0 g/t Au.

Conclusions

Although the above study is relatively concise (and somewhat academic in the context of this deposit) it demonstrates the ability of these techniques to provide the following benefits:

— production estimates may be reconciled with the kriged recoverable resource model and grade control outlines;
— the confidence is increased in short, medium and long

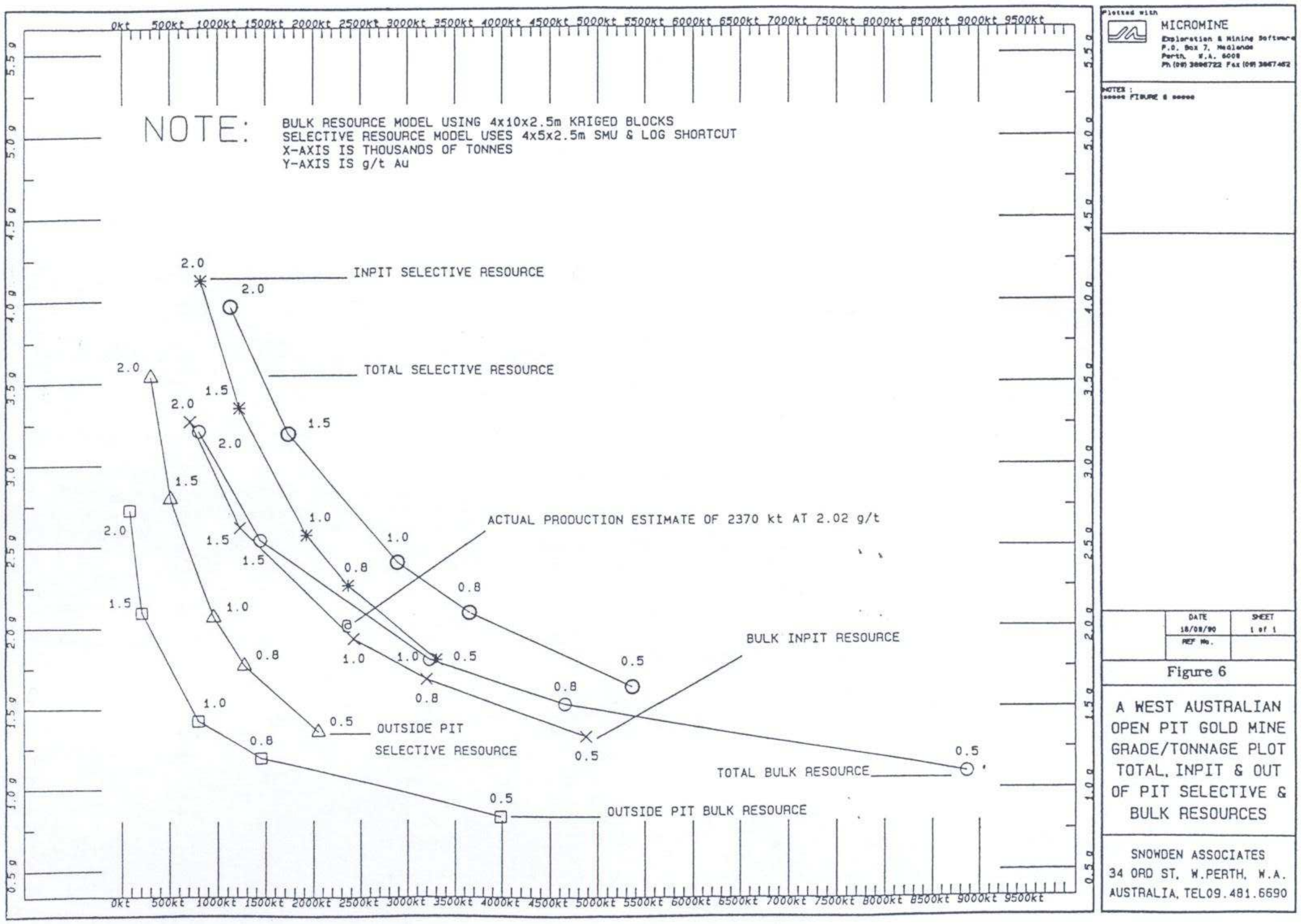

FIGURE 6 Grade/tonnage plot for a Western Australian open-pit gold mine showing total, in-pit and out-of-pit selective and bulk resources.

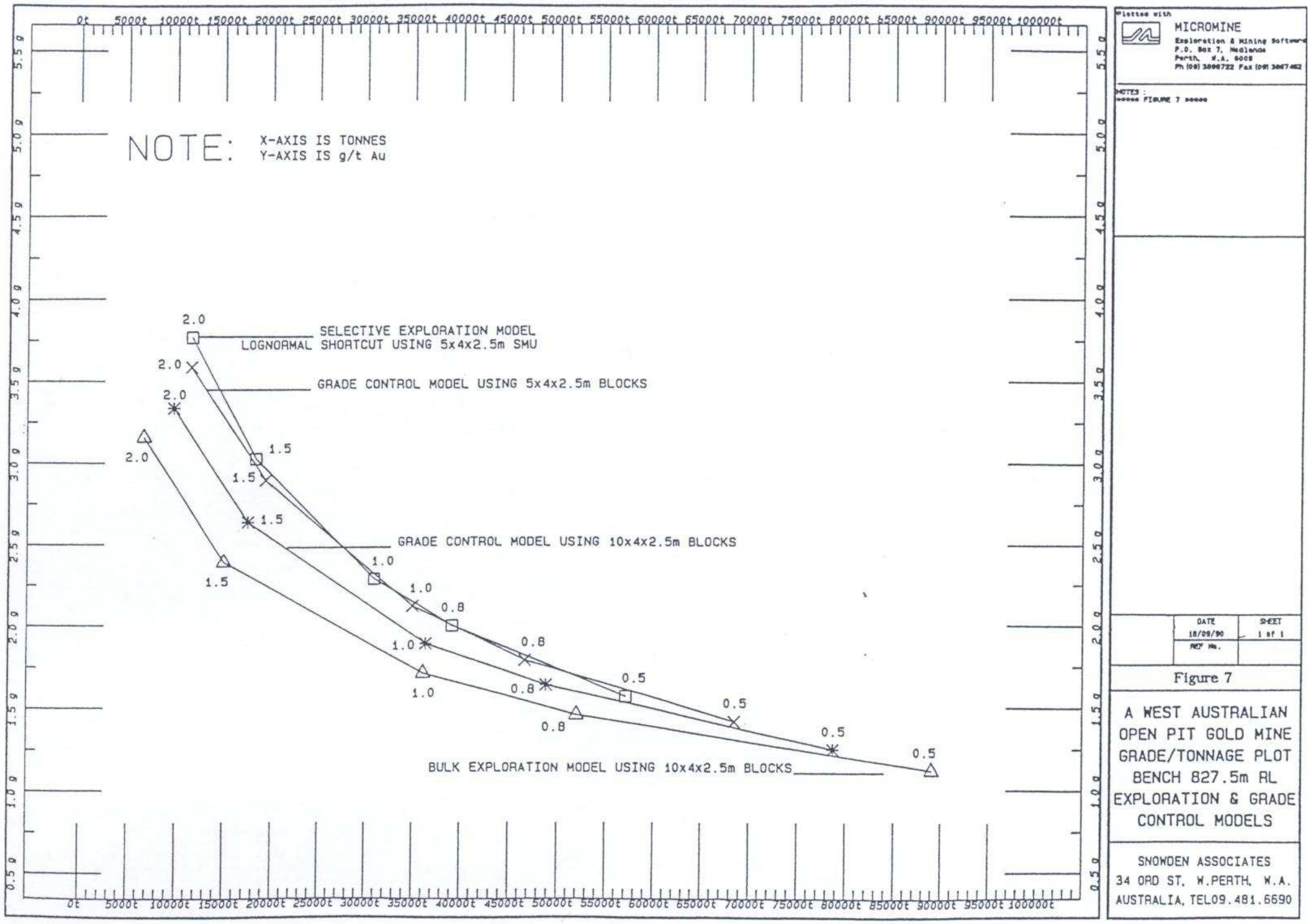

FIGURE 7 Grade/tonnage plot for a Western Australian open-pit gold mine showing the exploration and grade control models for the bench 827.5 m RL.

term ore reserves for the purpose of production and financial planning;

— effective operational cutoffs may be set on grades estimated for recoverable mining units; and

— the optimisation and understanding of the operation may be considerably improved.

Grade control may be much improved and the operation successfully optimised by applying careful consideration to the issues discussed in this paper. An understanding of the grade/tonnage relationship and the roles of the regression effect and the volume variance relationship will considerably aid geologists and mining engineers in the calculation of recoverable tonnes and grade and in reconciling estimates with actual production. Hopefully, such a rationale will be followed during feasibility and/or early in the production phase of the operation.

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