COLLOCATED COSIMULATION WITH MULTIVARIATE BAYESIAN UPDATING: A CASE STUDY ON THE OLYMPIC DAM DEPOSIT

Mario E. Rossi
GeoSystems International, Inc., USA

Colin Badenhorst and Shane O'Connell
Olympic Dam Resource Team, BHP Billiton, Australia

ABSTRACT

The Olympic Dam deposit is the world's largest single uranium resource, the world's fourth largest copper resource and Australia's largest gold resource, and it has been exploited by underground mining methods for more than two decades.

Conditional simulation (CS) models were developed to provide models of uncertainty which could be compared to the existing resource classification scheme, as well as to provide an assessment of mine plan risk and short-term variability of metallurgical feed profiles to the plant.

Developing the CS models presented several challenges. In addition to the massive size of the deposit and the spatial correlation among the different commodities, very large datasets and models provided some unique logistical challenges.

The uncertainty in the key geological variables (haematite abundance and sulphide mineral species) are characterised by 30 realisations derived using Sequential Indicator Simulation (SIS) and the Maximum A-posteriori Selection (MAPS) algorithm. Simulation domains were then constructed for each realisation and used to condition the simulation of copper (Cu), uranium oxide (U_3O_8), gold (Au), silver (Ag), sulphur (S), and in-situ bulk density (SG). The spatial correlation between Cu, U_3O_8, S and Au was modelled using Gaussian collocated co-simulation with Bayesian updating, while the remaining grade variables were independently simulated using Sequential Gaussian Simulation (SGS).

The resulting CS models are used to evaluate the resource classification scheme, provide an analysis of recoverable resources, and provide mill feed grade profiles for different time periods. The ability to evaluate this level of information at an early stage of the expansion project is invaluable to its progress and subsequent decision making.

INTRODUCTION

The Olympic Dam orebody represents the world's largest single uranium resource, the world's fourth largest copper resource and Australia's largest gold resource. The January 2009 resource model for the Olympic Dam deposit recorded a total resource of 9.080 billion tonnes at 0.87% Cu, 0.27kg/t U_3O_8 and 0.32 g/t Au, within approximately 12 km^3 of the mineralised Mesoproterozoic crystalline basement of the eastern margin of the Gawler Craton. It is covered by approximately 350 metres of flat-lying Neoproterozoic to Cambrian sedimentary rocks, separated from the basement by a major sub-horizontal unconformity.

The principal host for mineralisation is the Olympic Dam Breccia Complex (ODBC), which describes all breccias and related lithologies associated with the Olympic Dam mineralised environment. This complex is hosted within, and is largely composed of the Roxby Downs Granite, and includes lesser contributions of the felsic to intermediate volcanics and numerous intrusions of mafic/ultramafic and felsic dykes. Copper sulphide (bornite, chalcocite and chalcopyrite), coeval and contiguous uranium (uraninite, brannerite and coffinite) mineralisation occurred approximately 1,590 billion years ago, and is characterised by a continuum of weakly to strongly haematised breccias. Central to the deposit is a zone of intense haematite-quartz breccia which is largely void of mineralisation.

The major controls on mineralisation of the Olympic Dam deposit are described by the inter-relationship between haematite abundance and sulphide mineral species. Importantly, there is a significant and unequivocal spatial correlation between Cu, U_3O_8, Au (associated with sulphide) and Ag mineralisation across the deposit as a consequence of the co-precipitation of these elements as several minerals. Thus, the controls on Cu mineralisation are indeed the same controls on U_3O_8, Au (associated with sulphide) and Ag.

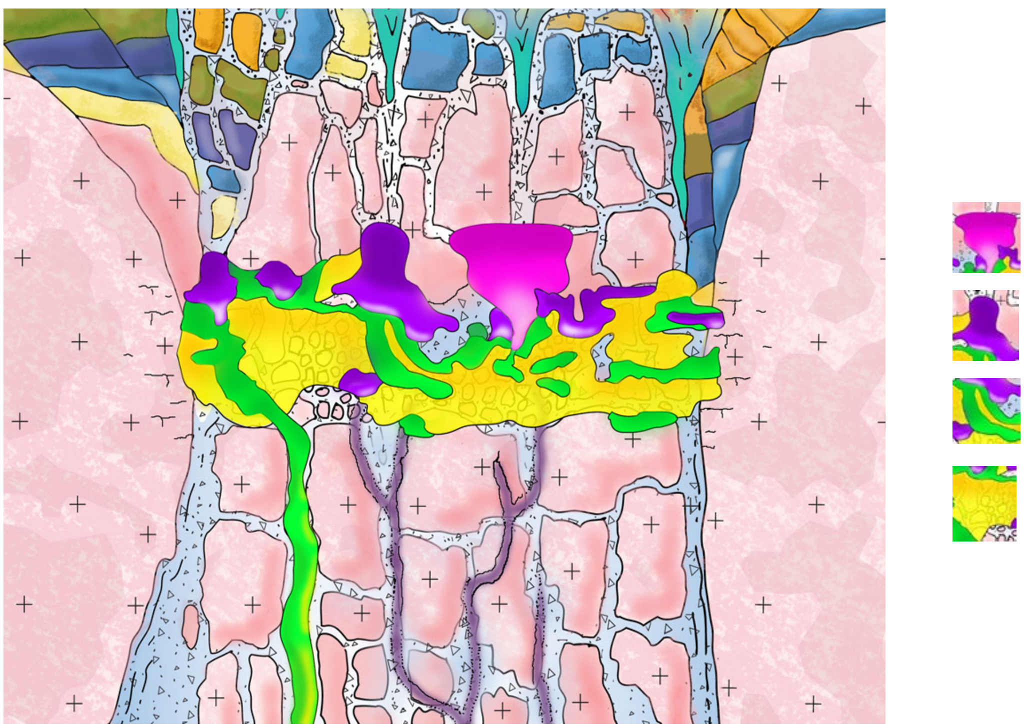

Figure 1: Depiction of an idealised cross-section through the Olympic Dam deposit showing the distribution of sulphide mineral species within the ODBC

METHODOLOGY

Simulation of Geologic Variables

The simulated geologic model was developed based on haematite (DomLit) and Cu mineral species (DomMin) variables that are used to define the estimation and simulation domains. The categorical SIS method [1] with a local-varying mean (LVM) uses the same principles as the Multiple Indicator Kriging (MIK) technique for grade simulation and estimation, except that it deals with a categorical variable [2].

The simulation parameters are not only dependent on the software used for simulation, but also are part of the "uncertainty model", in the sense that the different parameters (search ellipsoids, number of samples and simulated values to be used, the definition of octant searches, etc.) may provide different levels of uncertainty. Thus, these parameters need to be carefully considered [3].

Pangeos software (www.statios.com) was used for both geological and grade simulation. The main steps used to simulate the geological variables were:

- The categorical variables are transformed into a series of indicators: 7 for the haematite categories and 4 for the sulphide mineral species categories. The indicators defined the presence or absence of each category.
- The basic statistics (proportions or relative abundance) of each category are obtained, as well as the corresponding directional indicator variogram models.
- A locally-varying mean (LVM) model was created using Inverse Distance cubed, and the subsequent local mean value at each simulation node was then used to condition the simulated values. This local mean value aids the simulation process in accounting for trends and departures from the strict stationarity assumption required by the simulation method.
- At each node being simulated, a cumulative frequency curve representing the probability of each category present at that location is obtained using MIK. A random number between 0 and 1 is then drawn and the corresponding categorical value is then selected accordingly.
- After incorporating the previously simulated node into the simulation database, the process is repeated until all nodes on 10 x 10 x 5m spacing are simulated. This process is repeated independently for each domain, culminating in a model comprising 29.5 million nodes.
- A post-processing routine (MAPS, [4]) was used to locally modify the simulated values such that low probabilities for some categories in areas of unlikely occurrences were "cleaned up". This is important particularly in those areas where the category is known to be a singularly massive unit, but the simulated model may present non-existing simulated categories stemming from very low probabilities of occurrence. MAPS changes "clean-up" about 1 or 2% for each category, and thus provides a small improvement in the reproduction of the original statistics.

A total of 30 realisations were obtained for both categorical variables. The combinations, at each node, of these two variables define the 30 simulation domains used to uniquely condition each grade simulation. Thus, a measure of uncertainty as introduced by the geologic model is also introduced into the simulated grade model.

Validations

The simulated values should reproduce the basic statistics of the original data (5m composites), as well as the variogram models used in the simulation. In the case of the categorical (geological) variables, the basic statistics to be reproduced are simply the proportions of each category within the original database. Generally, these are well reproduced with the exception of volumetrically small domains.

The other aspect that should be checked is the reproduction of the spatial variability model used to simulate each indicator. Figure 2 shows the comparison for the chalcopyrite-pyrite (CPY-PY) unit in Domain 320, in the central area of the deposit. The overall tendency, with few exceptions, is for the simulated values to exhibit more continuity than suggested by the 5m composites, although within acceptable margins.

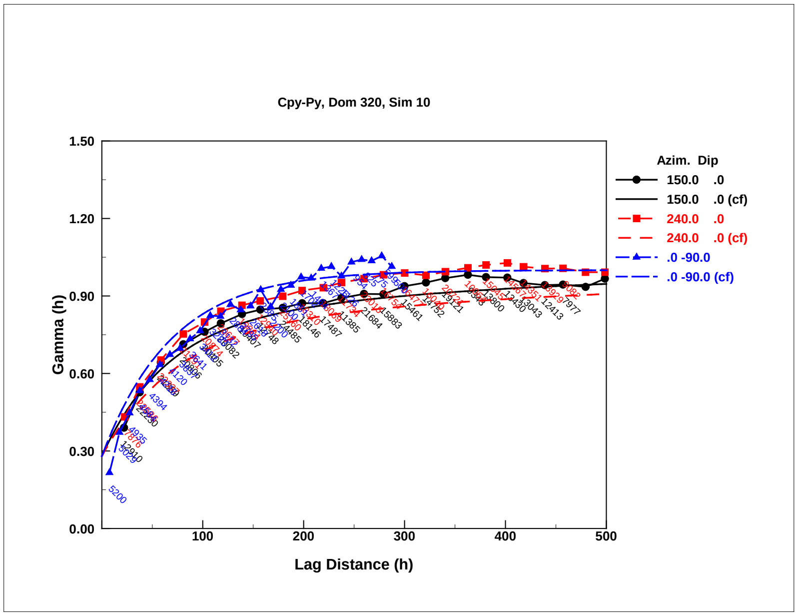

Figure 2: CPY-PY indicator variogram with 5m composite models – Domain 320, realisation No.10

Statistically, there is a tendency of the simulated values to disguise the differences in proportions observed in the 5m composites. This is partially due to local data clustering and difficulties in obtaining representative statistics for each domain. In addition, the variability in some domains is relatively high, such as Domains 310, 320, and 340, which are both small and narrow in certain directions with respect to variogram ranges.

Spatially however, the simulated values honour well the original data and reproduce the spatial textures and patterns of connectivity observed in the 5m composites and the resource model. As examples, Figure 3 shows the DomLit and DomMin variables for realisation No. 1, Bench -792.5m. The variability observed is deemed representative of that observed in the drill hole data and confirmed by underground geological mapping.

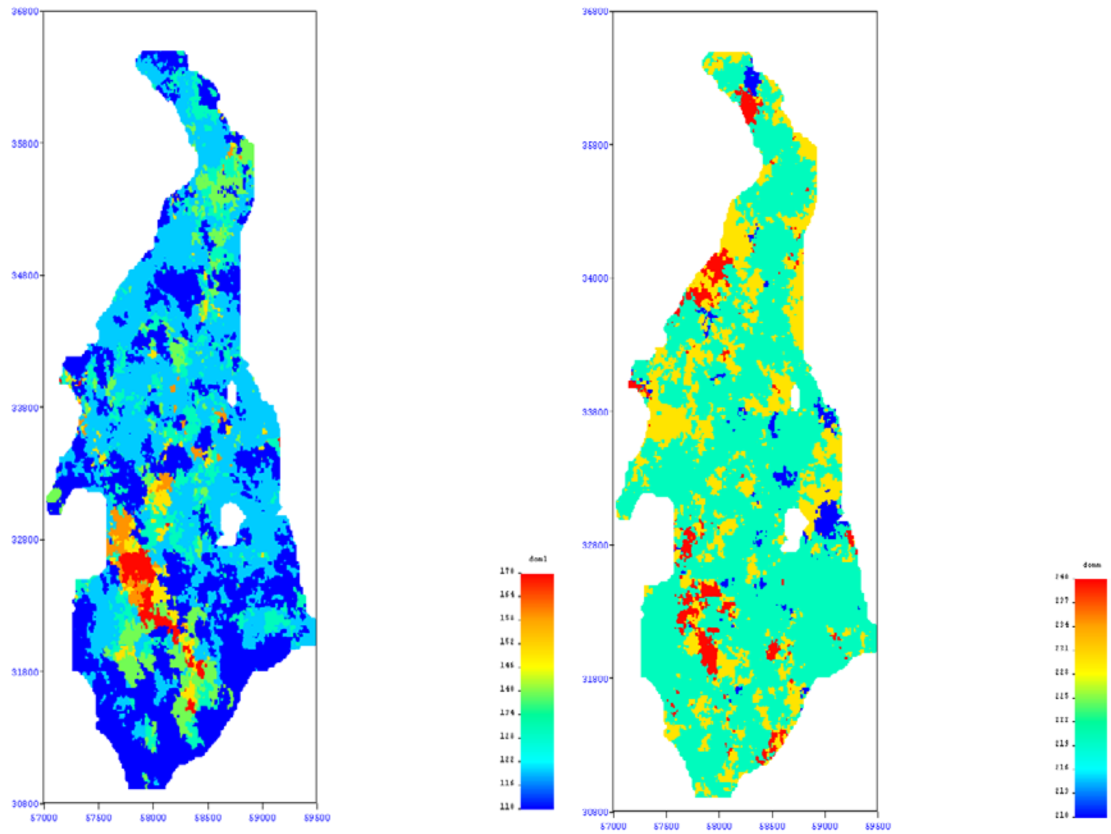

Figure 3: DomLit (left) and DomMin (right) realisation No.1, bench -792.5mRL

Collocated Co-Simulation with Multivariate Bayesian Updating

Cu, U_3O_8, Au and S were co-simulated using collocated cokriging [5] with Bayesian updating, while Ag and in situ density (SG) were simulated independently using Sequential Gaussian Simulation [6]. As with the SIS with LVM categorical simulations, 30 realisations were obtained. The steps used to obtain the grade simulations were:

- The basic statistics and variogram models were obtained, and declustering, despiking, Gaussian transformations and Gaussian variogram modelling were completed on the database.
- The collocated simulation was established with Cu being the first independently simulated variable. The correlation between U_3O_8 and Cu was modelled by simulation domain, and U_3O_8 was then simulated using the previously simulated Cu as a secondary collocated variable.
- S was then simulated after calculating the combined correlation of Cu and U_3O_8 as a linear combination of the individual correlations. This is called the super-secondary variable (SSV) of Cu-U_3O_8 [7], and is used as the collocated secondary variable. The use of SSV is justified by the fact that the dependencies between variables are linear. In the case of non-linear dependencies, the Stepwise Conditioning transformation [8] may be more appropriate. Figure 4 shows a schematic summarising the process for simulating S.
- After the simulation for S is completed, the process is repeated for Au. The corresponding SSV variable is generated as a linear combination of Cu, U_3O_8, and S, as well as the collocated correlation from the 5m composites.

- Note that each co-simulation uses updated collocated correlation values in the Bayesian sense, generating an SSV to account for the multiple correlations among the variables being simulated. The algorithm uses an LU decomposition method to account for the correlation between the data and the simulated values.

After validation, the 30 realisations were regularised to the same block size as the resource model, such that block-to-block comparisons could be made. The CS model was also used in several studies, which require the models to be on the same block size as the resource model.

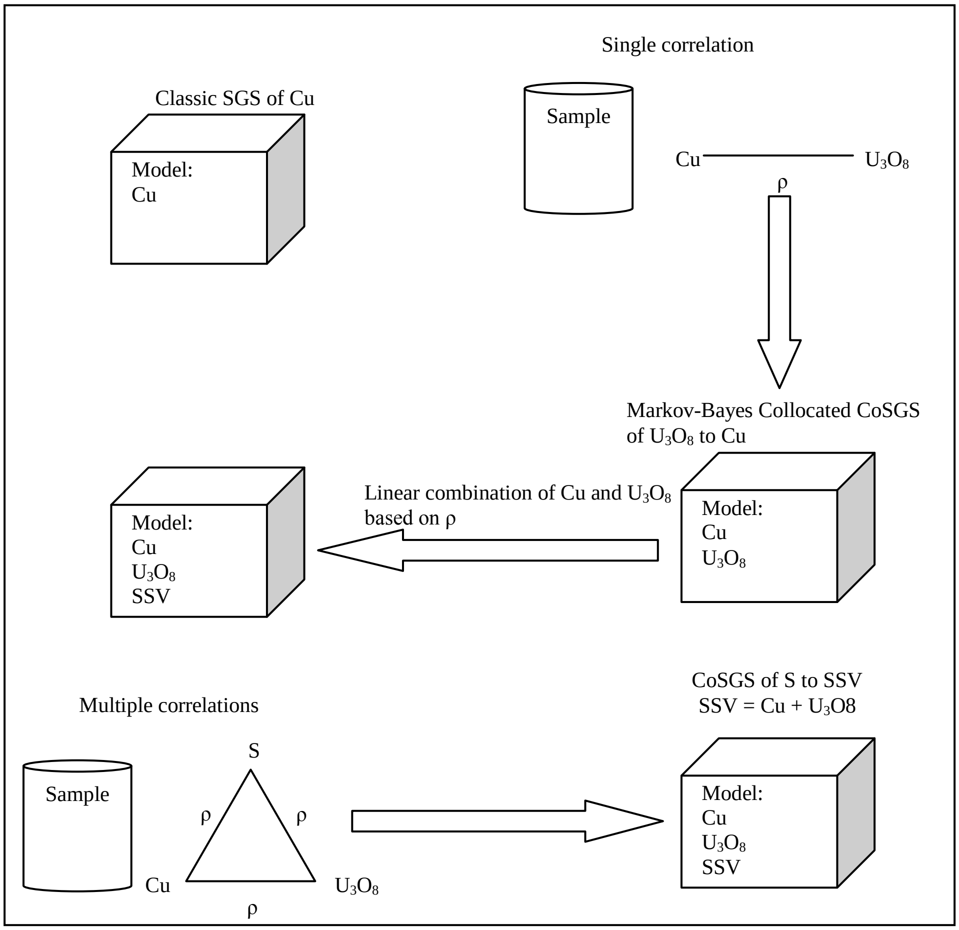

Figure 4: Accounting for multivariate correlations using the "super-secondary variable" concept. Here the schematic shows the correlations considered to simulate S, Cu and U_3O_8

Simulation Plans

The simulation models were obtained using search radii of 300 x 300 x 300m or 350 x 350 x 350m, depending on the variable being simulated. An isotropic search was used to provide sufficient opportunity for data from all directions to contribute to the simulated value. The variogram models were left with the task of reproducing the spatial anisotropies observed.

Between 10 and 12 total values were used as conditioning data, combining both original composites and previously simulated nodes. Several options were tried during the development of the models, including the option of restricting the simulation to areas were at least one 5m composite (original data) was found. A multiple grid search was used, but no octant searches were applied.

Variogram models for Gaussian data were developed for each grade variable and Domain. The data used for the transformation was the despiked 5m composites (see Section 3). Also, the minimum and maximum grades used in the back transformation from the simulated Gaussian space to the original were modified according to the ranges observed in the 5m composites and by looking at the corresponding probability plots.

Simulation Statistics and Validations

The reproduction of the basic statistics and histogram of simulated Cu grades (not shown here) is in general very good in terms of the mean and the median, as well as the variance and thus the coefficient of variation.

Figure 5 shows a Q-Q plot comparing simulated Cu values and 5m composites for simulation No. 25, Domain 4406, with a very good match shown. This is generally the case for most of the simulations and domains.

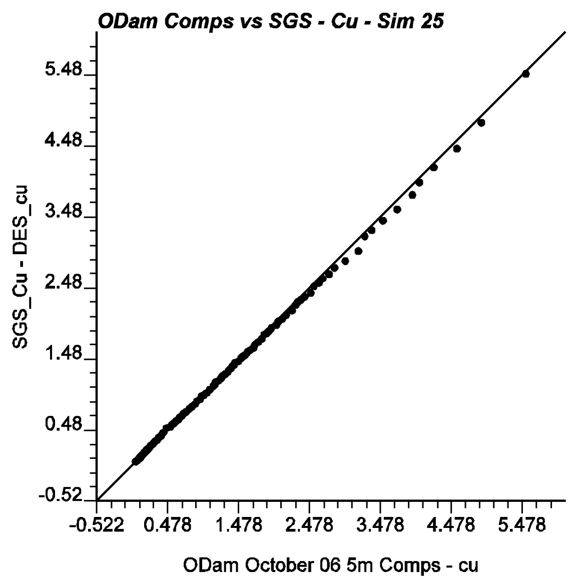

Figure 5 : Q-Q plot, realisation No. 25 vs. 5m composites, Cu, Domain 4406

The correlograms of the simulated values tend to show more variability than the models obtained from the 5m composites. This is opposite to what was observed in the case of the geologic variables. Figure 6 shows three directions for Cu, realisation and Domain 4109. These are some of the Domains where the correlogram model is better reproduced. The overall conclusion is that the level of reproduction of the spatial variability is acceptable, and thus that the simulation model adequately reflects the information used.

The other important aspect that should be analysed is the overall spatial patterns observed in the simulated values. As was done with the DomLit and DomMin categorical variables, the simulated grades were visualised in plan and sectional views. Figure 7 shows Cu simulation 1 at elevations -590m. The grade distribution is correctly reproduced in a global and local sense, validating the methodology applied.

In addition to the univariate validations, it is also important to check whether the correlations among variables are reproduced. This was the case for most domains, although the general tendency is for the simulations to reproduce less correlation (as measured by the linear correlation coefficient) than the original drill hole data shows, although the comparisons based on rank correlations were better. This is believed to be partly due to the higher variability of the simulated nodes, and partly due to the lack of robustness of the correlation coefficients derived from composites in small or highly variable domains. The comparisons among correlation matrices are not shown here due to space constraints.

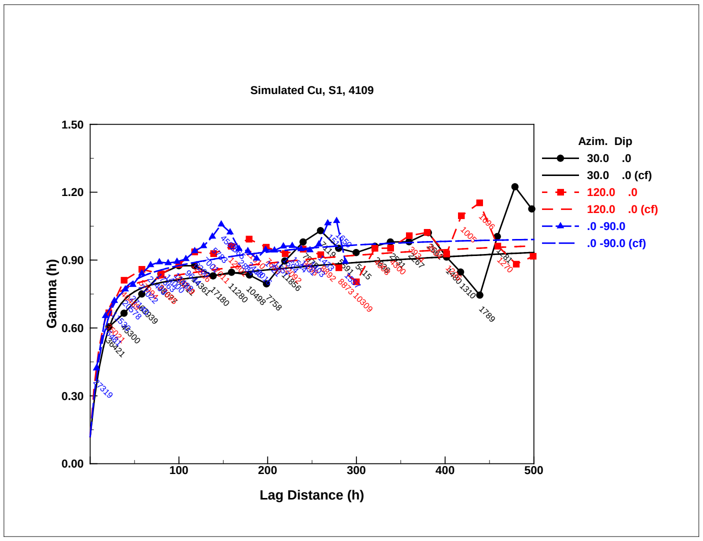

Figure 6: Directional Cu correlograms from simulated values with models from original 5m composites, Domain 4109, realisation 1

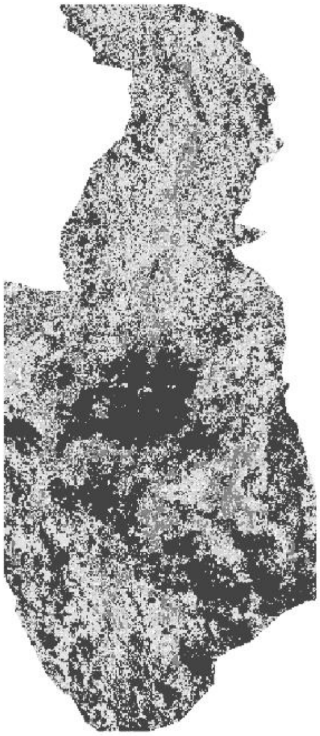

Figure 7: Cu realisation No. 1, -590mRL

CONCLUSIONS

The conditional simulation model for the Olympic Dam deposit has been developed using a co-simulation methodology that accounts for several correlated grade variables. The observed local variability is high, as expected, which is partially induced by the geologic variability. With a few exceptions, both the simulated geological and grade variables (and the correlation matrix between the grade variables) validate well against the original 5m composites used in the simulation.

The key findings of this work and the resulting uncertainty and risk analyses are:

- In some local cases, the CS model tends to be more optimistic in terms of grades and tonnages above cutoff than the resource model. This is particularly noticeable for Au mineralisation.
- The continuity and spatial characteristics observed in the 5m composites are reproduced well in the haematite and sulphide mineral species simulations (the underlying geological controls on mineralisation).
- The CS model has proven to be a useful tool for studying variability (uncertainty) and its associated risks. In this case, three specific applications were developed:
  - A comparison of the uncertainty model (CS) with the resource model suggests that for volumes greater than 15 to 20 million tonne parcels, the grade variability decreases rapidly.
  - The development of daily, weekly, and monthly concentrator and smelter material feed profiles. The method developed using the simulated grades and tonnages to obtain feed profiles shows the level of variability that can be expected for key variables such as the copper-sulphur (Cu:S) ratio, as well as the individual grades.
  - A comparison of the grade tonnage curves for different domains and mining periods with respect to the resource model. The most significant difference is observed with respect to Au grades, which is expected given its higher variability and the methodology used to estimate Au in the resource model.

The model developed has very few precedents in terms of methodology, and is challenging primarily because of its size. The uncertainty and risk analysis derived from the model highlights some areas of improvement required for subsequent resource models. The simulation model is also a useful tool that, when used in conjunction with the resource model, will allow the most uncertain aspects of mine development to be focused on, and thus provide a foundation for risk mitigation.

ACKNOWLEDGEMENTS

BHP Billiton is gratefully acknowledged for allowing us to publish this paper. Other members of the Olympic Dam Resource Team, in particular A. Bottrill and M. Smith, are also gratefully acknowledged for their support at various stages during project development.

REFERENCES

Alabert, F. (1987), *Stochastic Imaging of Spatial Distributions Using Hard and Soft Information*, MSc. Thesis, Stanford University, Stanford, CA, 197p [1].

Rossi, M.E. (2005), *Indicator Simulations of Categorical Variables*, Proc. of the 32nd International Symposium on Applications of Computers and Operations Research in the Mineral Industries (APCOM), Tucson, Arizona, March 30-April 1 [2].

Rossi, M.E. (2003), *Practical Aspects of Large-Scale Conditional Simulations*, Proceedings of the 31st APCOM, Cape Town, South Africa, May 13-15, [3].

Deutsch, C.V. (1998), *Cleaning Categorical Variable Realisations with Maximum A-Posteriori Selection*, Computers and Geosciences, 24(6), p 551-562 [4].

Almeida, A.S., and Journel, A.G. (1994), *Joint Simulation of Multiple Variables with a Markov-Type Coregionalization Model*, Mathematical Geology, Vol. 26, No. 5, pp. 565-588 [5].

Isaaks, E.H. (1990), *The Application of Monte Carlo Methods to the Analysis of Spatially Correlated Data*, PhD Thesis, Stanford University, Stanford, CA, 213p, [6].

Babak, O, and Deutsch, CV (2009), *Collocated Cokriging Based on Merged Secondary Attributes*, Mathematical Geosciences 41(8), pp. 921-926 [7].

Leuangthong, O., and Deutsch, C.V. (2003)**,** *Stepwise Conditional Transformation for Simulation of Multiple Variables*, Mathematical Geology, 35(2), p. 155-173 [8].