Measuring the Impact of the Change of Support and Information Effect at Olympic Dam

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Abstract

The change of support and information effect concepts are fundamental in every resource model. It underpins all aspects of resource estimation in every deposit worldwide, yet is poorly understood, rarely taught, and even more rarely applied. This paper describes the practical implications of these concepts using conditional simulation, by deriving a recoverable resource estimate for the first 11 benches of the proposed Olympic Dam open cut mine. The Olympic Dam deposit is one the world's largest polymetallic resources at 9 billion tonnes grading 0.8% Cu, 270ppm U_3O_8, 0.32g/t Au and 1.5g/t Ag. BHP Billion is currently undertaking a feasibility study of a large open cut operation with an estimated mine life in excess of 100 years. The resource estimation practices at Olympic Dam comprise of a combination of linear and non-linear techniques to estimate 16 different grade variables critical to the resource. In the southern portion of the deposit, at the site of the proposed open cut, the current resource estimate data spacing is insufficient to predict the recoverable tonnage and grade that will be selected using closely spaced grade control blast holes once mining commences. Conditional simulation has been used to generate a recoverable resource estimate by measuring the tonnage and grade uplift resulting from the change of support and the information effect that occurs at the time of mining. Ten realisations of Cu, S, U_3O_8 and Au were generated using Sequential Indicator Simulation. The simulations were validated visually and statistically, and a single realisation was then chosen to represent "reality". Several "grade control" databases were constructed by sampling the realisation at the expected blast hole spacing. Each database was used to estimate the first few pushbacks of the proposed open cut mimicking future grade control estimates. Variations were measured and grade tonnage curves at the smaller grade control support were compared to the larger blocks of the resource. This information has been used to optimize the predictions of expected tons and grades fed to the mill, adjusting the recoverable resource estimate to control its smoothing. This information is critical for optimal mine planning. The results and conclusions of this work unequivocally demonstrate why every resource geologist should have a deep understanding of the change of support and information effect, and how it can be applied in their resource models using conditional simulation.

This publication includes information on Mineral Resources which have been compiled by S. O'Connell (MAusIMM). This is based on Mineral Resource information in the BHP Billiton 2010 Annual Report which for can be found at www.bhpbilliton.com. All information is reported under the 'Australasian Code for Reporting of Mineral Resources and Ore Reserves, 2004' (the JORC Code) by Shane O'Connell who is a full-time employee of BHP Billiton and has the required qualifications and experience to qualify as Competent Person for Mineral Resources under the JORC Code. Mr O'Connell verifies that this report is based on and fairly reflects the Mineral Resources information in the supporting documentation and agrees with the form and context of the information presented.

	Measured Resource (Mt)	*Indicated Resource (Mt)*	*Inferred Resource (Mt)*	*BHP Billiton interest (%)*
Olympic Dam	*1,280 @ 1.08% Cu*	*4,725 @ 0.86% Cu*	*3,222 @ 0.74% Cu*	*100*

Introduction

The Olympic Dam deposit, situated approximately 570km NNW of Adelaide and 16km north of the township of Roxby Downs in South Australia, is one the world's largest polymetallic resources containing 75 million tonnes of copper, 2.4 million tonnes of uranium oxide and 97 million ounces of gold. The deposit was discovered by WMC Resources in 1975, and mining using sub-level open stoping techniques commenced in mid-1988 at a rate of 1.3 million tonnes per annum. Several expansion phases in 1992, 1995 and 1996 culminated in annual ore production of 9.8 million tonnes per annum by 1999. In June 2005, BHP Billiton purchased WMC Resources, and embarked on an in-depth feasibility study aimed at establishing a large open cut operation with an estimated mine life in excess of 100 years.
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The open cut expansion would be in the southern half of the deposit, which has been defined using both vertical and angled surface drilling on an average spacing of 50x35m, allowing a resource to be estimated to a block support of 10m x 10m x 5m. Five-meter long composites were used. Whilst the spacing is sufficient for a global resource estimate, it is insufficient to provide a prediction of the reserves recovered at the time of mining. During mining, closely spaced grade control drillhole samples will be used to define the ROM tonnage and grade. This close spacing of holes (information effect) and smaller blocks (support effect) will result in a tonnage and grade different to that estimated using the currently available wider resource drillhole spacing.

Conditional simulation was undertaken on the deposit, and a single realisation corresponding to the median copper metal content was chosen to represent "reality". A scripting technique was employed to sample this realisation at a spacing that mimics the likely grade control blasthole spacing that will be employed at the time of mining. These simulated blastholes were then used to produce a grade control estimate over the first 11 benches of the open cut. These estimates represent the recoverable resource at the time of mining, and their predictions allow mine planners to optimise the open cut design and better predict the variations in the expected tonnage and grade feed to the mill.

Conditional simulation was performed over the entire deposit for Cu, U_3O_8 and Au. For the purposes of this paper, only the Cu simulation was considered. In order to comply with BHP Billiton confidentiality requirements, all tonnage and grade information have been appropriately factored.

The resource model

Current resource estimation practices at Olympic Dam are complex and on a scale rarely observed in the industry. There is a rich dataset available, comprising of more than 1,600 surface HQ (63.5mm) and NQ (47.6mm) size drillholes sampled at 1m intervals, and 7,900 underground BQ (36.5mm) and LTK48 (35.6mm) size drillholes sampled at 2.5m intervals. Most surface drillhole depths average 1,000m below surface.

Copper sulphide abundance and type (chalcopyrite, bornite and chalcocite), and haematite abundances are the primary controls on ore mineralisation, and modelled using combinations of deterministic and probabilistic methods. These models are used to construct over 68 unique estimation domains for Cu, which is estimated using Ordinary Kriging (OK) with local sample sharing between domains tailored to honour the observed grade characteristics and relationships across unique domain boundaries. Density is estimated using OK, within domains defined by haematite abundance estimated using Multiple Ordinary Kriging (MIK).

Estimates are validated by comparing composites to block estimates both statistically and also visually through means of cross- and longitudinal sections and plan views. Discrete Gaussian (DG) change of support modelling is used to assess the amount of smoothing obtained during estimation, and the estimates tuned to DG models as required.

In the area of the open cut, the average drillhole spacing is 50x35m, with some spacing as close as 35x35m locally. The resource model in this area is estimated at a 10x10x5m support, and then regularised to 10x10x15m for mine planning purposes.

The simulation model

The Olympic Dam deposit has been simulated several times in recent years. Both Sequential Gaussian Simulation (SGS) and Sequential Indicator Simulation (SIS) techniques have been used, as well as a variant of SGS using Bayesian Updating (Rossi, et. al.). The simulation models have been used to:

1. Characterise the uncertainty in the resource estimates at several scales;

2. Predict recoverable resources and reserves (change of support and information effect);

3. Test the resource classification for different production rates;

4. Provide daily, weekly, monthly, and quarterly profiles of ore feed to the plant.

5. Provide input into the optimisation of underground stope design.

Data for this paper was drawn from a recent conditional simulation aimed specifically to characterise the selectivity required for the proposed open cut operation.

A SIS technique using 25 cut-offs and a median indicator variogram was used to generate 10 realisations of Cu, U_3O_8 and Au at a 2.5 x 2.5 x 2.5m node spacing. The basic inputs to the simulation were 425,000 samples, composited to 5m lengths, from 9,500 drillholes. Simulation was performed within the primary copper sulphide domains (chalcopyrite, bornite and chalcocite) to mimic the domain control employed in resource estimation.

For the purpose of this paper, a subset of the simulation covering the first 11 benches of the open cut footprint was extracted, and regularised to a 2.5x2.5x15m support. The15m vertical dimension corresponds to the proposed bench height of the open cut, and only the Cu realisation corresponding to the median metal content of the simulation was retained.

Figure 1 shows a comparison between the Cu estimate and Cu realisation in bench 6 at the -330m RL. Note that in order to expose ore, the open cut must first move 350 vertical metres of un-mineralised overburden.

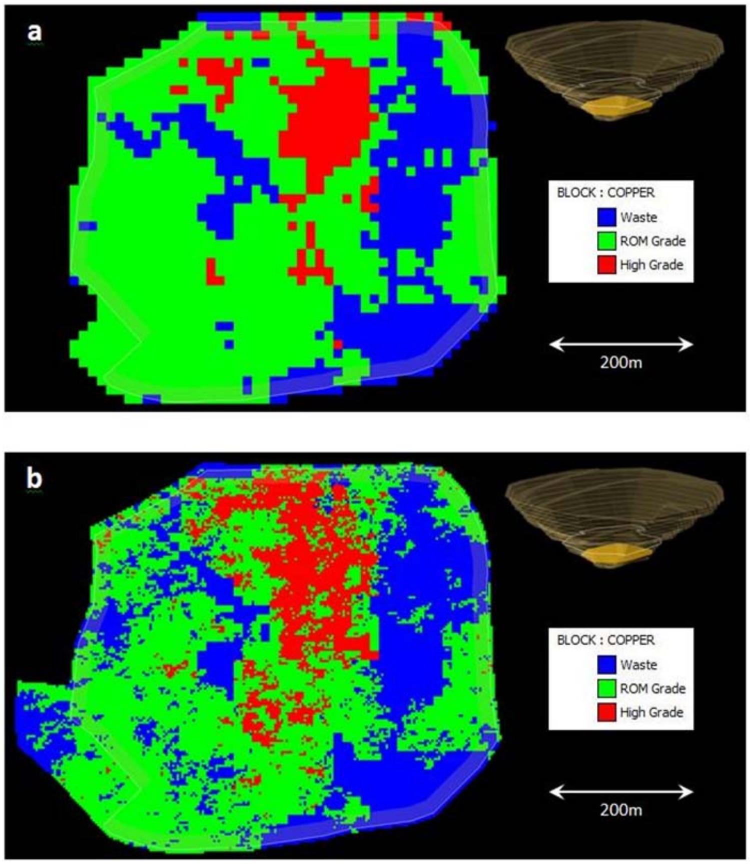

Figure 1 – Plan view of bench 6 at the -355mRL showing (a) Cu estimate at a 10x10x15m support in the resource model and (b) Cu realisation at a 2.5x2.5x15m support in the simulation model. The white line in the perspective view of the open cut shows the elevation at which mining exposes the first ore bench after having removed 350 vertical metres of waste overburden. Blue = 0-0.5% Cu, Green = 0.5-2% Cu, Red=>2% Cu.

The grade control model

The conditional simulation model is used to bridge the gap between a global resource estimate and the locally recovered reserves by predicting the change of support and information effect. This is done by mimicking the mining process and simulating the grade control process.

A script was developed to sample the simulation at a 10x10m spacing, and these samples were converted into a base case grade control database designed to mimic the likely production blast hole drilling at the time of mining.

The grade control at the time of mining was mimicked by estimating Cu grade into 5 x 5 x 15m blocks for each of the 11 benches using the simulated grade control drillholes. An Inverse Distance Weighting technique was employed using the same domain control/sharing as the resource estimate. The Inverse Distance technique was chosen in this exercise for simplicity and expediency, and does not impact the final results and conclusions. The grade control estimation plan is summarised in Table 1.

Table 1 – Grade control estimation parameters.

Estimation Domain	Estimation Pass	Block Support			Search			Samples		Sample Sharing
		X	Y	Z	X	Y	Z	Min	Max	
Non-Sulphide (NS)	1	5	5	15	12.5	12.5	15	4	5	NS
	2	5	5	15	25	25	15	3	5	NS+CP
Chalcopyrite (CP)	1	5	5	15	12.5	12.5	15	4	5	CP+BN
	2	5	5	15	25	25	15	3	5	CP+BN
Bornite (BN)	1	5	5	15	12.5	12.5	15	4	5	BN+CC
	2	5	5	15	25	25	15	3	5	BN+CC
Chalcocite (CC)	1	5	5	15	12.5	12.5	15	4	5	BN+CC
	2	5	5	15	25	25	15	3	5	BN+CC

Figure 2 shows a visual comparison between the resource and grade control estimates for a few benches. Note the effect of the increased data density and smaller block size. There is a sharper definition of the waste/stock/high grade contacts.

Comparing the resource and grade control estimates

The resource estimate and grade control estimate for each bench was compared by using classic grade-tonnage analysis and summarised in Table 2. The material is classified according to their destination:

- Waste material (Cu <0.5%)
- ROM (run-of-mine) material (0.5% > Cu < 2%)
- High grade (Cu > 2%)

In Table 2, a positive differential indicates more copper metal predicted by the grade control model, whereas a negative differential indicates more copper metal predicted by the resource model.

At higher cut-off's, the tonnage and grade undergoes a significant uplift (Figure 3). This is directly attributable to the resolution achieved through the change in support (smaller blocks) and the information effect (many closely spaced blast holes).

Bench 2 is considered an anomaly, in that for the high grade bench the grade control model suggests that the resource model overstates the copper metal at cut-offs less than 3% Cu, probably due to the presence of locally high grade Cu composites.

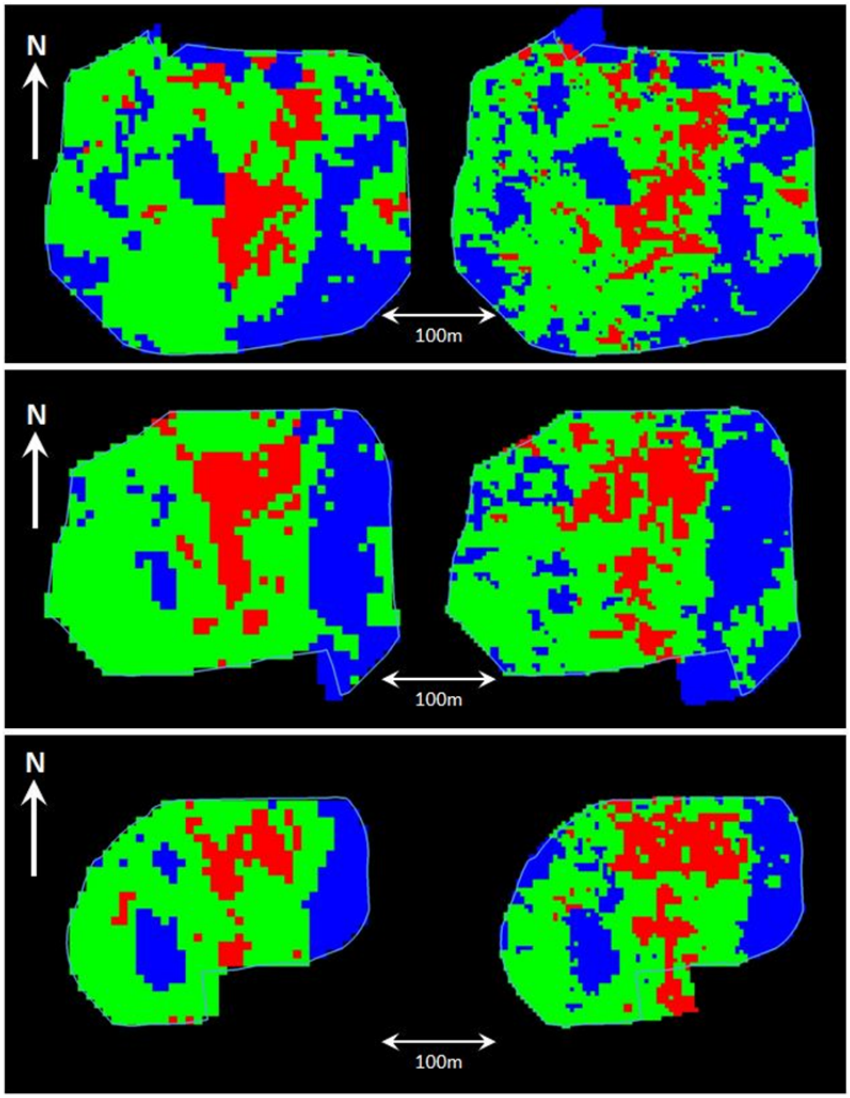

Figure 2 – Plan view of bench 3, 9 and 10 showing a comparison between the resource model (on the left) and the grade control model (on the right). The legend colour ranges are the same shown in Figure 1.

Table 2 – Comparison between resource model and grade control model on a free selection basis, showing the tonnage, grade and metal content for the Waste, ROM and High Grade classifications. Note that the change of support and information effects are more dramatic as the cut-off increases.

		Resource Model			***Free Selection Model***			
Bench No.	***Grade Category***	***Tonnes ($x10^6$)***	***Grade % Cu***	***Metal ($x10^3$)***	***Tonnes ($x10^6$)***	***Grade % Cu***	***Metal ($x10^3$)***	***% Diff. Metal***
1	Waste	9.43	0.07	7	9.78	0.11	11	63%
	ROM	4.58	1.04	48	4.20	1.03	43	-9%
	High Grade	0.70	2.54	18	0.73	2.84	21	17%
2	Waste	5.59	0.17	9	5.83	0.21	12	29%
	ROM	6.29	1.08	68	6.39	1.05	67	-1%
	High Grade	1.52	2.71	41	1.17	2.84	33	-20%
3	Waste	3.01	0.26	8	3.24	0.26	8	7%
	ROM	6.13	1.10	67	5.89	1.10	65	-4%
	High Grade	1.29	2.72	35	1.30	2.72	35	1%
4	Waste	2.91	0.25	7	3.26	0.26	8	17%
	ROM	5.96	1.07	64	5.57	1.07	60	-7%
	High Grade	1.27	2.71	35	1.31	2.68	35	2%
5	Waste	2.18	0.27	6	2.54	0.29	7	25%
	ROM	5.02	1.05	53	4.55	1.04	47	-10%
	High Grade	1.10	2.72	30	1.21	2.83	34	14%
6	Waste	1.90	0.26	5	2.17	0.28	6	23%
	ROM	4.92	1.06	52	4.35	1.01	44	-16%
	High Grade	0.79	2.59	21	1.09	2.67	29	41%
7	Waste	1.57	0.25	4	1.72	0.28	5	23%
	ROM	3.68	1.08	40	3.42	1.08	37	-7%
	High Grade	0.75	2.58	19	0.86	2.64	23	16%
8	Waste	1.13	0.22	2	1.43	0.26	4	49%
	ROM	3.26	1.10	36	2.97	1.13	34	-6%
	High Grade	0.82	2.64	22	0.81	2.81	23	5%
9	Waste	0.68	0.17	1	0.86	0.23	2	71%
	ROM	2.22	1.16	26	1.96	1.16	23	-12%
	High Grade	0.64	2.62	17	0.72	2.64	19	13%
10	Waste	0.61	0.22	1	0.77	0.27	2	55%
	ROM	2.10	1.12	24	1.74	1.16	20	-14%
	High Grade	0.32	2.96	9	0.51	2.77	14	52%
11	Waste	0.43	0.23	1	0.45	0.24	1	7%
	ROM	1.13	1.09	12	0.98	1.13	11	-10%
	High Grade	0.16	3.12	5	0.30	2.93	9	73%
Total Waste		**29.44**	**0.18**	**51.93**	**32.06**	**0.21**	**66.29**	**28%**
Total ROM		**45.28**	**1.08**	**488.69**	**42.03**	**1.07**	**450.30**	**-8%**
Total High Grade		**9.37**	**2.68**	**251.40**	**10.00**	**2.75**	**274.94**	**9%**

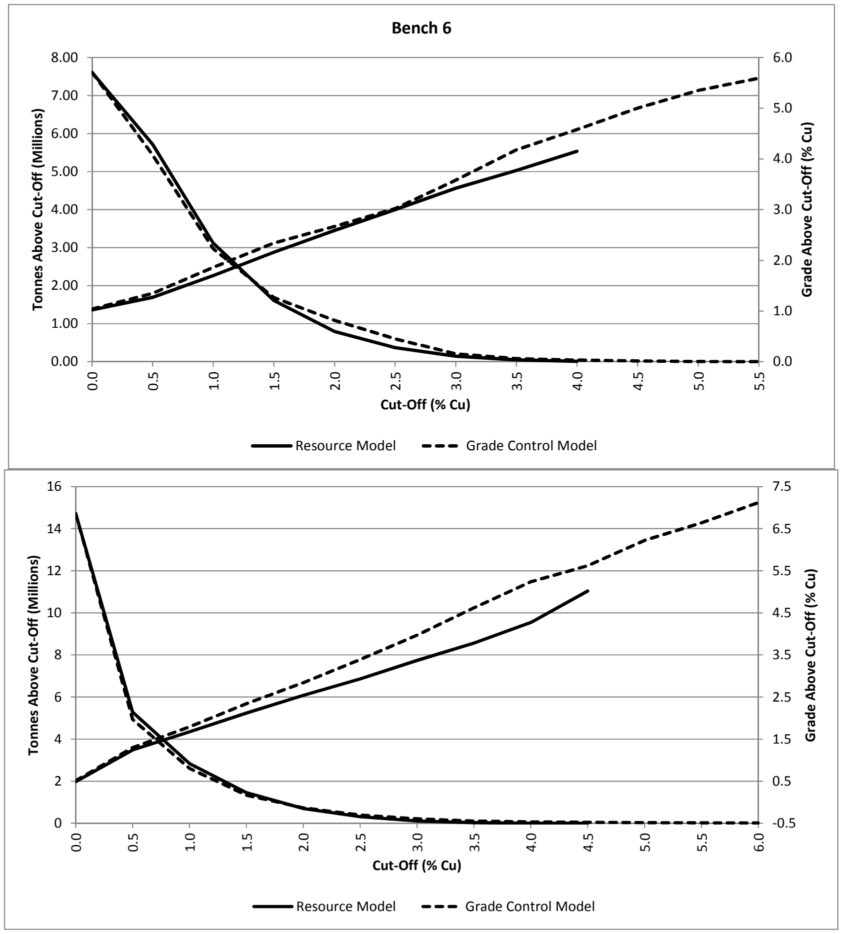

Figure 3 – Grade-tonnage curves for Bench 1 and Bench 6 demonstrating the tonnage and grade uplift achieved at higher cut-off's due to the change of support and information effect in the grade control model.

Real-world grade control model

The free-selection basis described earlier is a theoretical exercise that illustrates the metal uplift achieved if each block could be extracted against a specific cut-off on a block-per-block basis. In real-world mining scenarios, blasting and digging practices do not allow the blocks to be selected on this basis. Typically, dig lines are generated to derive practical mineable shapes that attempt to balance the maximum tonnage and grade with the production schedule and available mining equipment. Depending on the selectivity possible from the mining equipment, the dig-lines will be generated in such a way that some ore blocks are allocated to the waste category, and some waste blocks will be allocated to the ore category.

Practical mining shapes (dig-lines) have been generated for the 11 benches of the open pit. In practice, dig-lines like these would be used by the operation to select, load, and haul the material to the different destinations. Figure 4 shows an example of the dig lines generated for bench 2 of the open cut. Note that some of the shapes may be minable, or not, depending on the direction of mining. Still, it is a realistic example of what would be expected during the ore/waste selection process.

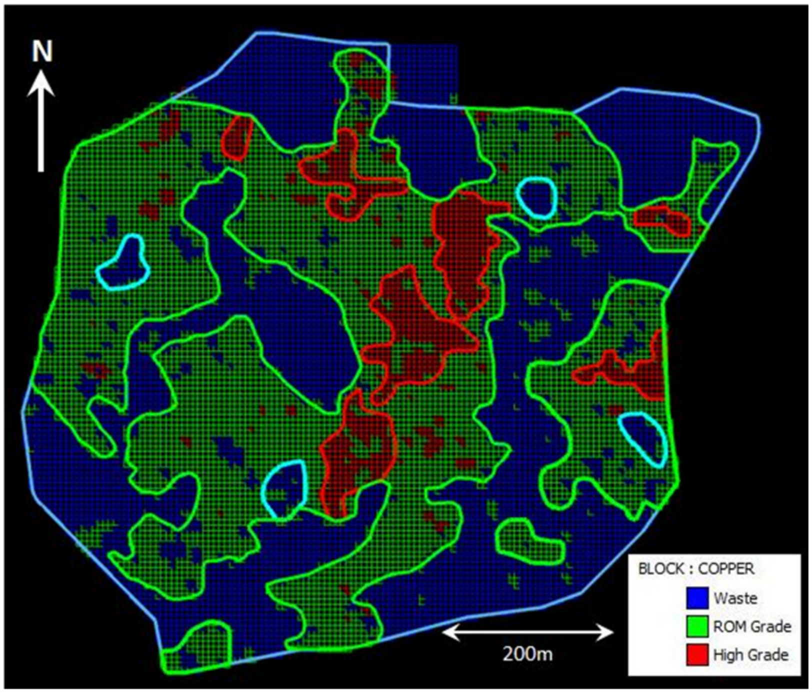

Figure 4 – Plan view of bench 2 showing the dig lines and dilution incurred at the time of mining.

Note from Figure 4 that there can be significant additional ore loss and dilution when the non-free selection scenario is considered. In this example, almost all miss-classifications that can occur do occur: waste to ROM (blue blocks inside green outlines), waste to high grade (blue blocks inside red dig lines), ROM to high grade (green blocks inside red dig lines), ROM to waste (green blocks inside blue dig lines, or with no dig lines at all), and high grade to ROM (red blocks insider green outlines). For this bench, the only exception is that there is no high grade sent to waste as this represents the more typical practice of sending more waste material to the ore (ROM and high grade) destinations. In the case of the small high grade dig-line to the NW in Figure 4, the high grade dig line butts against waste material, and some unplanned ore loss is possible.

Another critical issue to consider is the significant difference between the free selection and the "real" grade control model. While both are based on the same samples and grade control estimates, the process of adjusting the selection to what is likely to be mineable implies a significant loss in recovered grade and ore.

Table 3 compares the resource model with the ("real") grade control model after dig lines have been defined. Table 4 compares the grade control model without dig lines (free selection) with the "real" grade control model after dig lines have been defined.

The resource model (Table 3) in effect is not such a bad predictor of the "real" grade control model (i.e., recoverable resources/reserves) in some benches. But indeed, it is difficult to calibrate the resource model to accurately predict what is going to be recovered at the time of mining.

Comparing the free selection grade control with the "real" grade control (Table 4), it is evident that dilution and ore loss is significant at the time of mining. This is to the point that, for several benches, the significant uplift observed from the resource model to the free selection model is lost when defining dig lines. But this does not occur for all benches, with some gains in metal realised through gains in tonnages.

Table 3 – Comparison between resource model and "real" grade control model (using the dig-lines), showing tonnage, grade and metal content for Waste, ROM and High Grade classifications. Note that the change of support and information effects are more dramatic as the cut-off increases.

		Resource Model			*Grade Control Model*			
Bench No.	***Grade Category***	***Tonnes ($x10^6$)***	***Grade % Cu***	***Metal ($x10^3$)***	***Tonnes ($x10^6$)***	***Grade % Cu***	***Metal ($x10^3$)***	***% Diff. Metal***
1	Waste	9.43	0.07	7	8.72	0.05	4	-39%
	ROM	4.58	1.04	48	5.28	1.01	53	11%
	High Grade	0.70	2.54	18	0.71	2.45	17	-5%
2	Waste	5.59	0.17	9	5.60	0.24	14	47%
	ROM	6.29	1.08	68	6.71	1.04	70	3%
	High Grade	1.52	2.71	41	1.08	2.69	29	-30%
3	Waste	3.01	0.26	8	2.93	0.31	9	15%
	ROM	6.13	1.10	67	6.31	1.10	70	4%
	High Grade	1.29	2.72	35	1.19	2.50	30	-14%
4	Waste	2.91	0.25	7	3.11	0.30	9	24%
	ROM	5.96	1.07	64	5.73	1.08	62	-3%
	High Grade	1.27	2.71	35	1.30	2.50	32	-7%
5	Waste	2.18	0.27	6	2.41	0.33	8	36%
	ROM	5.02	1.05	53	4.62	1.02	47	-11%
	High Grade	1.10	2.72	30	1.27	2.67	34	13%
6	Waste	1.90	0.26	5	2.13	0.34	7	42%
	ROM	4.92	1.06	52	4.30	0.99	43	-18%
	High Grade	0.79	2.59	21	1.18	2.47	29	41%
7	Waste	1.57	0.25	4	1.59	0.31	5	27%
	ROM	3.68	1.08	40	3.38	1.04	35	-12%
	High Grade	0.75	2.58	19	1.03	2.37	24	23%
8	Waste	1.13	0.22	2	1.33	0.29	4	55%
	ROM	3.26	1.10	36	2.89	1.10	32	-11%
	High Grade	0.82	2.64	22	0.98	2.48	24	13%
9	Waste	0.68	0.17	1	0.82	0.29	2	106%
	ROM	2.22	1.16	26	1.89	1.11	21	-18%
	High Grade	0.64	2.62	17	0.83	2.46	20	21%
10	Waste	0.61	0.22	1	0.69	0.30	2	58%
	ROM	2.10	1.12	24	1.79	1.14	20	-14%
	High Grade	0.32	2.96	9	0.54	2.61	14	51%
11	Waste	0.43	0.23	1	0.43	0.22	1	-5%
	ROM	1.13	1.09	12	0.96	1.12	11	-13%
	High Grade	0.16	3.12	5	0.34	2.68	9	83%
Total Waste		**29.44**	**0.18**	**51.93**	**29.77**	**0.22**	**65.32**	**26%**
Total ROM		**45.28**	**1.08**	**488.69**	**43.86**	**1.06**	**463.94**	**-5%**
Total High Grade		**9.37**	**2.68**	**251.40**	**10.45**	**2.52**	**263.20**	**5%**

Table 4 – Comparison between free selection grade control model and the "real" grade control model (using the dig-lines), showing tonnage, grade and metal content for Waste, ROM and High Grade classifications.

		Free Selection Model			*Grade Control Model*			
Bench No.	***Grade Category***	***Tonnes ($x10^6$)***	***Grade % Cu***	***Metal ($x10^3$)***	***Tonnes ($x10^6$)***	***Grade % Cu***	***Metal ($x10^3$)***	***% Diff. Metal***
1	Waste	9.78	0.11	10	8.72	0.05	4	-60%
	ROM	4.20	1.03	43	5.28	1.01	53	22%
	High Grade	0.73	2.84	21	0.71	2.45	17	-19%
2	Waste	5.83	0.21	12	5.60	0.24	14	14%
	ROM	6.39	1.05	67	6.71	1.04	70	4%
	High Grade	1.17	2.84	33	1.08	2.69	29	-13%

3	Waste	3.24	0.26	8	2.93	0.31	9	7%
	ROM	5.89	1.10	65	6.31	1.10	70	8%
	High Grade	1.30	2.72	35	1.19	2.50	30	-15%
4	Waste	3.26	0.26	8	3.11	0.30	9	6%
	ROM	5.57	1.07	60	5.73	1.08	62	4%
	High Grade	1.31	2.68	35	1.30	2.50	32	-9%
5	Waste	2.54	0.29	7	2.41	0.33	8	9%
	ROM	4.55	1.04	47	4.62	1.02	47	-1%
	High Grade	1.21	2.83	34	1.27	2.67	34	-1%
6	Waste	2.17	0.28	6	2.13	0.34	7	15%
	ROM	4.35	1.01	44	4.30	0.99	43	-2%
	High Grade	1.09	2.67	29	1.18	2.47	29	0%
7	Waste	1.72	0.28	5	1.59	0.31	5	4%
	ROM	3.42	1.08	37	3.38	1.04	35	-5%
	High Grade	0.86	2.64	23	1.03	2.37	24	6%
8	Waste	1.43	0.26	4	1.33	0.29	4	4%
	ROM	2.97	1.13	34	2.89	1.10	32	-5%
	High Grade	0.81	2.81	23	0.98	2.48	24	7%
9	Waste	0.86	0.23	2	0.82	0.29	2	20%
	ROM	1.96	1.16	23	1.89	1.11	21	-7%
	High Grade	0.72	2.64	19	0.83	2.46	20	8%
10	Waste	0.77	0.27	2	0.69	0.30	2	2%
	ROM	1.74	1.16	20	1.79	1.14	20	1%
	High Grade	0.51	2.77	14	0.54	2.61	14	-1%
11	Waste	0.45	0.24	1	0.43	0.22	1	-11%
	ROM	0.98	1.13	11	0.96	1.12	11	-4%
	High Grade	0.30	2.93	9	0.34	2.68	9	6%
Total Waste		**32.06**	**0.21**	**66.29**	**29.77**	**0.22**	**65.32**	**-1%**
Total ROM		**42.03**	**1.07**	**450.57**	**43.86**	**1.06**	**463.94**	**3%**
Total High Grade		**10.00**	**2.75**	**274.94**	**10.45**	**2.52**	**263.20**	**-4%**

Sampling Variances

Additionally, the simulation sampling script was also used to create variations of the base case grade control database by varying the Northing and Easting collar positions to mimic real-world production scenarios. A total of 15 grade control database variations were created by offsetting the Northing and Easting collar positions from the base case scenario by 2.5m, 5m and 7.5m.

Figure 5 shows the changes in average Cu grades for each bench and at 0% cut-off for the 15 databases. The variance is shown as a relative difference between the maximum and minimum average grades with respect to its mean.

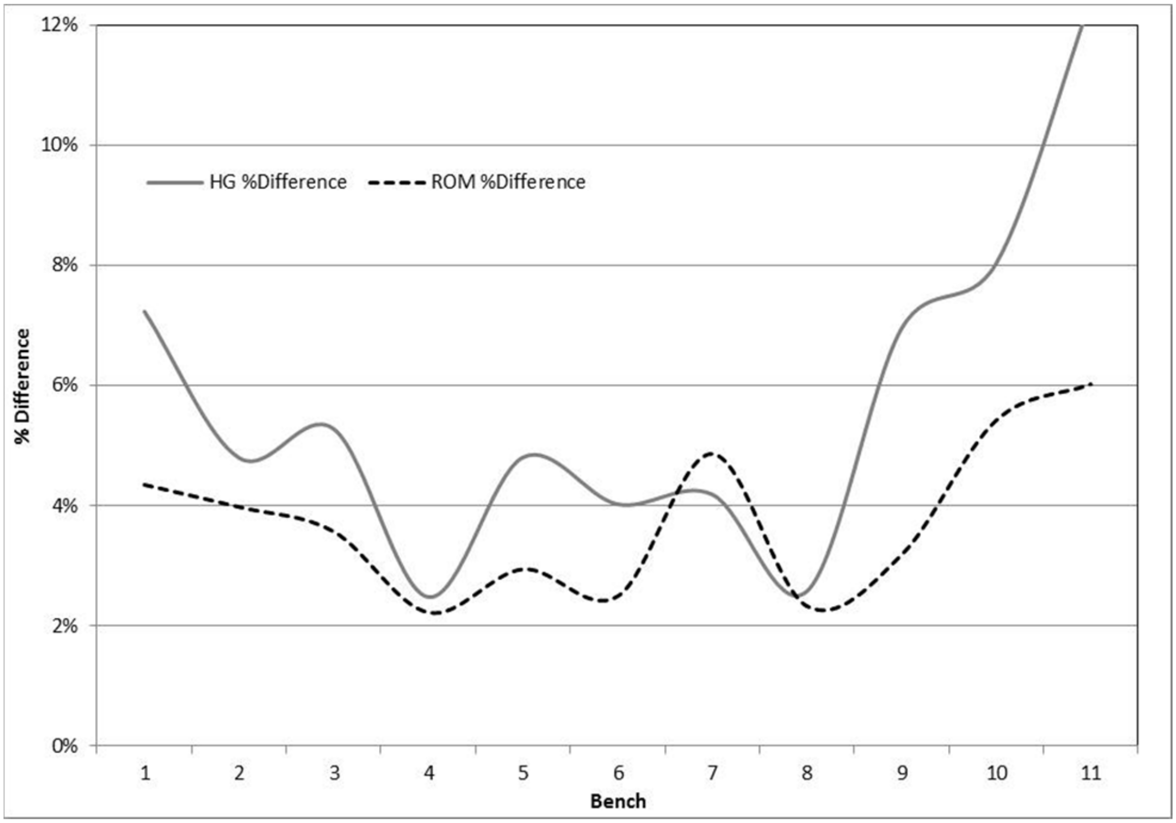

Figure 5: Sampling variance as relative difference of average Cu grades at 0% cut-off for all 15 databases, and for each Bench (1 through 11).

Figure 5 shows that the sampling variance for benches with lower ROM and High Grade tonnages (Benches 1, 2, 9, and 11) is larger. Even for the middle benches, the sampling variance is always greater than 2%. This is a spatial variance, in the sense that it quantifies the consequence of shifts in the position of the samples; it is equivalent to the stochastic variations that can be observed from one simulation to the next.

The conditional simulations developed reproduce the original variability of the drill hole data. In reality, the variances observed in Figure 5 can only be expected if the variability of the drill hole data, and the blast hole data used to select ore and waste, are similar.

Results and Conclusions

The results of this work unequivocally demonstrate why every resource and mine geologist should have a deep understanding of the change of support and information effects, and how these concepts need to considered in their resource models.

The main conclusions that can be extracted are:

1. The impact of the change of support and information effect at Olympic Dam is significant. Conditional simulation allows us to characterise them by themselves or as a combined effect, as presented in this paper.

2. The resource model should be built as a recoverable resource model, trying to incorporate future dilution and ore loss. This allows better prediction of the metal recovered at the time of mining.

3. The amount of dilution and ore loss to be incorporated into the resource model can be calibrated using conditional simulations and grade control. It is generally more significant for higher cut-off grades and at depth, where the high-grade ore zones are more continuous compared to the ore at shallower elevations. Grade control practices for the shallower benches will require more diligence than for benches deeper down into the deposit.

4. To adequately predict dilution and ore loss at the time of mining, it is necessary to develop the full grade control process. Assuming free selection would be dangerous and naive, in the sense that it predicts significantly higher metal recovered than what is actually achievable. This may raise unreasonable expectations, and leads to poor reconciliation.

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