FINANCIAL RISK ASSESSMENT USING CONDITIONAL SIMULATIONS IN AN INTEGRATED EVALUATION MODEL

GRANT NICHOLAS[1], STEPHEN COWARD[2] and JOHAN FERREIRA[3]

[1&2] Quantitative Group, Fremantle, Australia

[3] De Beers, Mineral Resource Management R&D Group, Wells, UK

ABSTRACT

This paper evaluates the financial impact of grade, density, revenue per carat and yield uncertainties on the net present value (NPV) of a diamond project through the use of conditional simulations applied to an open-pit mining method. Kriged estimates are usually accepted as the best linear unbiased estimators upon which the business model is based for valuing a mineral project. In this case conditional simulations have been used to express the variability in discounted cash flow terms and provide a cumulative probability distribution of the NPV for informed investment decision-making. An integrated evaluation model (IEM) is used to assess the impact of resource uncertainties at the scale of planned operational depletion, considering firstly the mining sequence and schedule, and then the impact on the treatment plant recovery model. The main objective is to express financial risk as a function of resource and reserve uncertainties at the appropriate temporal scale.

INTRODUCTION

It is often expected that managers of mining projects must make informed evaluation decisions at different stages of a project based on limited and uncertain data. The challenge is exacerbated by having to distil various sources of technical uncertainties into a financial model that is usually designed to capture production outputs, summed annually in a cash flow model to produce a single net present value (NPV) or internal rate of return (IRR) figure. While it may be assumed that the appropriate technical expertise is incorporated into the design process at each stage of a project, it remains a challenge to accurately incorporate spatial and system correlations between technical and financial processes and aptly capture the risks and opportunities in the financial output. It is even more demanding to capture and express risks of the project in 'digestible' financial terms. This challenge is magnified when the evaluation assessment has to incorporate several risk scenarios into 'one version of the truth' that is easily understood by decision-makers.

The main objective of this paper is to demonstrate how resource risks can be captured in a financial model as a better alternative to increasing the discount rate (or 'hurdle rate') as a proxy for technical risk. A secondary objective is to illustrate how an IEM can be developed as an extension of (rather than a substitute for) the traditional evaluation model using conditional simulations to reflect financial uncertainty around the kriged estimate.

EVALUATION PRACTICES

The standard NPV formula is well known where *CF* refers to the cash flow in each period *i*, and *r* is the discount rate (see equation 1). The discounted cash flow (DCF) component of the equation can be rewritten as a weighted sum to illustrate the impact of the discount rate on the variance of the DCF (see equation 2).

$$NPV = \frac{\sum CF_i}{(1+r)^i} - I_0 \qquad (1)$$

$$DCF = \sum CF_i * \left(\frac{1}{(1+r)^i} \right) \quad \text{or} \quad \text{DCF} = \sum CF_i * w_i \qquad (2)$$

If technical risks are incorporated into the discount rate, *r*, a tacit assumption is made that risks would increase exponentially over time. Most mining sequencing and scheduling optimization software packages attempt to generate the maximum cash flow in the early years of a project's life to maximize NPV. However, risks do not consistently increase, nor escalate exponentially, over the life of a project. It is not logical to assume that technical risks will increase over time because usually an effective management team will attempt to mitigate these risks by implementing various management and operational strategies over the life of the mine as more experience is gained.

In some cases the mine plan is reviewed from practical and probabilistic perspectives, which would include identifying mine blocks associated with greater technical risks and scheduling these blocks later in the project's life of mine schedule (Godoy and Dimitrakopoulos, 2004). Other workers have considered objective functions and simulated annealing techniques to focus on quantifiably maximizing value (and/or reducing costs) by prioritizing the sequence of mine blocks (Dimitrakopoulos and Ramazan, 2004). The particular problem discussed in this paper considers how technical risks in a mineral project can be assessed assuming a given mine plan, treatment design and financial model, all of which are derived from the kriged estimates of resource variables.

Typically mine and treatment plans are developed once a suitable amount of sample data have been acquired to attain the required project confidence. These plans provide cash flow input into a financial model to enable informed decisions to be made. The evaluation of a mineral project is complex with many sources of uncertainty ranging from sampling, estimation, mining and treatment to economics (Kleingeld and Nicholas, 2004). In order to optimise investment decision-making, an appropriately structured evaluation framework must be adopted that incorporates these uncertainties into its production figures while producing clear financial outcomes.

A project evaluation framework should be designed to encapsulate and integrate correlations and complexities, which are diverse and range from sampling support and scale effects to understanding the impact of variability, uncertainty and flexibility on operational efficiency and economic viability. When combining time and capital constraints, most models do not allow all facets of evaluation to be integrated into an evaluation model. Thus, the model should strive to strike a balance between the quantity and quality of sampling data, estimation techniques and sufficient incorporation of the technical, financial and economic aspects of the project that will make a material difference to the investment decision.

In this study the impact of spatial resource variability on the existing business model was assessed using conditional simulations for grade, density, revenue per carat and yield variables. It was deemed prudent to use spatial conditional simulations rather than try to reflect risks using Monte Carlo simulations (MCS) because the latter cannot easily incorporate the spatial covariance relationships of resource and reserve data for mineral projects. Usually MCS (e.g. using @Risk or Crystal Ball) is used to generate risk profiles of production outputs and financial parameters to produce a probability distribution of the NPV. While MCS may be useful to model variability around non-spatial variables, it is inadequate in the case of spatial resource variables for mineral projects because it does not consider the spatial distribution of variables nor the spatial covariances between variables.

An alternative approach may use summarized statistics from spatial modelling of the resource as input parameters (e.g. the mean and variance) into probability distributions for MCS modelling. This method is not recommended because it can lead to scenarios where independent, random draws have been taken from the MCS but do not honour the covariance relationships between geological units in adjacent mine blocks. The net result is that technical risks may be seriously over- or under-stated and lead to scenarios where the NPV risk probability profiles are either too broad or too narrow, misleading decision-makers. (Nicholas et al., 2007).

A more pragmatic and statistically acceptable approach to evaluate the impact of technical risks in mining projects is to use spatial simulations to reflect the resource uncertainty and run these simulated outputs through various production (reserves) and financial models, as discussed by (Dimitrakopoulos et al., 2002; Dowd and Dare-Bryan, 2004). The differences between kriged estimates and conditional simulations have been well documented (Journel and Kyriakidis, 2004). This paper incorporates contributions by these authors and in addition, utilizes an integrated evaluation model (IEM), (Nicholas et al., 2006) to quantify the financial impact of resource and reserve uncertainties of a diamond project, based on an open-pit operation. Results of the study were captured in quantitative NPV probability distributions to reflect the risks and opportunities in the cash flows of the project.

METHODOLOGY

The integrated evaluation model used the geological block model that was populated with spatially simulated data. This resource model was depleted and treated through a combination of mining and treatment simulations, and the output captured in a financial model. The detail of each of these steps is elaborated upon below.

A total of 25 spatial conditional simulations using the Turning Bands approach was produced for each variable using Isatis software and incorporated into a block model with dimensions of 25m x 25m x 12m. Each estimation unit of the block model comprised four resource variables (grade, density, revenue per carat and yield) of which there were 25 realizations for each variable. An initial study revealed no significant correlations between variables, thus each variable was simulated independently. The estimation units and the selected mining units (SMUs) were the same size. The mine plan was imported into Datamine software and merged with the resource block model to produce a depletion volume for each estimation unit. This volume was assigned to a specific year according to the depletion sequence.

The impact of dense media separation yield on throughput and the impact of density on both hardness and liberation were incorporated into the model. The process plant was designed to accommodate surges in yield by including several stockpiles and a purge system. A 17% (yield) threshold was incorporated into the risk model to quantify the impact of the high yield blocks. The model assumes that for every 1% yield above 17% in a block, the process throughput will reduce by 0.5%. A plant recovery factor was calculated based on a quadratic relationship between the density of the block and the liberation that is achieved by the plant. Throughput was calculated by multiplying the depleted tons by the throughput factor, and then the grade of the reduced tonnage was used to calculate the carats fed to the process. These carats were then modified by the plant recovery factor.

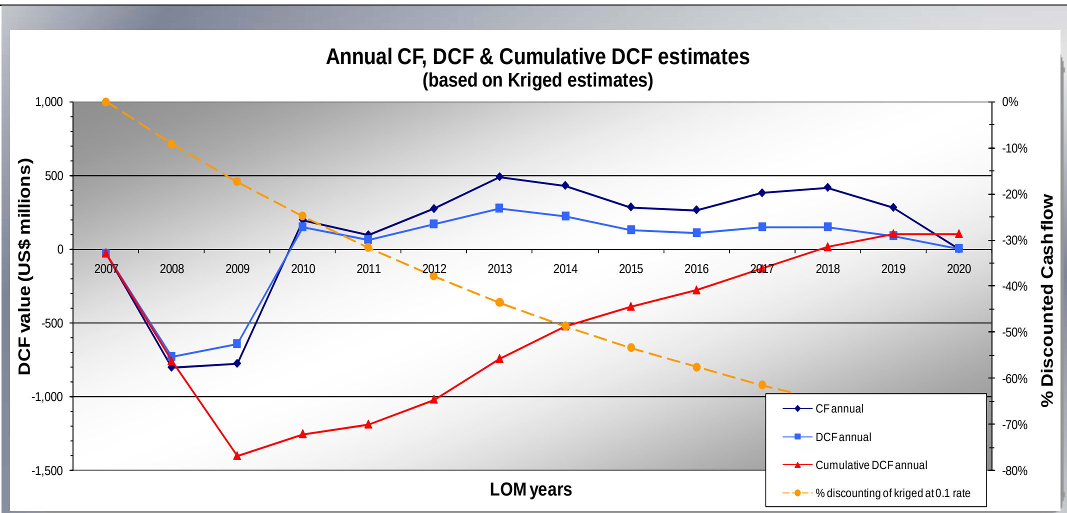
The depletion model was overlain onto the spatial realizations to generate an ore stream, translating the spatial data into a time-based framework. Outputs from the mining and mineral processing modelling were incorporated into the financial model. It is important to note that the mine and treatment plans were based on the kriged estimates, accepted as the best linear unbiased estimates. The study aimed to represent the impact of risks associated with the uncertainty of resource estimates given these ‘fixed’ mining and treatment processes and to demonstrate the uncertainty of the cash flows using conditional simulations around the kriged estimates.

Production outputs for each of the 25 simulations were imported into the financial model, which consisted of a sequence of Microsoft Excel spreadsheets. The resultant cash flow model for each of the 25 simulation outputs plus the cash flow model (based on the kriged estimates) were imported into a Risk Evaluation Model (using Visual Basic Applications code) and selected data analyses were carried out. The financial model was not altered in any way, other than importing the production outputs from each of the simulations and thereafter, exporting the estimated cash flows into the risk evaluation model.

ANALYSES OF RESULTS

Figure 1 plots the cash flows, discounted cash flows and cumulative discounted cash flows over the life of mine based on kriged estimates. A NPV of US$103 million was derived with an IRR equal to 11.35% at a discount rate of 10%. The kriged results show that the first 5 – 6 years (2008/9 to 2014/5) of the model were the main contributors of value to the NPV based on a discount rate of 10%. From 2016 onwards, less than 50% of the cash flow value contributes to the NPV (alternatively it could be stated that the cash flows beyond 2016 are discounted by more than 50%) implying that considerable time, money and effort would be needed to be expended during this time period to make an improvement to the NPV. As the discount rate was increased, the time window decreased placing more focus on the cash flows derived from the first few years. The ramp-up in production during 2010 - 2013 is pivotal in achieving tonnage throughput and ensuring positively contributing cash flows.

Figure 2 compares the kriged results (of Figure 1) with 25 conditional simulations plotted as cash flows, discounted cash flows and cumulative discounted cash flows over the project's life of mine. The solid black line represents the kriged cash flow, while the dashed black line shows the kriged cumulative discounted cash flow. The other lines represent 1 – 25 of the conditional simulated cumulative discounted cash flows. The P10 shows a 10% chance of getting a NPV of US$ -96 million or less; the P50 shows a NPV of US$ 39 million while the P90 indicates a 10% chance of getting above US$ 201 million. Note that the P50 simulated result of US$ 39 million is materially less than the kriged business case of US$ 102 million (62% less). Further analysis revealed inconsistencies in the mine plan (viz. the open-pit block volume calculations) applied to the kriged model, which had the biggest impact on tonnage errors during the first few years (mainly 2010 – 2011).

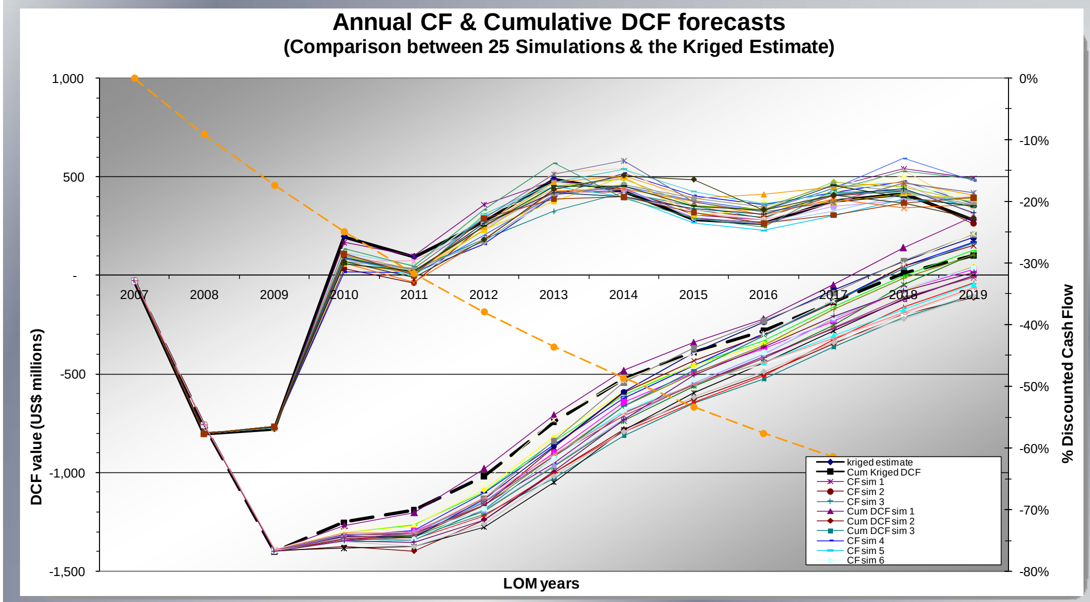


	rate 1
Discount rate over LOM	10.00%
NPV (US$ millions)	**103**
IRR	11.35%

Figure 1 illustrates the cash flows (CF), discounted cash flows (DCF) and cumulative discounted cash flows (cum DCF) for the business model based on kriged estimates

Once these block volume errors have been corrected, it is expected that the kriged model would lie closer to the mid-point of the 1 – 25 simulated discounted cash flow outputs. At the time of writing this paper, the mine plan was being amended. The second possibility for the lower P50 NPV is that each of the conditional simulations was run through an integrated evaluation model (IEM) at the operational scale of planned depletion. Each block (25m x 25m x 12m) was run through the transfer function, i.e. the mining and treatment plan with fixed constraints. A study by (Nicholas et al., 2006) revealed that the financial impact of running kriged estimates through an IEM can be materially different compared to the traditional assumption of using annual, average mining and treatment constraints. An IEM considers the constraints that would be imposed on a block at an hourly or daily temporal scale rather than assuming average constraints, calculated over 12 months.

The business model based on the kriged estimates was not run through an IEM (it was beyond the scope of the study) and instead assumed annual average constraints based on the transfer function parameters. Where sampling data were widely spaced, the 'smoothing effect' of kriging would have the biggest impact. As a result, even if an IEM was used based on the kriged estimates, there may be still be a bias in the results obtained by kriging. For this reason the use of conditional simulations using an IEM is recommended to better reflect the variability in cash flows.



Percentiles	P10	P50	P90
NPV (US$ millions)	**-96**	**39**	**201**

Figure 2 compares the cash flows (CF), discounted cash flows (DCF) and cumulative discounted cash flows (cum DCF) between the kriged estimates and conditional simulations

Figure 3 illustrates how conditional simulations can be used to assist production planning (short and long-term). Histograms of the cash flow for each year can be produced to represent realizations that consider the impact of resource uncertainties over time. The aim of producing these cash flow probability plots is to show the range in expected values and compare them to the budgeted/ forecasted values (based on the kriged model). The coefficient of variation (CV) can be calculated to highlight those specific years which have the greatest variability. The model has consistently found that the cash flow between years 2010 and 2012 have the CV. In the case where more than one resource variable is considered in the simulations, other variables can be dialled out one at a time to identify that particular variable that has the greatest impact on the CV of the cash flows. Capital could be made available to mitigate the risks by providing adequate flexibility (either in the mine plan or treatment plant) identified during these years – this should improve the process of capital budgeting.

Lastly, Figure 4 shows the cumulative probability distribution for the NPV of this project, which provides a better representation of the risk profile for this project than simply quoting a single NPV figure or stating fixed percentiles (e.g. P10, P50 and P90).

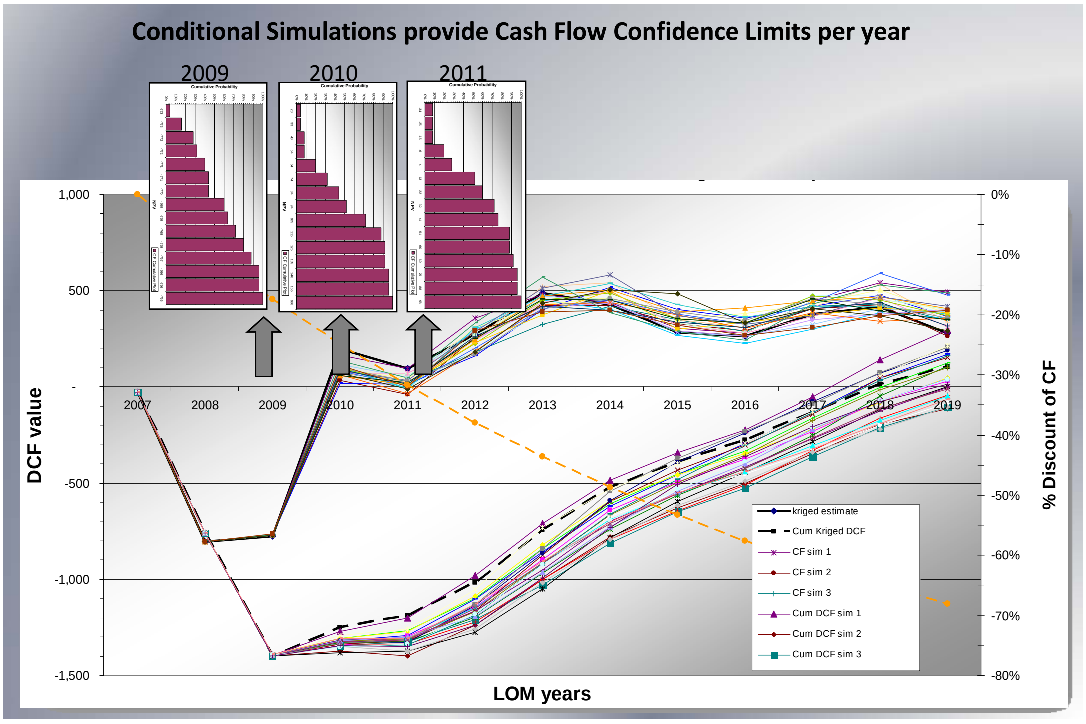
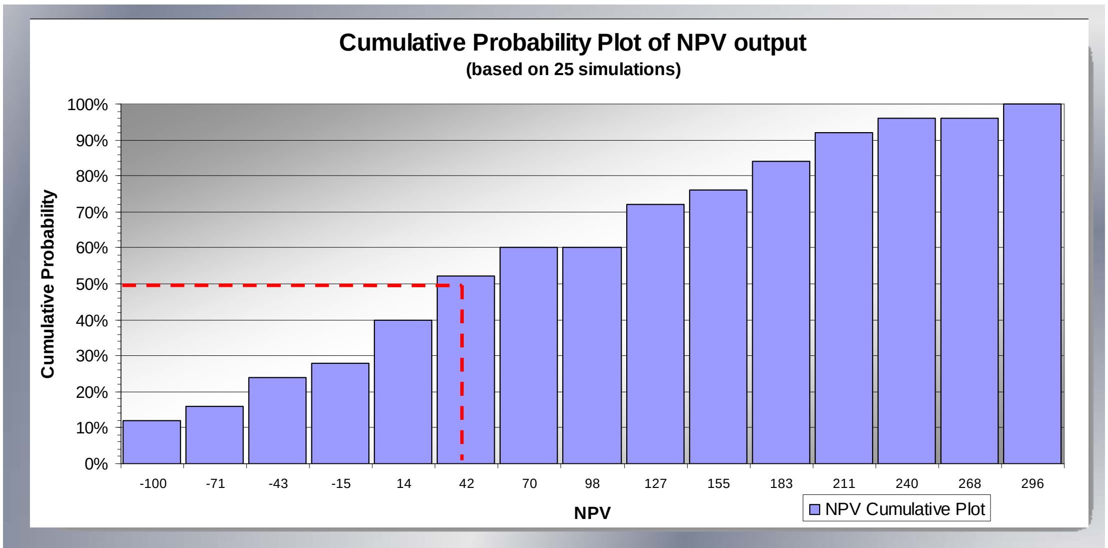


Figure 3 shows how histograms of the forecasted cash flows per year can be generated based on results from the conditional simulations



P10	P50	P90
-96	39	201

Figure 4 shows the cumulative probability plot for the NPV of this project based on results from the 25 conditional simulations

SUMMARY AND CONCLUSIONS

This paper demonstrated that conditional simulations can be used alongside kriged estimates to quantify the financial impact of resource uncertainties without adjusting the discount rate to compensate for technical risks. The financial impact of grade, density, yield and revenue per carat uncertainties were quantified. The findings of this study strongly suggest that an IEM should be an essential part of the business planning process. This is necessary to ensure that spatial resource uncertainties can correctly be translated into the time domain via depletion and treatment models, and compared to financial forecasts based on kriged estimates.

The use of an IEM is preferred to the approach of applying mining and treatment parameters (derived from annual averages) to production figures, which can provide 'smoothed' perceptions of the actual variability that will be encountered on a daily basis. This could result in an over- or under-estimated financial value of the deposit as it fails to capture the short-scale affects of the mining and treatment constraints that are imposed on the production estimates on a block by block basis. It can also fail to capture upside opportunities where greater resource variability could result in increased production recoveries provided the mine and treatment processes are appropriately designed to provide this flexibility.

Depletion of simulated blocks in space and in time allows the financial impact of variability during each year to be accurately quantified. While volume, grade and density estimates show little variation in the simulations over the life of mine on an annual scale, it is the variability of these simulations within each year and the selection and sequencing of blocks over time that dictates the contribution to the cash flow model. In the case of this deposit, the evaluation model exposed that the highest variability in cash flows occurred early on in the life of mine (2010 to 2012) which has the biggest impact on the time value of money. This highlighted the need for efficient operational execution to ensure that the 'right tons from the right areas are mined and treated during the right time'. The use of an IEM approach linked to financial modelling provides quantitative information about the expected variability of a deposit, which creates a basis for improved mine designing and operational planning.

ACKNOWLEDGEMENTS

The authors would like to extend their gratitude to the management of the De Beers Group for making data available, especially Rob Davies and the project team. For confidentiality reasons, all figures quoted in this paper were factored accordingly. Appreciation is also expressed to Datamine Ltd (notably the Wells, UK and Johannesburg, South Africa offices) for the many hours spent attempting to solve some of the complex block modelling problems. Special thanks are extended to John Vann (Quantitative Group Ltd) for his editing recommendations. Lastly, the authors would like to acknowledge the De Beers Mineral Resource Management R&D group in Wells, UK for providing the platform of understanding that has facilitated the development of the concepts in this paper.

REFERENCES

Dimitrakopoulos, R., Farrelly, C. and Godoy, M. (2002) *Moving Forward from Traditional Optimization: Grade Uncertainty and Risk Effects in Open-Pit Mine Design,* Transactions of the IMM, Section A, Mining Industry 111, p. A82-A89.

Dimitrakopoulos, R. and Ramazan, S. (2004) *Uncertainty Based Production Scheduling in Open-Pit Mining,* SME Transaction 316 (03-151): p. 1-9.

Dowd, P.A. and Dare-Bryan, P.C. (2004) *Planning, Designing and Optimising Production Using Geostatistical Simulation,* Orebody Modelling and Strategic Mine Planning, Perth, WA, Australasian Institute of Mining and Metallurgy.

Godoy, M. and Dimitrakopoulos, R. (2004) *Managing Risk and Waste Mining in Long-Term Production Scheduling of Open-Pit Mines,* SME Transactions 316: 03-327.

Journel, A.G. and Kyriakidis, P.C. (2004) *Evaluation of Mineral Reserves: A Simulation Approach,* New York, Oxford University Press.

Kleingeld, W.J. and Nicholas, G.D. (2004) *Diamond Resources and Reserves - Technical Uncertainties affecting their Estimation, Classification and Evaluation,* Orebody Modelling and Strategic Mine Planning, Perth, WA, The Australasian Institute of Mining and Metallurgy.

Nicholas, G.D., Coward, S.J., Armstrong, M. and Galli, A. (2006) *Integrated Mine Evaluation - Implications for Mine Management,* International Mine Management Conference, Melbourne, Australia.

Nicholas, G.D., Coward, S.J., Rendall, M. and Thurston, M.L. (2007) *Decision-Making Using an Integrated Evaluation Model Versus Sensitivity Analysis and Monte Carlo Simulation,* CIM International Conference, 2007, Montreal, Canada.