DECISION-MAKING USING AN INTEGRATED EVALUATION MODEL VERSUS SENSITIVITY ANALYSIS AND MONTE CARLO SIMULATION

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ABSTRACT

This paper compares an integrated evaluation approach to decision-making with more traditional sensitivity analysis and Monte Carlo simulation. The primary objective is to highlight the differences in NPV that can arise from using these evaluation methods in a top down and bottom-up approach. Results from three resource scenarios, derived from sampling a "virtual" ore body (reality) on grid spacings of 75m, 50m and 25m, are analyzed and compared.

INTRODUCTION

Decision-makers are often faced with the challenge of making investment decisions on complex mineral projects based on an expected financial return, which, in turn, is based on limited sampling data. There are different types of risks associated with a mineral project, unsystematic (specific) risks associated with technical aspects of the project related to resources and reserves, and systematic (market) risks such as foreign exchange (forex) and forward prices for labour, concrete, diesel, steel etc. Evaluation analysts often include a risk premium to account for specific risks. The challenge for effective decision-making is deriving the magnitude of this risk premium. There are several approaches that can be used to reflect technical risks in mineral projects including sensitivity analysis, Monte Carlo (MC) simulations and geostatistical techniques. This paper aims to explore the benefits and limitations of these three approaches.

Mineral project valuation has progressed substantially in the last decade with the emergence of CIMVAL (2003) and VALMIN (1998) valuation codes and guidelines that govern the technical assessment and valuation of mineral assets and securities. These valuation codes correspond to the NI43-101 (2001) and JORC (1995) resource and reserve classification codes, respectively. They are not prescriptive and do not require quantitative confidence limits to be assigned to tonnages, grade and revenue estimates. Even after classification, the uncertainty of resources and reserves cannot easily be translated into quantitative risks that can be incorporated within a cash flow model.

This paper focuses on exploring methods that assess the relationship between geological uncertainty, mining and treatment efficiency, and methods to calculate the impact that this relationship has on the valuation of a mineral project (see Figure 1). A cash flow model is used to demonstrate these effects by comparing results from a sensitivity and Monte Carlo analysis with an integrated evaluation model (IEM) that reflects a mineral project's technical risks. The IEM aims to reflect the technical linkages and spatial correlations between resource uncertainties and reserves and the cash flow model. The authors use an innovative method of 'back calculating' the average technical discount rate that should be applied to the cash flow model in a conventional DCF calculation.

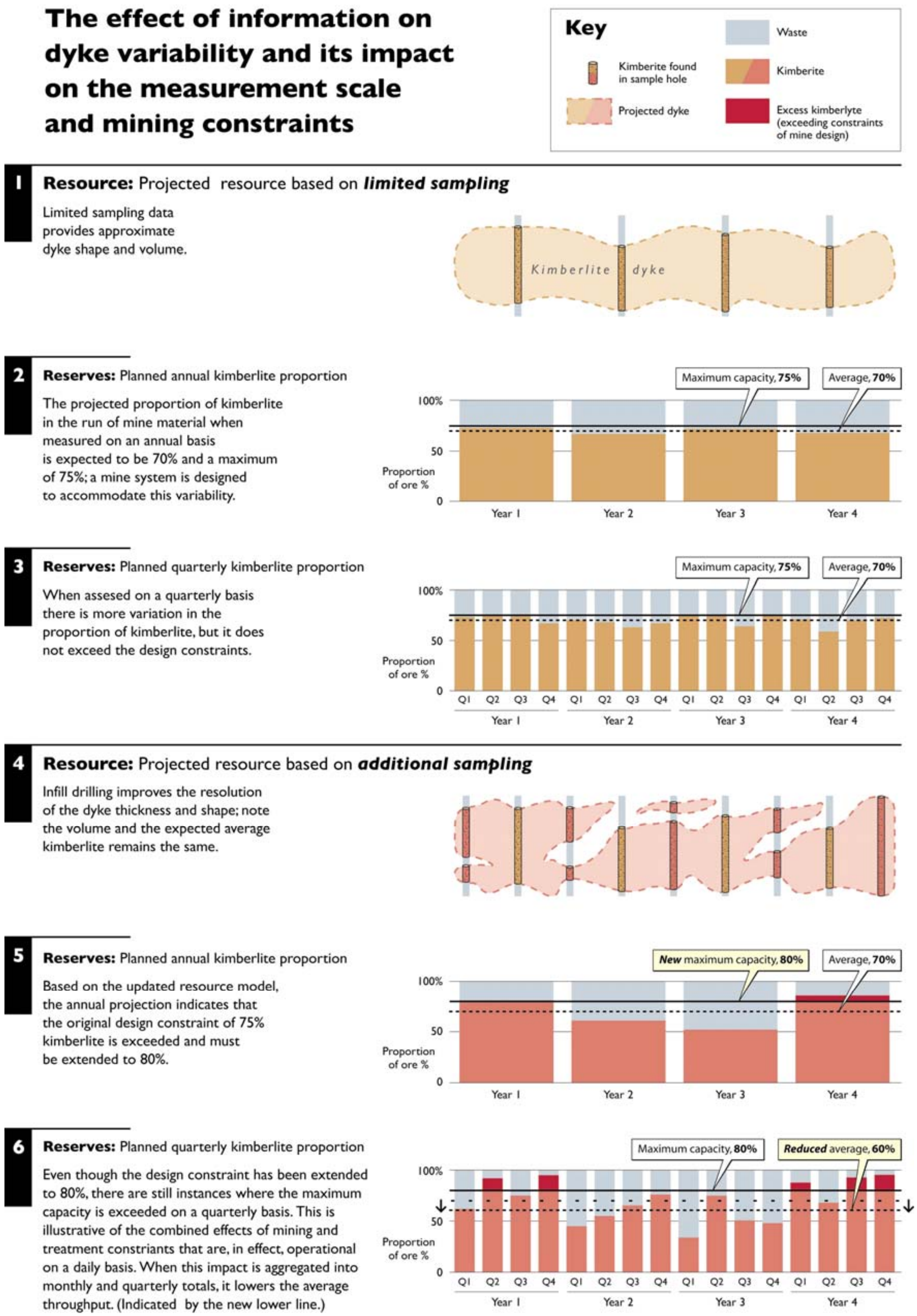

Figure 1 illustrates the effect of dyke variability on measurement scale and mining constraints

EVALUATION PRACTICES

Technical risk is inherent within sampling, resource models, mine plans, extraction and treatment processes and financial models. Risks within these areas can be expressed as a function of variability, the inherent stochastic nature of the deposit; and uncertainty, the assessor's lack of knowledge (Vose, 2002). While there are several types of risk analysis and assessment techniques available, the selection of an appropriate technique depends on a number of considerations such as the time available to conduct the analysis, availability and accuracy of data, scale of required estimate, number of uncertain factors, complexity of the relationships between factors and the competency of the analyst. A risk analysis and assessment study may combine one or more of these techniques.

There are a number of risk techniques including subjective probability impact studies using expert opinion (Aspinall and Brown, 2004); MC simulations and probability distribution modelling in spreadsheet based software programs (Vose, 2002); multivariate data analysis tools to describe complex statistical relationships (Esbensen, 2002); and geostatistical techniques to quantify the variability of spatially orientated variables in mineral projects. Since the application of geostatistical techniques, such as kriging and later, spatial simulations to mineral projects (Matheron, 1973, Journel and Huibrechts, 1978, Krige, 1951); among other applications, geostatistics has also been used to quantify the impact of resource uncertainties on mine planning, sequencing and scheduling (Ravenscroft, 1992, Dimitrakopoulos et al., 2002, Dowd and Dare-Bryan, 2004, Deriasme and Farrow, 2004).

While conventional discounted cash flow (DCF) is still used as the baseline for decision-making, there has been substantial research carried out to understand its advantages and limitations (Smith, 1982) and (Davis, 1995). A combination of statistics, MC simulations and geostatistical ore body simulations are used to address the uncertainty in cash flows while real options (Brennan and Schwartz, 1985, Mason and Merton, 1985) were developed to improve estimation accuracies with respect to addressing the lack of flexibility in DCF projections. Statistical, geostatistical and MC simulation modelling techniques are often combined with real options in the valuation of mineral projects (Galli et al., 2004, Goria, 2004)

BACKGROUND AND PROBLEM DEFINITION

The De Beers, Snap Lake kimberlite is located 220 kilometres northeast of Yellowknife North Western Territories, within the Achaean Slave Province craton of Canada. The body is a kimberlite dyke that dips at 15 degrees towards the north east and is on average 2.8m thick. A majority of the Snap Lake kimberlite dyke is hosted within an Archean multiphase suite of intrusive granitoids, with a minor portion of the kimberlite dyke emplaced within overlying metavolcanics and metasediments of the Archean greenstone belts.

The Geometry of the dyke is variable. On the regional scale (100s of metres) the Snap Lake dyke appears to be a continuous, gently dipping sheet, although three areas of offset have been identified by surface seismic imaging (McBean et al., 2001). At a more local scale (10-100m), orientation changes and splits and large splays have been observed. These are thought to be structurally controlled. On a small scale (0-10m), the dyke is typically controlled by two different host rock features. Within the strongly foliated metavolcanics, the kimberlite appears to roll and undulate on a small scale matching the foliation, while in the granitic host rocks, local variations occur along a primary set of joints that are flat lying but affected by secondary jointing at approximately 35° dip resulting in an angular step-like nature to the dyke (McBean et al., 2001).

To assess the impact of geological variability on the project valuation, the authors simplified the Snap Lake problem by assuming that dyke thickness and shape variability derived from face-mapping in the development tunnels were representative of the entire deposit. Three approaches were adopted; a sensitivity analysis where the variables dilution, tonnage throughput and recovery were changed by ±5%, 10% and 15% from their expected values; MC simulations were run on the same variables using expert opinion to parameterize the input variables; and finally an IEM was developed to allow both bottom-up and 'top down' evaluation methodologies. Results of these three approaches were compared with each other and against a virtual ore body (V-Bod).

BUILDING AN INTEGRATED EVALUATION MODEL

A virtual ore body (V-bod) was created using a non-conditional geostatistical simulation based on data gathered from a combination of drilling information, bulk-samples and face mapping from an exposed part of the dyke. It was assumed to be the 'reality' on which the various sampling campaigns were conducted to generate the sample data. Two variables were considered in the evaluation model, viz. geometrical variability of the top surface of the dyke (v1) and thickness related to the volume of the dyke. Grade was not deemed to have any significant variability between scenarios and thus, a single sampling campaign on a 50m grid sufficed.

Three sampling campaigns were used to virtually sample the V-bod at point support using the geostatistical software, Isatis from Geovariances. Vertical core drilling campaigns were designed on a 75m, 50m and 25m grid to sample for v1 and thickness variables, creating resource scenarios one, two and three respectively.

Resource models for v1 and thickness were generated for each scenario based on sampling data from each campaign. Ordinary kriging was used to generate estimates for each scenario into smallest mining units (SMUs) of 4m by 4m. The same grades were applied to each scenario in order to keep grade constant and only assess the impact of geological variability. Figure 2 illustrates the resource models for thickness. Although the statistical means and variances between the three scenarios show no significant differences, the spatial distribution of thickness is visually different. Warmer colours signify higher values while colder colours are low values.

Reserve considerations focused mainly on mining and treatment processes. A conventional room and pillar underground method was used with an option of slashing and drifting, depending on whether the dyke thickness was less than a specified mining threshold. An average extraction rate of 75% was imposed. Each large mining block of size 250m by 250m was depleted based on a combination of rim tunnels, stope tunnels and stope slashing. An average daily call of 3150 treatment tons was imposed on the project by management. A simplified treatment model was assumed for this study based on a linear relationship between the proportion of ore and waste. Recovery efficiency improved as the proportion of kimberlite increased. A plant surge capacity constraint was included to asses the impact of varying dyke thickness on the feed rate variability using an 'event-based' simulation. A total stockpile capacity of 3000 tons was created, which included capacity from an underground storage bin.

Thickness Variability

	Scenario 1 (75m)	Scenario 2 (50m)	Scenario 3 (25m)	V-bod
	Kriged	Kriged	Kriged	
Mean Thickness	1.70	1.70	1.70	1.70
Variance Thickness	0.11	0.11	0.13	0.23

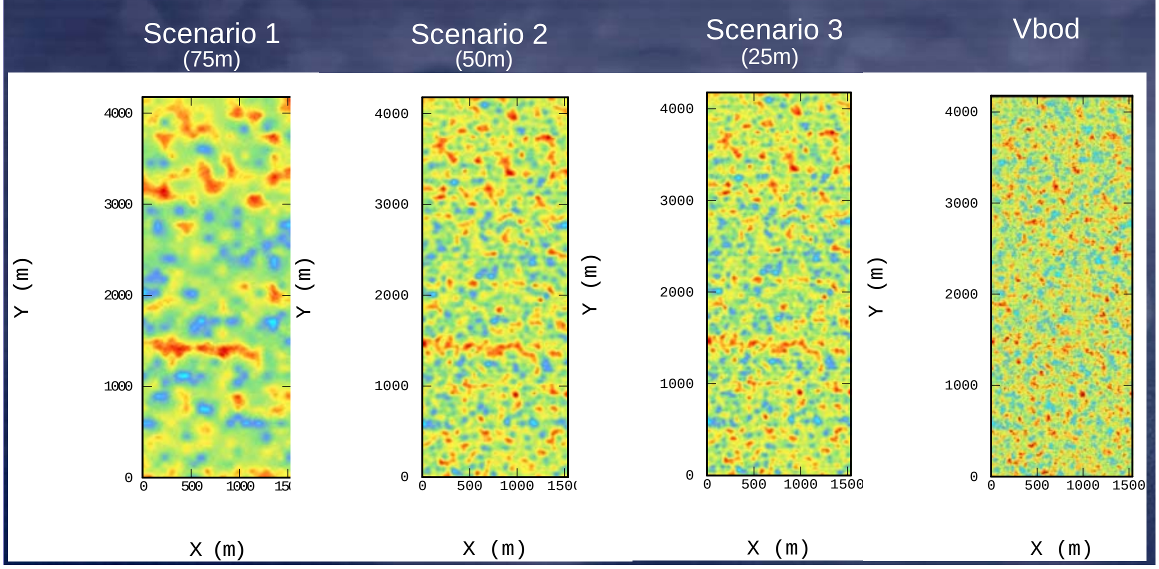

Figure 2 depicts the thickness variable for all three scenarios plus the V-bod

The IEM was designed so that the financial model was directly correlated with the mining and treatment database enabling all production estimates, revenues and costs to be accumulated from a blast by blast basis to a daily basis and collected quarterly and annually. These production outputs were inputs into the cash flow model. Conventional DCF valuation was used to calculate NPVs at an initial discount rate of 10%. NPVs were calculated in real money terms (after royalties and tax deductions, allowing for inflation). Economic forex modelling was not included in this study but the reader is referred to an earlier paper for more detail on the use of real options and forward modelling of forex (Nicholas et al, 2006). To simplify matters, an exchange rate of 1.21 CAD$/ US$ was fixed over the life of mine.

Two evaluation processes, a bottom-up and a top-down approach, were computed for three different scenarios, viz. 75m, 50m and 25m sampling grids to show the information effect (Armstrong and Champigny, 1989) on estimating NPV. Outputs from each scenario were compared to the V-Bod to quantify the error in the NPV estimates. A technical discount rate was calculated for each scenario to quantify the average risk premium that should have been used in the DCF calculation in order to attain the same NPV estimate as the V-Bod. Sensitivity analysis and MC simulations were run on the 'global' top-down evaluation methodology in order to compare the output from these two techniques with the results from the IEM (bottom-up) approach.

RISK MODELLING

The NPV of each scenario was calculated using the top-down versus bottom-up techniques to demonstrate the impact of measurement scale.

The IEM utilized a bottom-up evaluation technique that was based on depletions of the ore body at a local SMU scale of 4m by 4m. Production tonnages and grades were calculated from these blasts on a daily basis and accumulated monthly, quarterly and annually. Each SMU was analogous to a mine blast that was assessed whether it met the necessary mining and plant criteria before either contributing to the call of 3150 tons per day or being trammed to the waste bin if it comprised more than 70% waste. The increased short-scale variability of the dyke resulted in the mining and treatment constraints being hit more often than estimated in the top-down approach. Annual cash flow forecasts were derived from accumulations of daily depletions based on localised resource estimates.

The top-down evaluation approach refers to annual forecasts that were calculated from depleting resource estimates through a global mine plan. The average resource values for each year were run through the same mining and treatment constraints as imposed on the bottom-up approach. However, instead of accumulating actual tonnages from short-scale depletions, the top-down approach assumed a fixed daily plant call of 3150 tons per day would be achieved, then multiplied depleted carats with an average recovery factor per large-scale mine block. These production estimates were run through the financial model as before, providing NPVs. Figure 3 demonstrates that the two evaluation approaches provided materially different NPVs.

Global ('top-down) vs Local ('bottom-up') NPVs

	Scenario 1 (75m)	Scenario 2 (50m)	Scenario 3 (25m)	V-Bod
	Kriged	Kriged	Kriged	
Global Annual NPV	91.6	80.1	73.9	1.5
Local Annual NPV	32.9	31.4	28.3	1.5

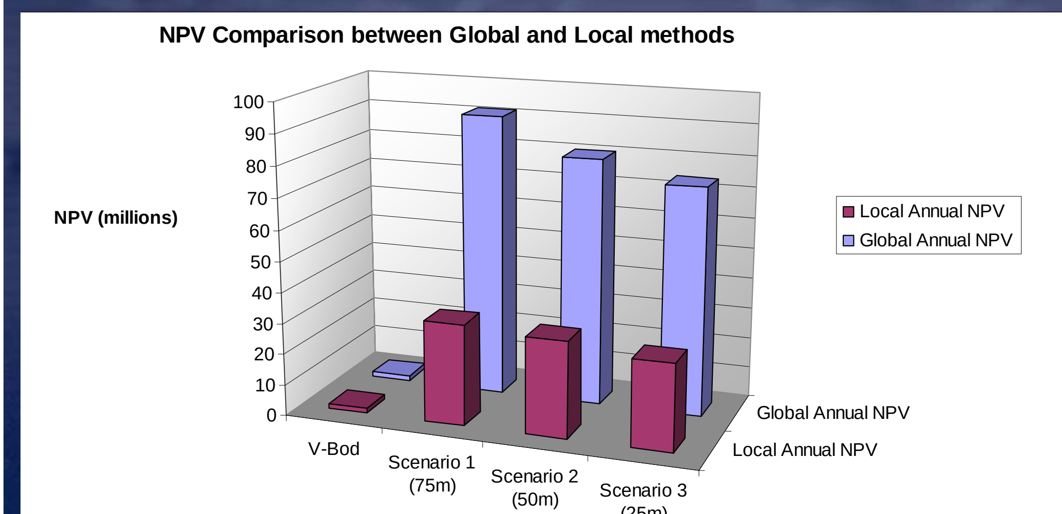

Figure 3 compares the NPV results between the top-down and bottom-up evaluation methods

Dilution loss, plant throughput and recovery loss can have a significant influence on NPV by affecting the number of carats produced. A simplistic sensitivity analysis shows the impact on NPVs for a given range around the chosen input. All other input variables are held constant so as to isolate the impact of the chosen variable. Figure 4 portrays sensitivities for Scenario 1 (75m). Figures for Scenarios 2 & 3 have not been included as they are very similar to Figure 4, below.

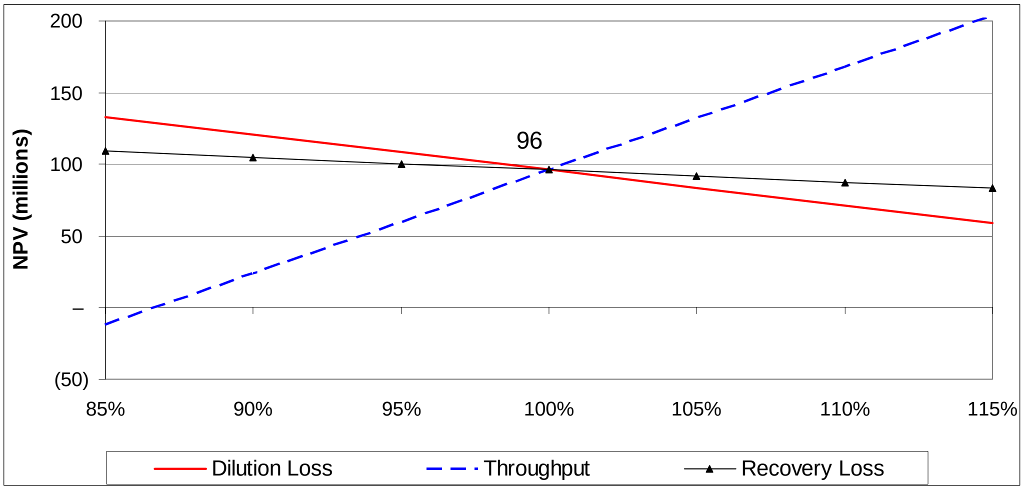

Figure 4 shows the sensitivity of NPV due to changing input assumptions of ± 15%

The sensitivity range (-15% to +15%) is not based on any probabilistic data and is not intended to provide any information on the chances of an event occurring. Sensitivities can also be skewed by the fact that they are based on an absolute value and more than one sensitivity is not usually shown on a single graph. Limitations of sensitivity analysis are many; however, if these limitations are recognized, it can assist in highlighting areas that require further investigation.

MC simulations are generally used to provide confidence intervals around an expected output. Expert opinions were used to define the probabilistic ranges for dilution loss, throughput and recovery loss. Non-parametric, triangular distributions were used to parameterize the input probability distributions. No statistical correlations were included between the three variables, which is recognized as a limitation of this analysis.

Figure 5 demonstrates the cumulative probability plot for NPV based on simultaneous random draws from dilution, throughput and recovery probability distributions. Scenario 1 (75m) is shown as the variance around the NPV was similar for all three scenarios.

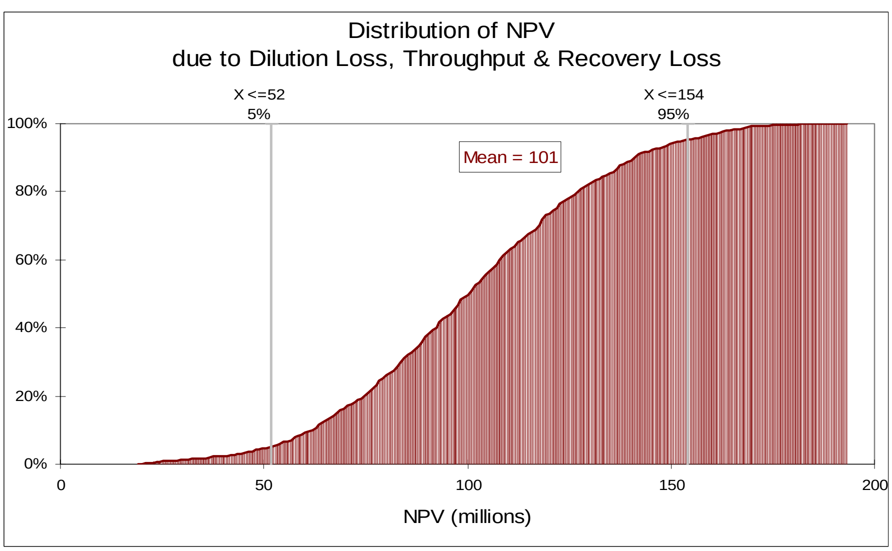

Figure 5 shows the Monte Carlo simulation output for NPV based on all three variables

INCORPORATION OF RISK IN DECISION-MAKING

Given the results of the three approaches to modelling risk, how should the decision-maker proceed? Results from the sensitivity analysis suggests that the range of NPV lies between negative CAD$ 5 million and positive CAD$ 200 million, which is considerably varied and has little confidence associated with these values. The output from the MC analysis is more informative as it allows the derivation of a NPV distribution associated with a confidence limit, although there is some debate about the rationale of a NPV distribution. NPVs may change substantially if correlation was included between input probability distributions. However, little evidence was available to calculate the source of these Pearson correlation coefficients and thus, independence was assumed between variables. An extensive NPV range (CAD$ 50 – 154 million) was generated at a 90% confidence limit using MC simulations with a probability of less than 5% of having a NPV below CAD$ 50 million.

The IEM approach requires more development and modelling time than the other two techniques but provides a unique platform to incorporate technical linkages between variables at the appropriate scale, specifically focusing on relationships between resources, mining and treatment processes and the cash flow model. Less subjectivity and greater transparency of risks and their associated impacts are credits of the IEM approach. Both the bottom-up and top down evaluation approaches were conducted on the IEM and utilized DCF to derive NPVs. Although limitations of using DCF are well known, it serves as a baseline for project comparisons.

The amount of technical risk that should be added to the weighted average cost of capital (WACC) to arrive at a discount rate has not been quantifiably defined in the literature reviewed. To address this issue, an average technical discount rate can be derived using the IEM and V-Bod to 'back calculate' a rate that equates the NPV for each scenario with that of the V-Bod. This implied that any deviations in NPV for each scenario compared to the V-Bod, occurred only as a result of geological variability. An algorithm was executed, which performed a sequential search for each year in the DCF model and attempted to find the average discount rate over the life of mine that discounted the cash flows back to the V-Bod NPV. This average computed rate reflected the technical discount rate premium that should be added to the WACC to account for project risk in a conventional DCF evaluation, the results of which are shown in Figure 6.

Global ('top-down) vs Local ('bottom-up') Discount Rates

	Scenario 1 (75m) Kriged	Scenario 2 (50m) Kriged	Scenario 3 (25m) Kriged	V-Bod
Global Annual NPV	8.19%	7.04%	6.49%	0.0
Local Annual NPV	2.69%	2.51%	2.25%	0.0

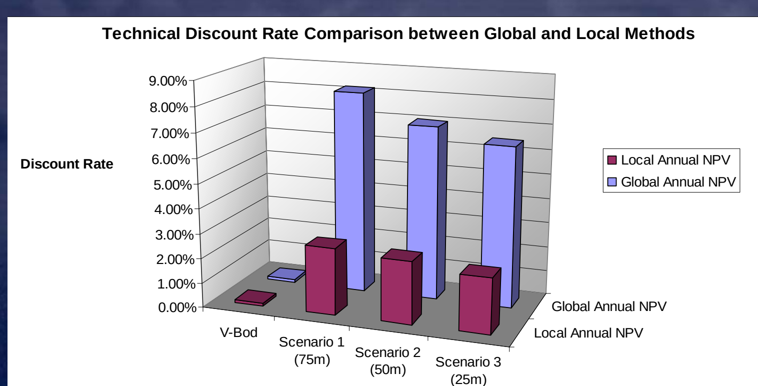

Figure 6 compares the discount rates between the top-down and bottom-up evaluation methods

CONCLUSIONS

The authors demonstrated that three evaluation approaches to mineral project valuation could result in materially different NPVs. Sensitivity analyses in the order of ± 5%, 10% and 15% were conducted on the top-down estimates and produced NPVs ranging from negative CAD$ 5 million to positive CAD$ 200 million. These results are considerably varied and incorporated no correlation between resources estimates, production processes or the cash flow model. MC simulations, based on input probabilities derived from expert opinion, yielded NPVs ranging from CAD$ 50 – 154 million, outside the NPVs from the IEM (CAD$ 28.1- 32.7 million). The respective NPVs for the three sampling campaigns (75m, 50m and 25m) conducted on the top-down evaluation method over-estimated the NPV derived from the IEM method in the order of 160% to 180%. Although both the top-down and bottom-up evaluation methods over-estimated the V-Bod NPV of $1.55 million by as much as $90.6 million and $31.1 million respectively, the IEMs results were closer to the V-Bods NPV.

The difficulty of valuing managerial flexibility in a mineral project usually results in mineral assets being undervalued using a traditional DCF approach, (Davis, 1995). However, in this study, limited sampling information resulted in a smoother, more continuous estimate of dyke thickness for both the top-down and bottom-up evaluation methods relative to the V-bod ‘reality’. The acquisition of additional sampling data is expected to further reduce deviations between estimated NPVs and the V-Bod. However, the likelihood that closer spaced sampling grids will actually be drilled is low due to high sampling costs, project delays and other practical limitations. The objective of applying an IEM approach is not to recommend closer spaced sampling grids but to find a balance between the required sampling resolution and the derivation of quantitative estimation errors in NPV. Technical discount factors were calculated to account for differences in NPV between the V-Bod and estimated resources. These discount rates may be considered as correction factors that are applied to evaluation scenarios where sampling data are limited and confidence limits around estimated NPVs are required.

The consequences of estimating into small blocks based on wide-spaced drilling are acknowledged (Armstrong and Champigny, 1989) and resulted in lower kriging variances for dyke thickness and v1 due to the smoothing effect, which results from a lack of sampling data. In this case, additional sample data would detect higher v1 and thickness variabilities that would hit the mining and treatment constraints more often and result in lower NPVs for the bottom-up method, resulting in even greater differences compared to the top-down method. Further work is underway to consider the information effect on estimation variances and their impact on technical discount rates. The IEM bottom-up approach facilitates an understanding of the sequence of events and their associated uncertainties. These aspects should be included into risk models as drivers of the simulations, rather than only generating probabilities of a risk occurring or focusing exclusively on a NPV output (Dowd, 1997). While many investment decisions are based on one or more financial metrics, often too much emphasis is placed on the outcome rather than the process itself. Bratvold and Begg (2002) recognized that people assumed that good outcomes imply that a good process was followed. Often the converse was assumed too. These assumptions can be very misleading and compromise the development of a sound decision-making process.

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