

Uncertainty-Based Grade Modelling of Kimberlite: a Case Study of the Jay Kimberlite Pipe, EKATI Diamond Mine, Canada

S. Harrison¹, O. Leuangthong², and B. Crawford¹

¹*BHP Billiton Diamonds Inc., Kelowna, Canada*

²*University of Alberta, Edmonton, Canada*

Introduction

Understanding uncertainty in resource models is a significant requirement of ore deposit evaluation. Uncertainty analysis allows the modeller to explicitly quantify the risk around their estimate, along with provide high/low estimates for mine design, assess project up/down-side, model financial forecasts, and reconcile the deposit after mining. Geostatistical simulation is one method that can be used to quantify uncertainty and Sequential Gaussian Simulation (SGS) is one of the easiest techniques to understand and implement. Using SGS provides both a spatial model of a given variable and the ranges around that variable at any number of scales.

The Jay kimberlite pipe is located in the southeastern quadrant of the EKATI property (Figure 1) in a 30 m deep depression in Lac du Sauvage, approximately 2 km from shore. It is within the EKATI Resource Development Plan, currently at a concept study level. As a relatively large, yet lower value pipe, understanding the risk associated with its value per tonne, and therefore diamond grade, is imperative.

Drilling to date has identified three kimberlitic domains characterized by varying lithological properties, including geological description, diamond grade, dry bulk density, and moisture content. These domains are not separated by hard contacts, but rather by boundaries that are transitional. Within these domains, strong vertical trends exist; in particular, diamond grade increases with depth. For these reasons, Jay required a unique uncertainty-based grade modelling method.

Understanding the geological interpretation of Jay was paramount to choosing the best modelling method and understanding the results. This contribution will introduce the geology of the Jay kimberlite pipe, and discuss how its geological interpretation affected the grade modelling technique chosen. Modelling methods will be discussed with a focus on uncertainty analysis and a discussion around risk. Finally, the Jay model will be compared with modelling techniques used for other pipes on the EKATI property, and uncertainty related to diamond grade will be discussed.

Data

The Jay kimberlite pipe was discovered in 1993 and has since been delineated by twelve core holes, with the lowest kimberlite intersection at 19 m elevation (roughly 350 m below the kimberlite surface). Five 31.1 cm large-diameter reverse circulation (RC) drillholes were drilled in 1996, collecting samples on 30 m composites and providing initial grade data. A further twelve 44.5 cm RC holes were drilled in 2006, sampling on 15 m composites, providing a detailed assessment of grade, and filling in a roughly 50 m grid across the surface of the pipe.

To date, 223 grade samples totalling over 1 100 dry metric tonnes have been collected, with the deepest sample collected to 52 m. All samples were processed at +1 mm cut-off and include enough stones and are materially large enough to be deemed statistically representative. On average, samples contain 154 stones and are 5 tonnes in size.

Downhole caliper surveys were collected for all RC drillholes to provide a measure of sample volume; samples without valid caliper data were rejected for modelling purposes. Recovered carats and sample volumes were used to calculate carats per cubic meter (cpm³), modelled grade variable. All samples were given a single spatial coordinate at the midpoint of the sample and assigned to a lithological domain based on this coordinate.

A dry bulk density model was created and used to convert the cpm^3 model to carats per dry metric tonne (cpt). This contribution will focus on the techniques and uncertainty surrounding the cpm^3 model. Further information on the methods used for RC drilling and grade calculation are outlined in Dyck et al., 2004.

Geology

The Jay pipe is one of the largest known kimberlite bodies on the EKATI property, modelled to be 11 Ha and roughly circular in plan view. The morphology is similar to most other EKATI kimberlites in that it is a steep-sided diatreme that tapers with depth (Figure 2).

From geological logging of core holes and RC samples, three internal geological domains have been interpreted: resedimented volcanoclastic kimberlite (RVK); transitional kimberlite (TransK); and primary volcanoclastic kimberlite (PVK). Boundaries between these sub-horizontal domains are transitional in nature.

The upper-most domain of the Jay pipe is 150 to 175 m of locally varying muddy to silty RVK, primarily defined by varying olivine size and content, as well as lithic composition and abundance.

Underlying the RVK domain exists a 25 to 85 m package of interbedded RVK, similar to that above, and PVK of varying degrees of alteration; this unit has been named transitional kimberlite (TransK). Interbeds are typically less than 2 m and can be as small as 30 cm.

Underlying the TransK domain, the pipe is infilled with massive highly competent medium- to coarse-grained olivine-rich PVK. The upper contact of the PVK domain is marked by the disappearance of RVK and intensely altered PVK. Mud is absent from the matrix and juvenile clasts are present, typically cored by pseudomorphed olivine. Small, irregularly shaped mudstone and granitic xenoliths are present, but decrease in abundance with depth.

Grade Modelling Methodology

The results of uncertainty-based modelling include both a spatial model of the variable, in this case grade, and a quantification of uncertainty ranges around the model at a given scale. The current uncertainty-based modelling method used at EKATI is Sequential Gaussian Simulation (SGS) (Isaaks, 1990). SGS is a combination of simple kriging and Monte Carlo simulation; the former is used to determine the local distribution of uncertainty while the latter is used to randomly draw a simulated value from this distribution. Multiple equally probable realizations are generated by drawing different random numbers. From these realizations, range analyses can be carried out from a block-by-block scale to a global level (Goovaerts, 1997).

While the premise of this technique ensures reproduction of spatial data, it is founded on a very strong assumption of stationarity – in particular, the mean is assumed to be the same at every location in the field (Journel, 1994). Domains can generally be used to constrain fields with a common mean. Yet, when no hard boundary between varying means exists, such as when there is a continuous trend in data, the stationarity assumption can not be maintained. Geological bodies, including kimberlites, often exhibit trends, which may require a special modelling technique.

The steps involved in completing uncertainty-based modelling using SGS are as follows:

1. Exploratory Data Analyses (EDA) investigating the nature of internal domains, boundaries, trends, and distributions;
2. Declustering data to ensure that there is no spatial bias;
3. Data transformation to Gaussian space, either using a normal scores transform or the stepwise conditional transform (Leuangthong, 2003);
4. Variography to characterize the spatial variability of the deposit;
5. Simulation using the SGS algorithm to generate multiple realizations;
6. Validation and back-transformation to original units; and

7. Post-processing, including up-scaling to different grid sizes and calculating the uncertainty around the estimate.

One-hundred realizations were simulated within the modelled pipe shell at a grid size of 5 x 5 x 5 m. The SGS algorithm works best when grid spacing is as small as possible. This grid size is approximately one-tenth that of the sample spacing and is small enough to accommodate SGS, yet is large enough for timely processing. Although resource reporting only requires the pipe be modelled to the extent of drilling, it was modelled deeper to allow mine evaluators the ability to fully maximise the Exploration Potential of the deposit.

Exploratory Data Analyses: As the Jay kimberlite contains three distinct geological domains, it was important to understand the relationship of these domains to grade. Classical methods, including histograms, scatter-plots, and contact analyses were used to describe the sample populations and to assess the appropriate method for grade modelling.

When all data is plotted as a histogram (Figure 3a), no clear domains are evident; however, geologically, some difference in grade between domains is expected. This becomes apparent when each domain is plotted separately (Figures 3b through d); the RVK domain approaches a log-normal curve while the TransK and PVK domains each approach a Gaussian-shaped distribution. All domains have different means and ranges, which indicates that these populations are different. Further analyses, including quantile-quantile plots, were conducted to ensure the distributions are indeed different.

There are no significant outliers present in any of the domains, as is additionally confirmed by the cumulative distribution functions. It is also important to note the few samples available in both the TransK and PVK domains; in particular, there may be too few samples to reliably infer spatial measures on the TransK domain alone.

Although these analyses prove that the domains are different in relation to grade, they do not illustrate the nature of the contacts between these domains. A moving-window technique was used to analyse these geological contacts (Figure 4). As all RC holes are vertical with negligible deviation, for each sample, the distance along the drillhole from its midpoint to the given contact was calculated. A 30 m distance-from-contact window spacing was used to calculate the average grade. There is no significant change in grade at either contact and both were determined to be transitional in relation to grade.

Due to the near-horizontal domain boundaries at Jay, vertical or near-vertical trends are the most likely trends to occur. From the above contact analyses there is a clear trend of increasing grade with depth through the deposit. An elevation versus grade scatter-plot clearly illustrates this (Figure 5). This trend was important to consider not only due to its magnitude (over a factor of two over the given depth), but due to the lack of samples available to reproduce it during modelling particularly in the lower portion of the pipe.

These analyses show that no hard grade boundaries are present within the kimberlite; therefore, grade will be modelled treating the entire pipe as a single domain, paying attention to the strong trend of increasing grade with depth.

Trend Modelling: A variety of methods are available to model trends, including hand mapping, moving window averages, inverse distance, simple kriging, ordinary kriging, and universal kriging (Leuangthong and Deutsch, 2004; McLennan, 2007). Trend models should represent the large scale features of the data rather than small scale fluctuations. It is easy to over-fit the trend which may lead to an over-constrained uncertainty model from simulation (i.e. no variability between simulations).

For the Jay pipe, a one-dimensional linear trend was modelled as a second-order polynomial (Figure 5) and the equation of the line was used to create a gridded model. Trend values were extracted from the gridded model at the sample locations. Below the lowest sample, a constant grade was assumed to reflect the interpreted continuation of the PVK domain.

Declustering: Although data were collected on a regular grid with no high-grade zones preferentially sampled, it was still important to decluster the data and apply the resulting weights during data transformation. Cell declustering was used, and by maximising the mean, the declustered mean increased from 3.98 cpm³ to 4.08 cpm³. The declustered histogram was used to validate the SGS results.

Simulation without a trend: SGS was first run without incorporating the trend to check if it would be implicitly reproduced. To create the SGS model without the trend, data were transformed to Gaussian space using the normal score transform with declustering weights applied. After intensive variogram analyses, an omni-directional spherical variogram with a nugget of 0.45 and range of 185 m was modelled.

Sensitivity analyses were run testing the number of samples and search parameters. Using many samples (48) and no octant search produced the best results where the output histogram approached the declustered histogram, and the output block variogram approached the normal scores variogram.

These results, however, did not fully reproduce the trend. Although the trend was reproduced to 100 m elevation, below this depth the results deviate from the inferred constant grade, back towards the population mean (Figure 5a and 6a). Therefore, the trend must be incorporated into simulation.

These results do, however, represent the variability of the samples. As there is limited data, the simulation results should vary considerably, particularly below the extent of data. This is shown by the variation in vertical averages.

Incorporating the trend into simulation: Decomposing the original variable into a trend and residual component is a common approach to working with trends (Deutsch, 2002). However, this method may lead to negative values since the relationship between the trend and residual is ignored, particularly when minimum data approach zero (Leuangthong & Deutsch, 2004). Residuals were initially used and negative results were returned, therefore, the stepwise conditional transform (SCT) was used.

SCT is a multivariate Gaussian transform whereby the k^{th} variable is transformed conditional to the probability classes of the first $k-1$ variables (Rosenblatt, 1952; Leuangthong, 2003). In the case of two variables (such as the trend and the original grade in this study), the secondary variable is transformed based on binning of the primary variable. Each bin or class of secondary data is transformed to normal scores; the result of independently transforming each class of data is that the resulting transformed variables are not only Gaussian, but the relationship between the variables is effectively removed. This permits independent simulation to proceed, thus avoiding any issues related to cosimulation and also ensures that the relationships between the original grade and the modeled trend is preserved.

To perform SCT there must be sufficient data. With two variables, between 10^2 and 20^2 data are required to perform SCT into 10 to 20 classes with 10 to 20 data each (Leuangthong and Deutsch, 2003). The sample population contains 223 data points and therefore, it is valid to go forward with SCT.

Grade data were transformed conditional to the trend using the SCT with declustering weights applied to create the SCT_cpm³ variable. Ten classes with a minimum of ten data each were used; sensitivities were performed and these parameters resulted in the best normal population and removed the most correlation between SCT_cpm³ and the normalised trend variable.

An omni-directional exponential variogram, with a nugget of 0.75 and range of 105 m, was calculated for SCT_cpm³ for use in simulation. Because the nugget of this variogram was quite high, a second omni-directional variogram with an artificially lowered nugget to 0.50, first exponential structure of 0.38 and 23 m, and second structure of 0.12 and 167 m, was modelled for comparison. In the end, the lower nugget variogram produced better results and was used for the final simulation.

Several sensitivities were performed testing the number of data, search parameters, and input variogram. Using many samples (48) and no octant search produced the best results where the output histograms match the declustered histogram and the output variogram matched the SCT_cpm³ variogram.

The model was then back-transformed to cpm³ using the transformation table produced during SCT. The resulting one-hundred equally probably realizations (SCT_SGS) reproduced the trend (Figure 5b and 6b). Although there is some small-scale fluctuation from the trend, overall the grade increases with depth and is constant through the PVK domain rather than tending back towards the global mean.

However, these results do not represent variability of the data. The impact of the explicit reproduction of the trend model via SCT is that uncertainty can be over-constrained in relation to the data as the uncertainty in the trend model has been removed. As a result, uncertainty is intrinsically lower in this model. From a practical perspective, this model under-represents the actual uncertainty in the model due to the amount and variability of sampling.

Uncertainty Quantification: While estimation gives local uncertainty, we are often interested in uncertainty as it relates to multiple locations simultaneously (e.g. over regions that represent production periods, mining units, and/or over the entire pipe). Simulation reproduces the inherent variability of the data, thus allowing us to assess and quantify both local and global uncertainty.

Uncertainty can be quantified on a variety of scales – it is important to understand the scale of the calculation and the results. At EKATI, results are reported on two scales: a global scale and a bench or level scale. To calculate ranges at a given scale, the mean grade of each realization at that scale is calculated, realizations are ranked and assigned a probability, and uncertainty ranges are calculated at given confidence intervals.

Uncertainty ranges were calculated on global and bench scales for both the SGS and SCT_SGS models (Figure 7a and b). The ranges calculated for the SGS model are meaningful to use as a measurement of risk. The ranges calculated for the SGS_SCT model however, were significantly smaller (the P10/P90 differences of the SCT_SGS model were roughly one third of that of the SGS model) and not a meaningful evaluation of risk.

For a practical assessment of uncertainty of the SCT_SGS model (the preferred spatial model for Jay), the ranges from the SGS uncertainty calculations were applied to the SCT_SGS model (Figure 7c).

Discussion on Uncertainty

The uncertainty-based diamond grade model presented in this study is consistent with standard geostatistical modelling practices. The presence of a trend required further consideration during simulation to ensure that it was properly reproduced. The stepwise conditional transformation is a relatively easy method to incorporate a trend into simulation. It has wide-ranging applications for kimberlite deposits based on their trends due to emplacement processes and, for grade in particular, their small sample populations due to the large sample size required and associated high cost.

Although the resulting grade ranges were not too narrow as to suggest that the trend was over-fit to the data, they were too narrow to be practically used for mining risk assessment. In this case, the intrinsic ranges from SGS were applied to the SCT_SGS results. This achieves a nice balance between (1) achieving a mean grade consistent with the trend in the absence of nearby conditioning data (e.g. lower pipe region), and (2) a conservative model of uncertainty for risk assessment.

This assessment however only takes into account the uncertainty around the grade model itself, and does not take into account a variety of additional factors including sampling error and parameter uncertainty.

An assumption of continuous geology has been made beyond the current extent of drilling. It is likely that a new kimberlite phase may be found with deeper drilling. Deterministic range analyses of a variety of variables, including grade, would be performed to capture this uncertainty. Based on the current understanding of other kimberlite bodies at EKATI, an unidentified phase at Jay may range from a near-barren late-stage magmatic intrusion with high dilution to a highly concentrated primary volcanoclastic phase with little dilution. The associated grade ranges would be considered during mining evaluation; however, these ranges would have no geostatistical basis.

Other variables such as resource tonnage, diamond value, geological variability, and bulk density add to the risk associated with any kimberlite resource evaluation. It is important to have a full understanding of the uncertainty of each of these variables to appreciate the risk associated with a deposit.

Uncertainty for use with resource classification

EKATI's kimberlite resources are classified using a combination of probabilistic and deterministic methods. Probabilistic-based classification is more robust than that based on drill-spacing as it takes into account not only the confidence in the resource based on sampling, but also the variability in the samples collected. However, probabilistic classification can not be used in isolation; it must be compared with drill-spacing methods and take into other variables.

As grade is the geostatistically calculated variable with the highest uncertainty, it is used to classify the resource using probabilities. Uncertainty ranges are calculated at given probability intervals over set

production periods based on a viable mining method. The tollgates used at EKATI are given in Table 1 and are based on those proposed by Yeates & Hodson, 2006. Sensitivities are run by reasonably varying the production rates and tollgates to ensure that the classification does not drastically change. Once probabilistic classification is complete, the results are compared to the drillhole spacing method to ensure reasonable consistency. The results are then downgraded to reflect uncertainty around other non-geostatistically modelled properties such as diamond value, metallurgical characteristics, or geotechnical properties. Results are also clipped to the extent of reasonable mining and lowest kimberlite intersection.

For Jay, the resource was classified on a block-by-block basis using a conceptual open-pit mining rate. Using the tollgates in Table 1, the majority of the deposit was classified as Indicated, with Inferred material near surface (due to increased variability and lower grades), and near the depth-extent of sampling (where sampling was sparser), and Measured material around samples. The sensitivity of these results was tested by varying the production periods and tollgates and found to be stable. Using the drillhole spacing method, the majority of the resource would be classified as indicated based on the average 50 m sample spacing. Note though that using the probabilistic classification also captures the increased variability near surface.

Based on other variables, such as diamond value, metallurgical studies, and geotechnical studies, all Measured blocks were down-graded to Indicated. Classified material below the lowest drill intersection was downgraded to Exploration Potential; using mine planning software, a conceptual maximum open-pit was designed and this was used to further limit the extent of the declared resource. Lastly, due to volume uncertainty at depth, areas of the pipe where there is no confirmation of kimberlite, were downgraded to Exploration Potential.

Table 1: Resource classification tollgates, from Yeates & Hodson, 2006.

	Inferred	Indicated	Measured
Production Period	Annual	Annual	Quarterly
Acceptable Range	± 30%	± 30%	± 15%
Confidence	80%	95%	95%

Comparison with Other Pipes

Kimberlite pipes on the EKATI property have a variety of relationships between geology and grade. Comparing the method used for Jay to the methods used for other kimberlite pipes is a useful exercise to further understanding the results. Two such kimberlite pipes with different modelling methods are the Pigeon and Sable pipes.

Pigeon: The Pigeon kimberlite is infilled with four main rock types: an Upper Crater domain (UC) consisting of mud-rich, variably olivine-rich resedimented volcanoclastic kimberlite; a Lower Crater domain (LC) of olivine-rich primary volcanoclastic kimberlite; a Coherent Kimberlite domain (CK) consisting of texturally complex massive coherent kimberlite comprised of olivine macrocrysts and phenocrysts in a dark, very fine grained crystalline matrix; and a South Crater domain (SC), a massive, fine grained autolithitic magmatic kimberlite with low abundance of olivine macrocrysts (Crawford et. al, in press). Each of these domains was spatially modelled. As the SC domain has not been sampled for grade, it will not be discussed further in this section.

From exploratory data analyses, the UC, LC, and CK domains all have distinct grade populations as their means and ranges differ. However, the LC domain has too few samples to model in isolation and, therefore, must be combined with either the UC or CK domain, or all domains must be combined together. By plotting the domains comparatively on Q-Q plots, the LC and CK domains are more similar than the comparison between the UC and LC domains. Contact analysis further points to the combination of the LC and CK domains as there is a minor, yet evident increase in grade across the UC/LC boundary, yet no change across the LC/CK boundary. This agrees with the genetic interpretation of the Pigeon pipe. The LC and CK domains are both interpreted as primary, syn-eruptive deposits, whereas the UC is interpreted to be post-eruptive collapse of well mixed extra-crater material (Crawford et. al, in press).

In contrast to Jay, contact analysis and geologic interpretation point to separating the UC domain and LC/CK domain with a hard boundary for grade modelling. In the UC domain grade is relatively constant

with depth, whereas the LC/CK domain has a distinct trend of decreasing grade with depth (from 1.3 to 0.3 cpm³). SGS results for the CK domain reproduce this trend without incorporation into modelling, likely due to the additional constraint of the hard boundary.

The Pigeon pipe is an example of where the use of a hard boundary is both geologically feasible and is required to produce the best model. As the LC domain could not be modelled as a separate domain, combining it with another domain was required, and geologically and in relation to grade, the best fit was with the CK domain. As the TransK domain at Jay also has few samples (33 samples), a similar approach may have been necessary had hard boundaries between domains been proven.

Sable: In contrast to Jay and Pigeon, the Sable pipe contains three recognizable lithological domains, but due to the complex nature of these domains, including gradational contacts, spatial domain models could not be created. These domains are as follows: an Upper Crater domain (UC) predominantly comprised of olivine-poor to olivine-rich resedimented volcanoclastic kimberlite; a Lower Crater domain (LC) dominated by very olivine-rich well-sorted volcanoclastic kimberlite; and a mud-rich volcanoclastic kimberlite (MVK) unit that occurs below the LC domain. Samples were flagged with their primary lithology for EDA.

EDA confirmed that there is no significant difference between these domains. A slight trend of increasing grade with depth exists (1.6 to 2.0 cpm³), yet this trend is reproduced during simulation. It is clear that for Sable the approach of modelling all samples as one domain without incorporating the trend is an appropriate method.

The Sable pipe is a good example of where a geologically complex deposit may be combined into one domain without further consideration. The samples adequately control simulation to reproduce the spatial distribution. If, however, these intermixed domains had distinctly different grades, it would be key to model the spatial location and relationships between these domains. Further, if a strong trend in data existed, it may be necessary to model this trend and take it into account during simulation.

Conclusion

Understand the uncertainty associated with the variables in a resource model is an important exercise. Although this study focussed on uncertainty associated with grade modelling, it is important to consider further sources of uncertainty, including sampling error, parameter uncertainty, resource volume, and diamond value.

Trend modelling is important to many resource studies. The general idea of the trend is to capture large-scale changes in the data; however, there are no explicit guidelines nor generally accepted approach to trend modelling. Acceptance and integration of a trend model is highly dependent on the modeller, yet it can have a large impact on the final simulated model. For this reason, multiple trend models should be considered. The use of SCT with SGS is relatively easy to implement and it has wide-ranging applications for kimberlite deposits based on their trends due to emplacement processes.

As the correlation between different variables and geology can vary, it is important to understand these relationships before embarking on any resource modelling exercise. The Jay kimberlite's transitional internal boundaries and distinct trend are prime examples of how this understanding can impact the modelling method chosen and therefore, the results.

References

- Crawford, B., Hetman, C., Nowicki, T., and Baumgartner, M., in press. The geology and emplacement history of the Pigeon kimberlite, EKATI Diamond Mine, Northwest Territories, Canada. Proceedings of the 9th International Kimberlite Conference, Frankfurt, Germany.
- Deutsch, C.V., 2002. Geostatistical Reservoir Modeling, Oxford University Press, New York.
- Dyck, D.R., Oshust, P.O., Carlson, J.A., Nowicki, T.E., Mullins, M.P., 2004. Effective resource estimates for primary diamond deposits from the EKATI Diamond MineTM, Canada In: Mitchell, R.H., Grütter, H.S., Heaman, L.M., Scott Smith, B.H., Satchel, T. (Eds.), 8th International Kimberlite Conference Selected Papers, Vol. 1, 317 – 335.

- Goovaerts, P., 1997. *Geostatistics for Natural Resources Evaluation*. Oxford University Press, New York, 483.
- Isaaks, E.H., 1990. *The application of Monte Carlo methods to the analysis of spatially correlated data*. PhD Thesis, Stanford University, Stanford, CA.
- Leuangthong, O., 2003. *Stepwise conditional transformation for multivariate geostatistical simulation*. PhD Thesis, University of Alberta, Edmonton, AB.
- Leuangthong, O., Deutsch, C.V., 2004. Transformation of residuals to avoid artifacts in geostatistical modelling with a trend. *Mathematical Geology*, Vol. 36, No. 3, 287 – 305.
- Journel, A.G., 1994. Modeling uncertainty: some conceptual thoughts. *Geostatistics for the next Century*, Kluwer, 30 – 43.
- McLennan, J., 2007. *The decision of stationarity*. PhD Thesis, University of Alberta, Edmonton, AB.
- Rosenblatt, M., 1952. Remarks on a multivariate transformation. *Annals of Mathematical Statistics*, Vol. 23, No. 3, 470-472.
- Yeates, G. and Hodson, D., 2006. Resource Classification – Keeping the End in Sight. 6th International Mining Geology Conference, 97 – 104.

Acknowledgments

The authors would like to thank BHP Billiton for permission to publish this study. Petrographic study of the Jay, Pigeon, and Sable kimberlites was completed by Mineral Services, with special thanks to Casey Hetman and Tom Nowicki. Further analyses of Pigeon and Sable were based on original work completed by Peter Oshust. His guidance during this study, along with Darren Dyck and Jon Carlson, is much appreciated. Lastly, the authors would like to thank the many EKATI geologists for their tireless logging of the Jay kimberlite.

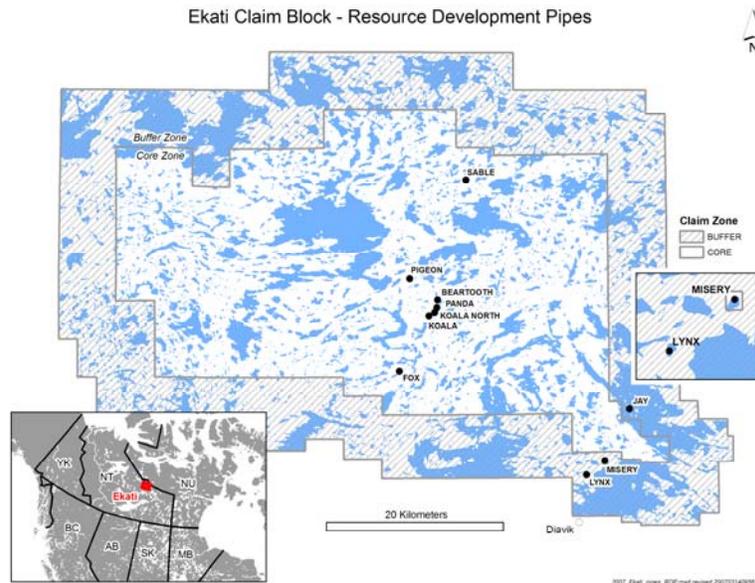


Figure 1: The location of the EKATI Claim Block and the kimberlites in the current Resource Development Plan, including the Jay kimberlite pipe.

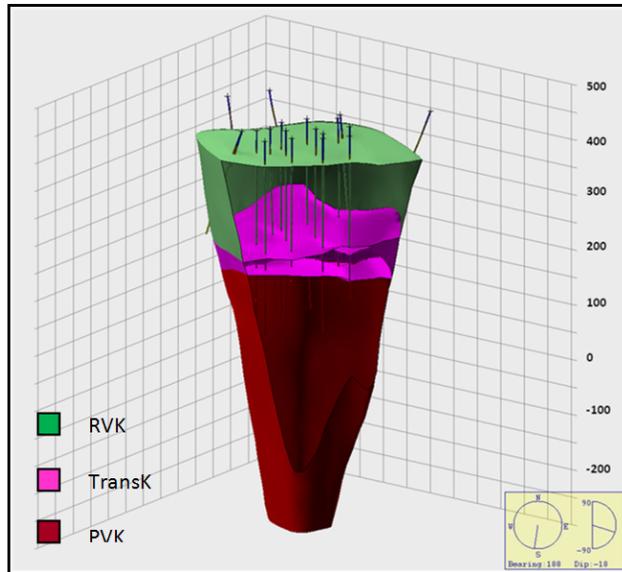


Figure 2: A cut-away 3-dimensional isometric view of the Jay kimberlite pipe, showing the internal geology showing and both core and RC drilling to date.

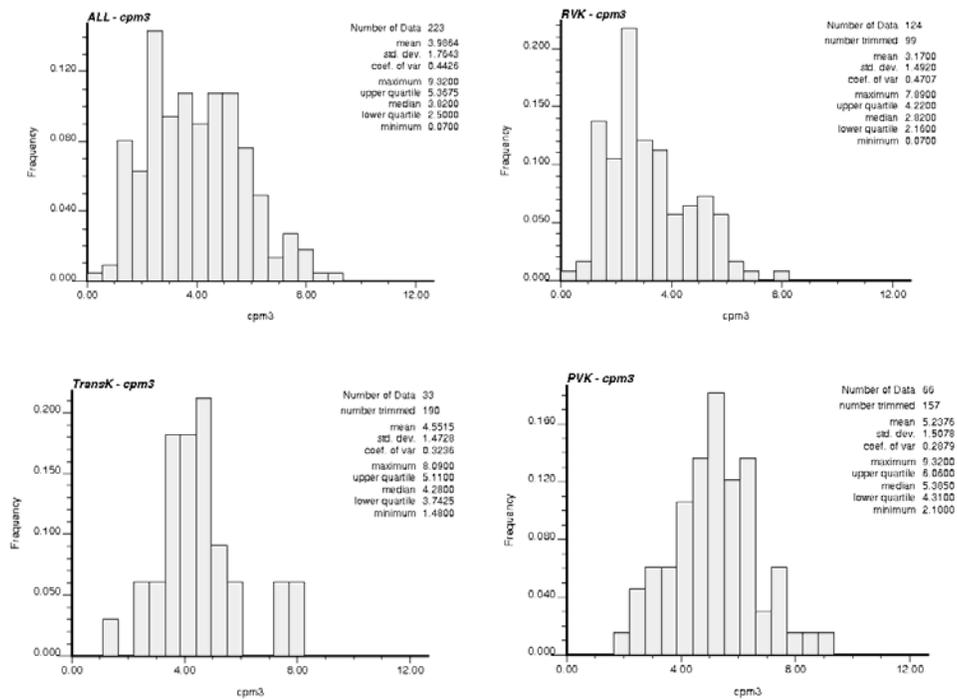


Figure 3: Histograms and summary statistics for: (a) all data; (b) the RVK domain; (c) the TransK domain; and (d) the PVK domain.

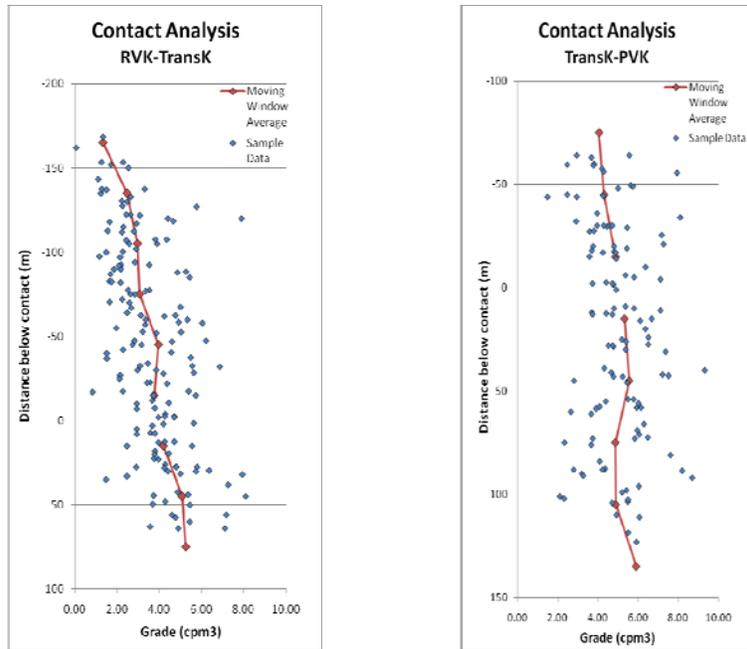


Figure 4: Contact analyses illustrating the transitional nature between the (a) RVK and TransK domains; and (b) TransK and PVK domains.

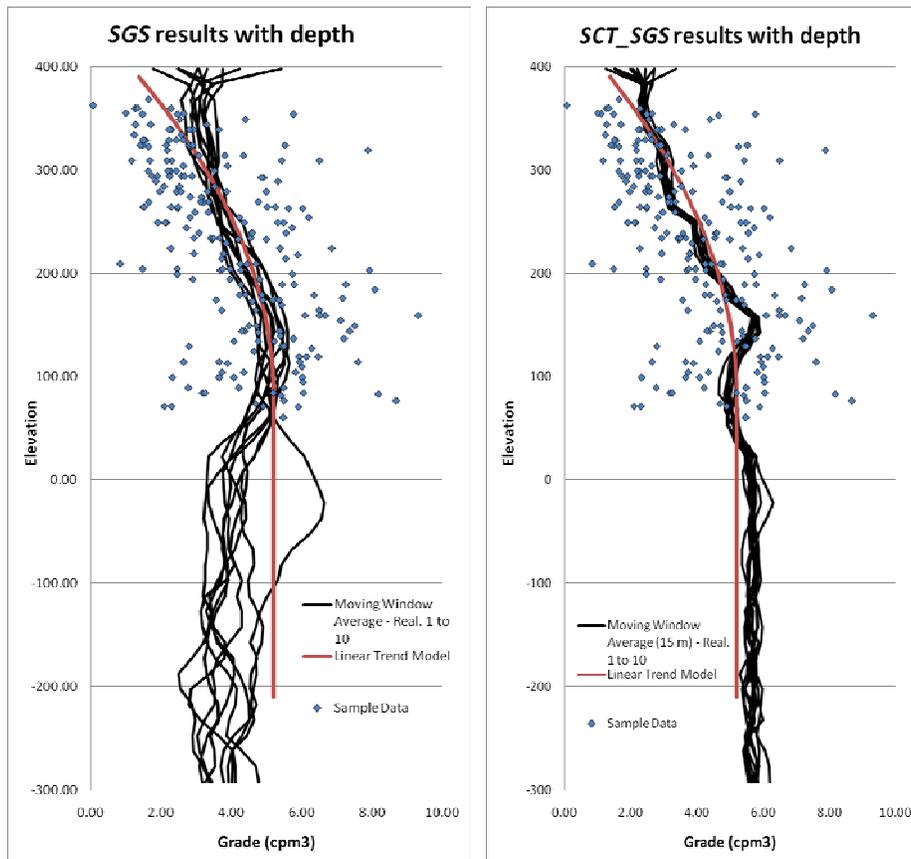


Figure 5: Moving window averages of 10 realizations of the simulation results plotted against elevation for (a) the SGS model created without incorporating the trend; and (b) the SCT_SGS model incorporating the trend. Also shown are the sample grade data and the modelled trend.

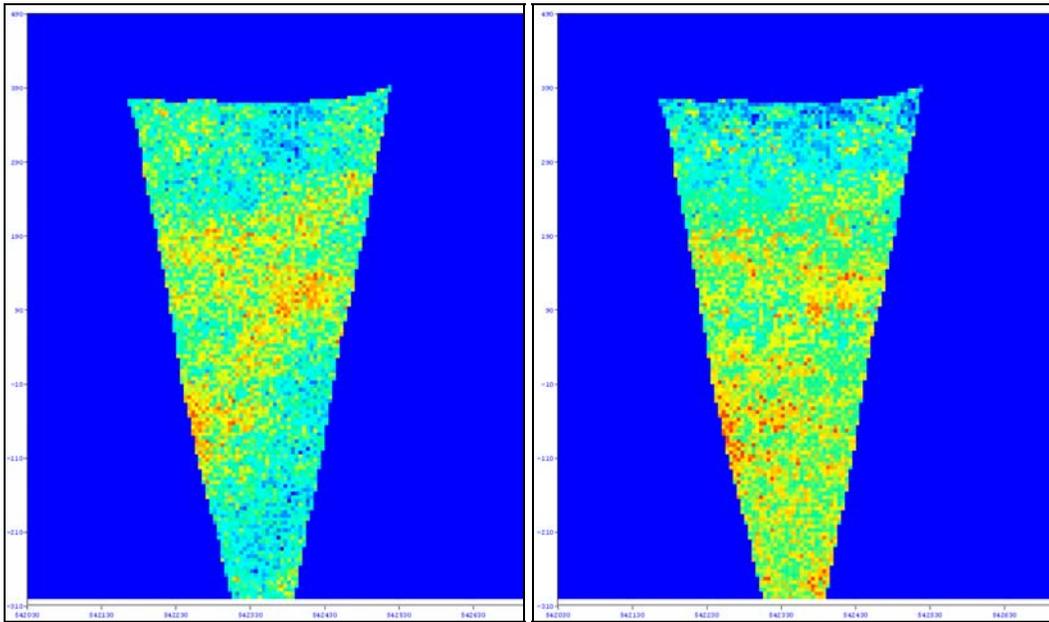


Figure 6: Vertical cross-section of a one realization of (a) the SGS model; and (b) the SCT_SGS model.

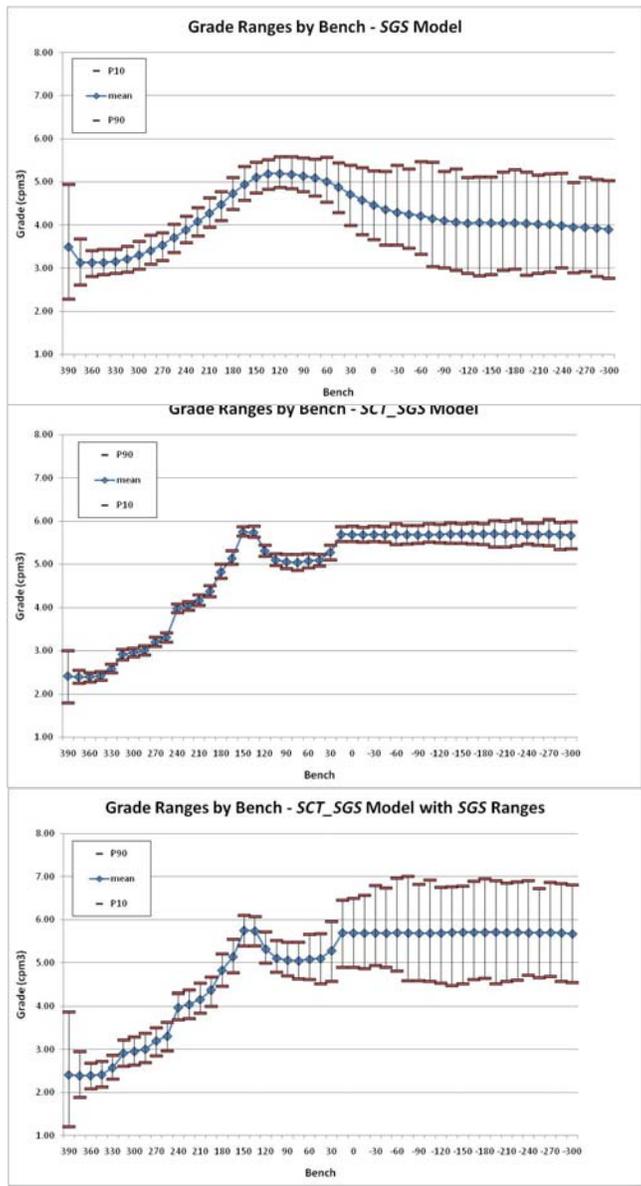


Figure 7: Bench averages plotted with P10/P90 grade ranges for (a) the SGS model; (b) the SCT_SGS model; (c) the final assessment using SCT_SGS as the spatial model with the SGS ranges applied.