Application of Modern Geostatistics for Mine Planning

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Abstract

The application of conditional simulation in mining practice is being adapted slowly due to the increased complexity of the modelling approach and the lack of experience in post-processing of multiple realizations to address the practical issues of mine planning. This paper addresses the latter obstacle by discussing some of the possible applications of geostatistical realizations. Specifically, the assessment of local and global uncertainty for both the grades, the ore/waste classification, recovery and reserves are considered.

Schematic illustrations of the methodology are provided. Implementation of these applications are also shown using the simulation models generated for a Zn deposit.

Introduction

One of the main benefits of conditional simulation is the ability to assess uncertainty in the model results. This, however, is also part of what hinders its acceptance for mineral characterization and mine planning. Although simulation first originated in the mining industry in the 1970s, its adoption into everyday practice has lagged behind other industries, in particular the petroleum industry.

One reason for the seemingly slow acceptance of simulation in mining practice is the comparatively complex workflow involved relative to more conventional approaches. This is true. Geostatistical simulation is a more complex process of modelling than classical estimation methods like hand or machine contouring, polygonal and inverse distance methods. Kriging is an estimation technique that is commonly used in ore reserve estimation; it is remarkably robust given non-stationary data. Theoretically, simulation only requires minor incremental effort for analysis and computation to that required for kriging, but it is also more sensitive to stationarity assumptions.

Another reason for reluctance in practice lies in the fact that most people just want one number, and simulation provides multiple responses. We are left to grapple with the multiple realizations from simulation. The objective of this paper is to show how multiple realizations can be post-processed to address meaningful and practical problems.

There are many ways that the information from multiple realizations can be exploited to yield meaningful results for mine planning and risk assessment. This paper discusses a few simple applications such as assessment of local uncertainty, along with recovery forecasting, resource estimation and uncertainty in short term production.

Although the applications addressed here are not necessarily new, many practitioners are not acquainted with the range of applications for the suite of realizations obtained from simulation. All of the following applications are shown for the geostatistical simulation models constructed for Red Dog mine, Alaska, USA [2]. The Red Dog models consist of 40 geostatistical realizations for each of the following variables: Zn, Pb, Fe, Ba, sPb, Ag and TOC. Note that the applications are for illustrative purposes only; some parameters have been chosen arbitrarily to illustrate the application(s).

Applications using Local Uncertainty. Multiple realizations allow distributions of uncertainty to be constructed at each location. With these local distributions, different summary statistics can be calculated such as the expected value and probability of exceeding a cutoff grade. The models that result from these calculations are based on all realizations simultaneously; they are not one realization.

The probability of exceeding a cutoff grade can be assessed using the local distributions. Figure 1 shows a schematic illustration of the method to determine the probability of exceeding a cutoff grade using local distributions from simulation. The use of a high cutoff grade shows areas that are surely high, that is, those areas with a high probability to be high grade. Similarly, a map that shows the probability to be below a low threshold reveals the areas that are almost certainly low.

Figure 2 shows three probability maps for Zn grade and one for Ba grade. The top two figures shows the reduced area of certainty of finding low and medium grade Zn as a result of increasing the Zn threshold (cutoff grade). The bottom two figures allows for a visual comparison of the region of very high Zn grade ($> 25\%$) and that corresponding to low Ba grade ($< 7\%$). For these maps, the Zn and Ba grades were chosen arbitrarily, while the Ba cutoff grade corresponds to the grade specified by the mill for grade control purposes. Since Ba grade adversely affects Zn recovery, it is important to determine the locations within the pit where Ba exceeds the maximum allowable for production. These maps provide one way to quickly determine the general areas where Ba grade may be an issue.

Probability Map of Ore/Waste. For Red Dog, stockpile blending is based on as many as seven different criteria, ranging from grade values of multiple metals, grade ratios between metals, and particle textural criteria. The decision of which material to send to a particular stockpile is initially based on model values, and may be refined by on-site inspection by mine geologists.

Greater accuracy in the ore/waste classification and stockpile construction can be achieved by using the simulated realizations to determine the transitional zone. Probability maps constructed using the blending criteria would show the transition between ore and waste. Areas of indeterminant probability (0.3 to 0.7) may warrant further sampling.

The methodology to generate such a model is fairly straightforward (see Figure 3). The first step is to classify each block within a set of realizations as either ore or waste, and apply a straightforward binary code (e.g. 1=ore, 0=waste). This classification requires taking the first realization for all variables, visiting each block and applying the classification criteria. When all blocks have been visited, the result is an indicator model showing the blocks as either ore or waste. This step is performed for all sets of realizations.

The second step involves summarizing the 40 ore/waste models to yield a probability model. This step requires that each block in the ore/waste indicator models is visited (over the 40 realizations), and a simple count is taken of the number of times this block is classified

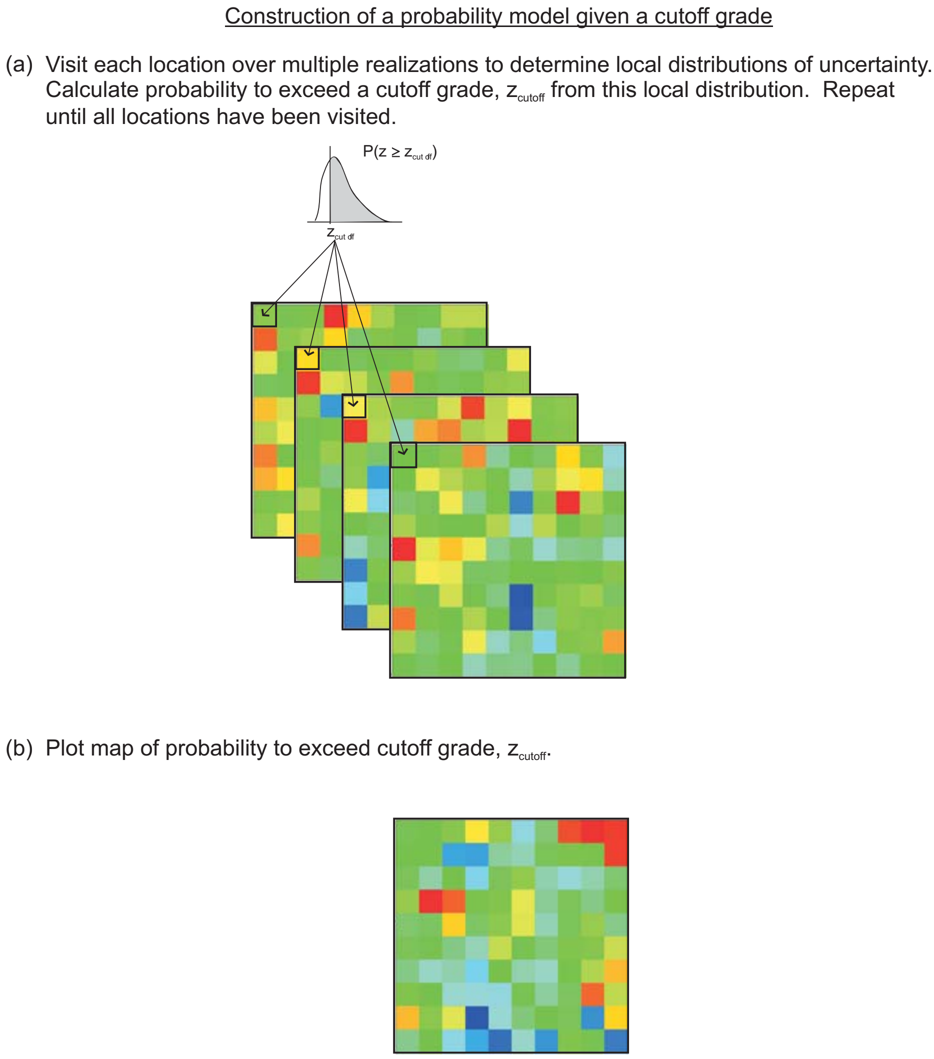


Figure 1: Schematic illustration of determination of probability map to exceed a cutoff grade, z_c.

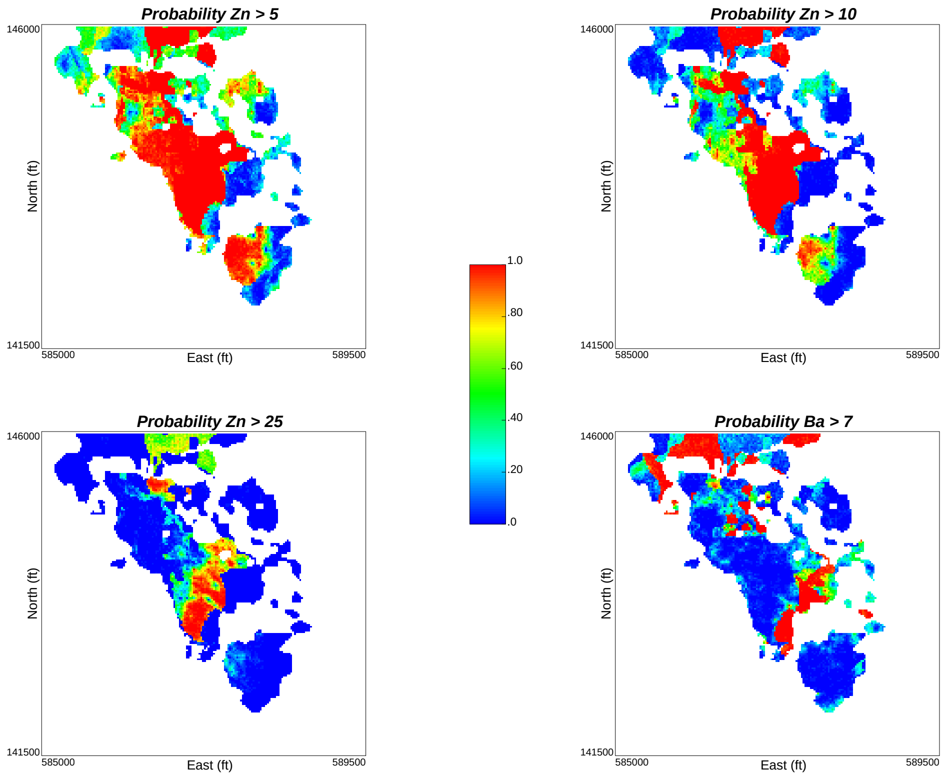


Figure 2: Probability maps to exceed a specific cutoff: $Zn > 5\%$ (top left), $Zn > 10$ % (top right), $Zn > 25$ % (bottom left), and $Ba > 7$ % (bottom right). The section shown corresponds to bench 850. Note that the bottom two figures show areas of where the Zn grade is sure to be high (where the probability is close to 1.0) and the corresponding areas where the Ba grade is sure to be low (where the probability is close to 0.0).

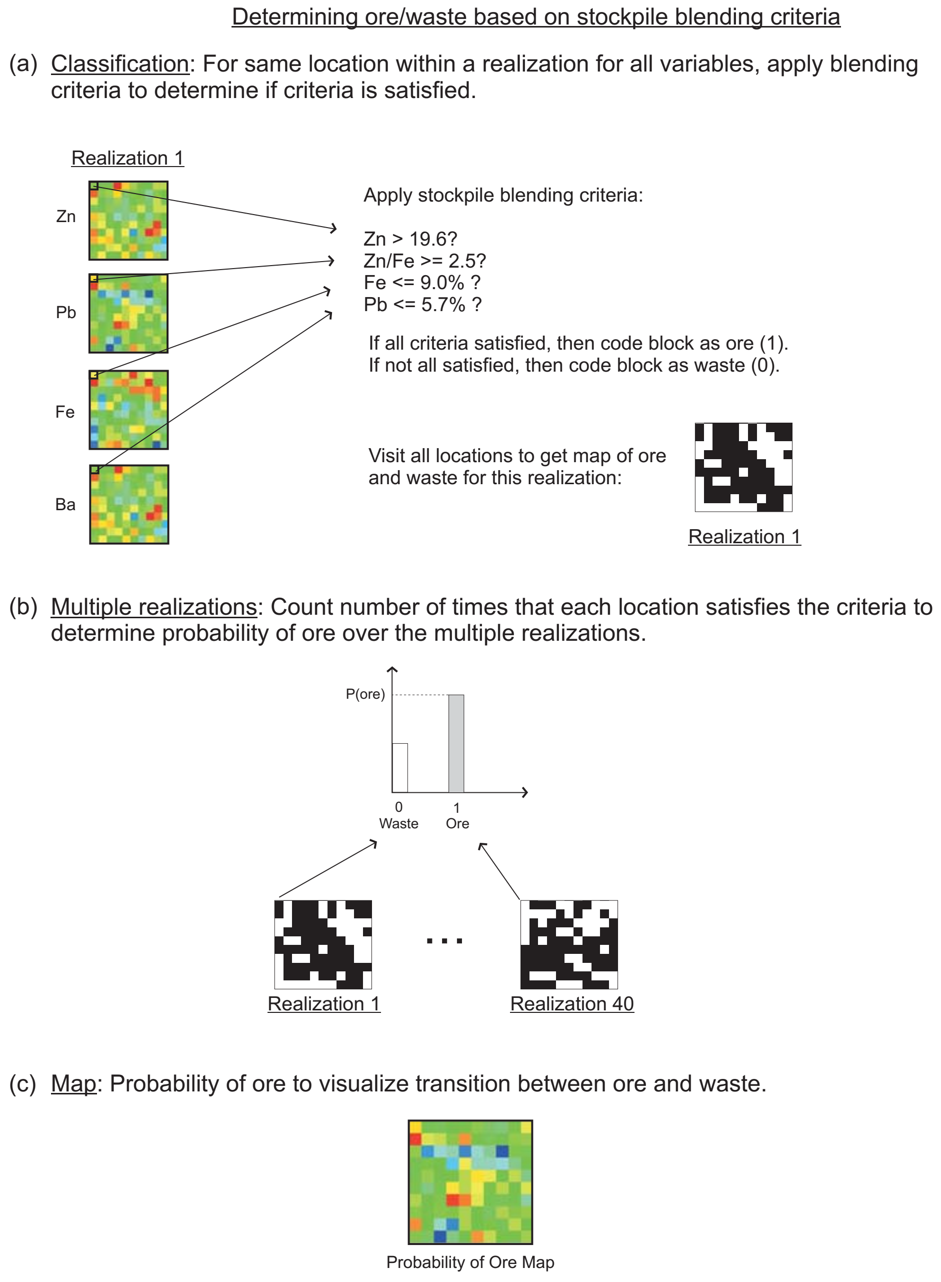


Figure 3: Schematic illustration of construction of a map of probability of ore using multiple realizations and stockpiling criteria.

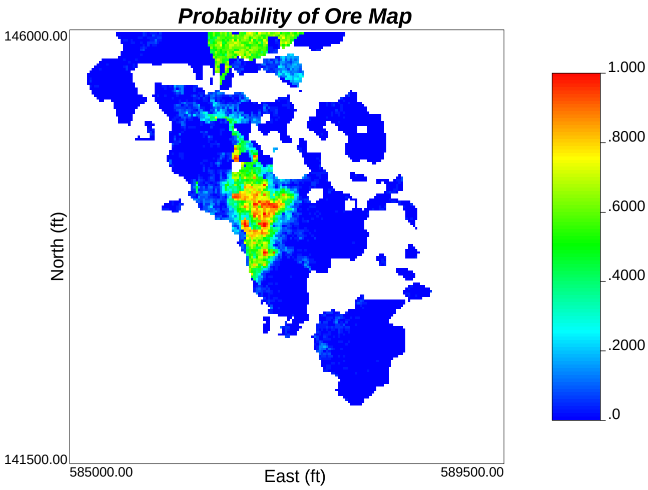


Figure 4: Probability of ore map based on stockpile criteria. The section shown corresponds to bench 850.

as ore. Divide this number by 40 to yield the probability of ore for this location. This is repeated until all locations have been visited to give a probability of ore model.

The last step is to visualize this probability model (Figure 4). The result shows areas that are highly likely to be ore, highly likely to be waste and the transition from one zone to the other. Note that in this case, the stockpile blending criteria, which consists of five different conditions (only grade-based conditions were applied), was used as the classification criteria.

In practice, economic criteria could be used to establish a map of profitability. A block that yields negative profit would be classified as waste, while a block that gives positive profit would be considered ore. This would also give a probability of ore map.

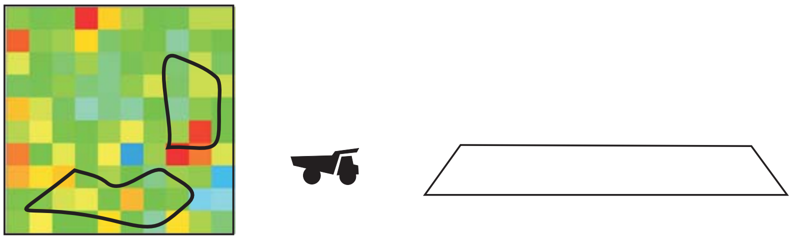
Simulating Stockpiles from Models. This application is similar to the previous application. The idea is to apply the blending criteria to specific volumes being planned for a stockpile rather than on each block independently. These volumes will be the construction of one or more stockpiles.

The methodology is illustrated in Figure 5. The classification criteria are applied to each of the blocks within the volume over the multiple realizations and multiple variables. A table can be constructed to summarize the grade values from all 40 realizations to assess the mean and variance of the grade distribution for the specific volumes. The probability of ore can be calculated.

Recovery Forecasting. Rather than applying economic cutoffs, or the stockpile blending criteria as in the above case, to determine probability maps, one could also apply recovery functions to obtain multiple realizations of recovery. Of course, this requires an understanding of the metallurgical processes and the effect of metal and contaminant grades on recovery.

Simulating stockpiles from Simulation Models

(a) Select large volumes consistent with blast patterns to build stockpiles. Apply these volumes to simulated realization to determine average grade for the stockpile.



(b) Repeat (a) for all realizations to get average grades from each realization. This information can be used to determine the probability that the volume will satisfy blending criteria or economic cutoff.

Realization	Zn	Pb	Fe	Ba	....	Satisfy criteria?
1	20.2	5.2	8.9	4.3	....	1
⋮	⋮	⋮	⋮	⋮		⋮
40	14.3	8.9	6.2	10.3	....	0
Average Grade	16.3	7.9	8.2	7.3	....	65% prob. of satisfying criteria
Average Variance	6.5	5.1	6.7	10.2	....	0.23

Figure 5: Schematic illustration showing how multiple realizations could be used to 'simulate' stockpiles.

Figure 6 shows the methodology to apply a transfer function to realizations of multiple grades to calculate the recovery at a specific location. The result is that at each location, a local distribution of uncertainty in the recovery can be constructed. Alternatively, consideration of the recovery at all locations over the multiple realizations would yield the uncertainty distribution in global recovery.

Recovery functions were provided by Teck Cominco. These transfer functions were applied to realizations of multiple grades to calculate the Zn recovery at a specific location. Figure 7 shows six realizations of the recovery models generated, while Figure 8 shows the maps that correspond to the minimum, average and maximum calculated recovery at each location. The map of minimum local recoveries shows regions that are surely to have high recoveries; the map of maximum local recoveries shows those areas that will surely have low recoveries.

The result of generating these recovery models is that at each location, a local distribution of uncertainty in the recovery can be constructed (Figure 9). Alternatively, consideration of the average recovery based on all locations over the realization would yield the uncertainty distribution in the global recovery (Figure 10).

Uncertainty in Global Resource. In practice, the global reserve (within an entire pit) is reported as a single number with no indication of the uncertainty in this value. Using multiple realizations, simulation allows for uncertainty assessment of the global reserves. Figure 11 shows a schematic of how this type of assessment could be performed.

In the same manner as the recovery models were generated (above), a transfer function to calculate reserves can be applied over a single realization of all variables to determine the reserves based on that realization. This calculation would be repeated for all the 40 realizations to obtain 40 different values for the global reserves. A histogram of these 40 values would show the uncertainty in the reserves.

As the model generated for this case study was only a small portion of the actual mine, and the pit limits were not available, the reserve cannot be determined, however the resource within the model limits can be calculated.

Specific tonnage factor equations were provided by Teck Cominco. These equations account for the Zn, Pb, Fe and Ba grades at each block within the grid. As a result, the density for each block within the model limits could be directly calculated.

From the previous application of determining the recovery at each block location, the recoverable resource can be calculated as:

$$\text{recoverable resource} = \text{recovery} * \text{tonnes of material} * \text{Zn grade}/100\%$$

The above equation was applied to each location within the models to determine the available Zn resource. Note again that no economic constraint has been applied (e.g. defined pit limits and/or cutoff grades), so the above calculation is a simple estimate of the material that can be recovered by the mill.

Figure 12 shows six realizations of the resource models generated, while Figure 13 shows the maps that correspond to the minimum, average and maximum resource estimates at each location. Similar to the assessment of the local recovery, uncertainty in the local resource can be determined at each location (Figure 14). Further, uncertainty in the global

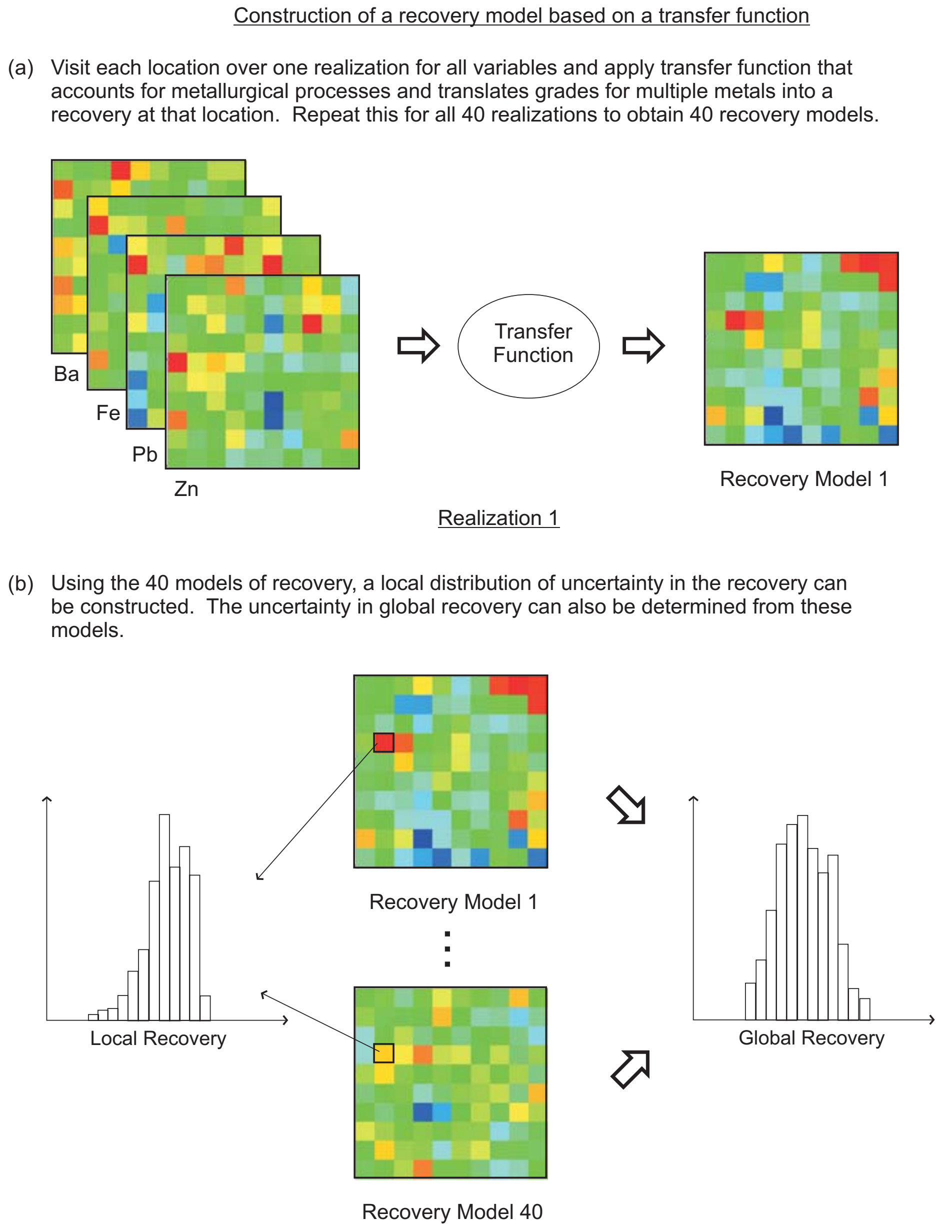


Figure 6: Schematic Illustration of Methodology to Forecast Recovery with Uncertainty Assessment.

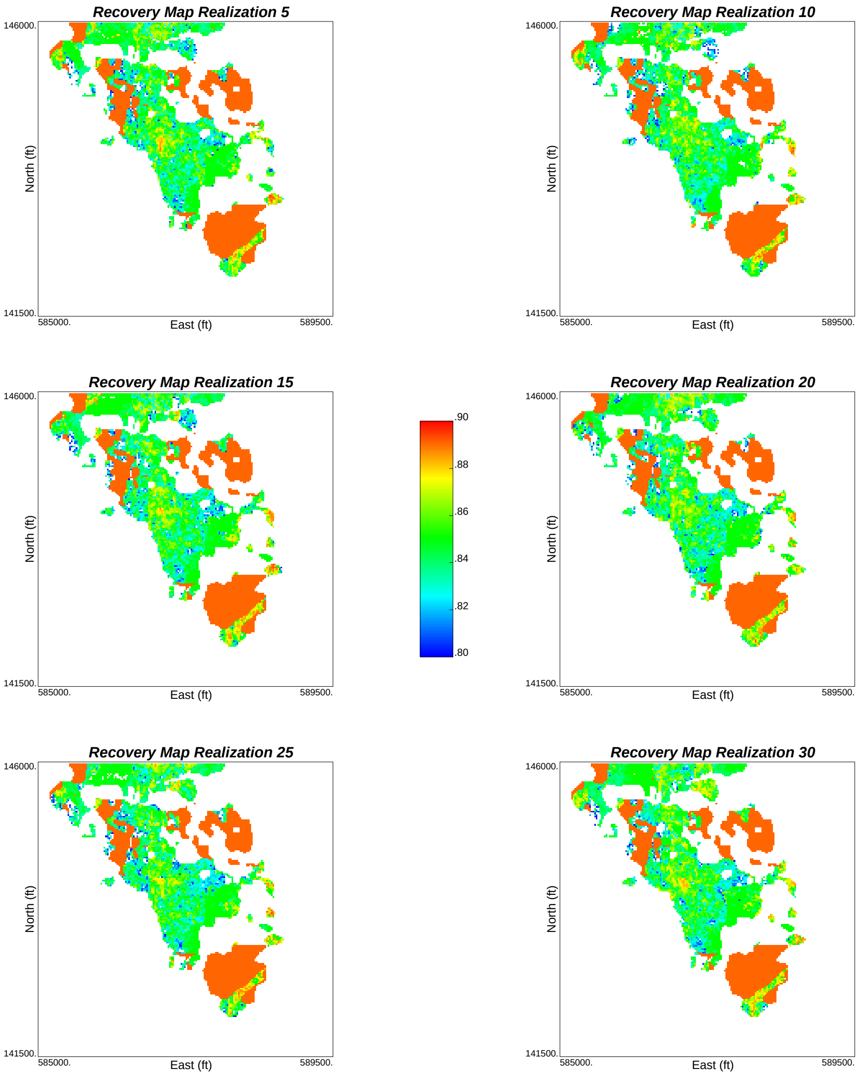


Figure 7: Six realizations of the recovery models as calculated based on recovery functions provided by Teck Cominco.

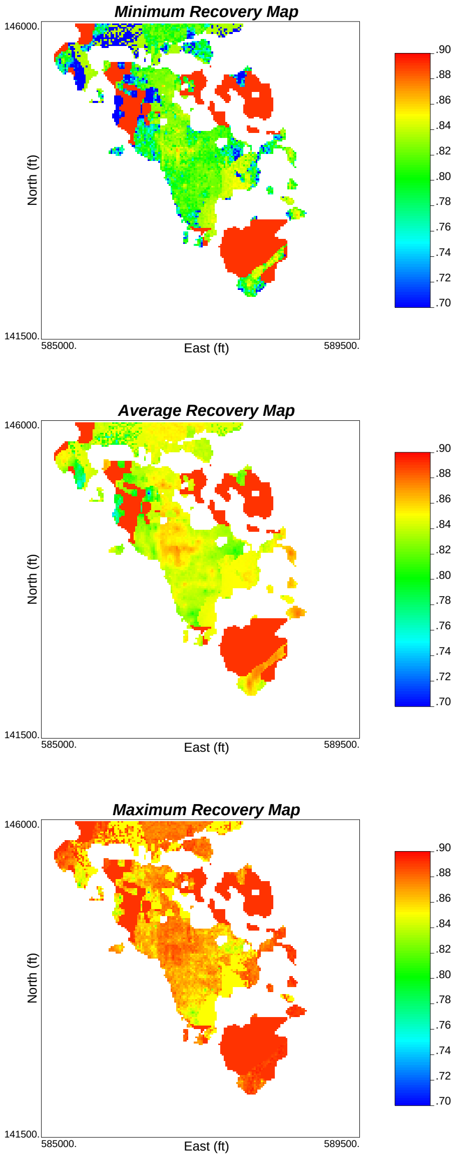


Figure 8: Summary maps of the 40 recovery realizations: the minimum (top), average (middle) and maximum (bottom) recovery at each location.

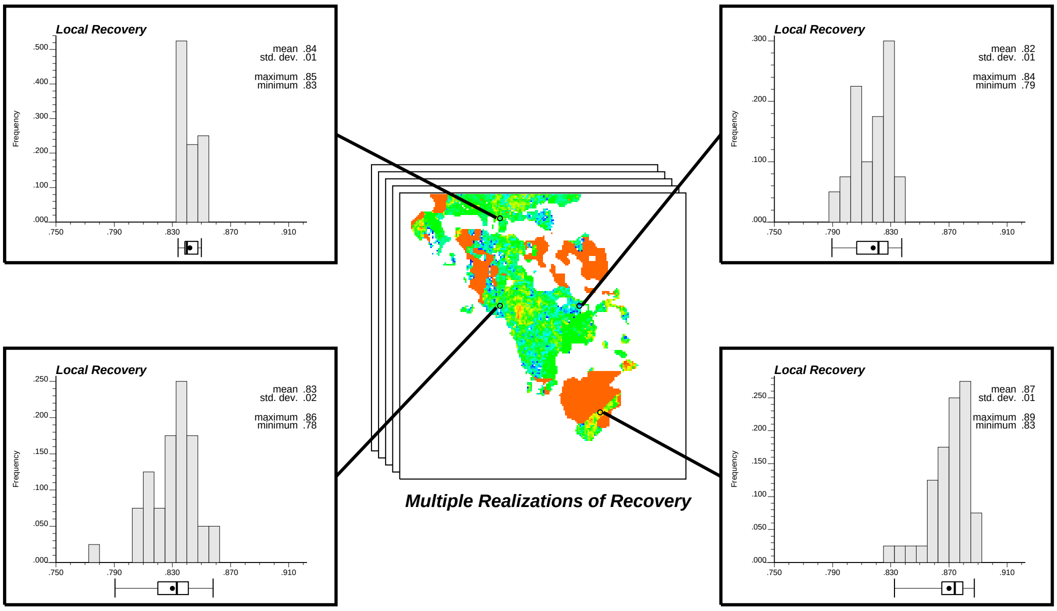


Figure 9: Uncertainty in the local recovery is shown for four arbitrarily chosen locations within the model. In all cases, the reference point plotted in the box plot of the histograms corresponds to the mean value.

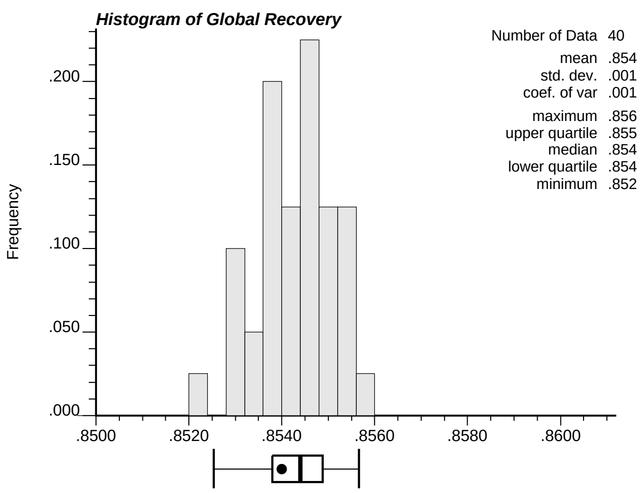
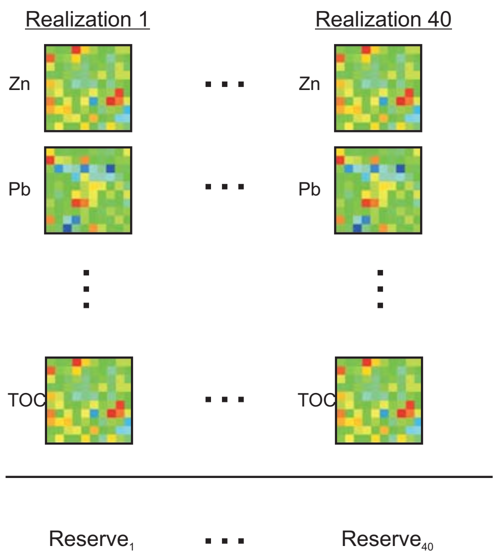


Figure 10: Uncertainty in the global recovery based on all 40 realizations of recovery. The reference point plotted in the box plot of the histograms corresponds to the mean value.

Uncertainty in Reserves

(a) Calculate Global Reserves: For each realization, calculate global reserves using all relevant metal grades.



(b) Uncertainty in Reserves: Plot histogram of reserves using the global reserves calculated from the 40 realizations.

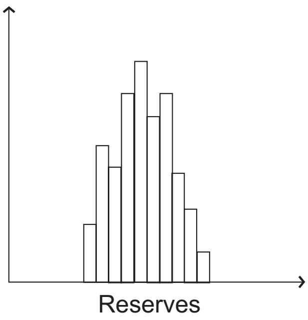


Figure 11: Schematic Illustration of Determining the Uncertainty in Global Reserves.

resource can be assessed by calculating the global resource from multiple realizations and plotting these in a histogram (see Figure 15).

Another directly related application is to assess the uncertainty in the resource over a short term period. In this case, the short term period may correspond to monthly or quarterly production, which can be directly traced to a specific volume of material that is planned for mining in the next month or the next quarter. This essentially involves determining the available resource within the specified volume. Figure 16 shows an example of this type of application with an arbitrarily chosen volume, and the uncertainty in the available resource is also shown.

Remarks

Geostatistical simulation models provide a basis for some interesting applications for decision making and risk assessment. These applications range from classification of ore/waste regions based on complex criteria to recovery forecasting given a clear understanding of metallurgical processes and relations.

Most of these applications are straightforward and can be applied in a quick and efficient manner. Mine planning based on uncertainty quantification allows the mine engineer to assess future production. Improved planning can be achieved with better forecasting.

References

[1] O. Leuangthong. *Stepwise Conditional Transformation for Multivariate Geostatistical Simulation.* PhD thesis, University of Alberta, Edmonton, AB, 2003.

[2] O. Leuangthong and C. Deutsch. Multivariate geostatistical simulation of red dog mine, alaska, usa. Technical report, Centre for Computational Geostatistics, University of Alberta, Edmonton, AB, September 2003.

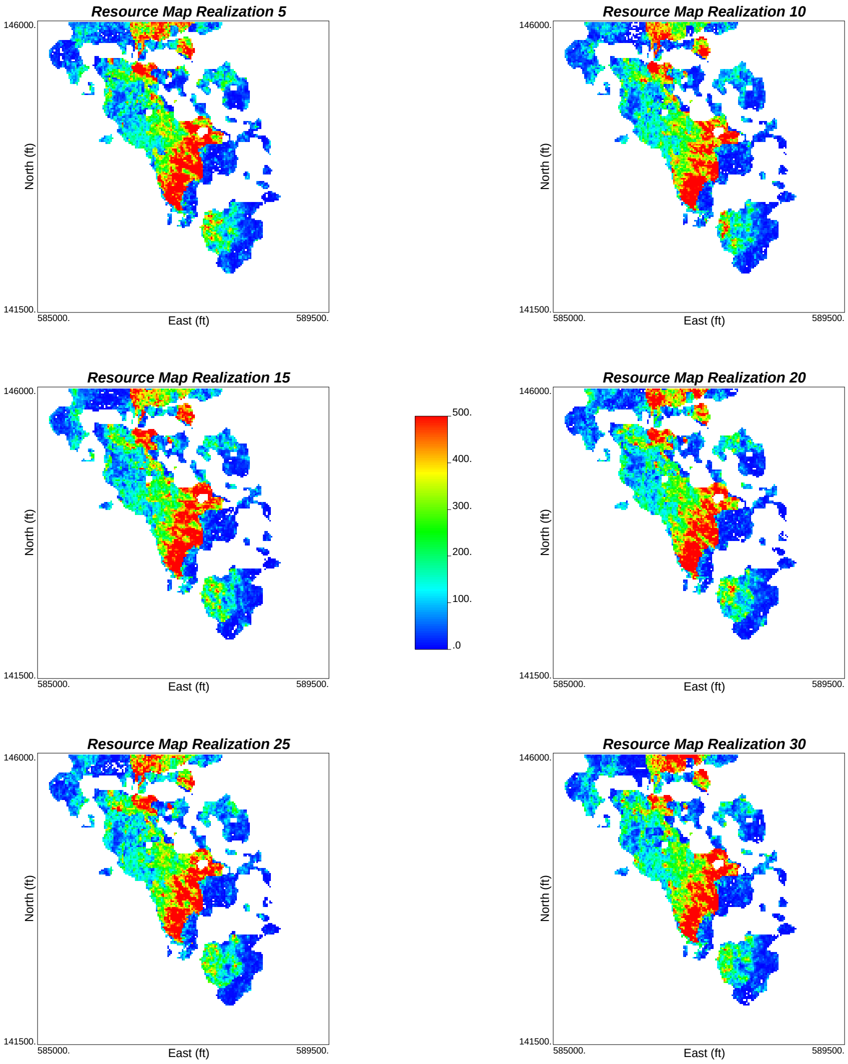


Figure 12: Six realizations of the resource models as calculated based on tonnage factors and recovery functions provided by Teck Cominco.

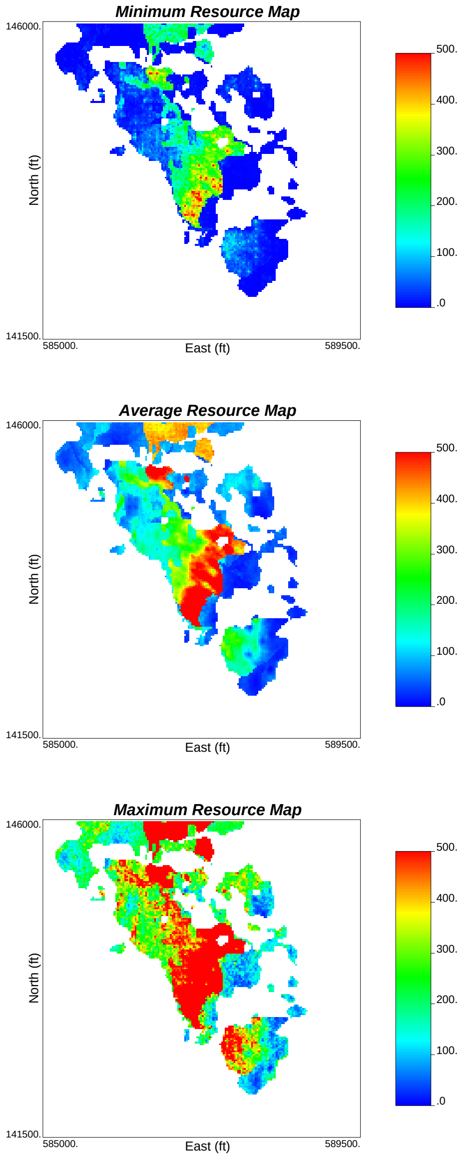


Figure 13: Summary maps of the 40 resource realizations: the minimum (top), average (middle) and maximum (bottom) resource map at each location.

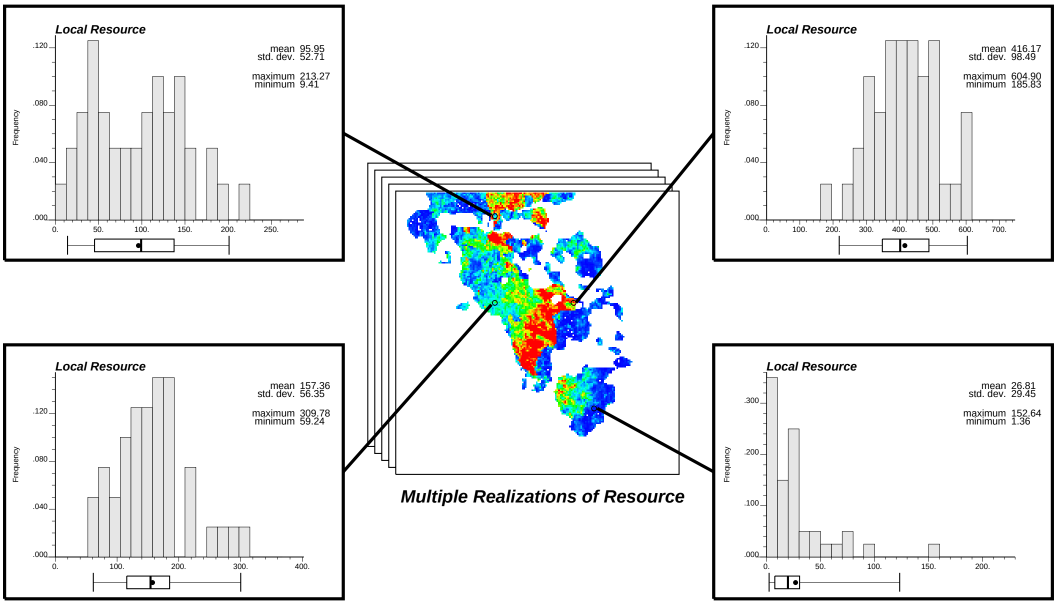


Figure 14: Uncertainty in the local resource is shown for four arbitrarily chosen locations within the model (same locations as shown in Figure 9). In all cases, the reference point plotted in the box plot of the histograms corresponds to the mean value.

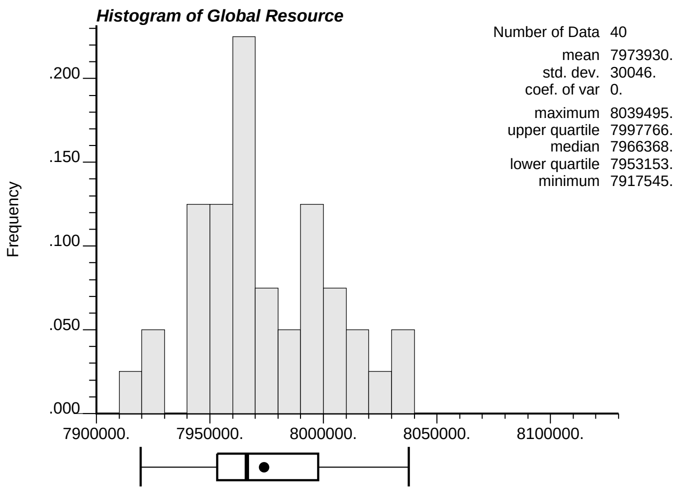


Figure 15: Uncertainty in the global resource based on 40 realizations. The reference point plotted in the box plot of the histogram corresponds to the mean value.

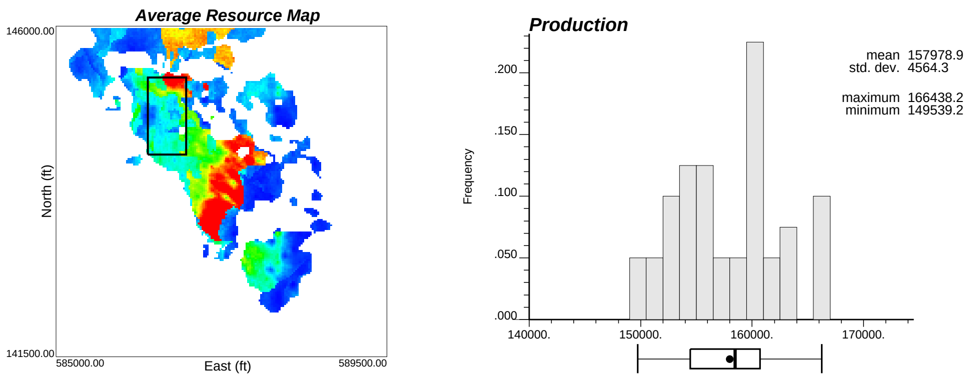


Figure 16: Illustration of application for short term planning. The volume of material associated to the planned production for one month is shown on the left, and the uncertainty in the resource available is shown on the right. The reference point plotted in the box plot of the histogram corresponds to the mean value.