Optimal Drillhole Spacing and Uncertainty in Prediction of Oil Sands Bitumen and Fines Content

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Abstract

The *optimal* drillhole spacing for oil sands reserve determination depends on (1) the reduction in uncertainty attainable for decreasing the drillhole spacing and (2) the economic value in knowing the bitumen and fines content more precisely. Although both factors are discussed in this paper, we focus on the first aspect, that is, quantifying the improvement in the bitumen/fines estimates with increased drillhole density.

The "goodness" of bitumen/fines predictions depends on the variability of the geological formation as well as the drillhole spacing. Geostatistics provides numerical tools to quantify geologic variability, make optimal predictions, and assess spatial/temporal uncertainty. We demonstrate the application of geostatistical tools to quantify the "goodness" of bitumen/fines predictions for different drillhole spacing.

The economic value in improved knowledge of bitumen and fines depends on the stage of development. Precise local information is important at the time of mining; however, long term planning and permitting requires confidence in large-scale estimates of recoverable oil sand and stripping ratio, which does not require such local precision. This notion is partly addressed by the volume-variance relations of geostatistics. For the same drillhole spacing, it is easier to predict a large volume than a small volume. We demonstrate the quantification of uncertainty for different volumes.

Notwithstanding the importance of geostatistical tools to quantify uncertainty, there are many subjective factors that must be considered to arrive at the optimal drillhole spacing. These include management decisions with respect to acceptable risk and governmental regulations. We discuss these additional factors and their implications on optimal drillhole spacing.

INTRODUCTION

A common issue in orebody / reservoir delineation is to determine the optimal drillhole spacing. It would be convenient to have a simple criterion (say, a 200 m square grid) that is universally applicable to all oil sand deposits; however, reality is not that convenient. The details of the depositional system (depositional setting, sedimentary structures, hydrocarbon source and migration, net-to-gross, and so on) affect the continuity of the oil sands. Some sedimentary structures are laterally continuous over large distances and require few drillholes to accurately determine the in-situ resource and mining reserve. Other sediments are laterally discontinuous and require much denser drillhole spacing to achieve the same precision.

Geological variables such as bitumen and fines content depend on the geological environment. Geological environments with greater variability include certain low energy fluvial settings or where diagenesis is pronounced. Typical or average behavior is expected for fluvial, estuarine, and deltaic settings. Geological settings with little variability include certain deltaic settings and carbonate platform environments. These generalizations about variability versus geological setting provide valuable information early in exploration. Once drillhole data becomes available it is appropriate to quantify the site-specific variability. The *variogram* is a geostatistical tool that quantifies geological variability. In particular, the variogram defines the length scales over which the variability in the petrophysical property is explained. The variability of a highly discontinuous property is explained over short length scales whereas the variability of a continuous property is explained over longer length scales. The rate at which the uncertainty decreases with reduced drill spacing depends on the variogram.

There are two main reasons for reducing the drillhole spacing. First, from a geostatistical / mathematical perspective reduced drillhole spacing reduces uncertainty in the prediction of petrophysical properties such as bitumen and fines content. Second, more drillholes permits a more accurate geological interpretation of the stratigraphy and sedimentology. We do not consider this second motivation; in general, in the advanced stages of exploration and production the stratigraphy is understood. Additional drilling can reduce the unavoidable uncertainty in predicting unsampled volumes.

The uncertainty at a particular location **u** is characterized by a probability distribution $f(\mathbf{u};z|(n))$, which depends on the volume being estimated and the set of drillhole information, *(n)*, available for estimation. This location and information dependent distribution of uncertainty often takes the discrete form of a histogram rather than an analytical function of the threshold *z*. The local distribution of uncertainty also depends on unavoidable assumptions, which permit inference away from limited sample data. These time-tested assumptions are understood by practicing geostatisticians, see David, 1977, and Journel and Huijbregts, 1978 for more detail.

The set of probability distributions for all locations in the area of interest, $\{f(\mathbf{u};z|(n)),\ \forall\,\mathbf{u} \in A\}$, provide a full assessment of uncertainty; however, the local variance $\sigma(\mathbf{u})$ provides a summary. A single measure of uncertainty can be calculated as the average of the local variances over all locations:

$$\overline{\sigma} = \frac{1}{n}\sum_{\forall \mathbf{u}\in A}\sigma(\mathbf{u}) \tag{1}$$

This single measure, $\overline{\sigma}$, characterizes the average uncertainty over the entire area, but, in general we must refer back to the local distributions for a complete assessment of uncertainty. Recall that these measures of uncertainty depend on the volume being estimated. There is greater uncertainty associated with prediction of small volumes.

In ideal situations, it is possible to analytically calculate the local variances as a function of the variogram and the drillhole spacing. In practice, geostatistical simulation can be used to quantify the uncertainty for a particular volume of prediction and drillhole spacing. Both methods are demonstrated below. There is no universal relationship between uncertainty and drillhole spacing since each deposit has its own distribution of properties and variogram measure of spatial variability. The results presented below are applicable to the data available for a small area of the oil sands near Fort McMurray.

The *optimal* drillhole spacing can only be determined once a measure of optimality is defined. The measure of optimality adopted in engineering studies is an economic one, that is, minimum cost or maximum profitability. In terms of cost, additional drilling costs more money *and* reduces the cost of possible future mistakes. In terms of profit, additional drilling reduces profitability by increased drilling cost and professional time to interpret and use the additional data, *and* improves profitability by allowing for the best future decisions. We discuss the factors that go into a definition of optimality and illustrate the optimal drillhole spacing with some sensitivity studies.

DATA TO ILLUSTRATE METHODOLOGY

The concepts behind choosing the optimal drillhole spacing will be illustrated with real data from oil sands deposits in the Fort McMurray area. The data and statistics presented below are for the sole purpose of illustrating methodology; they are not presented in their entirety nor are they necessarily representative of any particular region.

Bitumen and fines measurements from 875 vertical drillholes were composited to 15 m regular "bench" composites. Although significant geologic detail is lost at this composite length, it is compatible with mine selectivity. A single variable, say % bitumen, could have been used to illustrate the methodology. Nevertheless, both bitumen and fines are considered for completeness and to illustrate geostatistical modelling in presence of multiple variables, which is a common problem. We will show a large negative correlation between these two variables; uncertainty in both variables is reduced simultaneously.

Figure 1, at the top of the next page, shows a location map of the drillholes. There are some data outside this area.

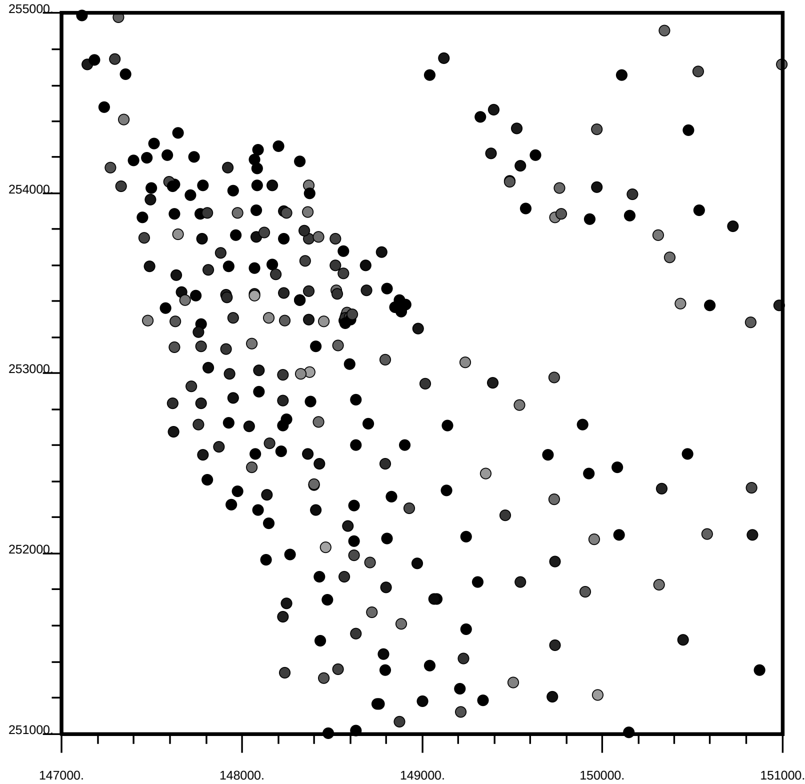

FIGURE 1: locations of drillholes in area of interest. The scale is in kilometers. Note some clustering of the drillholes and areas of no drillholes due to access.

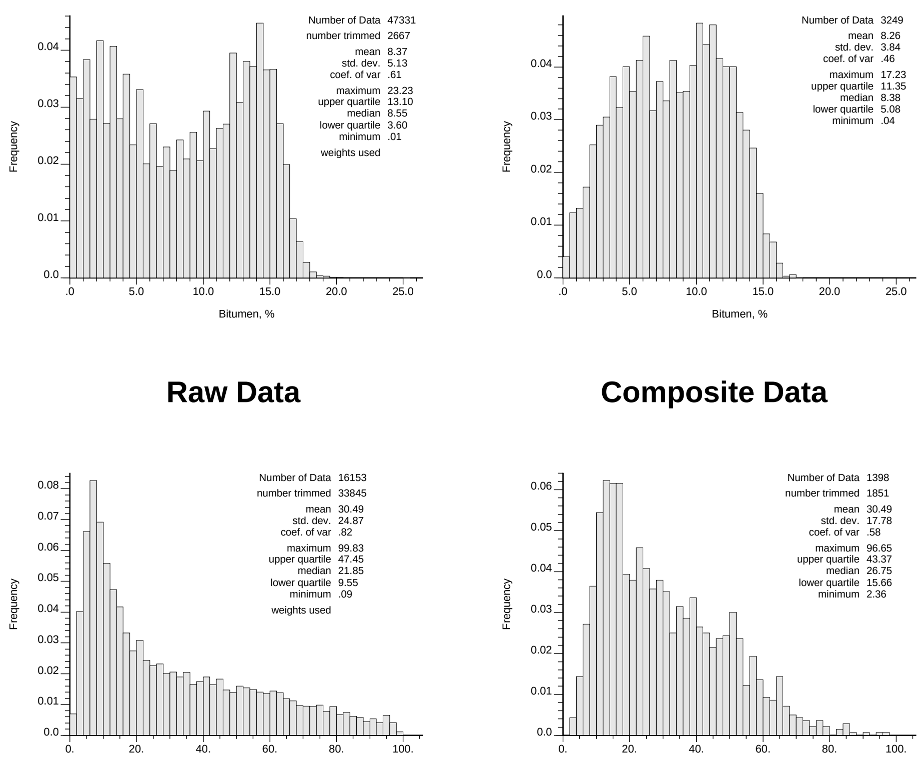

FIGURE 2: histograms of %bitumen and %fines before and after compositing to a length of 15m. Note the reduction in variance.

Assuming the drillholes are on a square grid, the drillhole spacing *ds* (in metres) and drillhole *density* (in drillholes per square kilometre) are related by:

$$density = \frac{1{,}000{,}000}{ds^2} \qquad (2)$$

Although drillhole spacing and drillhole density are directly related and, therefore, redundant, they are both useful for conveying information on the number of drillholes; both will be used in the following. Space restrictions prohibit showing maps of drillhole density for the area of interest.

The bitumen content (see Figure 2 on previous page) appears to have a bimodal distribution related to either porosity or water saturation. The bimodality is preserved after compositing. The fines do not show this behavior; which is expected since the fines content is most likely controlled by original sedimentation and not the subsequent migration of hydrcarbon. The cross plot of the 1398 collocated composited bitumen / fines pairs is shown on Figure 4 on the next page. As expected, bitumen and fines show a negative correlation; the presence of fines reduces the available space for bitumen in the pores.

Many geostatistical algorithms have been devised to work with the normal distribution (as a consequence of the central limit theorem); therefore, the bitumen and fines data (denoted Z_1 and Z_2) are transformed to standard normal distributions (denoted Y_1 and Y_2) prior to variogram calculation. The transformation to and from the standard normal distribution is done with no loss of generality. Inference of uncertainty in normal-space $f_Y(\mathbf{u};z|(n))$ can be transferred straightforwardly to uncertainty in the units of the original data variable $f_Z(\mathbf{u};z|(n))$, either % bitumen or % fines, see Verly 1986.

A complete three dimensional variogram study was conducted. Surprisingly, there was no preferential anisotropy in the horizontal plane. Of course, the vertical continuity is much reduced compared to the horizontal. The omni-directional horizontal variograms for bitumen and fines are shown on Figure 3. The horizontal bitumen semivariogram shown on Figure 2 was fit with an analytical model:

$$\gamma(h) = 0.3 + 0.3\, Sph_{200}(h) + 0.15\, Sph_{1000}(h) + 0.25\, Sph_{5000}(h) \qquad (3)$$

where γ(h) is the semivariogram[1] function for horizontal distance h, 0.3 is the isotropic constant nugget effect, and $Sph_a(h)$ is the spherical variogram function with isotropic horizontal range *a*. The nugget effect of 30% represents irreducible variance; regardless of the drillhole spacing, this 30% short scale variability cannot be removed. The spherical variogram structures may be interpreted as follows: 30% of the variability is explained from 0 to 200 m (60% at distances less than 200m), 15% of variability is explained from 0 to 1000 m (75 % < 1000m), and a final 25% of variability is explained from 0 to 5000 m. There is no spatial correlation at distances greater than 5000m. Although not shown, the vertical variogram shows an effective correlation length of about 40 m. A vertical to horizontal anisotropy ratio of 1:100 is typical of sedimentary formations. Note that compositing to 15m increases the vertical correlation range.

The semivariograms of bitumen, fines, and the cross variogram of bitumen and fines must be modeled together to form a licit model of coregionalization. As a consequence the three semivariograms must all be modeled with the same semivariogram function (see equation 3 above), but with different coefficients. The coefficients must also follow specific constraints (see any geostatistical text for discussion on the linear model of coregionalization). As expected, the spatial structure of the three semivariograms is similar; however, note the increased short scale variability in the fines; the relative contributions to the variogram structures are 0.4, 0.2, 0.25, and 0.15 (see above). Figure 4 shows the cross relationship between fines and bitumen (contributions of -0.25, -0.1, -0.2, -0.15). The solid variogram curves on Figures 3 and 4 constitute a licit model of coregionalization required for the joint modelling of bitumen and fines.

[1] The *semi*variogram γ(**h**) is one half of the variogram γ(**h**). Both terms are used (almost) interchangeably.

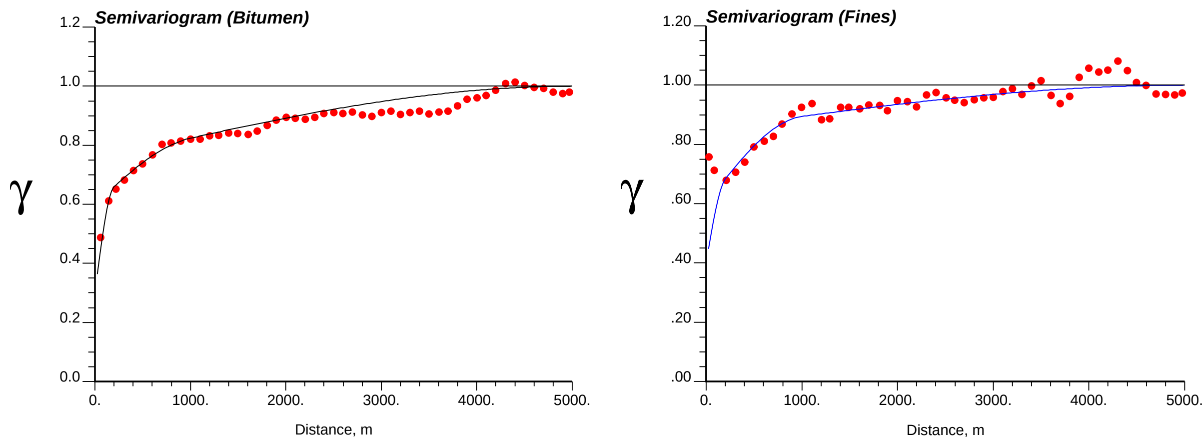

FIGURE 3: semivariogram of the normal scores of %bitumen and the normal score of %fines. Note the increasing behavior reaching the sill of 1 at about 4000 m. Also note the similarity between the two semivariograms.

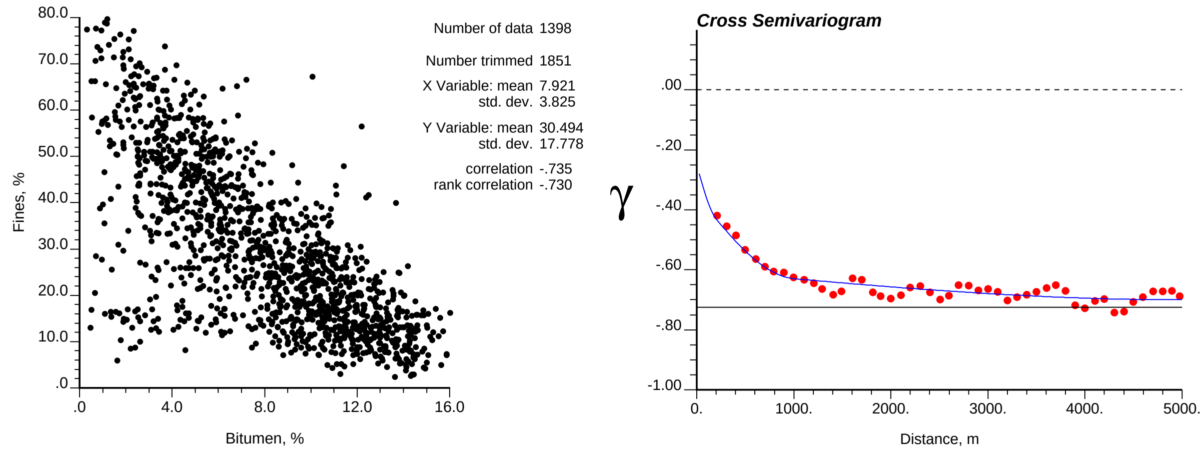

FIGURE 4: Cross semivariogram between %bitumen and %fines. Note the decreasing behavior reaching the cross correlation of –0.73 at about 4000 m.

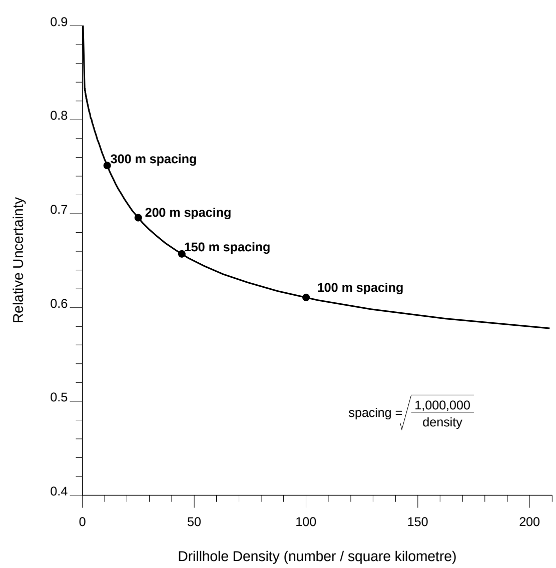

FIGURE 5: Reduction in uncertainty for increasing drillhole density. Note the “asymptotic” relationship of uncertainty with drillhole density.

UNCERTAINTY VERSUS DRILLHOLE SPACING

Firstly, we need to define "uncertainty". The probability distribution, denoted $f(\mathbf{u};z|(n))$, provides a full specification of the uncertainty about the unknown quantity at location **u**. The probability distribution at the location of a drillhole has zero-variance. The probability distribution at an unsampled location has a non-zero variance, increasing as the location gets farther away from drillholes. Although the probability distribution provides a full quantification of uncertainty, we summarize the uncertainty of a probability distribution by the variance. In particular, we use the dispersion variance, which explicitly accounts for the volume we are predicting $\mathbf{u}_v$ and the volume of interest, G:

$$D^2(\mathbf{u}_v, G): \quad \text{the variance of grades of volume } v \text{ at location } \mathbf{u} \text{ within volume } G \qquad (4)$$

This variance decreases as more data become available. For the same data configuration (drillhole spacing), the variance $D^2(\mathbf{u}_v, G)$ decreases as the volume v we are predicting increases. Large volumes can be predicted more accurately than small volumes; it is difficult to predict hourly fluctuations in % bitumen and % fines, but the yearly averages are much easier to predict. Figure 2 gives an illustration of dispersion variances; the variances on the left represent the variability of "point" samples within the deposit whereas the variances on the right represent the variability of "composite" samples within the deposit. The variance of %bitumen reduces from $(5.13)^2$ to $(3.84)^2$, a reduction of 44%. To filter the effect of the volume being estimates, we can standardize the dispersion variance with the global point variance. Thus, maximum uncertainty (no drillhole information) is at 1 and minimum uncertainty (at a drillhole location) is 0:

$$U_{\mathbf{u}} = D^2(\mathbf{u}_\bullet, G) \,/\, D^2(\bullet, G): \quad \text{dimensionless uncertainty at location } \mathbf{u} \qquad (5)$$

This dimensionless measure of uncertainty $U_{\mathbf{u}}$ can be scaled by the global variance $D^2(\bullet,G)$ to establish an absolute measure of uncertainty (in units of $\%^2$ bitumen or fines). As a first approximation, we could scale by the global dispersion variance $D^2(v,G)$ to establish an absolute measure of uncertainty corresponding to an arbitrary volume v.

There are two ways to assess uncertainty at a particular location **u** for a particular volume v for a particular set of data (n): (1) kriging, and (2) stochastic simulation. Block kriging is computationally quicker and provides a reasonable first approximation to the uncertainty; however, simulation is more flexible. Stochastic simulation provides a joint measure of uncertainty at all locations simultaneously, which would be necessary to quantify the spatial / temporal variability of bitumen / fines entering the plant. Moreover, simulation does not require strong assumptions regarding the nature of averaging or the shape of the distribution of block grades.

Uncertainty Assessment with Kriging

Kriging or, more specifically, cokriging can be used to simultaneously provide "best" estimates (in a minimum error variance sense) of the bitumen and fines content at an unsampled location. Kriging also provides an estimation variance $\sigma^2_K(\mathbf{u})$. The kriging equations are classical (see David, Journel and Huijbregts, and many others) and will not be repeated here. It is sufficient to recall that the essential control on the estimated grades and estimation variances is the variogram. In the present context of assessing uncertainty for different drillhole spacing, we are particularly interested in the estimation variance. In fact, we can calculate the estimation variance for a specific configuration of data (drillhole spacing) *before* collecting the data. It is important to note that, given the decision of stationarity, the estimation variance $\sigma^2_K(\mathbf{u})$ *is* the variance of the local distribution of uncertainty $f(\mathbf{u};z|(n))$.

As mentioned in the introduction (equation 1), the uncertainty at different locations $\sigma^2_K(\mathbf{u})$, $\mathbf{u} \in A$, can be averaged over all locations to provide a single measure of uncertainty. Thus, kriging can be used to assess uncertainty by the following steps (1) propose a specific drillhole spacing (assuming a particular configuration of bitumen and fines data), (2) perform cokriging on a dense grid of points, and then (3) average the estimation variance for all locations. This can be done with any cokriging program, e.g., the `cokb3d` program from GSLIB (Deutsch and Journel) among others. The `cokb3d` program was modified to sequentially consider many different square drillhole spacings, calculate the kriging variance for a dense grid of points, and calculate the relative uncertainty. Figure 5 on the bottom of the preceeding page shows the result. Note the asymptotic behavior, that is, short scale geologic variability leads to intrinsic uncertainty that cannot be removed by drilling more holes.

Uncertainty Assessment with Simulation

Stochastic simulation is a more direct, but computer intensive, approach to quantify the uncertainty U_u as a function of drillhole density or spacing. In addition to the advantages discussed above (joint variability and less strict assumptions), simulation accounts for the fact that there is often greater variability in high grade areas; the kriging variance is independent of the grade values.

Conditional simulation constructs realizations of the petrophysical variables that honor the correct histogram, variogram, and drillhole data. The theory and practice of simulation is presented in Deutsch and Journel, 1997; Goovaerts, 1998. A cosimulation procedure analogous to cokriging is used to construct realizations of multiple variables that honor a pattern of joint variability (see variograms and cross variograms on Figures 3 and 4). The `sgsim` program in GSLIB can be used for both simulation and cosimulation. A color / gray scale image of a 3-D realization of % bitumen is shown below on Figure 6. The realization is not smooth like a kriged map. By construction, the pattern of variability honors the input variogram.

Multiple equally probable realizations may be constructed by using a different random number seed in the stochastic procedure. The variance for any arbitrary volume may be directly calculated from the set of multiple realizations. Another set of realizations can then be created using different drillhole conditioning data; the more drillhole data available, the less variability there will be between the realizations. The drillhole data are taken from one realization chosen as the reference. It is preferable to take the drillhole data from a realization so that their pattern of variability is realistic and consistent with that inferred in the variogram.

100 realizations were constructed for a drillhole spacing of 200 m and for 100 m using `sgsim` in GSLIB. The `postsim` program in GSLIB can then be used to calculate the local variances. The average local variances can be standardized by the point dispersion variance (see equation 5) to arrive at results similar to Figure 5.

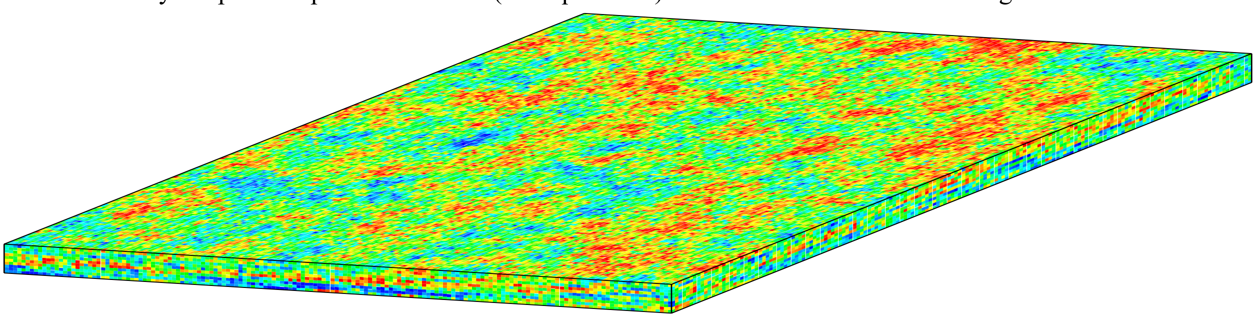

FIGURE 6: Simulated realization of %bitumen on a 15 m vertical resolution. The semivariogram used to generate this realization is shown above on Figure 3.

OPTIMAL DRILLHOLE SPACING

The main point of this paper is that we can quantify the reduction in uncertainty of bitumen and fines with increased drillhole density. Figure 5 shows a summary of the results for the particular variogram inferred from actual oil sands data. It is interesting to note that short scale geologic variability leads to an asymptotic behavior – there is some intrinsic uncertainty that cannot be removed by drilling more holes. The results of Figure 5 may be used qualitatively to determine drillhole spacing; increasing the drillhole density beyond a 150-100 m spacing does not significantly reduce uncertainty.

A decision regarding *optimal* drillhole spacing calls for a clear definition of optimality an accounting for (1) the cost of drilling and (2) the benefit of knowing the bitumen/fines content more precisely. Insufficient information is available at this point to put definitive numbers to those costs. Nevertheless, approximate costs can be used to illustrate how the optimal drillhole spacing would be calculated. A minimum cost criteria would be used. The unit cost of drilling is *X*$ per drillhole. Some savings in the unit drilling cost could be achieved with a large number of drillholes; however, this will not be considered.

The *cost* of not knowing the precise spatial distribution of bitumen is more difficult to quantify. There is no cost due to reduced hydrocarbon recovery, since careful grade control practices and short term planning can account for any surprises. The cost of uncertainty in the bitumen / fines is a combination of the following factors: (1) increased cost due to not knowing the exact amount of stripping, (2) cost of mid-course adjustments in the number and size of different operating mine faces, (3) cost of sub-optimal planning and movement of roads, equipment, and pipelines, and (4) increased costs incurred in the plant due lack of knowledge in the delivered bitumen / fines content. As a first approximation we assume that the cost of uncertainty is a linear function of uncertainty.

Figure 7 shows the procedure for determining the optimal drillhole spacing. The uncertainty cost is proportional to the uncertainty (a linear scaling in this case). The drilling cost increases linearly with drillhole density. Arbitrary units have been assigned to the costs. The ratio of drilling cost to the uncertainty scaling factor is the single factor for the optimal drillhole spacing. A sensitivity study on the uncertainty cost (considered less well known) leads to optimal drillhole spacings between 150 and 250 m.

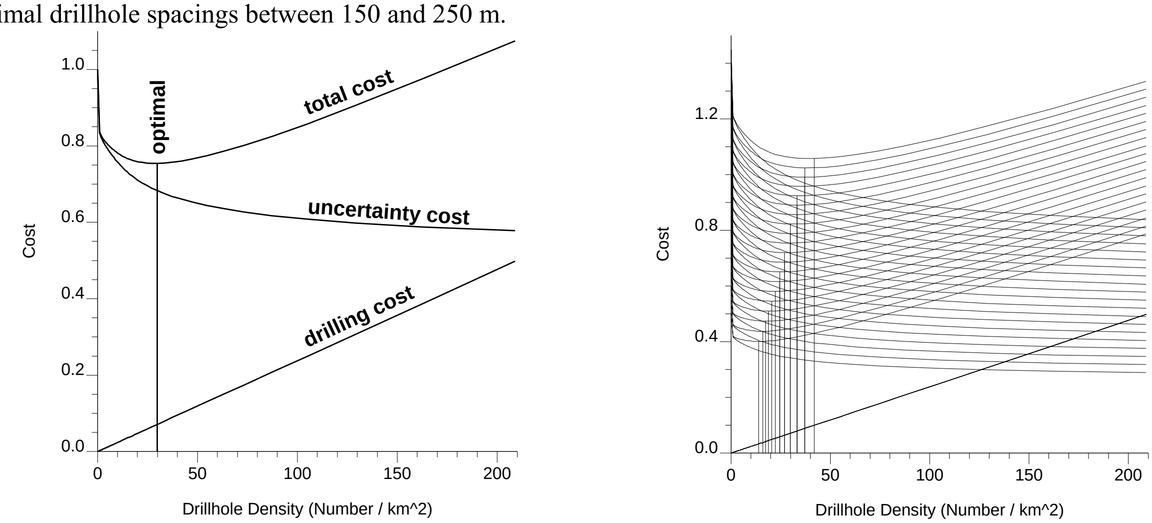

FIGURE 7: Calculation of optimal drillhole density / spacing for particular drilling and uncertainty costs.

CONCLUSIONS

Uncertainty in oil sands for different drillhole spacing may be quantified with geostatistical techniques. Assuming a cost of drilling and a cost of uncertainty in the local bitumen / fines permits calculation of an optimal drillhole spacing. The assignment of the *cost of uncertainty* has not been addressed satisfactorily.

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