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A Case for Geometric Criteria in Resources and Reserves Classification

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Classification is required for public disclosure. Resources must be allocated into measured, indicated and inferred. Reserves must be allocated into proven and probable. A longstanding problem is the determination of a consistent and rational scheme to assign these categories. We make a case for *geometric criteria such as drillhole spacing backed up by an assessment of uncertainty with geostatistical techniques. The choice of geometric criteria should be based on common practice for the deposit type, site-specific considerations and an expert judgment of other factors. We recommend* against *the exclusive use of probabilities for classification. An arbitrary choice of probabilistic criteria will often lead to unreasonably large or small volumes in each category. Our advice is to directly apply geometric criteria and support them with probabilistic analysis. The probabilistic analysis may cause the competent person to reconsider their geometric criteria, but the geometric criteria are used for disclosure. Geometric criteria are transparent, easy-to-understand, and leave little room for mischief.*

Keywords: geologic modeling, geostatistics, simulation, public disclosure, uncertainty

INTRODUCTION

The intent of this paper is to discuss some details beyond the information contained in codes such as the JORC code, SAMREC code, SEC Industry Guide 7 and NI 43-101. We are not proposing anything in contradiction with those codes. Our case for geometric measures is a reasonable interpretation consistent with all of those codes. There is a need for open discussion on actual numbers and procedures used for the classification of resources and reserves.

Resources and reserves classification aims at providing the estimation of the grade of a volume with an assessment of its confidence. Resources are classified in decreasing order of geological confidence as measured, indicated and inferred, whereas reserves are classified as proven and probable. Resources and reserves incorporate many modifying factors related to the environmental, social, financial and technological risk of mining.

Classification is commonly performed on a block-by-block basis, but the volumes are chosen reasonably large and contiguous, since we often believe that our confidence in the grade should not change abruptly between adjacent blocks. Many procedures for block-by-block classification lead to a slightly noisy map or a map with isolated regions around drillholes. In some cases, classification changes abruptly from measured to inferred resources in adjacent blocks without a transitional indicated block as one might expect. A posterior cleaning/smoothing of the classification may be required.

Geostatistics provides the best techniques available today to model heterogeneity and uncertainty in mineral deposits and petroleum reservoirs. Early applications of geostatistical techniques were based on using the kriging variance as a measure of confidence (Blackwell, 1998; Diehl and David, 1982; Froidevaux, 1982; Royle, 1977). The development of indicator techniques allowed the determination of the local distribution of uncertainty in the grade, which together with a change of support model provides a distribution of uncertainty at block support. This can be used as a measure of the confidence for each block and be the base of a classification scheme (Froidevaux et al., 1986).

Geostatistical simulation techniques provide an ability to predict uncertainty in multiple variables at any specified scale (Deutsch and Journel, 1998; Deutsch, 2002; Goovaerts, 1997; Wackernagel, 2003). It seems reasonable to base classification decisions on a probabilistic assessment of uncertainty provided by geostatistics. We could use those probabilities for more than risk assessment and blending decisions. There have been a number of papers advocating the use of probabilities for classification (Dohm, 2005), for example, measured may be defined as monthly production volumes that will be within 15% of their estimated grade with 90% probability. Indicated could be defined as yearly volumes that meet the same 15%/90% criteria. This seems reasonable. Geostatisticians understand that there is nothing particularly special about monthly/15%/90%, but those numbers are commonly mentioned. These categories are assigned only within areas where we have a minimum level of geological confidence.

Codes for public disclosure increasingly suggest a quantification of the error associated with the estimation of the grade for classification. In many cases, mining companies consider a migration to a probabilistic classification approach to be compliant with the suggestion to quantify risk and uncertainty. At a minimum, some probabilistic assessment is considered to support or back-up the chosen classification scheme. Current classification techniques are often based on geometric criteria constrained by geological knowledge.

Although, we support the increased use of geostatistics to measure uncertainty and risk, it seems more reasonable to base classification on *geometric criteria supported by a measure of uncertainty*. This paper presents the basis for this assertion. In a nutshell, we will develop the following points:

1. Uncertainty is model-dependent and stationarity-dependent. Uncertainty can be changed dramatically by minor changes to these decisions. For example, high resolution rock type models can lead to large uncertainty in the grade of mineralized zones.

2. Many parameters affect the distributions of uncertainty in a non-intuitive and non-transparent manner. For example, an increased nugget effect drastically reduces the uncertainty at a large mining scale.

3. Uncertainty in the histogram and spatial continuity parameters are not commonly considered, but can have a significant affect on large mining-scale uncertainty. For example, considering the declustered histogram as known and fixed for geostatistical analysis can lead to a significant reduction in block uncertainty.

4. Choosing the parameters of uncertainty for classification cannot be universal and is highly deposit specific. For example, choosing relative uncertainty versus absolute uncertainty causes low grade regions to have large uncertainty. Moreover, certain deposit types have less uncertainty, but cannot be considered as completely measured with sparse drillhole.

We expand on these points and recommend a geometric approach to classification whereby drillhole spacing or the number of drillholes per unit area/volume is used for classification. The choice of geometric criteria should be supported by geostatistical simulation and assessment of risk. The transparency and openness of geometric criteria combined with the problem of directly using probabilistic statements are overwhelming practical considerations.

GEOMETRIC CRITERIA

Geometric measures such as drillhole spacing, drillhole density and closeness to the nearest drillhole are direct measures of the amount of data available. Although seemingly simple, there are subtle differences in these geometric parameters and their calculation in presence of irregularly spaced data. Geometric measures are among the most commonly applied in industry; nevertheless, these measures will be defined and explained, then we discuss their calculation in presence of irregular spaced drillholes.

Figure 1 shows an illustration of drillhole spacing, density and radius. The relationships between these measures are presented. The terms and units are given on Figure 1. The relationship between drillhole spacing and density is clear:

$$\left(\frac{L_1+L_2}{2}\right)^2=\sqrt{\frac{10000}{d}} \quad \text{and} \quad d=\frac{10000}{L_1\cdot L_2}$$

The relationship to the radius from the drillhole is less clear. Assuming that the drillhole radius should include everything at the particular spacing (see Figure 1):

$$L_1^2+L_2^2=(2r)^2 \quad \text{and} \quad r=\sqrt{\frac{L_1^2+L_2^2}{4}}$$

It is not common to use the radius from a drillhole in mining applications; it is more common in petroleum applications with widely spaced wells. This paper is aimed at classification in mining and we recommend drillhole spacing or drillhole density.

The application to 3-D with deviated drillholes is more complex. There are a number of ways that we could define the drillhole spacing, but a straightforward approach consists of defining the equivalent square drillhole spacing for the number of composites within some nominal 3-D volume, see Figure 2. The volume defined in Figure 2 is a rectangular parallelepiped defined by L_A, L_B, and L_C. An ellipsoidal volume could be used. The spacing of the composites is “c”. Considering the rectangular volume, the equivalent L is defined by:

$$L = \sqrt{\frac{L_A \cdot L_B \cdot L_C}{c \cdot n}}$$

where n is the number of composites found in the volume defined by L_A, L_B, and L_C. This calculation depends on the volume size and orientation. No data are relocated; an equivalent regular spacing is calculated so that the number of data per unit volume is the same. Sensitivity studies would have to be performed to establish robust and reasonable results. This same concept can be applied to irregularly located vertical drillholes; however, we could use a simpler 2-D approach.

Figure 3 shows a sketch for the calculation of drillhole density in an irregular 2-D configuration of data. The number of data within a window (defined by radius r_s in the sketch) are counted (n=13 in the sketch) and divided by the area.

$$d = \frac{10000 \cdot n}{\pi \cdot r_s^2} \quad \text{and} \quad L = \sqrt{\frac{10000}{d}}$$

The calculation depends on the choice of r_s. The results will be smooth and locally imprecise if r_s is too large. The results will be too noisy if r_s is too small. Sensitivity studies would have to be performed to establish robust and reasonable results. These measures could also incorporate anisotropy by defining anisotropic regions for the search of drillholes or samples in the neighborhood. In general, the measure should be kept as simple as possible.

There are many different geometric measures and methods of calculation. The ideas documented in this section are adequate for the purposes of this paper. Site specific considerations such as the calculation within geologic domains, anisotropy, and robustness of calculation in presence of irregular locations will have to be addressed. A calculation of d or L (or L_1/L_2 in presence of anisotropy) is always possible. Classification should be based on thresholds applied to these variables.

The critical geometric thresholds for classification are based on (1) industry-standard practice in the country and geologic setting, (2) experience from similar deposit types, (3) a calibration with uncertainty quantified by geostatistical calculations (see later), and – most importantly – (4) the expert judgment of the competent or qualified person. Defining measured/indicated/inferred based on drillhole spacing thresholds by geologic domain is transparent and understandable.

OTHER CRITERIA

There are a number of criteria that fall between the geometric measures discussed above and the probabilistic measures that will be discussed in the next section. One procedure includes multiple pass estimation with different search strategies – blocks that are estimated with a restricted search have greater confidence and blocks estimated with a larger second-pass search have less confidence. Kriging passes can be used to reflect geologic confidence, grade continuity, and other criteria for informing blocks. Kriging variance or relative kriging variance could also be used – blocks with lower kriging variance have greater confidence than blocks with high kriging variance. The kriging variance could be associated to a particular drill hole spacing. These criteria are reasonable in some contexts; however, in the context of this paper, we do not recommend them. Purely geometric criteria are more easily understood and transparent. Purely probabilistic criteria based on sound estimates of uncertainty are also understandable.

PROBABILISTIC CRITERIA

There has been increased interest in applying probabilistic measures of uncertainty coming from (geo)statistics. Geostatistical approaches lead to a model of uncertainty. Although there is no objective true quantification of uncertainty, geostatistical models of uncertainty have been developed that provide reliable measures of uncertainty. Uncertainty at the data scale is accomplished analytically with a variety of methods including a multivariate Gaussian model or indicator geostatistics. Uncertainty can be defined numerically by simulation with a variety of methods including object-based simulation and multiple point statistics. These techniques to establish the uncertainty at the data scale can be found in many software packages and discussed in many geostatistical books (Caers, 2005; Deutsch, 2002; Mallet, 2002).

Uncertainty at the scale of the data is rarely relevant for technical and economic decision making. The uncertainty at the data scale is scaled-up to a volume relevant to mining. The scale-up procedure is almost universally simulation, that is, realizations of the variability at the small scale are simulated and then averaged to the relevant larger scale. Distributions of uncertainty at the large scale are assembled by multiple realizations. One hundred realizations (or less) is a common number because of the computational burden of simulation.

Figure 4 shows a distribution of uncertainty represented as a histogram (solid line of frequencies). The schematic illustration also highlights three parameters often used in probabilistic classification schemes: (1) volume related to a production period, (2) precision, and (3) probability to be within the specified precision. The volume need not be a contiguous block, but often it is chosen as a simple volume. The second two parameters are one way to summarize uncertainty. The meaning of these probability numbers may be unclear to practitioners.

Probabilities have a precise meaning to statisticians. They are proportions over a defined population. The probabilistic statement that *there is a 90% probability that the grade of a monthly production volume be within 15% of the estimated grade* means that 90 out of 100 true grades of similarly classified monthly production volumes will be within their estimate plus or minus 15%. Probabilities are checkable with actual proportions. Prior to mining, we can only check the uncertainty at the scale of the drillhole samples; however, operating mines have the luxury of checking actual monthly production volumes.

We were involved in this type of checking with a large oil sands mining operation in Northern Alberta. We were provided with the surveyed topography at the end of each month for more than a year. We extracted the uncertainty for those monthly volumes from the geostatistical model of uncertainty. Then, the actual monthly grades of bitumen were checked against the uncertainty. We projected that 11 out of 12 months should be within the 11/12ths (91.7%) probability interval. The fairness or reasonableness of the probabilities was verified by actual production. This is not always possible, but should be attempted.

Some classification should be based on probabilities. The petroleum resource/reserve classification scheme presented in NI 51-101 and the accompanying CIM guidelines mention specific probabilities. There should be a 90% probability to exceed proven reserves and a 50% probability to exceed probable reserves. This is less common in the mining industry – there is no mention of probabilities in codes such as the JORC code, SAMREC code, SEC Industry Guide 7 and NI 43-101. There is encouragement to quantify uncertainty where possible, but there is no mandate to use probabilistic criteria for classification.

There are compelling reasons to use probabilistic criteria, particularly if the uncertainty has been verified by actual production: (1) the magnitude of the grades and the local configuration of data are accounted for, (2) the mining volume is explicitly accounted for, and (3) uncertainty is perceived as more objective and transportable to different deposits. Despite these reasons, we believe that probabilistic results should be used to support or backup a choice of geometric criteria (within chosen geologic units). This recommendation is based on a number of concerns with the direct use of probabilities for classification.

CONCERN 1: MODEL DEPENDENCE

Uncertainty is model dependent. The modeling approach and model parameters evolve as the deposit is understood. It is common for uncertainty to increase once the geological model is refined, detailed rock types and geologic units are established and spatial continuity measures are reliably informed. Thus, classification based on uncertainty could change drastically with additional drillholes and geostatistical study.

Delineation drilling may be acquired with the purpose of proving-up or increasing the confidence in areas of the deposit. If probabilistic criteria are used for classification, there is no fixed drillhole spacing that would ensure an area is measured or proven. The classification could change as the geostatistical approach and modeling parameters are updated. This provides a moving target for delineation, which is undesirable. Clearly, there are times when the required drillhole spacing should be changed; for example, a smaller spacing may be warranted when the mineralization is found to be more erratic and discontinuous than first assumed. The model dependent nature of probabilistic predictions leads to unwarranted reclassifications.

Probabilities rely on stationarity that is difficult to establish early in resource evaluation. In fact, a decision of stationarity, that is, how to group the data is difficult to make at any stage of resource evaluation. The sensitivity of classification results to the decision of stationarity is a significant concern. An example is shown to illustrate the point.

Figure 5 shows 21 drillholes in an area 3000m by 3000m. The statistical parameters in the shaded ellipse on the right side of the figure are the true statistical parameters for this area. Inference of reliable statistical parameters in presence of sparse data is an important point;

however, the point being made in this example relates to the decision of stationarity. The true statistical parameters were used. The map in the lower left shows the predicted probability for the true value to be in the interval defined by the estimate +/- 50%. There is a high probability near the drillholes and in high valued areas where the probability interval is wider.

Figure 6 shows 169 more data – for a total of 190 data. The gray shaded zone in the south central region of the location map (see upper left) was separated from the remaining low grade zone. The statistical parameters are shown in the shaded ellipse on the right side of the figure. The map in the lower left shows the predicted probability for the true value to be in the interval defined by the estimate +/- 50%. The probability has increased from Figure 5 because of the additional drilling. Although there are nearly 10 times more drillholes, the probability for the truth to be within 50% of the estimate has decreased in 15.8% of the locations, see Figure 7.

This example was not fixed to show an exaggerated sensitivity; it is typical. Geostatisticians know that uncertainty is model dependent and the uncertainty will change significantly as the modeling approach and parameters changes. This has an unwarranted and unpredictable affect on probabilistic classification.

CONCERN 2: NON-TRANSPARENT PARAMETERS

Many parameters affect the distributions of uncertainty in a non-intuitive and non-transparent manner. Relatively minor changes in geostatistical parameters can affect probabilistic estimates. The nugget effect is an important parameter that can operate in a non-intuitive manner. Intuitively (for many people), an increased nugget effect entails increased short scale variability and increased uncertainty. In practice, however, an increased nugget effect leads to a decrease in uncertainty because of averaging. Uncertainty in large volumes decreases quickly when the nugget effect is high and/or the variogram range is short. This makes statistical sense. When the grades are random they average out when large scales are considered.

Figure 8 shows 104 drillholes. Two variogram models were fit to the isotropic normal scores variograms at the bottom of the figure: with and without a nugget effect. The variogram fit to the experimental points is equally good in both cases. Figure 9 shows one realization (of the 100 created) for each variogram and the probability for blocks 4 grid nodes square to be within 50%

of their estimate. The probabilities are significantly higher when the realizations with a nugget effect are used, see Figure 10. The mean probability increases from 53% to 61% by simply including a nugget effect in the variogram model.

Classification could easily be arbitrarily changed by adjusting the variogram. The nugget effect is an important parameter, but other parameters can be important. The range and directions of anisotropy are sometimes important. A zonal anisotropy can have a large affect on uncertainty predictions. The probability to be within an interval is not robust with respect to the variogram model.

CONCERN 3: PARAMETER UNCERTAINTY

Uncertainty in the histogram and spatial continuity parameters is not commonly considered, but can have a large affect on mining-scale uncertainty. For example, considering the declustered histogram as known and fixed for geostatistical analysis can lead to less uncertainty. It is common practice to consider global statistical parameters as fixed. A bootstrap procedure accounting for spatial correlation could be used to assess uncertainty in input parameters such as the mean. That uncertainty could be transferred into the results of geostatistical simulation to provide a more realistic assessment of uncertainty.

Figure 11 shows the histogram of data from the previous concern (see also Figure 8) with the uncertainty in the mean shown on the figure. The standard deviation in the mean is 1.31 versus 9.67 for the original data. Although there are 104 drillholes, the variance only goes down by 1/54.5 because of spatial correlation. This reduction was calculated using the no-nugget effect variogram. The results are nearly the same with the nugget effect variogram because most of the data are more than 40m apart. The probability for the true value to be inside +/-50% of the estimates decreases by about 6% – from 0.53 to 0.50. The increase in uncertainty (reduction of the probability to be in a fixed interval) is case dependent.

CONCERN 4: DEFINING THE PROBABILISTIC CRITERIA

The qualified/competent person chooses risk thresholds based on varied technical, economic, and managerial considerations. The considerations are site-specific, but the uncertainty statements can appear as universal and independent of the deposit type. The statement that *there is greater than a 90% probability that the grade of monthly production volumes is within 15% of their estimated grades* does not depend on the deposit type. There is nothing special about 90%/monthly/15%, but they seem reasonable.

Choosing the parameters of uncertainty for classification must be customized for each deposit. For example, choosing relative uncertainty versus absolute uncertainty causes low grade regions to be uncertain (see Figure 12). Moreover, certain deposit types have less uncertainty, but cannot be considered as all measured.

Figure 13 shows a histogram of probability for grade of quarterly production volumes to be within +/- 15% of their estimated grades. These results are for a large mineable area for an active oil sands mining operation in Northern Alberta. The two modes on the distribution are for high grade and low grade areas. The +/- 15% intervals are a lot narrower when the grade is low, therefore there is a lower probability to be inside that interval.

In the same oil sands example above, we can also observe that there is great sensitivity to the chosen probabilistic thresholds. Suppose that a probability threshold of 90% is chosen to differentiate between measured and indicated resources, based on the same information in Figure 13, this means that 25% of the deposit would be classified as measured. Now if we relax this threshold to 85% then the amount of measured increases to 33%. Further, the presence of a second mode near the 50% probability threshold implies that the sensitivity to a chosen probability threshold also applies to the amount of indicated/inferred resources calculated. The classified resources can change significantly with slight changes in probabilistic thresholds.

Methodology to Back up Geometric Criteria with Probabilistic Meaning

Despite the four concerns discussed above, there is merit to validating geometric classification measures with a probabilistic meaning. Probabilistic measures of uncertainty are provided through geostatistical simulation of multiple realizations. A cross plot of the geometric measure and the probability to be within a certain level of precision provides a relationship between uncertainty and drillhole spacing. Probabilities can be calculated from multiple realizations; often 100 realizations are used. Figure 14 shows an example of such a plot wherein conditional quantiles are also illustrated. These results are dependent on the conditioning data locations, and not on proposed data spacing.

While stationarity and an uncertainty model are still required, we can propose a second method where we begin with an unconditional simulation at the required resolution and sample at the geometric spacing of interest. This permits different sample spacings, other than those from available data, to be considered under the same uncertainty model. The following methodology is proposed:

1. Consider a region that is nominally large relative to the data spacing. Using the representative histogram and variogram (as analyzed from the data), generate an unconditional realization using geostatistical simulation. We start with unconditional simulation to facilitate multiple realizations and conditioning in subsequent steps.
2. For a specific drillhole spacing (e.g. 100m), sample from the unconditional realization. This becomes conditioning data for the following steps:
   a. Generate a conditional simulation with the same reference histogram and variogram (as in Step 1), but using this sampled pseudo-data set. Generate many realizations, say 100.
   b. Block average up the realizations to a volume that is representative of a production period of interest, such as monthly or quarterly.
3. Assess the distribution of uncertainty in the block averaged grade at each location. Choose a precision level (e.g. +/- 15%) and calculate the probability to fall within this interval. This assumes that level of precision is symmetric about the expected grade (or E-type estimate) at that location.
4. Calculate the data spacing (or other geometric criteria) over the entire grid; this should require only the grid definition and the available drillhole data.
5. Crossplot the probability to fall within the precision window about an estimate against the geometric criteria. From this crossplot, we can also calculate for a given spacing or density:

a. The expected probability to fall within the chosen precision level.

b. The 90% probability interval for these calculated probabilities.

These five steps can be repeated many times, say 20 or 25, with the purpose of removing the influence of the initial conditioning data. Expected statistics from the multiple runs could also be plotted against drillhole spacing or density. Further, consideration of larger volumes will tend to shift the relationship between probability within an interval and spacing up the probability scale. This occurs as a result of the narrowing of the distribution of uncertainty as volume increases; this is not an unexpected result given the well understood volume variance relations. Figure 15 shows a schematic and an example of the shift in this relationship with volume. The example shows trend lines of the relationship, while the actual points are due to ergodic fluctuations from considering multiple sets of realizations.

RECOMMENDATION

Geometric criteria such as drillhole spacing or drillhole density are recommended for resource/reserve classification. Distances are easily understood and transparent to all stakeholders. Some subjectivity is required in the calculation of these geometric measures in presence of irregularly located data, but that is relatively minor. Geostatistical realizations should be constructed to lend a clear probabilistic meaning to the chosen classification procedure. The uncertainty for each category (measured, indicated and inferred) should be quantified on average (at the average spacing in the category) and at the geometric threshold (the maximum distance for the category). These probabilistic statements could cause the competent/qualified person to reconsider their geometric choices. If possible, the probabilities should be checked with actual production data.

Geostatistics provides models of heterogeneity and uncertainty that are invaluable for resource/reserve evaluation. The theoretical basis for geostatistics is sound. The practice has evolved over the last 30 years to become an indispensable part of resource/reserve evaluation. We see no end to the utility of geostatistics. It may be dangerous to make a case against the use of probabilistic measures for classification. The recommendation against a purely probabilistic basis for classification is made on the basis of transparency. The risk of public misunderstandings due to innocent mistakes or intentional mischief is high.

Although we believe that geometric measures are more objective and transparent than probabilistic predictions, they too are prone to mistakes and intentional mischief. There is no replacement for the expertise of a qualified person.

CONCLUSIONS

Uncertainty is inescapable and widespread. There are many aspects of uncertainty including geologic uncertainty as a result of incomplete or widely-spaced data. Resources calculated based on such information must be classified by confidence into categories such as measured, indicated and inferred prior to public disclosure. There are many schemes for such classification. We make a case for the use of geometric measures such as drillhole spacing. The selection of distance thresholds should be based on local practice, similar deposits, site-specific considerations and uncertainty quantified by geostatistical procedures.

Geostatistics provides important support information for the classification of resources and reserves. We recommend against classification based on purely probabilistic criteria for a number of reasons including: (1) uncertainty depends on the choice of stationary geological populations and modeling procedures, (2) uncertainty is sensitive to non-intuitive parameter choices, (3) uncertainty can be increased greatly with the consideration of parameter uncertainty, and (4) the choice of parameters for probabilistic classification cannot be universal.

This paper will be aligned with the thinking of many practitioners. Others will disagree. There is no scientific proof of optimality that can be applied to resource/reserve classification. The expert must make choices accounting for many factors.

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REFERENCES

- Blackwell, G. H., 1998, Relative kriging errors – a basis for mineral resource classification, Exploration and Mining Geology, Vol. 7, Nos. 1 and 2, p. 99-106.
- Caers, J., 2005. *Petroleum Geostatistics*. Society of Petroleum Engineers
- Canadian Securities Commissions (CSA), 2005. *National Instrument 43-101: Standards of Disclosure for Mineral Projects.*
- Deutsch, C.V. and Journel, A.G., 1998, *GSLIB: Geostatistical Software Library: and User's Guide*. Oxford University Press, New York, 2nd Ed.
- Deutsch, C.V., 2002, *Geostatistical Reservoir Modeling*. Oxford University Press, New York.
- Diehl, P., and David, M., 1982, Classification of ore reserves/resources based on geostatistical methods, CIM Bulletin, Vol. 75, No. 838, p. 127-136.
- Dohm, C., 2005, Quantifiable Mineral Resource Classification - A Logical Approach, in Leuangthong, O., and Deutsch, C. V., eds., Geostatistics Banff 2004: Kluwer Academic, Dordrecht, The Netherlands, Vol. 1, p. 333-342.
- Froidevaux, R., 1982, Geostatistics and ore reserve classification, CIM Bulletin, Vol. 75, No. 843, p. 77-83.
- Froidevaux, R., Roscoe, W. E., and Valiant, R. I., 1986, Estimating and classifying gold reserves at Page-Williams C zone: a case study in nonparametric geostatistics, in David, M., Froidevaux, R., Sinclair, A. J., and Vallée, M., eds., Proceedings of the Symposium on Ore reserve estimation – methods, models and reality: Canadian Institute of Mining, Metallurgy and Petroleum, Montreal, p. 280-300.
- Goovaerts, P., 1997, *Geostatistics for Natural Resources Evaluation*. Oxford University Press, New York.

- Joint Ore Reserves Committee (JORC), 2004. *Australasian Code for Reporting of Exploration Results, Mineral Resources and Ore Reserves (JORC Code)*, http://www.jorc.org/pdf/jorc2004web.pdf, accessed on June 12, 2006.
- Mallet, J.L., 2002. *Geomodeling*. Oxford University Press, New York.
- Royle, A.G., 1977, How to use geostatistics for ore reserve classification. World Mining, Vol. 30, p. 52-56.
- South African Mineral Resource Committee (SAMREC) within the South African Institute of Mining and Metallurgy, 2000. *South African Code for Reporting of Mineral Resources and Mineral Reserves*, http://www.saimm.co.za/codes/samrec_version.pdf, accessed on June 12, 2006.
- United States Securities and Exchange Commission (SEC), *Industry Guide 7*, http://www.sec.gov/divisions/corpfin/forms/industry.htm#secguide7, accessed on June 12, 2006.
- Wackernagel, H., 2003, Multivariate geostatistics: an introduction with applications, 3rd edition, Springer, Berlin, 387 p.

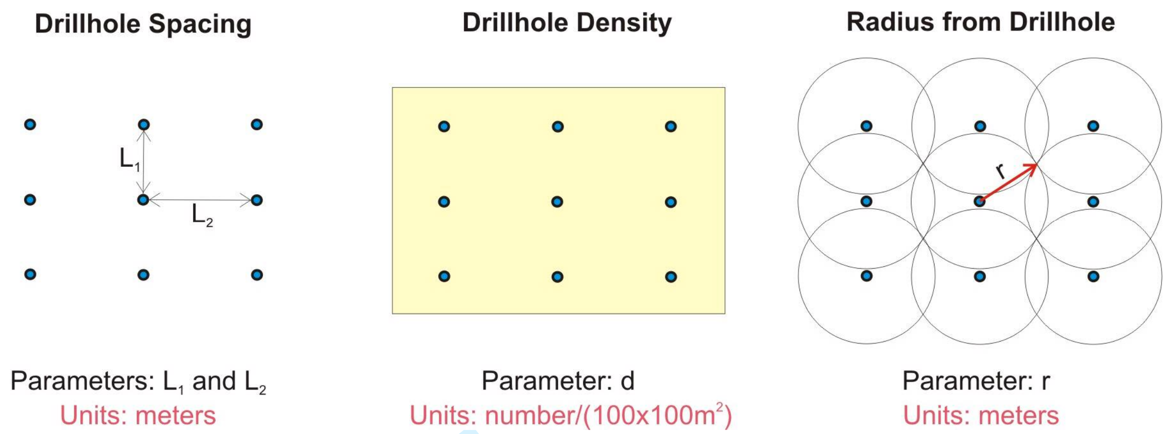

Figure 1: schematic illustration of the different geometric measures of the amount of data: drillhole spacing, drillhole density and radius from drillhole.

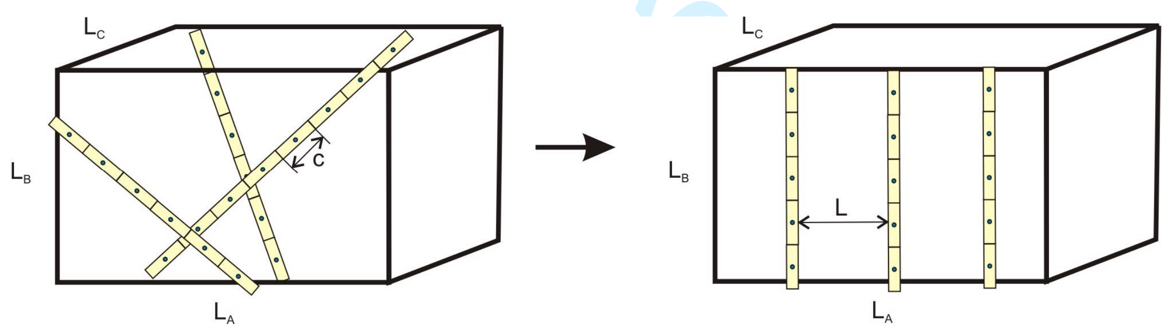

Figure 2: sketch showing a 3-D volume defined by L_A, L_B and L_C. The nominal spacing L is defined such that there are the same number of data in the 3-D volume. The spacing of the composite data is denoted c in the sketch.

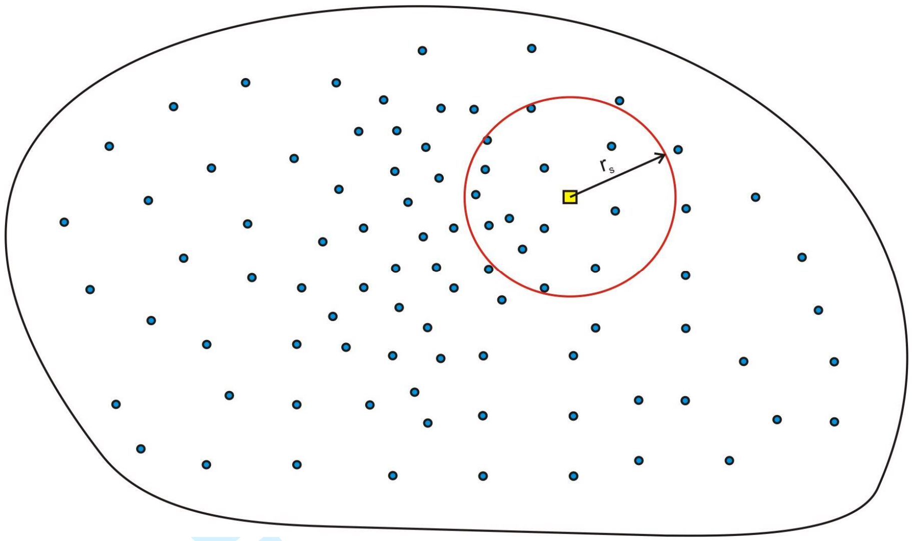

Figure 3: sketch showing the calculation of drillhole density in an irregular 2-D configuration of data. The number of data within a window (defined by radius r_s in the sketch) are counted (n=13 in the sketch) and divided by the area.

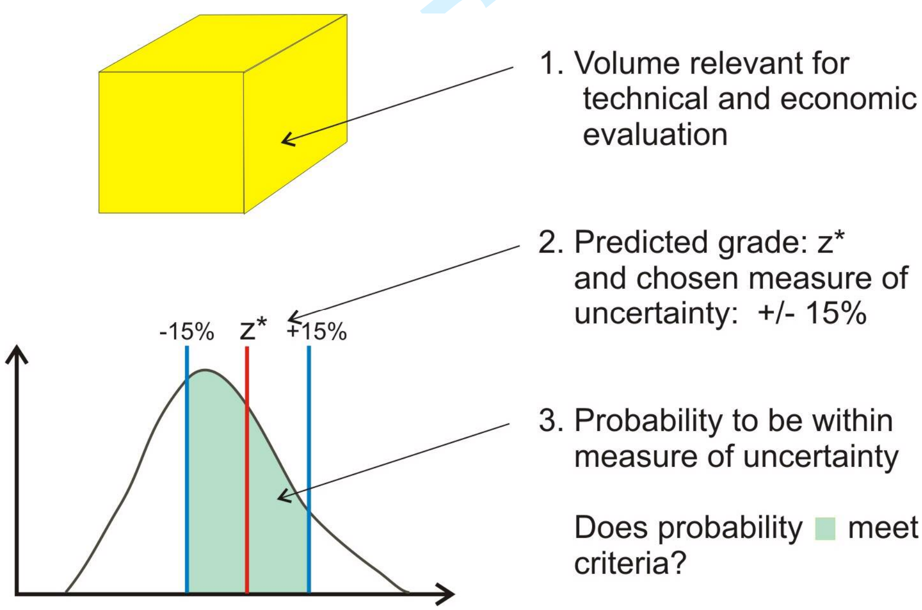

Figure 4: schematic illustration of the three parameters often used in probabilistic classification schemes: (1) volume related to a production period, (2) precision, and (3) probability to be within the specified precision.

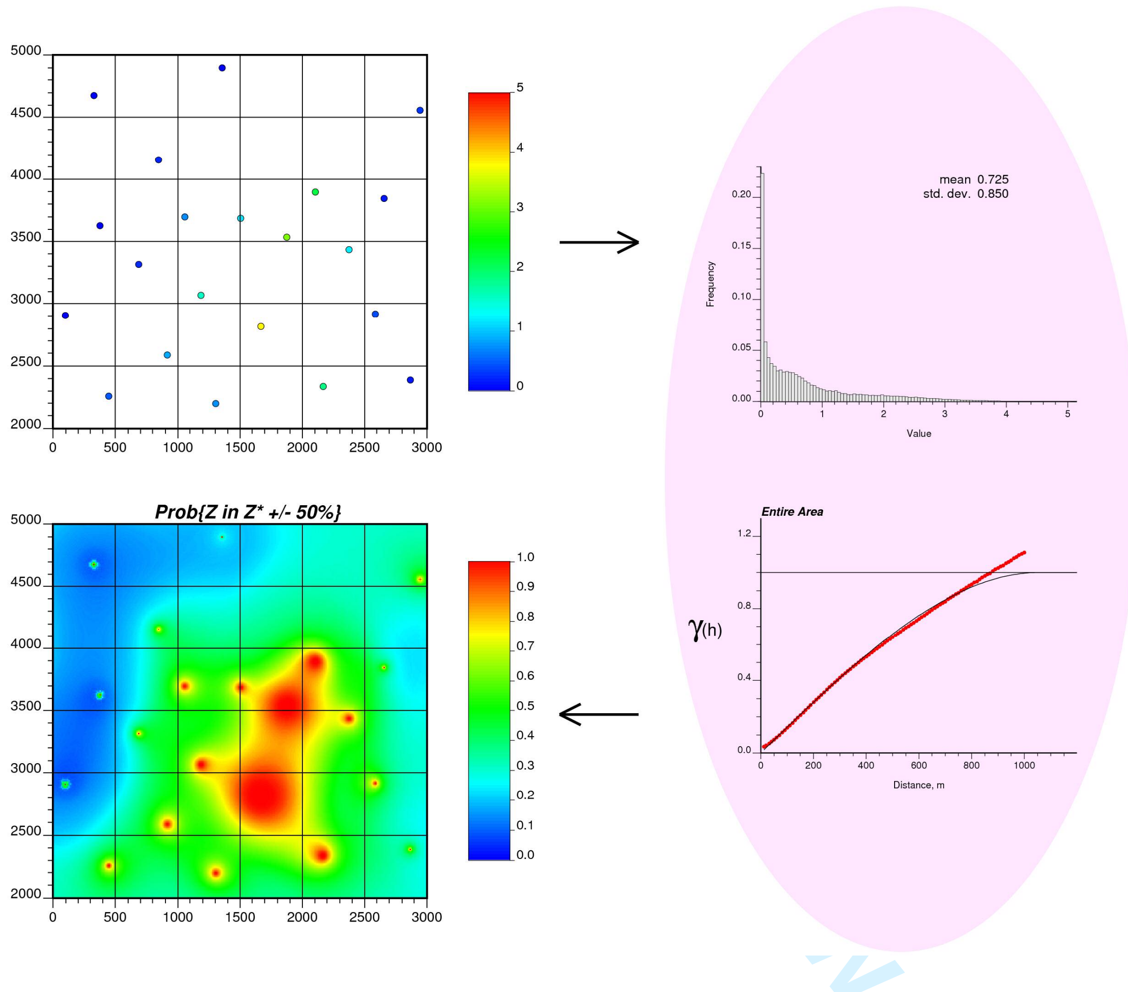

Figure 5: 21 example data (upper left), statistical parameters – histogram and variogram (right) and resulting map of the probability to be within +/- 50% of the estimate (lower left).

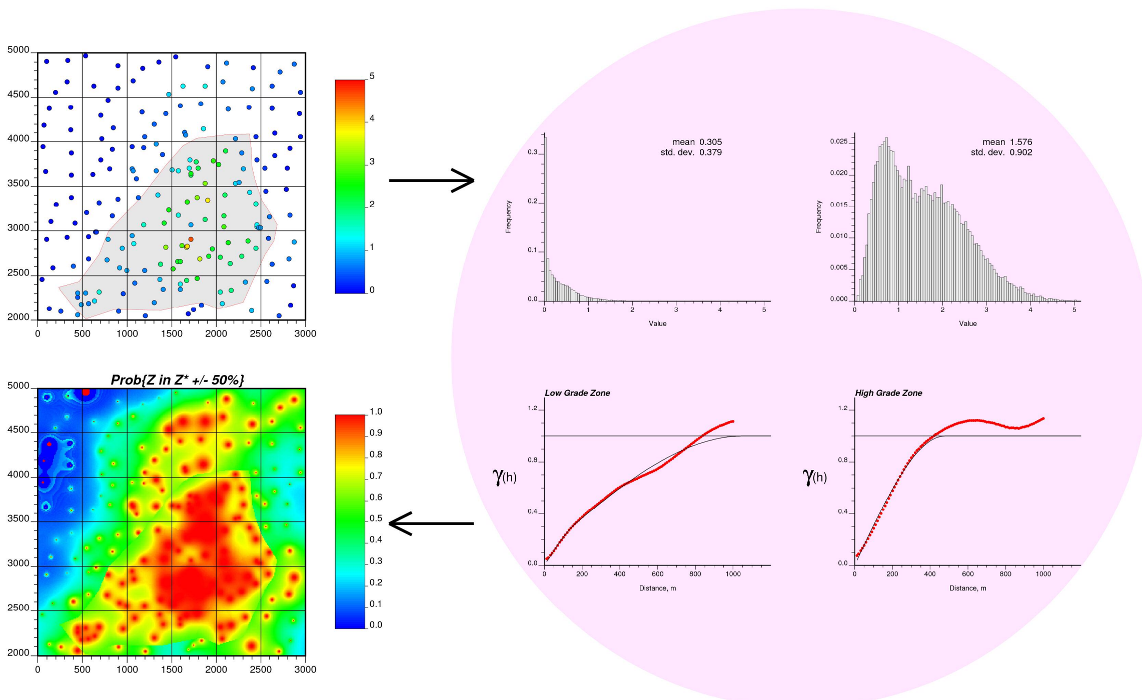

Figure 6: more data (190 total) (upper left), statistical parameters for the low grade zone and the high grade zone – histograms and variograms (right) and resulting map of the probability to be within +/- 50% of the estimate (lower left).

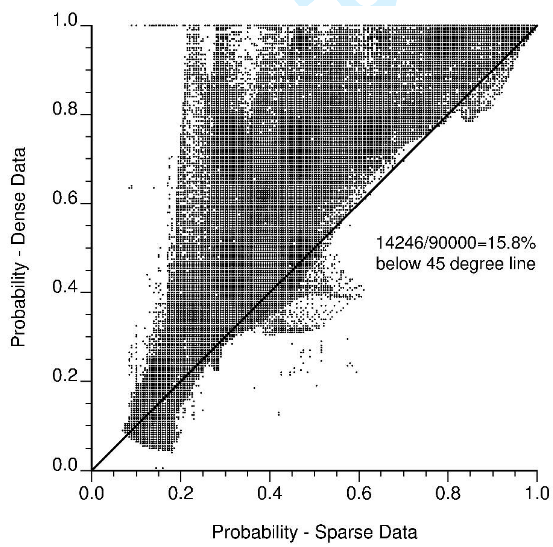

Figure 7: comparison of probability to be inside the +/- 50% interval with the sparse (21) data and the dense (190) data.

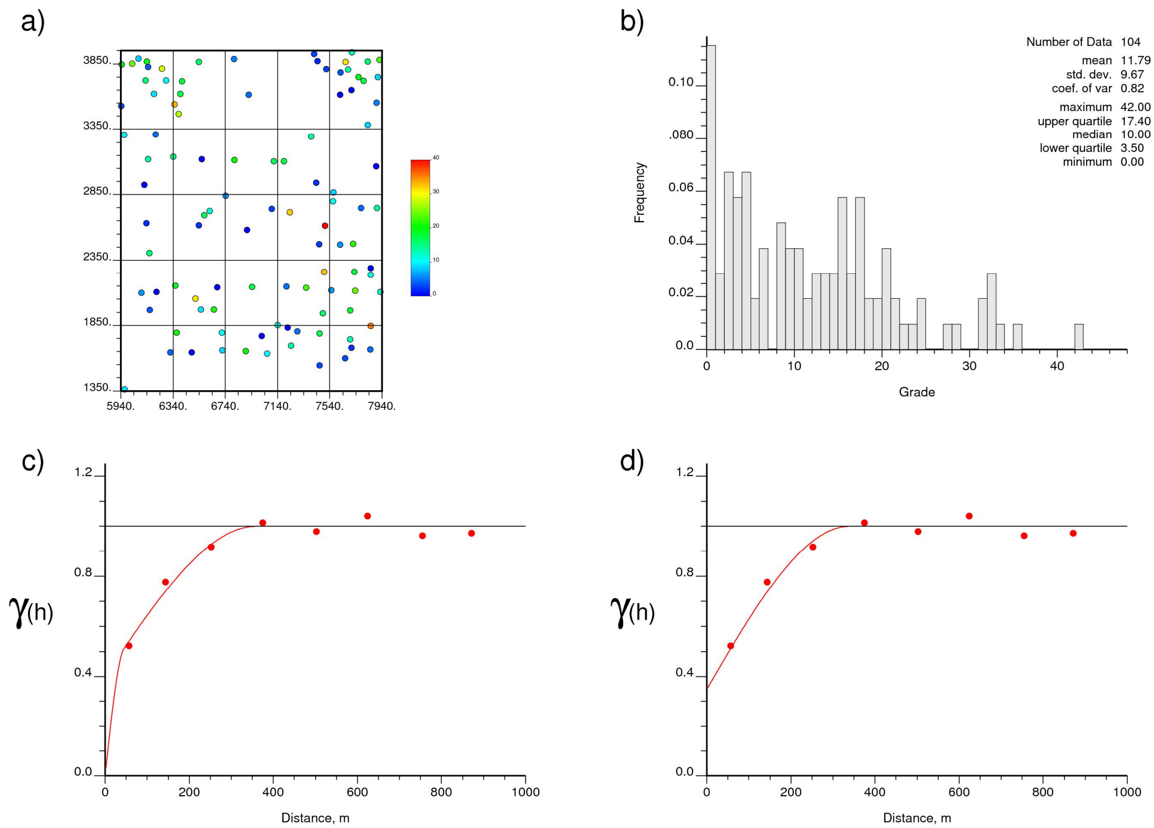

Figure 8: example dataset from an in situ heavy oil project: (a) the drillhole locations, (b) the grade, (c) variogram modeled with no nugget effect, and (d) variogram modeled with a nugget effect.

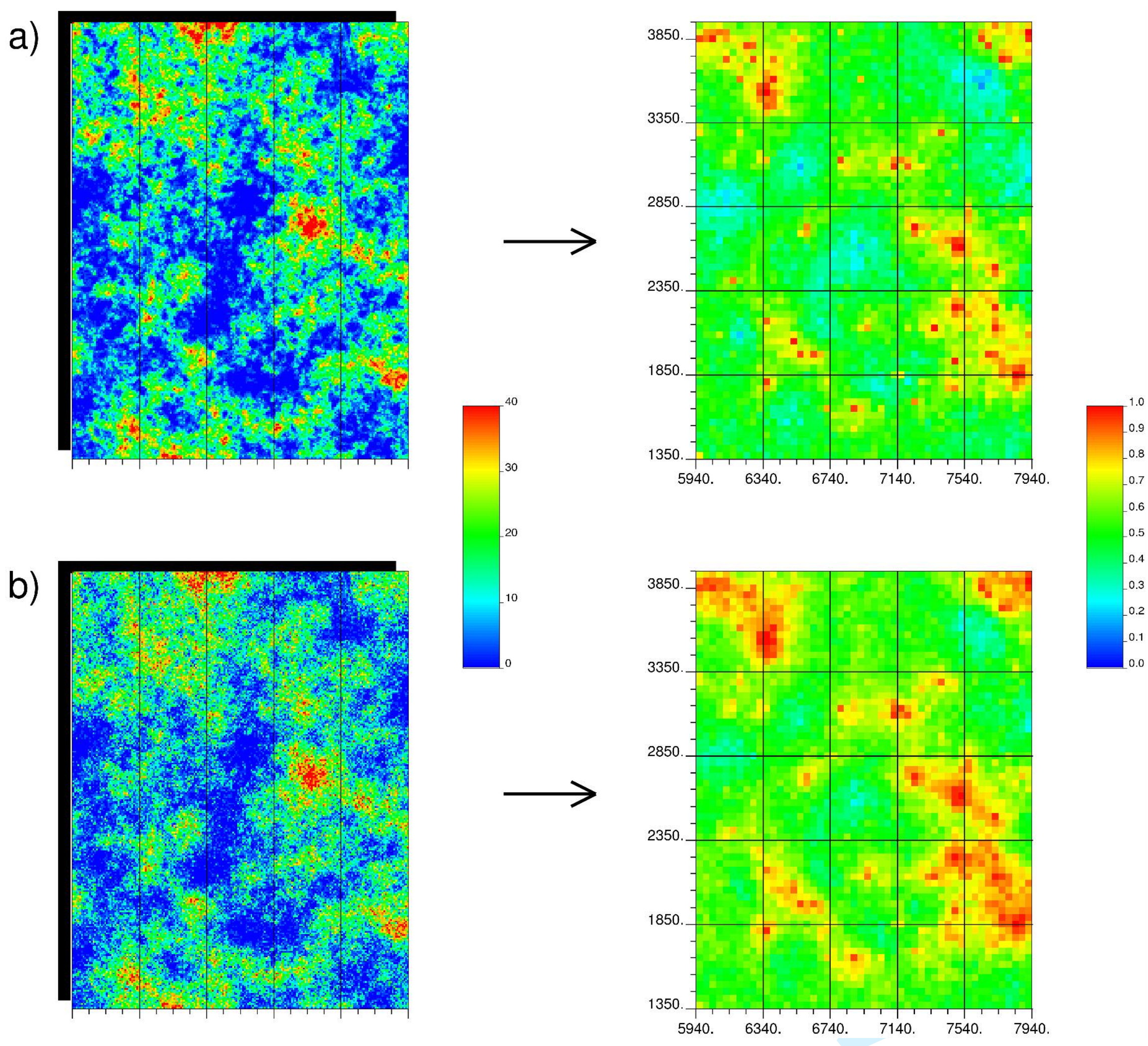

Figure 9: Simulated realizations are shown on the left and probability of scaled up 4 by 4 blocks to be inside the +/- 50% interval are shown on the right. The top (a) is with no nugget effect and the bottom (b) is with a nugget effect.

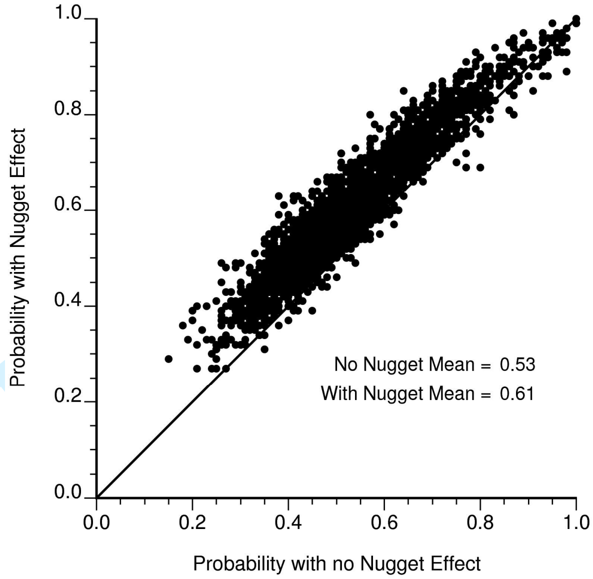

Figure 10: comparison of probability to be inside the +/- 50% interval with no nugget effect and with a nugget effect.

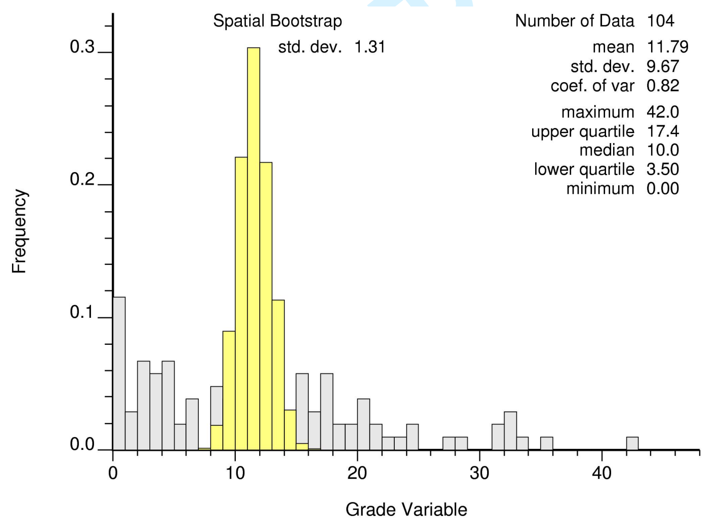

Figure 11: histogram of original data and uncertainty in the mean. Note the standard deviation of the mean (1.31) versus that of the original data (9.67).

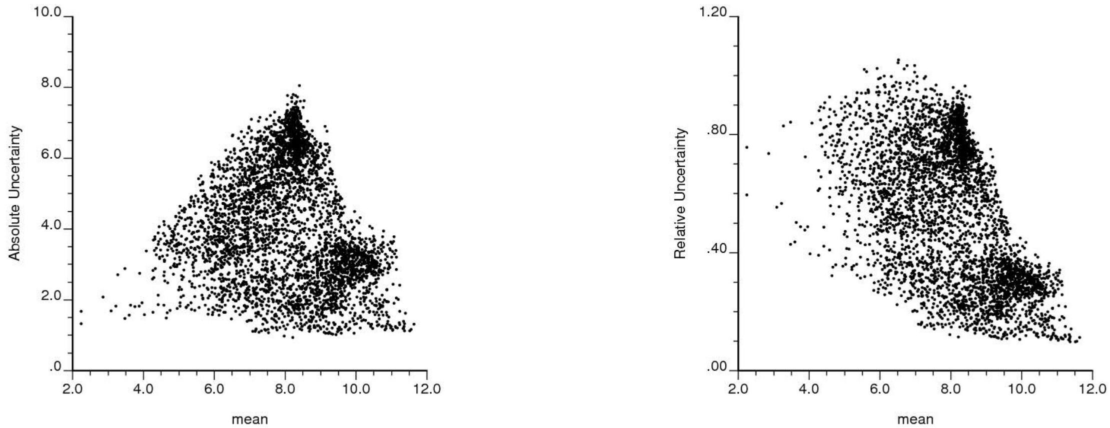

Figure 12: comparison of uncertainty measures plotted against the local mean: absolute uncertainty (left) and relative uncertainty (right).

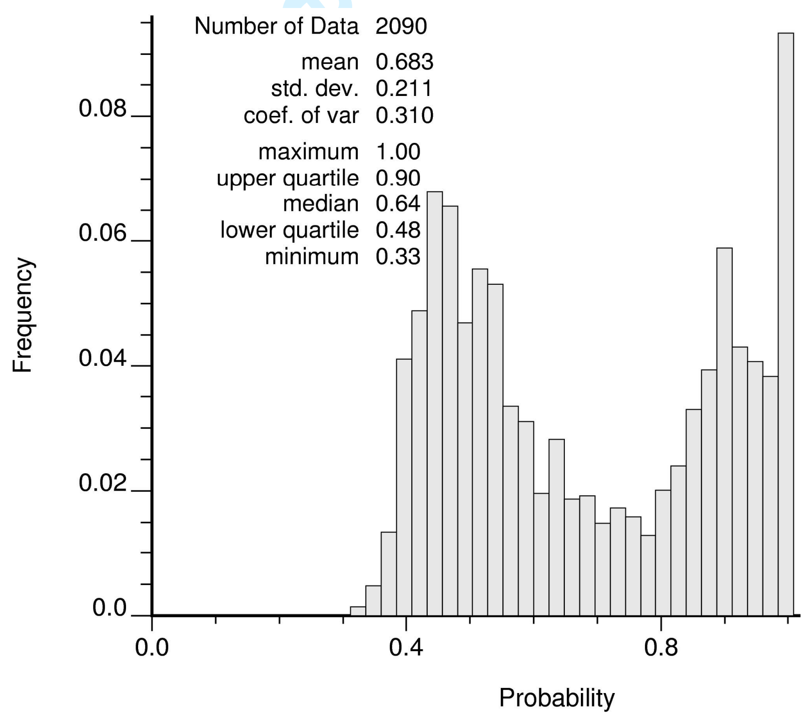

Figure 13: histogram of probability for grade of quarterly production volumes to be within +/- 15% of the estimated grade.

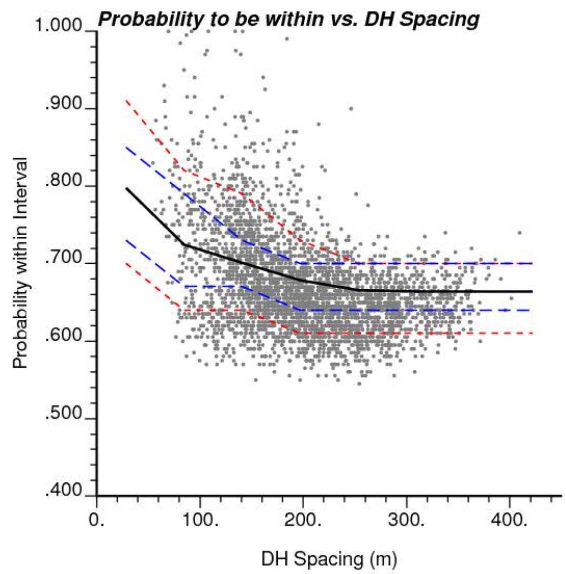

Figure 14: crossplot (right) of the probability to be within +/-15% interval and drillhole spacing using conditional simulation results: Lines indicate conditional quantiles: average (solid black line), interquartile range (two large dashed blue lines), and the 90% probability interval (two fine dashed red lines).

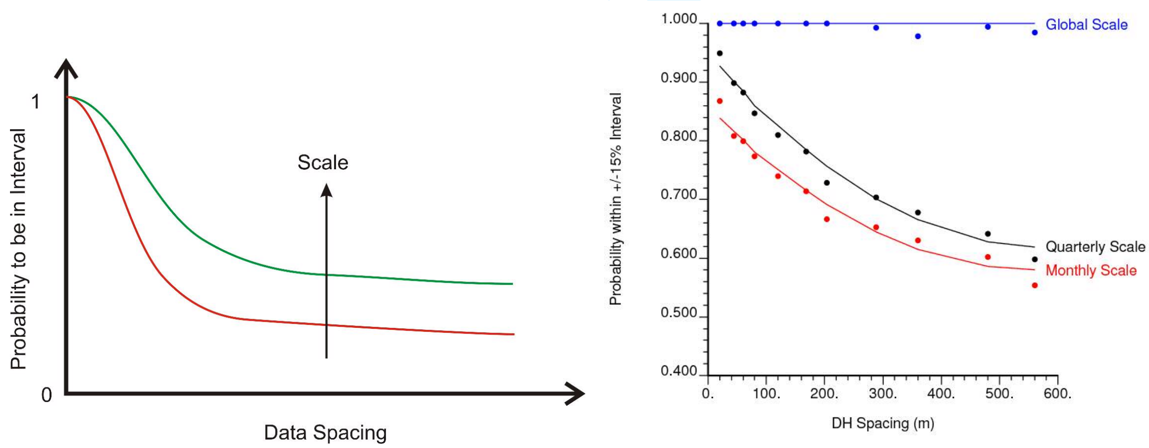

Figure 15: Schematic illustration of impact of volume on the relationship between the probability to be within +/-15% of the estimated grade and the drillhole spacing (left), and an example of this same relationship shown for a monthly, quarterly and global production scale (right).