

Full Calibration of C and β in the Framework of Vein-type Deposit Tonnage Uncertainty

Michael J. Munroe and Clayton V. Deutsch

One method of calculating the tonnage uncertainty in vein deposits is through the use of a distance function. The distance function allows for the introduction of uncertainty into the modeling process by helping to define a zone or bandwidth that is quantifiable. Three dimensional models are extracted for probability intervals across the bandwidth. Modifying the distance function modifies the size and shape of the bandwidth. Two parameters, C and β are used to modify the distance function. The C parameter controls the bandwidth and therefore the uncertainty. The β parameter controls position of bandwidth. With proper calibration, values of C and β used to modify the distance function will result in models that are both accurate and precise. A method for full calibration of C and β is presented. An example using synthetic models is also presented and demonstrates that the method does produce results that are accurate and precise within a defined tolerance.

Introduction

Consider a tabular orebody that has a discrete three dimensional shape with well defined boundaries, two axes with similar dimensions and one opposing axis often an order of magnitude less than the other two. Characteristics of a vein type deposit. These types of orebodies are often drilled on some regular grid to gain geologic knowledge of the orebody. Geological interpretation of level plans and cross sections provides a geologic model which is used to construct a wireframe model. The model is deterministic and is incapable of providing a measure of uncertainty. A second model built from a different interpretation of the same data would introduce a level of uncertainty about the model. Either of the two models is valid but which one could possibly be a better choice.

Instead of using plans and sections, we use a method based on a distance function to create the models. The distance function calculates the distance from a sample to the nearest known contact. Like the geologist, the distance function honours the contacts in the drillhole. But the similarity ends there. The distance method creates a zone that connects drillhole to drillhole. Within the zone, we can assign a probability to each of the possible boundary limits, unlike the single line drawn by a geologist on a map from one drillhole to another. Extracting tonnages associated with the probability provides a distribution of possible tonnages for that model.

The zone connecting drillhole to drillhole is controlled by two parameters, C , the uncertainty parameter, controlling the width of the distribution or precision, and β , the parameter controlling the position of the distribution or accuracy. With increasing C the width of the distribution increases along with the range of possible tonnages and an increase in uncertainty. With changing β there is a shift in the distribution which also causes change in tonnage. With careful and full calibration of C and β , we can get a reasonable and fair measure of the uncertainty associated with a model.

To validate the calibration of C and β a set objective functions are used. The optimal values of C and β are those which provide a zero solution for both functions. Any other values produce results that are neither accurate nor precise. Finally, many reference models are needed to produce a stable result. A single model cannot be used to get precision. Multiple models are needed for a good measure of uncertainty.

Distance Function

A distance function (DF) is used to interpolate and map the boundary of a vein type deposit with uncertainty. The DF is based on the Euclidean distance between a sample and the nearest sample with a different indicator type, Figure 1. The Euclidean distance, with modification to account for geometric anisotropy is defined by the equation;

$$dist = \sqrt{\left(\frac{dx}{hx}\right)^2 + \left(\frac{dy}{hy}\right)^2 + \left(\frac{dz}{hz}\right)^2} \quad (1)$$

where d is the distance component and h the geometric anisotropy component with respect to each axes. The Euclidean distance is transformed into a distance function through the application of two parameters, C and β . The application of C and β are discussed separately below.

Figure 1 illustrates the concept of the DF. Each illustration consists of two drillhole with a separation of 10 units. The sample interval is uniform at 1 unit. White samples signify the presence of non-vein and are given a Vein Indicator (VI) code of 0, while grey samples signify vein and are given a Vein Indicator (VI) code of 1. The numbers located to the side of each sample denote the distance to the closest sample with a different VI and are aided by the use of arrows. By design, the boundary between non-vein and vein is zero. Consider the left example in Figure 1, the boundary between ore and waste is zero, midway between +1 and -1. As one moves away from the boundary, the distance from the boundary increases. The distance is given a positive sign when located outside the orebody and a negative sign when located inside the orebody. Since the sample interval is 1 unit, the first sample on either side of the boundary is one unit away from the boundary; it is also one unit away from a sample with a different VI.

The C parameter is an additive constant applied to (1) as shown in the following simplified equation;

$$DF = \begin{cases} (dist + C) & \forall VI = 0 \\ (dist + C) \cdot -1 & \forall VI = 1 \end{cases} \quad (2)$$

The C parameter controls the width of uncertainty across the boundary. By adding a constant value, C , to the Euclidean distance, we are increasing the separation between the two samples. The distance across the boundary from $-C$ to $+C$ is the modified space through which the non-vein/vein boundary passes. Consider Figure 1 right, a C constant equal to 4 has been applied to the drill string from Figure 1 left. In the left example, $C=0$, the distance from the boundary is 1 and there is no uncertainty. In Figure 1 right, $C=4$, the distance from the boundary is 5 which defines a bandwidth from -5 to +5. Samples on either side of the boundary always share the same value, with the exception of sign. At each boundary in the drillhole we have the complete bandwidth compressed and coincident with the contact between the samples. Recall the contact between samples in the drillhole is always zero by definition and therefore is always honored in the drillholes regardless of the value of C .

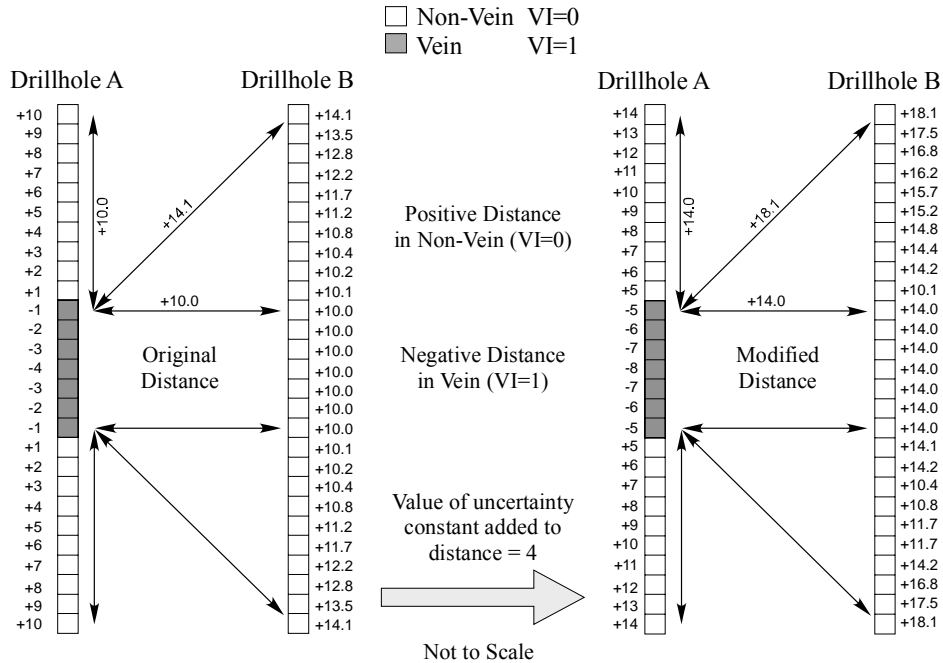
The boundary between positive and negative distances is called the iso-zero boundary or iso-zero surface. The iso-zero is also the $p50$ contour or surface sitting at the midpoint between $+C$ and $-C$. The value of C is expressed as a percentage of drill spacing. The value applied to the DF calculated as;

$$\frac{1}{2} C \cdot DS \quad (3)$$

where C is in the range $[0,1]$, and DS is the drillhole spacing. One half of the value is applied so that a C value of 1 will produce an uncertainty bandwidth equal to drillhole spacing where half the bandwidth lies in non-vein the other half in vein. For example, if we use a C value of 0.8, (80% drillhole spacing), and the drillhole spacing is 10, then the value applied in (2) is 4, as shown in Figure 1. The maximum value of C is 1 in which case the total width of the uncertainty bandwidth will be equal to the drill spacing.

The β parameter adjusts the location of the bandwidth defined by C . The parameter is applied to the original DF to create a modified DF;

$$DF_{mod} = \begin{cases} DF / \beta & \forall VI = 0 \\ DF \cdot \beta & \forall VI = 1 \end{cases} \quad (4)$$



Distance Function (DF): Shortest Distance Between Points with *Different* Vein Indicator (VI)

Figure 1 (left) Euclidean distances to samples with different VI values, negative values are VI=1, Positive values are VI=0. (right) The distances applied by the DF when the value of the uncertainty constant equals 4. (Dark grey squares = vein, White squares = non-vein.)

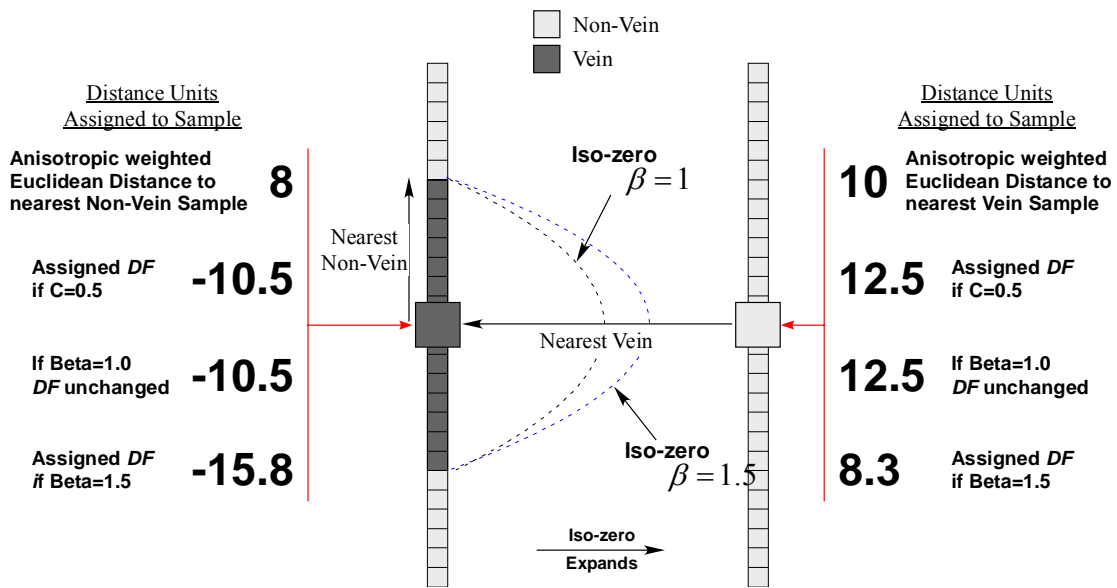


Figure 2: As β increases from 1, the iso-zero surface expands.

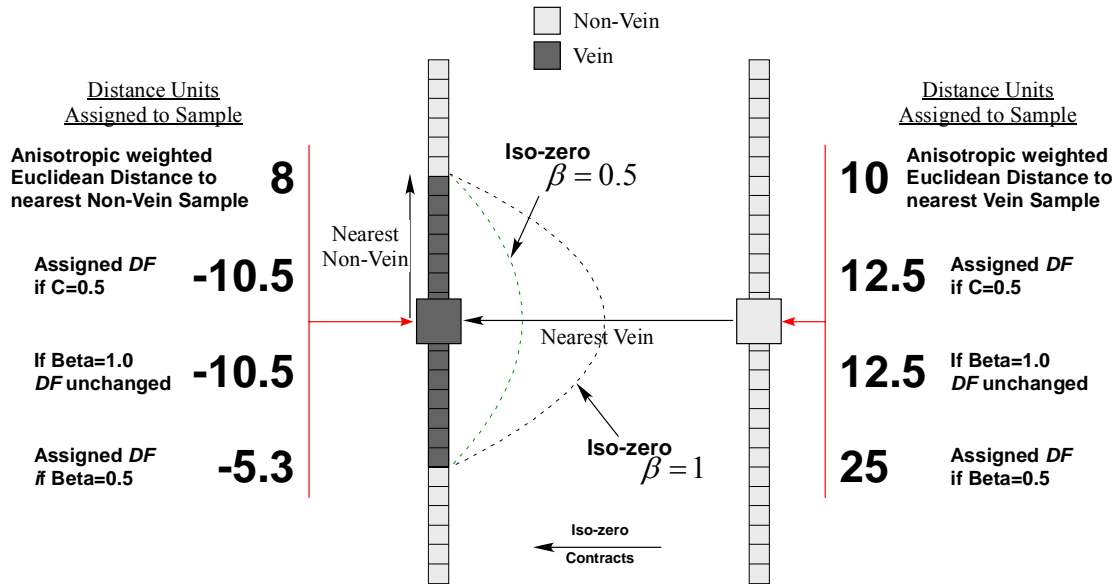


Figure 3: As β decreases from 1, the iso-zero surface shrinks.

The β parameter shifts uncertainty bandwidth created by the original DF using C . Values of $\beta > 1$ cause the iso-zero to expand, whereas values of $\beta < 1$ cause the iso-zero to contract. Consider the iso-zero contour described above. Referring to Figure 2, as β increases from 1, the modified DF inside the orebody becomes more negative, $DF \times \beta$, for example, $-(10.5 \cdot 1.5) = -15.8$, and less positive, DF/β , outside the orebody, $10.5/1.5=8.3$. Counter intuitively, this causes the iso-zero to expand as the apparent distance from the drillhole to the iso-zero has increased.

The opposite occurs when β decreases from zero. For values of β less than 1, the modified DF becomes less negative $-10.5 \times 0.5 = -5.3$, while outside the vein becomes more positive, $10.5/0.5=25$, outside the orebody. The shift causes the position of the iso-zero to contract as shown in Figure 3.

Drillhole datasets that are modified using C and β are used to construct gridded models of the vein deposit. Tonnages are calculated corresponding to selected probability intervals based on the size of the uncertainty bandwidth and the appropriateness of the values selected for C and β are evaluated.

Parameter Calibration

The choice of values for C and β are subdivided into three categories representing the level of accuracy required versus the amount of time desired. The categories are (1) empirical selection, (2) partial calibration and (3) full calibration. This paper discusses only full calibration of C and β .

Empirical Selection

Empirical selection refers to the practical application of C and β based on predetermined values and/or expert knowledge.

Partial Calibration

In a light calibration scenario, the interpolated models are compared to a single solid model (wireframe) representation of the orebody. A value for the uncertainty constant C is chosen based on the interpretation of representative sections and the expert judgement of the person(s) making the interpretation. The value of C is chosen so that a reasonable range of uncertainty is produced. Once a reasonable value for C is chosen, β is modified until the p50 tonnage value of the interpolated model coincides with the solid model.

Full Calibration

To complete a full calibration, multiple reference models are needed. For each reference model an optimization program is used to calculate the optimal C , β combination that provides an unbiased and fair estimate of uncertainty. A single run requires the interpolation of all reference models using a single C , β combination. To calculate the optimal C , β combination under full calibration requires multiple iterations using different C , β combinations. The average number of iterations needed for full calibration is between 9 and 12. Full calibration requires considerable CPU time and increases with the size and number of reference models used.

Reference Models

The modified drillhole data set is used to create gridded models of the orebody. To validate the models, reference models are needed for comparison. The accuracy and precision of the specified values used for C and β are measured by direct comparison of the gridded models with the known reference models. For full calibration of C and β we have to have precision. Precision cannot be calculated using a single model. Precision is a measure of reproducibility and therefore multiple reference models are required. The number of reference models needed is determined through sensitivity analysis.

Thresholds

The determination of the limits and thresholds to be applied to the gridded models is an important part of the calibration process. To measure uncertainty we need to know the limits of the uncertainty bandwidth created using C and β . With the limits defined, tonnages can be calculated for any probability interval (p -interval), across the uncertainty bandwidth. The limits change with C , β and the drillhole spacing (DS). The inner limit, DF_{min} , of the uncertainty bandwidth is defined as;

$$DF_{min} = -\frac{1}{2}C \cdot DS \cdot \beta \quad (5)$$

the outer limit, DF_{max} , by the equation;

$$DF_{max} = \frac{1}{2} \frac{C \cdot DS}{\beta} \quad (6)$$

Figure 4 is an illustration showing the relationship between DF_{min} and DF_{max} .

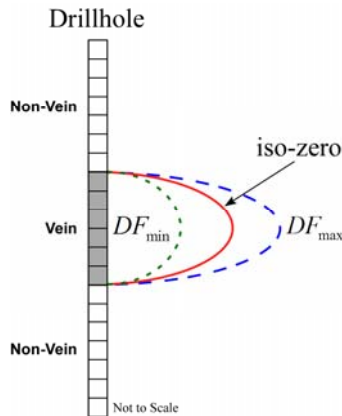


Figure 4: Illustration showing the limits of the uncertainty bandwidth.

To extract the tonnage at any probability we need to standardize the values from the gridded model. Recall that the gridded values are interpolated distances, we standardize, the distances using the limits of uncertainty defined above, so that values $<DF_{min}$ will be <0 , values $>DF_{max}$ will be >1 , and values falling between DF_{min} and DF_{max} are contained in the range $[0,1]$, as depicted in the schematic Figure 5. The p -value or probability value is calculated using;

$$p = \frac{z - df_{\min}}{df_{\max} - df_{\min}} \quad (7)$$

where z is the interpolated distance from the gridded model. If $p < 0$ the value is definitely inside the orebody and classified as vein. If $p > 1$, the value is definitely outside the orebody and classified as non-vein.

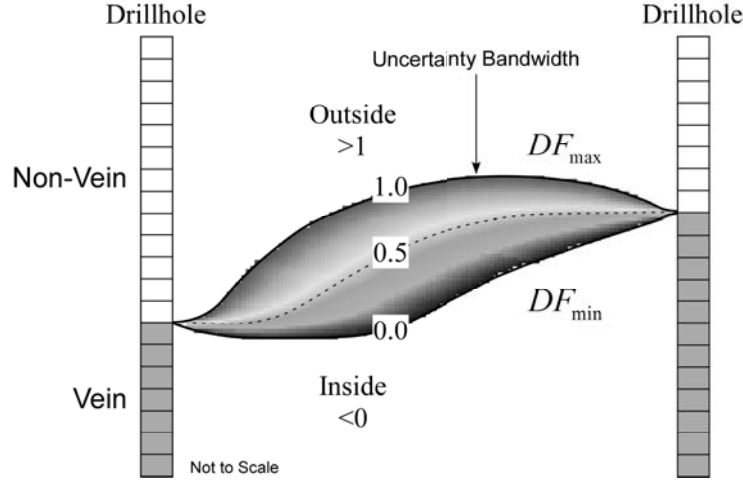


Figure 5: Standardization of uncertainty bandwidth

Once the limits have been standardized to the interval $[0,1]$, the tonnage corresponding to any probability level, P , can be calculated simply by selecting all p -values that are $\leq P$. The probability interval tonnages are used to compare the gridded model to the reference models. The probability interval P_i is defined as the mean centred interval;

$$P_i = Z^* \pm \frac{P}{2} \quad \forall p \in [0,1] \quad (8)$$

where, Z^* is the mean (p_{50}) tonnage, and i is the percentile. For example, the p_{80} interval defines the 80th percentile which extends from the p_{10} ($p_{50}-p_{40}$) to p_{90} , ($p_{50}+p_{40}$). The probability intervals are used during calibration to assess the goodness of a gridded model based on a selection of C and β .

Criteria for Good Uncertainty

Having criteria for good uncertainty helps the selection of the best possible combination of C and β . There are three criteria for good uncertainty, 1) unbiasedness, 2) fair uncertainty, and, 3) Low uncertainty. These are discussed in the order of importance.

Unbiasedness

Unbiasedness simply means that the results are free from bias, which means, the expected value of the estimate equals the expected value of the true value;

$$E\{Z^*\} = E\{Z\} \quad (9)$$

If a bias exists then the expected value of the estimate will not equal the expected value of the truth. We show bias using a scatter plot of true values plotted against estimated values. An unbiased plot will have all the points fall along the 45° line, Figure 6, left. Points that tend to deviate away from the line indicate a bias, Figure 6, right.

Fair Uncertainty

Fair uncertainty is the precision with which the reference models estimate the truth. Recall the discussion of thresholds, and the definition of the probability interval in Equation 8. Expanding Equation 8 by adding the constraint that the interval in question must also contain the true value;

$$E\left\{Z \in Z^* \pm \frac{P}{2}\right\} = P^* = P \quad \forall P \in [0,1] \quad (10)$$

the equation reads, the expected true value falls within an interval defined as the p_{50} estimate bounded by the tolerance $\pm \frac{P}{2}$ so that the actual fraction, P^* , is equal to the expected fraction, P , for all percentiles in the range 0 and 1.

If the true tonnage of a defined reference model is contained within the tonnage interval defined by the probability, we say that the estimate is accurate. If the number of times a reference model falls in the interval is equal to the probability of the interval, we say the estimates are precise. For example, consider the p_{80} probability interval. The limits of the interval are the tonnages located at p_{10} and p_{90} . If there are 10 reference models, then it is expected that the tonnage for 8 of the 10 reference models fall within the interval p_{10} to p_{90} , and is written as $80\% \in p_{10} - p_{90}$. Having more than 80% is still accurate but imprecise suggesting the uncertainty bandwidth is too narrow. Having less than 80% means the estimates are not accurate and the uncertainty bandwidth may be too wide.

Figure 7 shows the plot of the nine p-intervals, p_{10} to p_{90} for three different scenarios

Figure 7 left shows an accurate and fair plot. All intervals contain the expected fraction of true tonnages therefore the points plot close to the 45° line.

Figure 7 centre shows an accurate but imprecise plot where the more than the expected number of models fall within the interval. Finally,

Figure 7 right depicts an inaccurate and imprecise plot, where all the p-intervals have less than the expected number of reference models falling in the intervals.

Low Uncertainty

The last and least important of the three criteria is low uncertainty. We intuitively expect that all ‘good’ estimates have low uncertainty. The lower the uncertainty associated with an estimate, the more comfortable we are likely to be with it. Quantifying uncertainty allows for direct comparison of estimates generated using different parameters. Low uncertainty is quantified by measuring the spread of the p_{80} interval. The measure is standardized by dividing by the p_{50} yielding a unitless measure and allows reference models to be compared regardless of size.

$$Uncert = \frac{P_{90} - P_{10}}{P_{50}} \quad (11)$$

The measure provides an indication of the relative size of the p_{80} interval. The smaller the p_{80} interval, the lower the uncertainty. Figure 8 shows a plot of uncertainty for 50 reference models. The models all show similar values suggesting similar ranges. Recall that the thresholds for the p-intervals are determined by the drillhole spacing and the values assigned to C and β . In the event that similar C/β combinations produce similar fair and unbiased results, we choose the combination that produces the lowest uncertainty.

Objective Functions

Objective functions are used to decide if a result obtained is good. Objective functions are used to measure the criteria for good uncertainty as mentioned previously. The first objective function, O_1 , is a measure of the bias in the estimates and is defined as;

$$O_1 = \frac{E\{T^* - T\}}{E\{T\}} \quad (12)$$

where T^* is the estimated tonnage and T is the ‘true’ reference tonnage. Dividing by the reference tonnage creates a standardized unitless measure useful for comparing results. The function can carry a positive or negative sign.

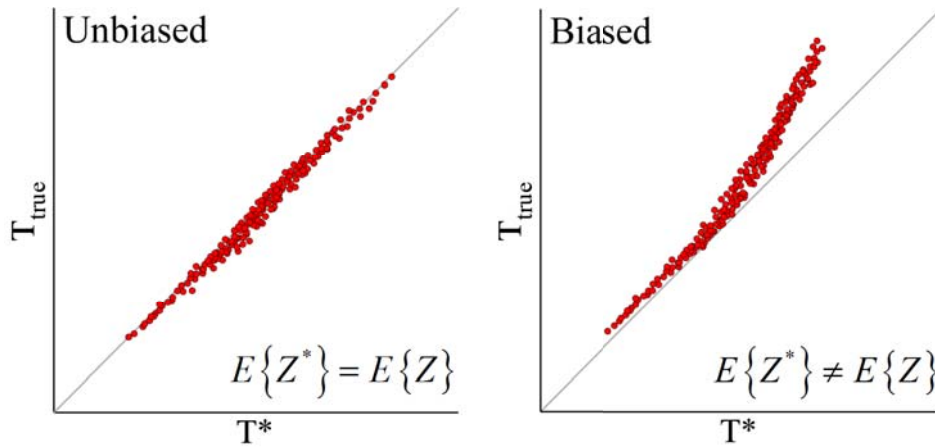


Figure 6: Schematic of: (left) an unbiased Scatterplot; (right) a biased Scatterplot.

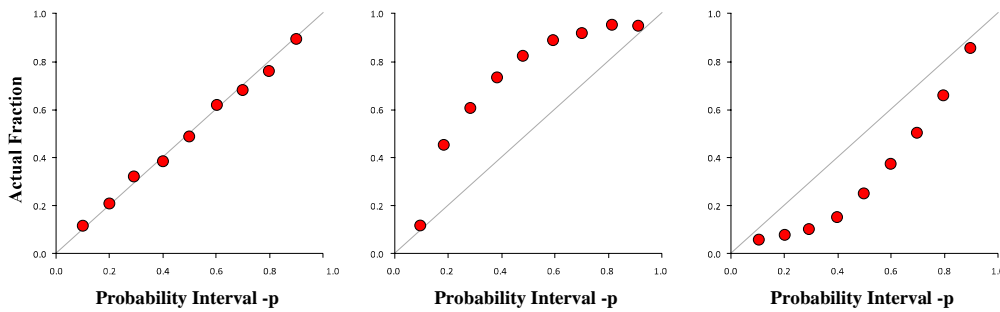


Figure 7: (left) Fair uncertainty, (centre, right) Inaccurate and imprecise

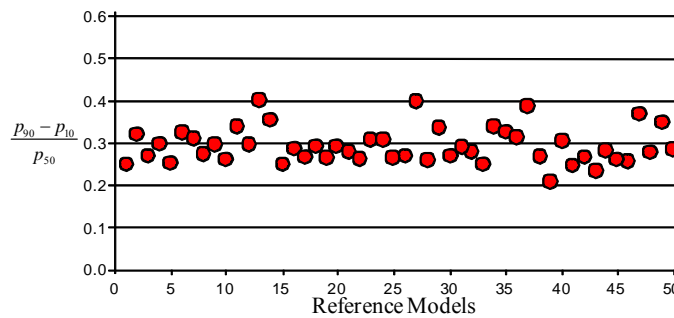


Figure 8: Uncertainty measured over 50 reference models

Figure 9 shows a scatter plot of T vs. T^* used for evaluating the objective function $O1$. If $T^* = T$ then the points will plot along the 45° line. When $T^* < T$ the point plot above the line and if $T^* > T$, below the

line. A good calibration requires that on average, over multiple reference models, that $O1 = 0$ indicating the results are unbiased.

The second objective function, $O2$, is a measure of the fairness of the predicted tonnage and is defined as;

$$O_2 = \frac{\sum_{i=1}^{n_p} (P_i^* - P_i)}{\sum_{i=1}^{n_p} P_i} \quad (13)$$

where P_i^* is the actual number of estimates falling in the probability interval P_i . The result is unitless and like the objective function $O1$, can have a positive or negative sign.

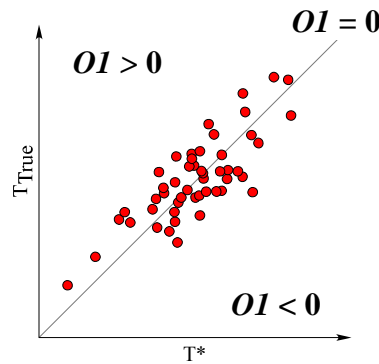


Figure 9: Scatter plot T vs. T*.

Figure 10 shows a scatter plot of P vs. P^* used for evaluating the objective function $O2$. If $P^* = P$ then the actual fraction of models equals the expected fraction of models for the selected probability interval P , and the points will fall close to the 45° line. When the actual fraction is less than the expected fraction, $P^* < P$, the points plot below the line, Figure 11 left. If the actual fraction is greater than the expected fraction, $P^* > P$, the points plot above the line, Figure 11 right. The range of values for $O2$ is -1 to +1. When $O2 = 1$, then $\sum_{i=1}^{n_p} (P_i^* - P_i) = \sum_{i=1}^{n_p} P_i$ meaning that all the tonnages from the reference models fall within each of the defined probability intervals P , Figure 12 left. When $O2 = -1$, then $\sum_{i=1}^{n_p} P_i^* = 0$ meaning that none of the true tonnages from any of the reference models falls within any of the ranges defined by P^* , Figure 12 right.

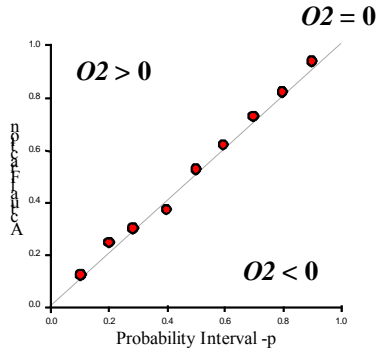


Figure 10: Scatterplot objective function O_2 , P^* (actual fraction) vs. P (probability interval)

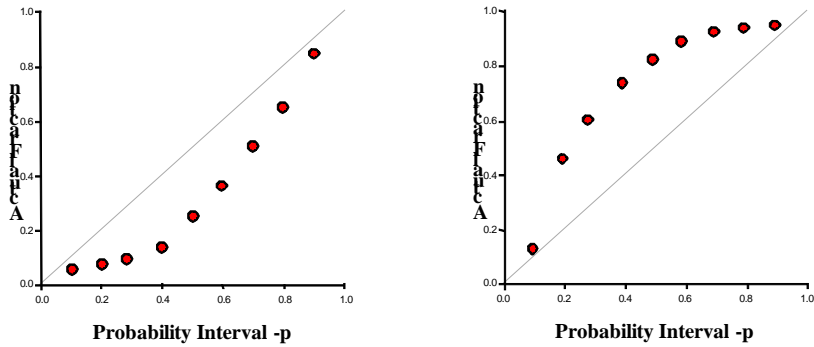


Figure 11: Scatterplot objective function O_2 , (Left): $P^* < P$, (Right) $P^* > P$

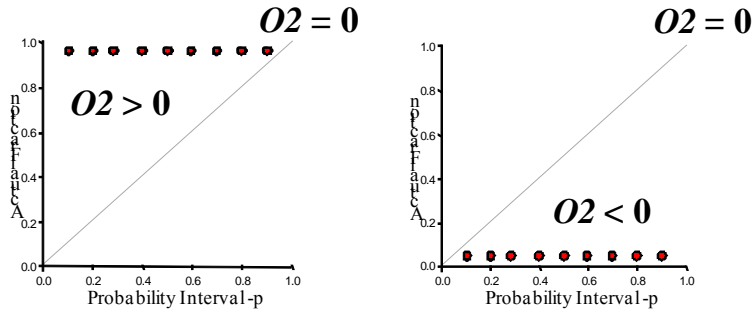


Figure 12: Scatterplot objective function O_2 , (Left): $O_2=1$, (Right) $O_2=-1$

Full Calibration

Full Calibration of C and β makes use of the objective functions outlined above. Full calibration finds the combination of C and β where both objective functions equal zero. Consider the space defined by the objective function O_1 illustrated in Figure 13. There are two characteristics of O_1 that are characterized by the plot. First, O_1 changes more quickly with β . Recall Figure 2 and Figure 3, as β increases, the iso-zero expands causing an increasing the estimated tonnage and therefore an increase in O_1 . Conversely, as β decreases, both tonnage and O_1 decrease. Second, increasing C has little effect on the iso-zero and therefore little effect on O_1 . O_1 is quite stable with increasing C . The small positive slope is caused by a

slight increase in the iso-zero with increasing C therefore, an increase in β is needed to compensate and maintain the value of $O1$. The first step to full calibration is defining the contour where $O1 = 0$.

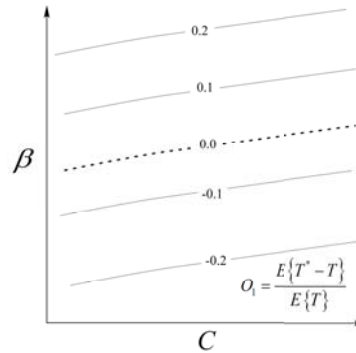


Figure 13: $O1$ space defined by C and β

Recall that the $O2$ objective function is a measure of precision. When $O2 = 0$, estimates are considered precise. Figure 14 depicts the space defined by $O2$. The function $O2$ changes with all values of C . Since C determines the width of uncertainty, any change in C will change the position of the actual fraction intervals and therefore which true values fall in which interval. The larger the value of C , the more likely the true values will be contained in the defined p-intervals. As C decreases and $O2$ becomes more negative, more and more true values are eliminated from the defined probability intervals. The contours in Figure 14 are curved because different β values applied with the same C value can cause similar results to be calculated by $O2$. However, it should be noted that there is only one solution that is accurate and precise and that is at the intersection of $O1=0$ and $O2=0$ as illustrated in Figure 15. In all other instances the results are biased and should be discarded. The intersection point defines the optimal value of C and β that will produce an unbiased and precise estimate of tonnage.

To automate the full calibration process a FORTRAN program was written to pass parameters to, and execute a bash script file. The script file calls a series of programs used to complete the following;

1. simulate drilling the reference model to create a sample drillhole data set;
2. apply the distance function using the desired C and β values to the drillhole data set;
3. create 3d gridded model from the modified drillhole data;
4. calculate tonnages for desired p-intervals;
5. calculate the $O1$ and $O2$ objective functions.

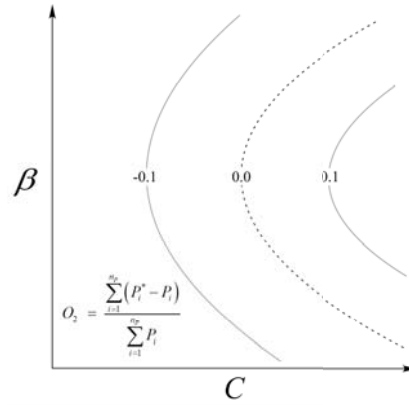


Figure 14: O_2 space defined by C and β

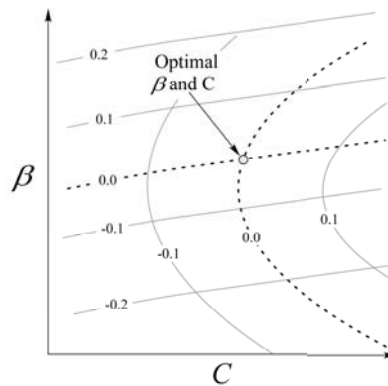


Figure 15: Intersection of $O_1=0$ and $O_2=0$.

The process is repeated for many reference models using the same C and β . After the modeling is complete, the objective functions O_1 and O_2 are calculated for the set of newly gridded reference models. Control is returned from the script to the main program which supplies a new set of values for C and β and repeated. The first four points are supplied to the program by the parameter file, and consist of the minimum and maximum values for C and β . Values are chosen so that the intersection of O_1 and O_2 will be contained within the bounding box defined by the points, Figure 16.

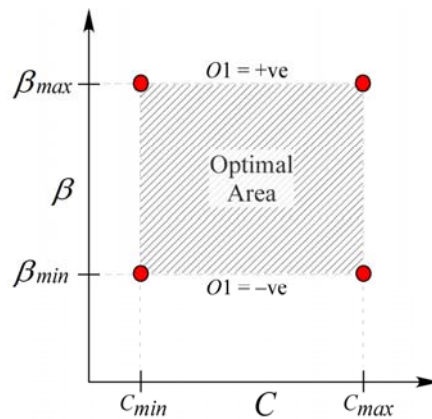


Figure 16: Initial four points used in Full Optimization of C and β

When the program has finished with the initial four points, it will have completed four runs calculating multiple reference models at each location. If the initial four points are chosen correctly, the objective function $O1$ for the two locations defining β_{\max} will be positive, while the two locations defining β_{\min} will be negative. If not the initial points need to be redefined. As was illustrated in Figure 13, the $O1$ objective function is linear. The position of the point where $O1 = 0$ is located between the points β_{\min} and β_{\max} . To find the point we interpolate using the equation of the line defined by the values of $O1$ at β_{\min} and β_{\max} . The set of reference models are interpolated again using C_{\min} and the value of β where $O1 = 0$ shown as point β_A in Figure 17. The process is repeated at C_{\max} and β_B . The points β_A and β_B define the line where $O1 = 0$. The number of complete runs now totals six.

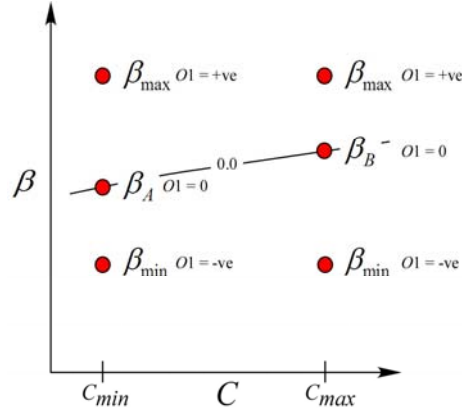


Figure 17: The line $O1=0$ defined by β_A and β_B .

With the equation of the line $O1=0$ defined, the next step is to find the point where $O2=0$ on the line $\beta_A - \beta_B$. The newly created points β_A and β_B shown in Figure 18, define points where the C / β combination produces an $O1=0$. Calculating $O2$ at these points show that $O2$ is negative at β_A and positive at β_B such that $O2=0$ lies at some point along the line between the two.

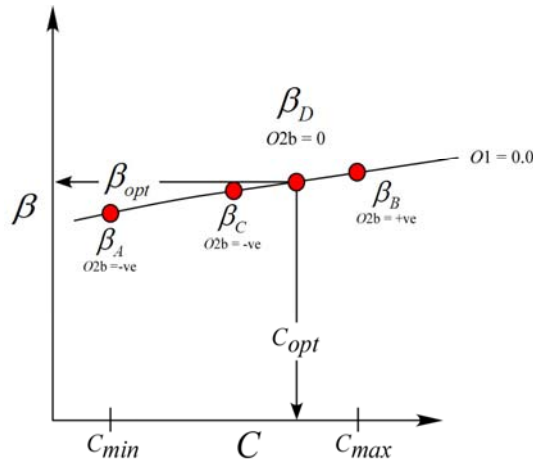


Figure 18: Optimal values of C and β .

Selecting the midpoint β_C between β_A and β_B and estimating the reference models using the new values for C and β will yield new values of $O1$ and $O2$. $O1$ should be zero and $O2$ will be either positive or negative depending on its position relative to the point where $O2 = 0$. Referring to Figure 18, if the value of

O_2 at β_C is negative and positive at β_B , then simple interpolation is used to find the location of the point where $O_2=0$ using the equation of the line between β_C and β_B . The point is labeled β_D in Figure 18. The final run is done using the values of C and β corresponding to the point β_D and is used to confirm that the resulting objective functions O_1 and O_2 are both zero. If so, the set of estimated reference models are both accurate and precise. In the following example 50 synthetic models were tested. A total of ten points runs were needed to find the optimal values of C and β for a total of 500 kriging runs.

Example

A set of 50 unique synthetic 3-dimensional orebodies were created for the test using SGS. Each orebody has a similar geometry; a circular to elliptical closed solid, thicker in the centre tapering towards the edges. The orebodies each have measured true tonnage. The example illustrated here uses a drill spacing of 20. The numbers are unitless. Figure 19 left shows one of the 50 synthetic orebodies. Figure 19 right shows a thickness map of a synthetic orebody along with the superimposed drill grid. White areas have zero thickness increasing with grey level. The thickest part of the orebody is at the centre of the map.

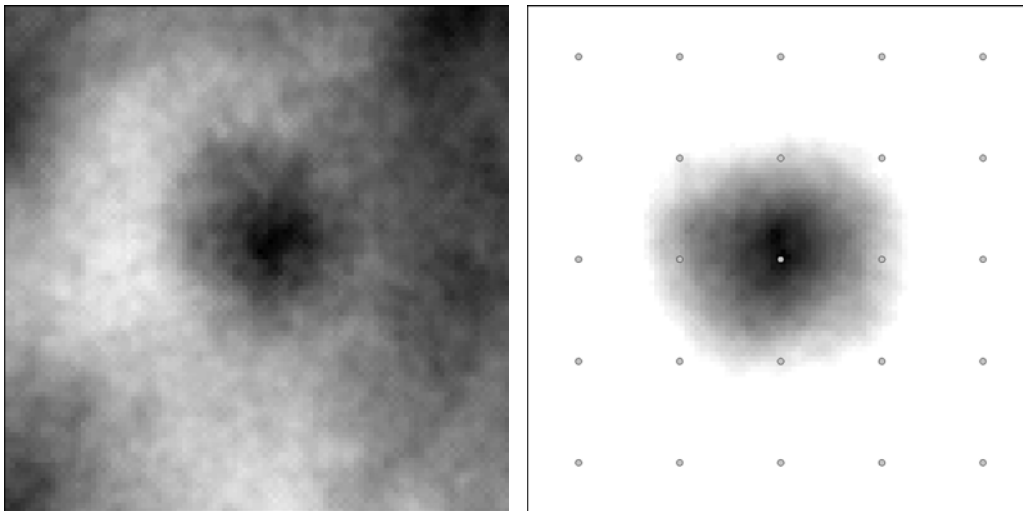


Figure 19: (left) simulated orebody, (right) thickness map with drill pattern, white = 0 thickness.

The optimization program was run using initial values of 0.1 and 0.3 for C , and 1.4 and 1.6 for β . The optimization took ten iterations to find the optimal values of C and β . The results are listed in Table 1.

Table 1: Optimization Results

Run	N	C	β	O1	O2
1	50	0.100	1.400	-0.08	-0.44
2	50	0.100	1.600	0.08	-0.32
3	50	0.100	1.498	0.00	-0.49
4	50	0.300	1.400	-0.11	-0.02
5	50	0.300	1.600	0.03	0.42
6	50	0.300	1.560	0.00	0.41
7	50	0.200	1.529	0.00	0.10
8	50	0.183	1.524	0.00	0.02
9	50	0.150	1.514	0.00	-0.16
10	50	0.181	1.524	0.00	0.00

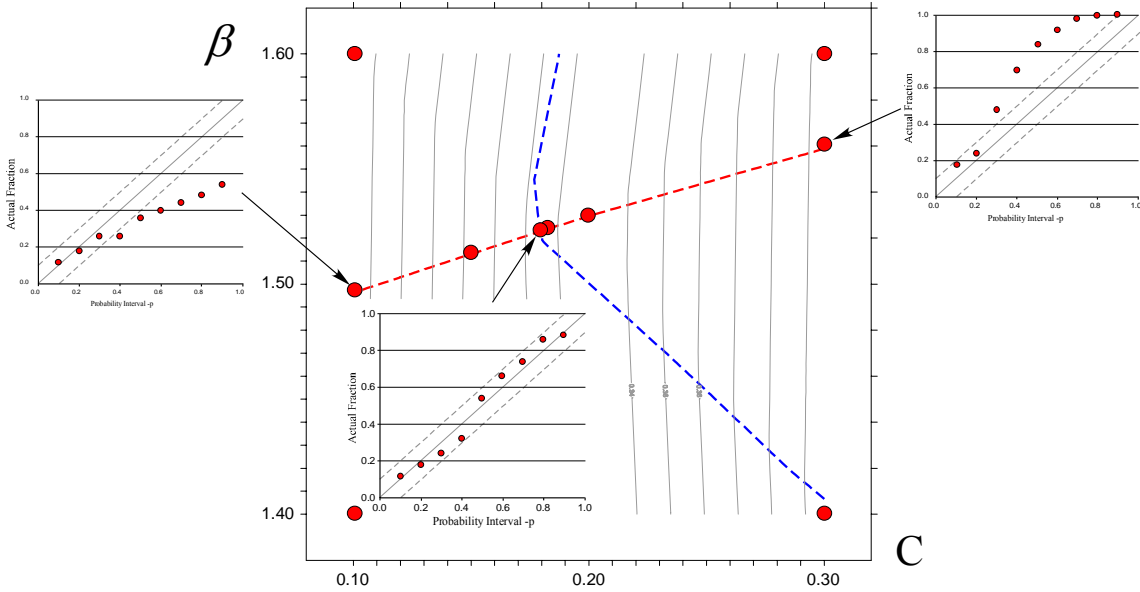


Figure 20: Final optimization

Figure 20 shows a map of the C / β space and the selected points used in the process. The four corner points are specified by the user the remaining are determined from the results of estimation process and the values of the objective functions. Three of the 10 accuracy plots produced are shown for reference. Two plots are located at the endpoints of the line that is $O1=0$, the third plot is the accuracy plot for the optimal values of C and β , 0.181 and 1.524 respectively. The plot on the left side shows most of the points plotting below the 45° line. Recall that this indicates an inaccurate and imprecise estimate where too few of the true tonnages from the 50 reference models fall within the higher probability intervals defined by the estimates. This indicates that the majority of estimated tonnages are much less than the true tonnage. At the other extreme, the right side, we see the situation reversed. Most of the points plot above the 45° line indicating that too many of the true tonnages fall within the probability intervals defined from the estimates. This also indicates that the uncertainty is too narrow and the estimates too optimistic. The accuracy plot in the centre is for the 50 models created using the optimal C and β . This plot shows the points falling along the 45° line and within the dashed lines representing a total tolerance of 10%. Points within these limits are considered accurate and precise.

Computational Considerations

The primary issue with the optimization method is time. The most time consuming process is the kriging. The test case presented here required about three hours per run, or about 30 hours in total. The computer used was a 3 GHz Pentium 4 with 1Gb of ram. There were 50 reference models kriged in each run for a total of 500 kriging runs. Each 3d grid had a total of 800,000 cells. Changing the drill spacing or model size will have a significant impact on the time needed to carry out a similar optimization.

Significant time could be saved by reducing the number of models needed to produce a stable result. Initial indications suggest that the total number could be reduced by half to 25 as shown in Figure 21 which plots the cumulative value of O_2 with increasing number of reference models. The graph shows the value of O_2 becoming stable after about 25 reference models. The time reported here used a kriging optimization method not discussed. The technique places a bounding box around the complete orebody and instructs the kriging program to skip any cells located outside the limits of the box. More effective methods could be developed to improve efficiency. The speed of the optimization program itself could be improved through a redesign of the algorithm and improvements in the source code.

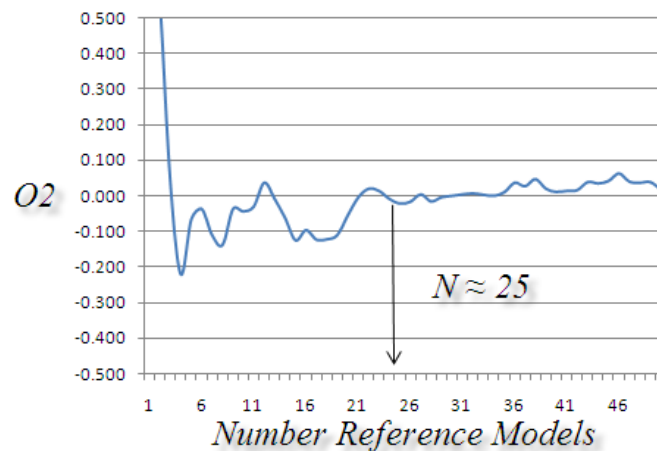


Figure 21: Value of O_2 with increasing number of reference models.

Conclusions

The purpose of this paper was to demonstrate the full optimization of C and β . The technique was shown to work within the framework presented. The optimization process is time consuming, requiring a minimum of ten runs to completely optimize C and β . The time required increases with the size of the reference models and the number used. The number of reference models required could be reduced through a sensitivity analysis. Further efficiency could be obtained through modification of the optimization process. Nonetheless, the foundation has been established for a methodology to accurately and precisely evaluate tonnage uncertainty in vein-type deposits.

References

- Deutsch, C.V., A Short Note on Prediction of Uncertainty in Tonnage and Grade of Vein Type Deposits, paper #305. In Centre for Computational Geostatistics, Report 7, 2005.
- Deutsch, C.V., Direct Assessment of Local Accuracy and Precision, In Geostatistics Wollongong '96, Volume 1, 115-125, E.Y. Baafi and N.A. Schofield, eds.
- McLennan, J. and Deutsch, C., Implicit Boundary Modeling (Boundsim), paper #102. In Centre for Computational Geostatistics, Report 8, 2006.