Compositing and regularization of drillhole data for geostatistical resource estimation

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Abstract

Compositing or regularization of drillhole data is common practice in mineral resource estimation and is deemed a necessary step in producing unbiased estimates of mineral resources and reserves. Commonly, data are collected over irregular distances due to the varying relative thicknesses of lithologies drilled or sampling/assaying strategies. This necessitates data transformation to regular lengths of equal size to ensure that all data have the same sample support. However, there have been few detailed publications on the effect of this process on the composited data that are subsequently taken forward for the estimation process. In this paper, three currently available compositing methods are reviewed and the effects of inappropriate compositing methodologies presented. It is shown through a case study that compositing samples to different lengths leads to changes in the average and variance of the grades in the drillcores in the dataset, which will impact the final estimated value. These differences are exacerbated by breaks or gaps in data where, for a variety of reasons, there has been no data collection or data have been lost. The importance of appropriately treating blank and zero data is also presented. Globally, these differences might be minimal, but locally may be substantial, affecting the efficiency of the estimation and subsequent use of the results in, for example, mine planning and reconciliation. Further detailed investigation of compositing practices is required if the full implications of compositing are to be understood and any induced bias effectively defined.

Keywords

resource estimation, geostatistics, compositing, regularization, drillhole data, bias, uncertainty

Introduction

Data gathered from drilling are extensively used within the mining industry for the purpose of resource estimation and, ultimately, resource delineation. As part of the standard data-processing procedure for resource estimation (or grade-control purposes), it is common practice to composite or regularize multiple samples together and take the results forward for further analysis (Rossi and Deutsch, 2013). The purpose of compositing is to ensure that all samples have the same weighting, so further analyses are not affected by bias. Compositing is a linear-weighted averaging approach, where the sum of the product of the lengths and the measured variables is divided by the total length of all samples considered in calculating a composite value.

Regularization is performed whether solid core, for example, from diamond coring (DC), or chips from rotary air blast (RAB) or reverse circulation (RC) are recovered. Drillholes are commonly non-vertical, to ensure that the best possible intercept with lithologies and/or mineralization is achieved (Biel et al., 2010; Lomberg, 2014; Moorhead et al., 2001). The compositing method may be adjusted to take this into account.

Sampling of core or chips for assay is a complex process. The number and nature of samples taken depends on several factors, including the nature of the geology, the drilling method, the location of the deposit, the cost of obtaining reliable assay results, and the degree of compliance of the project with international reporting codes, such as the SAMREC (2016), JORC (2012), and CIM (2010) codes. If the geology is highly complex, then more samples need to be taken spatially to elucidate the geological picture. If the drilling method is more basic (chip recovery) or poorly executed, sample collection will be less efficient. If the project is located in a challenging or remote environment, the cost of sending samples for assaying increases, which makes it likely that fewer samples will be analysed. If the project is to be compliant with JORC or other reporting codes, then more, and higher quality, samples are likely to be taken.

To illustrate some of the potential issues that poor treatment of drillhole data can cause, a hypothetical example is presented (Figure 1). Here, drilling was conducted across a zone of interest, the results of which will subsequently be used to best delineate a mineralized zone in a gold deposit. Each sample was analysed for gold and arsenic. These two variables, Au (g/t) and As (%), form the basis of the resource estimation.

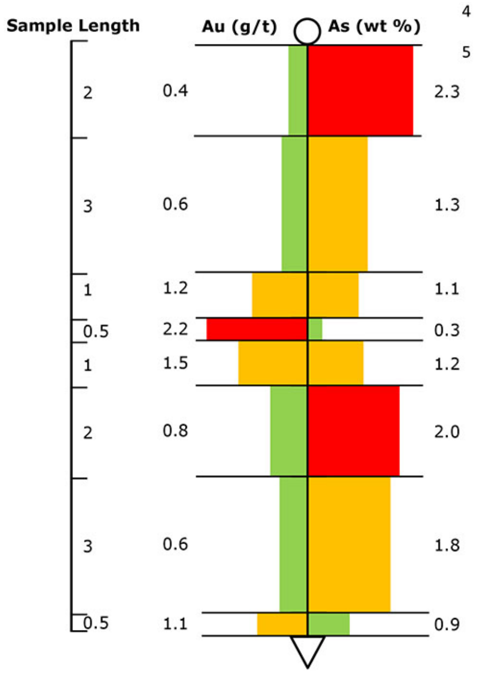

Figure 1—Sampling results (sample length and assay values) for two variables of interest, Au and As, in a hypothetical drillhole

Arsenic has no economic value, but could affect downstream processing efficiency and, ultimately, the value of the project. Higher density sampling was conducted across the area of highest gold mineralization.

The arithmetic average of the gold assay values data is 1.05 g/t, compared with the length-weighted composite value of 0.80 g/t. This shows that the original arithmetic average considerably over-valued the Au grade for this drillhole. In the biased arithmetic average, all samples are equally weighted, irrespective of the length that the sample assay represents; in calculating the average, the 0.5 m sample at 2 g/t receives the same weighting as the 3 m sample at 0.6 g/t. The arithmetic average ignores representivity of the sample, resulting in this grade difference. A composite sample is a more representative value of the grade, and is obtained by weighting every sample assay according to the length it represents. Considering the As data, we see that the arithmetic average under-estimates the actual As levels by selectively over-sampling specific targets where lower values of As are found: the arithmetic average of the As sample data is 1.36% and the length-weighted average is 1.60%.

It is known that the variance of a grade variable decreases as the sample support increases, which is a derivation of Krige's relationship (Krige, 1951). This is known as the volume-variance relationship, or dispersion variance, and is used in the operation of estimators that make use of the change of support rule, the most common being uniform conditioning (Abzalov, 2014; Chiles and Delfiner, 2012) and its derivatives (Emery, 2008). The volume-variance relationship has also been used as a tool for mine planning (Parker, 1979) and to analyse the variance associated with blending of different size stockpiles (Marques and Costa, 2014).

Previous studies have empirically shown (Figure 2) that as the sample support (size and shape) increases, the variance of data decreases, which causes a corresponding decrease in the variogram sill-and-nugget effect (Clark, 1979). This is highly significant because the variogram is the key tool in the application of geostatistical estimation techniques, such as kriging: any change

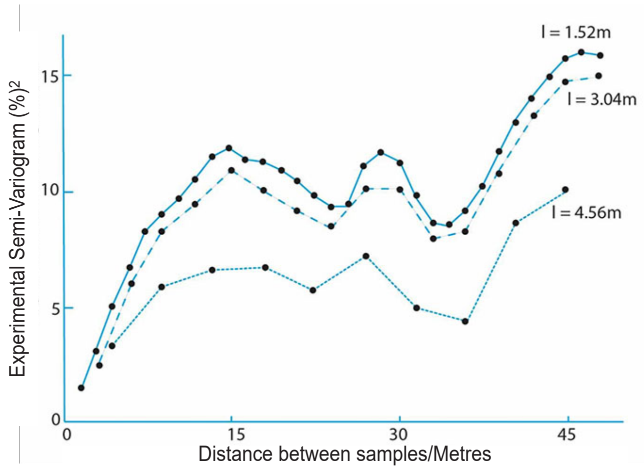

Figure 2—Experimental semi-variograms constructed from core regularized to three lengths for a lead/zinc sample (adapted from Clark, 1979)

to the variogram used will have an impact on the results produced, whether considering estimating (Isaaks and Srivastava, 1989) or simulating (Palmer and Glass, 2014) using the data.

Current published best practice on compositing focuses on the methodology (Noble, 2011; Rossi and Deutsch, 2013; Sinclair and Blackwell, 2002), rather than on how a suitable length for compositing should be selected that does not bias the variance of the data or the variography. An additional important consideration is whether there are unsampled locations present within a database, which can occur for a variety of reasons. Gaps in data can be produced as part of data-cleaning exercises; for example, by removal of data deemed to be spurious during data validation (Rossi and Deutsch, 2013). More commonly, however, the database made available for resource estimation will already contain gaps that have to be accounted for and accordingly treated by the resource estimation team.

Gaps in databases can take two forms: blanks (no value or assay recorded, and treated as a missing value) or true zeros (value or assay recorded, but assigned zero because it is a true zero assay value). Different types of gaps need to be treated in different ways during resource estimation; however, the nature of gaps in sample records is not always apparent. Blanks can be caused by losses in sample during drilling, resulting in no sample being collected or not enough sample being collected for analysis to be conducted. Samples can be lost during analysis or during the digitization of old data, resulting in blanks. Zero values are normally the result of analysis being completed; however, values reporting below the analytical detection limit are also often designated as zero.

In this study, a review is conducted of the contemporary practice of regularization, followed by a short investigation, using real data, into the effect that regularization can have on data variability. The effects on key statistical parameters, such as the average, variance, and variogram, of the composite data are described. The results are discussed with relevance to published recommended practice in the estimation of mineral resources and reserves.

Overview of Published Practices

Best practice details three main procedures for producing composites of drillhole data: downhole, by bench, or by domain boundaries (Rossi and Deutsch, 2013; Sinclair and Blackwell, 2002).

Downhole compositing involves splitting the data into regular lengths based on the true length of the sample, regardless of orientation (Figure 3, Case A). This is the most commonly used

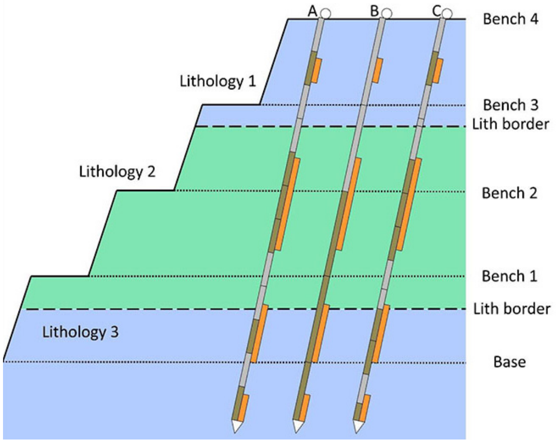

Figure 3—Three common practice methods of compositing. The bars on the right of the drillholes represent the raw data that are the same for all three drillholes. Drillhole A has been regularized by bench, Drillhole B has been regularized by length, and Drillhole C has been regularized by lengths and within domains defined by changes in lithology

method of regularization and is appropriate in most scenarios, especially when drillholes have been orientated in multiple directions and/or the future bench height is unknown.

Composites are generally calculated using the bench method in open-pit scenarios when the drilling is nearly vertical (Rossi and Deutsch, 2013). Here, the tops and bottoms of benches are defined and the assay values are averaged into these lengths on a length-weighted basis, regardless of the true length and orientation of the drillhole (Figure 3, Case B). In-pit drilling in more mature mining projects is often vertical, as, by this time, the nature of the geology is fairly well understood and oriented core is an unnecessary complication. Vertical drilling can be used in other circumstances where it is particularly relevant to understand grade by depth in less well-understood deposits.

Regularising to the same height as the blocks can be unsatisfactory in cases where the height of the blocks is unknown or the resource estimator wishes for the block size to be optimized during the kriging parameter optimization process, through methodologies such as Qualitative Kriging Neighbourhood Analysis QKNA (Vann et al., 2003). Compositing to domain boundaries can be performed using either the downhole or bench method, and can be performed earlier in the estimation process, so each geospatial domain taken forward will have its own set of composited samples (Figure 3, Case C). This has the advantage that it becomes apparent early in the data-validation process whether a sample is inside or outside a domain; if the assignment seems inappropriate, it can be adjusted. Difficulties can be encountered if very narrow or small domains are used with a relatively long compositing length, resulting in few samples remaining in the domain for estimation (Dominy et al., 2013).

The length to which samples should be regularized is not so obvious from a review of the literature. It is common practice (although not necessarily best practice) to composite samples to the same height as the blocks for which the estimate will be produced, when this height is known (Rossi and Deutsch, 2013). Theory states that this should be the case, but, in practice, this will have little impact, as the following example illustrates.

A core of 15 cm diameter and 9 m in length was regularized to produce estimates of a 25 m × 25 m × 15 m regular block, assuming a density of 2.75 t/m^3. The volume of this block is 9375 m^3 and the mass is 25 781.25 t. The practitioner has a choice of regularising to 15 m (the same as the block height) or to 3 m (which is more representative of the initial sample spacing). If the former is used, the resulting volume of the regularized sample is 0.265 m^3 ($\pi r^2 h = 3.14 \times (0.075 \text{ m})^2 \times 15$ m); in the latter case, three samples of 0.053 m^3 are generated ($\pi r^2 h = 3.14 \times (0.075 \text{ m})^2 \times 3$ m), giving a total volume 0.159 m^3. The masses of the two sets are 0.729 t and 0.437 t, respectively. The block volume/core volume ratios are 2.83×10^{-5} or 5.65×10^{-5} for the 15 m and 3 m composite lengths, respectively. It can be seen that regularising the samples to 15 m does not greatly improved the disparity between the sample and block volumes, but may result in significant smoothing of data and therefore affect the parameters of the variogram: the nugget effect will be lower and the ranges longer, leading to smoothed estimates.

In recent mining and exploration, drill-core sampling is regularly performed down the hole, resulting in little fluctuation in the sample support when different compositing lengths are applied. This is often not the case in many older and historic datasets, where sampling was conducted in a more haphazard fashion, with many changes in drilling type and sampling methods present across an area of interest. In some cases, such as sampling chips from RC or RAB drilling, a single sample might represent an entire drillhole, which is a challenge for the production of resource estimates.

At the bottom of the drillhole (and in gaps in the data), a decision has to be taken whether the last part of sample remaining after compositing has been performed should be kept or discarded (see Figure 4). As with other parts of compositing, little has been concluded concerning the best method to employ (Coombes, 2008). A general rule-of-thumb is to use half the composite length as a cut-off, so if samples are regularized to 3 m, a sample of 1.5 m will be kept and anything else discarded. This can cause problems when drilling stops due to lost core associated with weak ground conditions and corresponding low recovery of core. Weak ground conditions can often be encountered alongside mineralization in deposits such as Mississippi Valley-type lead-zinc and epithermal gold deposits (Robb, 2005; Stevens, 2012), resulting in some sources keeping the sample, even if a low percentage of the composite length remains due to the correlation between gaps in the drillcore and grade (Annels and Dominy, 2003).

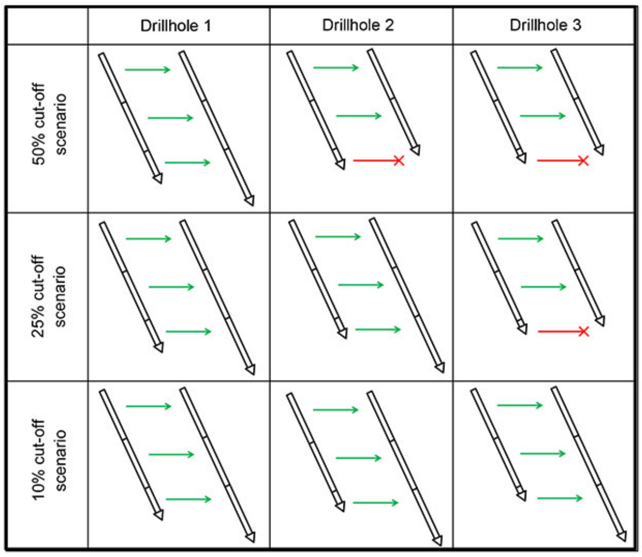

Figure 4—Effect of changing minimum kept length at the end of drillholes. The changes to three drillholes are investigated using three different scenarios, each with a different length of cut-off

Case study

The effects of compositing to different sample supports was investigated in this case study using data for samples collected using DC drilling from a kaolinized granite in Cornwall, Southwest England. Bristow (1993) and Palmer and Glass (2015) provide overviews of the history and genesis of the deposit. Drilling was performed as part of the standard orebody delineation and resource-estimation procedures across the kaolinized mass of the St Austell granite.

DC drilling was employed. The samples were analysed using X-ray fluorescence spectroscopy for elemental Fe, which occurs in minor to trace amounts. Data from eight drillholes were compiled to study the effects of compositing in detail. The most common sample length in the data was 3 m, and ranging between 2 m and 5 m. There are gaps present in the data ranging in length from 1 m to 5 m. The drillholes ranged in depth from 18 m to 40 m. Regularization was performed on each drillhole to a range of lengths, from 50 cm to 20 m. The average (arithmetic mean) and variance of the resulting data were calculated for individual composites in the drillcores and the dataset as a whole.

The statistics for the Fe variable are presented in Table I, along with the original sample lengths present in the data. From a comparison between the arithmetic average of the raw data and the length-weighted average, it can be seen that the sampling generally overestimated the Fe%, relative to the unbiased average. This is unsurprising. Although Fe is not a target element, understanding its concentration in the granite mass is important for process-control purposes, and was thus a focus of sampling effort. For three (DC01, DC07, and DC08) of the eight individual drillholes, the arithmetic average produces a lower estimate of Fe% than the composite Fe%; in the remaining five cases (DC02, DC03, DC04, DC05, and DC06), this biased estimate is higher than the composite Fe%. From interpretation of Krige's Law, it is understood that the variance of data would decrease as bigger composites are produced, whilst the average remains constant. However, it can be seen that this is not always the case (Figures 5 and 6), especially when drillcores are considered, as is the case here. Most drillholes clearly exhibited the expected downward trend in variance, but drillhole DC03 showed the reverse pattern, with the variance increasing as composite length increased. The most likely cause of this is the clear grade trend seen in this drillhole, where grade generally increased from 0.86% Fe to 5.39% Fe down the hole over six samples. When the sample was composited to increasingly longer lengths, increasingly different samples were brought into contact, thereby increasing the variance. The data here originate from the same geological unit (a kaolinized granite), but this effect could also have been caused by different geological units becoming into contact. This compositing process can thus be seen as a kind of moving-average estimation, with an increasing window size.

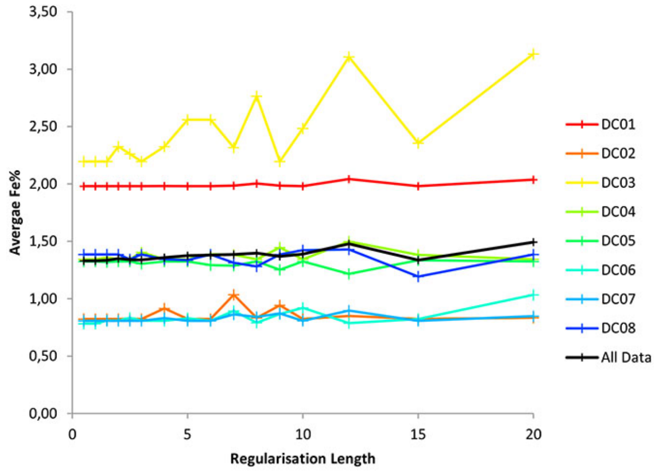

Figure 5—Change of average Fe (%) for eight drillholes holes for compositing lengths between 0.5 m and 20 m

Within the general downward trend of the variance that most drillholes display, there are composite lengths that exhibit relatively low variance compared with the surrounding values. This relatively low variance appears to correlate with multiples of the most common composite lengths in the original data; in this case, 3 m. Not all drillholes exhibit this, however, and the relatively large change in variance in DC03 (Figure 6) significantly differs from the overall pattern.

The directional (down-hole) semi-variogram produced from the data regularized to different lengths (Figure 7) displays the predicted pattern. The shorter composite lengths have a lower nugget effect due to more samples with the same grade coming into conjunction as the pre-existing samples are divided. The longer composite lengths have a generally lower sill, although the picture is more complex due to the reduction in sample pairs (Figure 7). The general shape of the variogram is repeated in composite lengths below 4 m and follows a similar pattern above 4 m, but presents a more complex picture with the 5 m and 11 m lengths all having a

Table I

Statistics of raw Fe(%) data used for compositing analysis

Drillcore number	Arithmetic (raw) average Fe %	Length-weighted average Fe%	Raw variance	Total length sampled (excluding blanks)	Total drillcore length	Number of assays	Average sample length, m
DC01	2.30	2.33	1.89	25.5	30	8	3
DC02	1.06	0.99	0.28	25	30	8	2.5
DC03	2.20	1.98	3.99	30	30	8	3.4
DC04	1.56	1.51	0.36	35.5	40	12	3.1
DC05	1.69	1.56	1.25	34	40	13	2.6
DC06	0.94	0.90	0.12	20	23	7	2.6
DC07	1.09	1.10	0.07	22	30	9	2.5
DC08	1.78	1.92	0.88	13	18	5	3

Raw average and raw variance are the arithmetic mean and the sample variance, respectively, of the data prior to regularization, excluding blank values. The number of samples is the number of individual assay values in each drillhole, including blanks prior to regularization

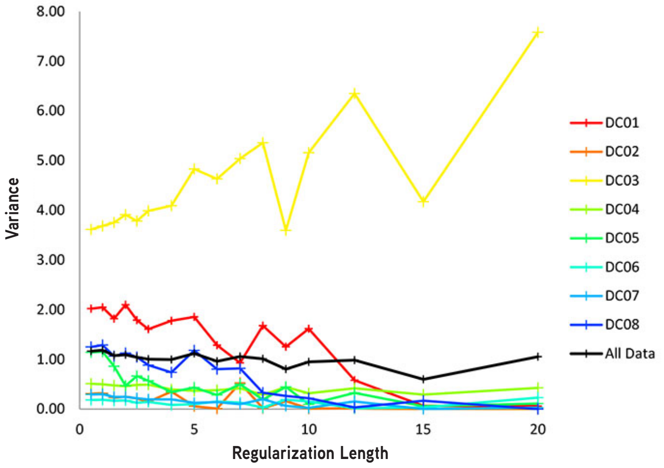

Figure 6—Change of variance for eight drillholes holes for compositing lengths between 0.5 m and 20 m

similar sill to those of the shortest composite lengths of 0.5 m and 1 m. Owing to the short nature of the drillholes, long regularization lengths would not normally be applied (unless they are necessary to conform to bench or block heights) (Clark 1979), but are included here to give a complete picture of the variogram behaviour if long composites are applied. The composite lengths of 12 m and 15 m are made up of four and five points, respectively, which would not normally be used for modelling due to lack of data, and thus losing coherency. Nevertheless, these provide useful illustrations of the effects of applying too great a composite length.

This analysis indicates that it is not readily apparent which composite length to select. If a shorter length is used, then the variance will be overall artificially increased by the increasing chance of differing values coming into contact due to the splitting of samples. At the same time, the nugget effect will decrease because samples split due to the regularization process will have zero variance between them, thereby decreasing the variance at small distances and hence the nugget effect. However, if a longer length is used, detail is lost and the variances decreases. Identifying a stable medium between these extremes is not simple and requires careful consideration by the practitioner.

The drillhole data used in these analyses contained numerous blanks, where sample had not been collected or, if collected, not analysed. The dataset contained 72 assays, with 15 blanks contained within these analysed samples. The nature and reason for observing blanks is not of interest for the purpose of this study; however, identifying the true reason for blanks in data, as either lack of grade or lack of sample, is key for successful mineral resource estimation. A separate analysis was conducted to investigate the effect that misapplication of treating breaks has on the regularization process.

Gaps in the dataset, previously treated as blanks (lack of sample) during the regularization process, were instead treated as zeros (lack of grade in analysed sample) to illustrate the effect of changing this classification (Figure 8). As expected, the average is significantly reduced by the change of classification of blanks to zeros, represented by the negative movement in Figure 8(a). The variance (Figure 8(b)) is also affected by changing the zeros in the data to blanks, although the picture is more complex. The broad pattern is that the variance of the data increased, which is expected due to a lot of the same (zero) values having been removed. However, some drillholes (for example, DC05) displayed the opposite pattern and others (DC02 and DC08) exhibited variances both above and below that of the initial data. Any change to the variance will impact the variogram and thus any geostatistical procedure that follows.

Discussion

The case study confirms the initial premise that it is probable that unintentional bias is present in drilling campaigns, even with best practice sampling and assaying procedures, and irrespective of the presence or absence of any unavoidable problems associated with sampling procedures. Regardless of whether a particular variable is targeted by the sampling/drilling regime, bias may be produced. Bias can be overcome by the drillcore regularization process, but further bias many be introduced if the full effects of compositing are not understood. Whilst Krige's Law theoretically explains the changes seen in the variance between different regularization lengths, it does not explain the full picture when real data are used. Drillhole DC03 is an example of this, where the variance increased as composite length increased (although, as a single drillhole, it is important not to read too much into this result). Effects like these could be taken to result from domaining issues, although the data used here was sourced from a single geological domain, so this is not considered a cause. Even within the general pattern of decreasing variance with increasing composite length, the pattern is more complex, with particular lengths that demonstrate relatively lower variances.

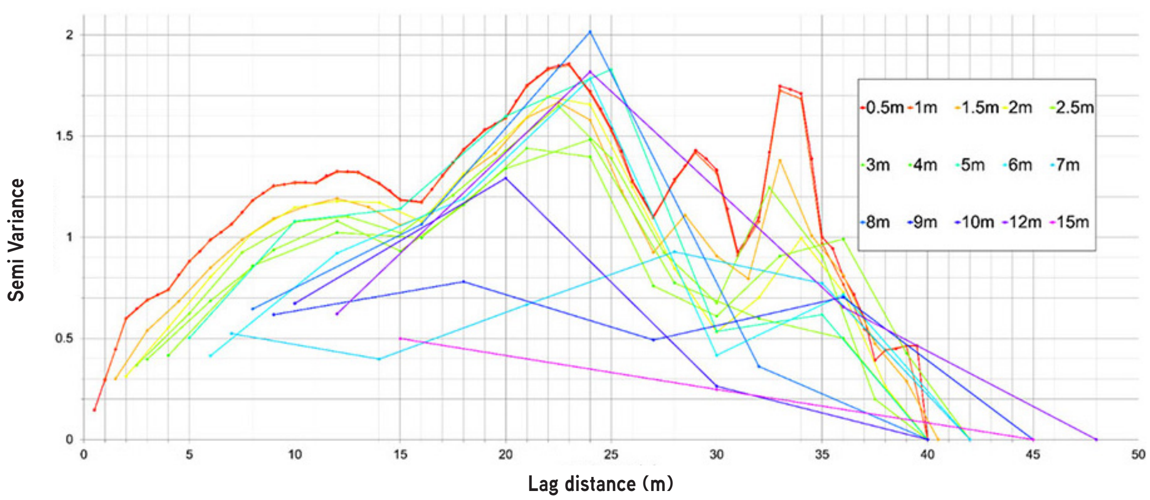

Figure 7—Experimental semi-variogram for data at different regularization lengths

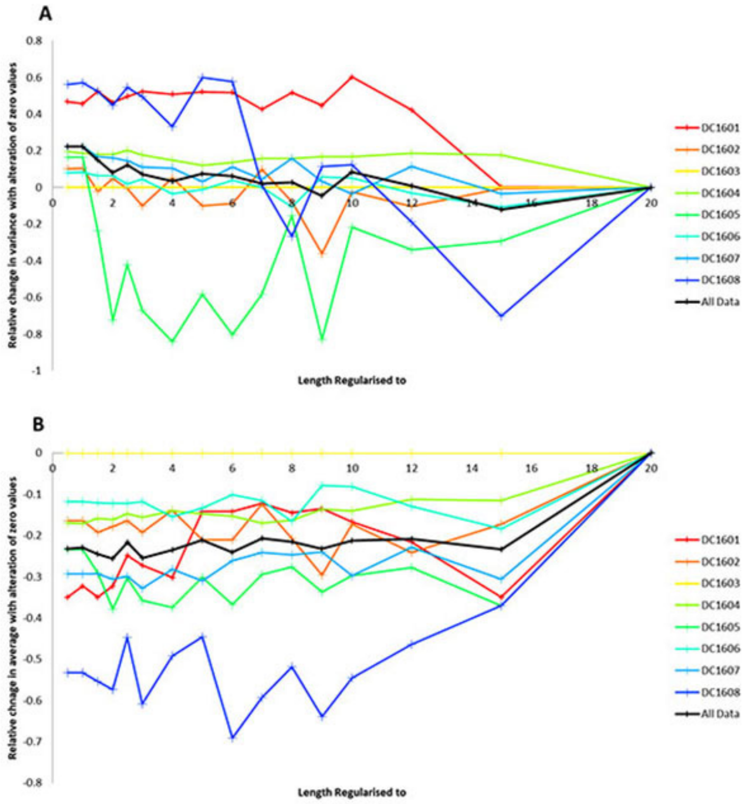

Figure 8—Illustration of the effect of misapplication of zero values on the average (A) and variance (B). Gaps in the data were initially treated as zero values (the correct interpretation) but were subsequently treated as blanks (data not presented) and the relative difference calculated

Globally, the bias produced by regularization may be negligible; however, if small changes in variance are concentrated in a particular area of a deposit, this could lead to significant divergence of local estimates. This is significant for purposes of local grade control or reconciliation between production and reserve data.

Ensuring that blanks and zero values are properly assigned is another key stage of data processing. It is shown (Figure 8) that if zeros (lost core, non-sampled, etc.) are treated as blanks, then this greatly decreases the average of the data and can change the variance.

The difference seen in the variograms, which are a key geostatistical tool, produced at different composite lengths presents a complex and unexpected result. Overall, the pattern follows that predicted by Clark (1979), where the longer compositing lengths have lower variances and higher nuggets, but some lengths do not fit this pattern, with longer lengths and actually displaying a higher variance. This makes it more difficult to select an appropriate length to which to regularize, when the basic rules of regularization seem not to hold true. This study highlights that a more detailed investigation into the effects of regularization on variography—and, ultimately, the estimate produced—is undoubtedly warranted, if a best practice solution is to be determined.

Conclusions

This study showed that there has been little recent interest in the process of optimising regularization of drillhole data for the mining industry, despite it long being known that regularization can induce bias into the estimate, by changes to the average, variance, and, ultimately, the variogram of data produced. These changes may be small, but locally significant, resulting in bias in estimates of mineral resources and reserves.

Recent academic and technical focus has mainly been on the practice of regularization, rather than best practice, resulting in a lack of guidance to the practitioner. The effects of potential bias regularization on geostatistical estimates requires further study, with focus on developing an accepted best practice or guidance in what is good practice under certain circumstances, considering the variety of ore deposits, styles of mineralization, and the demands of the regulatory framework of mineral resource estimation.

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